ESSAYS ON REGIONAL POWER SYSTEM INVESTMENT: VALUE OF PLANNING MODEL ENHANCEMENTS, TRANSMISSION GENERATION STORAGE CO-OPTIMIZATION, AND BORDER CARBON ADJUSTMENT

by

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Thesis Abstract

This thesis is composed of three essays on power system planning models, which are models that identify what assets of transmission, generation, storage, and demand-management would be beneficial to invest (or retire) over a multidecadal time horizon for large geographic regions. In the first essay, I propose a framework to systematically evaluate the economic benefits of enhancements to planning models, facilitating meaningful comparisons among model enhancements. I test the framework in a transmission expansion planning (TEP) context for the western U.S. and compare four enhancements: (1) consideration of multiple scenarios of long-run policy, economy, and technology scenarios, (2) refined representations of short-run operational variability due to demand and variable energy resources, (3) refined power flow modeling, and (4) inclusion of generation unit commitment costs and constraints. Results show that the consideration of long-run uncertainties provides the most benefits, while benefits from the other three enhancements are relatively small.

The interaction between storage and transmission can be both complementary and substitutive. In the second essay, to quantify the benefits of considering this interaction in TEP, I enhance the TEP model with storage expansion capability and test it in a planning context for the western U.S. Results show that the benefits of anticipating storage expansion in TEP increase when the assumed cost of building storage decreases but are sensitive to assumed carbon prices. Compared to the total value that storage can bring to the power system, the value of anticipating storage expansion in TEP can be significant, showing a strong impact from TEP decisions upon the profitability of storage investors.

In the third essay, I use the TEP model to test the effectiveness of different border carbon adjustment policies in the western U.S. power system, in which California is a uni-laterally regulates carbon emissions. The results show that charging electricity imports based on the facility-specific emission rate of the import contract can lead to substantial emissions leakage and even increases in total system emissions. Meanwhile, assuming the same emission rate across all electricity imports can partially mitigate leakage and result in small system-wide emissions reductions. Finally, basing the import emission rate on the marginal emission rate external to the carbon pricing regime can encourage a system-wide emission reduction, achieving the best economic efficiency.

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This dissertation is dedicated to my parents,

for their infinite patience, warm encouragement, and endless love,

and to my homeland, China

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Chapter 1 Introduction

1.1 Purpose and Problem

At 3:00 PM, on September 4th, 1882, Thomas Edison and his associates flipped the switch at his Pearl Street Station and started to generate and deliver electricity to consumers in a small area of lower Manhattan, NY. This event marked the Pearl Street Station as the first generation-to-end-use power system in history (Glover et al., 2011). Since then, power systems have evolved in many ways: direct current (DC) to alternating current (AC), higher voltages and capacities, encompassing larger regions and providing reliable, cheap electricity to almost every corner of the globe. Electricity has become the lifeblood of our civilization, and electrification has been called the most important engineering achievement of the 20th century by the National Academy of Engineering (National Academy of Engineering, 2018).

Due to ever-increasing demand as well as public yearning for a cleaner environment, power systems are constantly expanding and changing their generation technologies. Due to the gigantic size and complexity of power systems, planning for their expansion requires extremely careful consideration and often relies on powerful computerized models. Power system expansion planning models are a family of well-utilized and researched optimization models/frameworks that inform the planner where, when, and what kind of asset (transmission, generation, and, in the future, storage) is the optimal choice to be built so that the power system can reliably and sustainably meet demand at the lowest possible cost (Hobbs, 1995).

Power generation, storage, and use technologies are constantly evolving and growing in complexity, as are the systems that interconnect and coordinate them. Thus there exists much demand for and research on better power system planning models. To the planners, nevertheless, several questions still persist: *What, exactly, is a better planning model? How can we value, in economic terms, the extent to which one planning model performs better than another? Does more model complexity equate to better performance?*

The role of storage in power system planning models is crucial, and a defining characteristic of those models. Electricity has differentiated itself from other commodities such as oil by the high cost of storage and, accordingly, power system planners and electrical engineers have designed and developed the power system to maintain a minute-by-minute and even second-by-second balance of generation and consumption. With the plummeting cost of large-scale energy storage, such a restriction is fading. For a transmission planner, the question to be answered is: *How will decreasing costs of storage technology affect the transmission expansion planning?* Meanwhile for the potential investors of energy storage technologies, however, the reversed question is also intriguing: *How will the transmission expansion planning affect the profitability of the storage technology?*

The deregulation of the electricity sectors started in South America in the 1990s and has spread to the rest of the globe in the past two decades (Hobbs and Oren, 2019). This process unbundled vertically integrated utilities into different market participants: generation companies whose prices would be lightly regulated, transmission system operators who would operate the system and provide transmission services on a "common carrier" basis using cost-based rates, load serving entities who would acquire supplies for

consumers, and distribution utilities who would build and operate the low voltage grid. Among all of the multifaceted impacts, one is particularly important to power system planners: planning of transmission and generation is no longer the responsibility of one central entity, as transmission planners are to make plans for transmission expansion, and generation companies take responsibility for generation investments.

The decentralization of planning is a conceptual challenge for investment modeling, as a model for transmission investment has to make assumptions about where generation investment under the control of generators will be sited, and generation planners have to make assumptions about the availability of grid capacity to convey their power to buyers. This has stimulated a whole new area of research into "proactive" planning models that plan transmission explicitly considering the possible reaction of generator investments in terms of where, when, and what type of generation investment will occur (Sauma and Oren, 2006). In particular, they model subproblems of generation expansion and dispatch as the market-based reaction to a given transmission expansion plan. The simplest approach, which is adopted in this thesis, is to assume that the generation sector is competitive and makes investment decisions based on the marginal value of power to the system at different locations (termed "locational marginal pricing"), e.g., van der Weijde and Hobbs (2012) and Spyrou et al. (2017). These models can be formulated as single optimization models, which I prove in the Appendix A. Alternatively, if there are market imperfections, such as strategic generation companies that can exercise market power, more complex bilevel models such as, for example, Pozo et al. (2013), have been proposed.

If we assume that transmission is planned by a benevolent central authority that is attempting to maximize market efficiency subject to environmental and other policies, and

the reaction of a competitive generation sector to those policies as well as transmission prices, the basic proactive planning model described above can be conceptually extended into a policy assessment tool. This extends the basic principle of Samuelson (1952), who showed how a market benefits-maximizing optimization model is equivalent to a simulation of a competitive market. By altering the design of policies, their effect upon optimal transmission plans and the competitive generation sector can be assessed (Hobbs, 1995; Hogan, 2002), answering questions like *What is the impact of a certain policy on the power sector's economic efficiency and environmental impacts? How will individual market participants react to this policy, and how is their welfare or profits affected?* In this vein, I will use my power system planning tool to investigate important questions about carbon pricing policy.

Pricing carbon emissions, in particular emissions from power systems, has become an important strategy to combat climate change. Due to the political system, carbon pricing activities in the United States are often local, i.e., at a multistate- or even single-state-level. In an interconnected power system, if electricity generated in one place becomes more expensive because of carbon pricing, consumers can just buy electricity elsewhere. Carbon emissions, though, also leak elsewhere. At the national-level, emissions may not change at all. Nevertheless, *What can a local emission regulator do to mitigate such emissions leakage? Can he choose to tax or price the carbon flowing on the state boundary? How will this action affect the power system and the resulting emissions?*

1.2 Scope

The first part of this thesis addresses the development and economic valuation of better planning models. Numerous ways exist to enhance a power system planning model

to render it "better" (more realistic); most of them come with heavier computational burdens and result in a longer solving time. Just like a forecast model is useless if it needs 10 minutes to forecast the future 10 minutes away, a planning model can lose its value if it takes months or years to provide a plan. Comparing and choosing a valuable enhancement to a planning model is thus imperative. I ask the following questions that have never been systematically answered: *What, exactly, is a better planning model? How can we value, in economic terms, the extent to which one planning model performs better than another? Does more model complexity equate to better performance?*

To answer these questions, I developed a framework called the "Value of Model Enhancements" to systematically quantify the economic benefits to add any enhancement, for instance, higher temporal resolution, in the planning model. As a demonstration, I tested this framework to evaluate the benefits of four enhancements to a planning model of the western United States: the addition of unit commitment modeling, the addition of accurate power flow modeling, the refinement of higher temporal resolution, and the consideration long-term uncertainty.

The second part of my thesis is to answer the following two questions: *How will the merging storage technology affect traditional power system planning*, and in turn, *how will traditional power system planning affect the storage profitability?* With my established evaluation framework in Chapter 3, I further enhance the existing planning model with battery storage expansion functionality and quantify the value of such enhancement (in Chapter 4). As an illustration, I provide numerical results for the power system planning for the western United States.

The third part of my thesis involves answering: *What can a local emission regulator do to mitigate carbon leakage? Can he choose to tax or price the carbon flowing on the state boundary? How will this action affect the power system and the resulting emissions?* I limited my scope to one potential approach: the border tax adjustment on carbon emission (Ismer and Neuhoff, 2007), also known as border carbon adjustment (BCA). With a further enhancement in the planning model to include better carbon policy representation, in Chapter 5 and 6, I comprehensively assess the impact of different BCA schemes of the California carbon emission trading system on the western power system by reviewing local and system-wide emissions, generation production, and consumer cost.

I organize the remainder of the thesis as follows. In Chapter 2, a comprehensive view of the Johns Hopkins Stochastic Multistage Integrated Network Expansion (JHS-MINE) tool is given, including the modeling rationale, notation, formulation, and equation explanation. This tool serves the Chapters 3-5, present the main results of this dissertation. Each is organized with its own chapter introduction, literature review, formulation/theory development, experiment design, numerical results, and conclusion. Chapter 7 concludes this thesis. The database of the thesis involves millions of entries, and part of it is proprietary, and it is thus not reproduced int this thesis; however, the important procedures for the database development, such as network reduction, are provided as Appendices.

Chapter 2 Johns Hopkins Stochastic Multistage Integrated Network Expansion (JHSMINE) Planning Model[1]

2.1 Chapter Summary and Introduction

In this chapter, I demonstrate the general structure and detailed formulation of the Johns Hopkins Stochastic Multistage Integrated Network Expansion (JHSMINE) planning model. JHSMINE is a long-term Transmission-Generation-Storage expansion planning model based on stochastic programming and it shares the goal of other power system planning models, which is to help the power system planner to answer the question of the three "W's": when and where to add what kind of facilities into the grid so that the social welfare (a metric of market efficiency) is maximized.

JHSMINE evaluates the performance of alternative designs and operations using the objective of societal welfare (or societal cost, if assuming perfect inelastic demand and a constant value of the lost load.) This performance is estimated by JHSMINE's detailed generation, transmission, and storage operation modeling, as well as renewable energy policy and power system reliability requirements. JHSMINE's generation operation modeling includes decision variables and constraints for unit commitment and dispatch. As for transmission operation modeling, JHSMINE includes the linearization of ac power flows (i.e., the DC OPF model, described later in this chapter). Storage operation includes the charge, discharge, and state-of-charge management decision variables and constraints. JHSMINE includes detailed renewable energy policy modeling, which involves renewable portfolio

[1] This chapter is in part based on previous works in which I paricipated, including Ho et al. (2016) and Hobbs et al. (2016).

standards (RPS) fulfillment constraints and renewable energy credit trading. For reliability of the power system, JHSMINE models operating reserves, resource adequacy requirement as well as flowgate limits. In short, JHSMINE adopts a bottom-up engineering-economic approach.

JHSMINE is also featured by its capability to model long-term uncertainties, as well as short-term risks. Here, long-term uncertainties refer to uncertain system conditions set by factors that are usually on a yearly or larger time scale: for example, the electricity demand set by the economic growth and policies that promote energy efficiency. Long-term uncertainties modeled in JHSMINE are exogenous, and I will discuss them in the following sections of this Chapter. Short-term risks, on the order hand, are uncertain system conditions that occur on a sub-yearly time scale: for instance, hourly wind variability and forecast uncertainty. Notably, short-term uncertainties are sometimes endogenous; to wit, the wind uncertainty stems from both the newly installed wind capacity (a decision variable) and wind profiles (an exogenous parameter).

To handle uncertainty, JHSMINE adopts the approach of scenario-based stochastic programming; imagine a scenario tree where each tree node associates with a marginal probability and a cost. Stochastic programming is to minimize the expected cost of the whole tree. In the same manner, JHSMINE picks the optimal set of facilities to install so that the probability-weighted sum of scenario-specific system costs is minimized.

This chapter is organized as follows. Initially, I present the development process and the general structure of JHSMINE. Then, I define the JHSMINE nomenclature, after which I present a detailed formulation of JHSMINE.

2.2 The General Structure of JHSMINE

A prototype of JHSMINE first appeared in van der Weijde and Hobbs (2012) for the U.K. power system and was then applied to the power systems of Western U.S. in (Munoz et al., 2014) with the enhancement of DC OPF power flow modeling. Both and later versions of JHSMINE are based on the idea of "proactive" transmission planning: the transmission planner in JHSMINE stands as a societal welfare maximizer and selects the best set of transmission lines while anticipating the reactions from other market participants in the power sector (Sauma and Oren, 2006; Sauma and Oren, 2007). The justification of "proactive" transmission planning relies on multiple assumptions, such as the perfect competition among generation companies, full knowledge of the cost function of generation and capacity expansion, etc. For a more comprehensive review of required assumptions, I refer readers to Krishnan et al. (2015) and Spyrou et al. (2017).

The model team at Johns Hopkins University later enhanced the model with renewable energy credit trading (Ho et al., 2016) and unit commitment (Kasina et al., 2013) and then officially named the model as JHSMINE; a full formulation is provided in Xu and Hobbs (2019) and Xu and Hobbs (2017). I, here in this thesis, refined JHSMINE by expanding it from two-stage to multi-stage and adding the modeling of storage operation (Xu and Hobbs, 2018). In this chapter, I present the latest version of JHSMINE.

Since the very first beginning of the JHSMINE development (van der Weijde and Hobbs, 2012), the structure of it has been composed of three things: a planning horizon, a set of operation simulations, and a scenario tree. A planning horizon defines (1) how investment decisions made in the previous years will affect the years after and (2) how JHSMINE will discount the cash flow stream. The operation simulation defines the power

system operation within the planning horizon: it answers the question of *given the existing and new facilities and other system conditions (e.g., load and fuel price), how the system will be operated to achieve the minimal system cost*; also, operation simulation also generates the operation cost cash flow as well as the investment cash flow. A scenario tree is a stochastic extension of the planning horizon, and it defines the relationship between "here and now" decisions, the resolution of long-run uncertainties, and "wait and see" decisions. In the remainder of this section, I will provide details concerning the planning horizon, operation simulations, and the scenario tree.

2.2.1 Planning Horizon

A planning horizon of JHSMINE is composed of a set of decision-making time points and operation simulation intervals. An example is shown in Figure 2.1: the square shows one decision-making point, and the gray boxes show three operation simulation intervals. One operation simulation interval can include more than one year, but JHSMINE assumes that all years within one interval are identical; to wit, see Figure 2.1 and observe that (1) each operation interval has three years, (2) operation cost cashflows (black dashed arrows) occur at the end of each year, and (3) operation cost cashflows within each operation intervals are identical in length. For a certain facility (e.g., a transmission line), JHSMINE makes an expansion/retirement decision at a decision-making point, and this decision will realize (i.e., commissioned or decommissioned) in the system after the decision lead time[2]; the solid arrow in the upper part of Figure 2.1 shows investment decisions made at the decision-making point will be available to the system at year y_3. Such a commission

[2] Lead time is the time between the issue time of the decision and the realization of the decision; such a lead time can be caused by the permitting, the construction of the facility, or an announcement in advance.

(or decommission) introduce an overnight cost (or salvage revenue) at the beginning of year y_3, which is represented by the red dashed arrow in Figure 2.1.

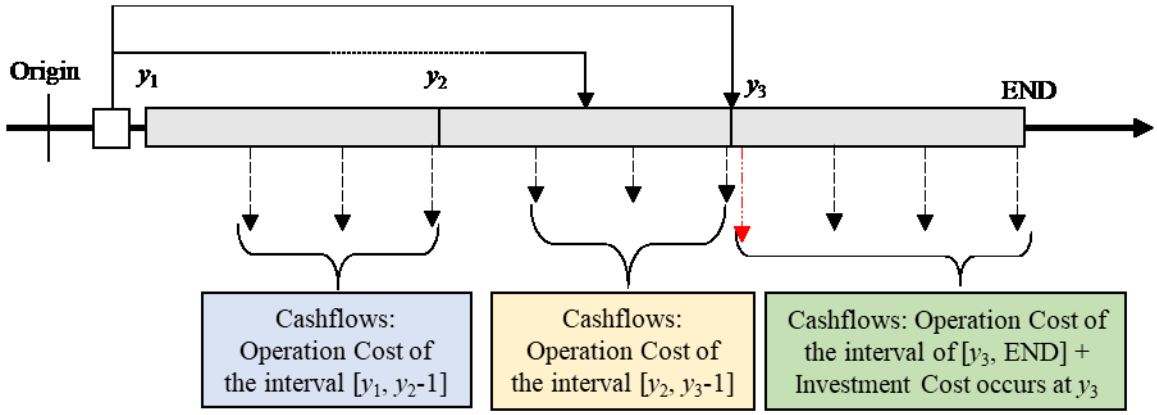

Figure 2.1. The example diagram of the JHSMINE planning horizon. The red arrow stands for the occurrence of the capital cost, while the black dashed arrows stand for the occurrences of operation costs.

A special case may emerge: a decision is made, but its lead time ends between y_2 and y_3 (the dashed arrow in the upper part of Figure 2.1). To comply with the assumption of identical cashflows within operation simulation intervals, JHSMINE pushes the realization of such decision to the beginning of the next operation simulation interval; to visualize, from the middle of y_2 and y_3 to the beginning of y_3 in Figure 2.1. All of the cash flows, including overnight costs of facility construction and system operation cost (fuel cost, operation and maintenance costs, etc.), are then discounted back to the beginning of the planning horizon, yielding the net present value of the system cost.

2.2.2 Operation Simulations

The core of JHSMINE is the operation simulation intervals (the gray boxes in Figure 2.1), for they define the performance of the investment decisions. As mentioned in the previous section, each operation simulation interval can include one or more years; JHSMINE assumes them to be the same as the first year of the interval, which is called

operation year. In this section, I provide a general review of the operations simulated by JHSMINE; I will show detailed formulation starting from Section 2.3.

Within each operation year, JHSMINE simulates participant activities down to the hourly level. Table 2.1 summaries the participants and their activities modeled in JHSMINE. The participants include the independent system operator (ISO), load-serving entities (LSEs), generation companies, and storage companies. Government and other participants such as fuel suppliers, construction companies are exogenous to JHSMINE.

Table 2.1. Power Sector Participants and Activities Modeled in JHSMINE. Cell contents show whether a participant (top row) is a buyer/seller or arbitrager of each commodity/service (first Column.)

	ISO (Transmission)	LSE (Load)	Generation Company	Storage Company	Government	Others
Electricity Market	Arbitrager	Buyer	Seller	Buyer/Seller	-	-
Spinning Reserve	-	Buyer	Seller	Seller	-	-
Resource Adequacy	-	Buyer	Seller	Seller	-	-
Renewable Credit	-	Buyer	Seller	-	Seller*	-
Carbon	-	Buyer (Taxpayer) **	Buyer (Taxpayer)	Buyer (Taxpayer)	Seller (Tax collector)	-
Short-term Cost	-	-	Buyer	Buyer	-	Seller
Long-term Construction Cost	Buyer	-	Buyer	Buyer	-	Seller

*: Government is the supplier of alternative compliance credit
**: LSE is a consumer of carbon allowance or a subject to the carbon tax when the load-based carbon pricing or the first-deliver carbon pricing is adopted

For electricity (2nd row of Table 2.1), JHSMINE assumes that (1) LSEs, Generation companies, Storage companies trade electricity at the load marginal price settled by ISO, and (2) demand functions are purely inelastic (i.e., fixed load). The ISO is responsible for the unit commitment and economic dispatch and operates the transmission system. For ancillary services (3rd row of Table 2.1), JHSMINE currently only models the spinning reserve market.[3]

The annual resource adequacy requirement (or planning reserve, 4th row of Table 2.1) of each load-serving entity is modeled in JHSMINE. The state-level renewable portfolio standards (RPS) and carbon price/tax are modeled (5th and 6th rows of Table 2.1). The RPS is modeled at the load end, meaning that LSE needs to buy renewable energy credit (RECs) from generators to meet the requirement. Each generator needs to buy emission allowances (or pay the carbon tax) if applicable.

To provide the commodities and services, generation and storage companies need to pay the fuel cost, operation, and maintenance cost, and startup cost if applicable; these payments are received by entities outside of JHSMINE, such as natural gas producers (7th row of Table 2.1). Similarly, the parties who receive revenues from constructing transmission lines (from the ISO), generators (from generation companies), and storage facilities (from storage companies) are also external to JHSMINE (8th row of Table 2.1).

The objective function of JHSMINE is the summation of the welfare of all endogenous market participants (the first four columns of Table 2.1). Since the load is purely inelastic, the welfare of the LSE is the negative of its payments for energy and other

[3] Spinning reserve market is the market where, on behalf of LSEs, ISO purchases the reserved capacities from running (thus, "spinning") generators who promise that the purchased capacities can be readily ramped-up (e.g., in 10 mins) to fulfill an extra net load caused by contingencies. An example is CAISO's spinning reserve as part of the ancillary service market (CAISO, 2019).

commodities. Thus, each of the rows of Table 2.1 will sum to zero; to pick the electricity market as an example, the net of LSEs' payments, generation companies' revenues, storage companies' revenues, and the ISO's congestion rent will be zero. Furthermore, because the welfare of the government and other players are exogenous to JHSMINE, the summation of the first four columns is just the summation of the gray boxes in Table 2.1. In other words, for each operation year, the cash flow happens at the end of the year is:

$$\textit{Operation Cost} = \textit{Fixed O\&M Cost} + \textit{Variable O\&M Cost} + \textit{Fuel Cost} + \textit{Start-up Cost} + \textit{RPS non-Compliance Penalty} + \textit{Emission Allowance Payment}$$

The investment cost happens at the beginning of operation simulation intervals is:

$$\textit{Investment Cost} = \textit{Expansion Cost} - \textit{Salvage Revenue}$$

2.2.3 Scenario Tree

After the planning horizon and operation simulations are defined, I can expand the planning horizon to a scenario tree by adding a scenario-axis in JHSMINE. A node of the scenario tree can be defined as a pair of scenario and year; scenario tree nodes representing the operation simulation interval are referred to as the operation node and represented as (*scenario, the first year of operation simulation interval*.) And the long-run uncertainty parameters (Table 2.2) are realized in each scenario tree nodes. For example, a scenario tree node can have the following entries in the year 2020, the cost of building a solar farm is $1500/MW in scenario 1.

Table 2.2. Default Available Long-run Uncertainty Parameters in JHSMINE

Long-run Uncertainties	Description
Carbon Policies	State-level carbon price/tax in each operation simulation interval
Fuel Price	Fuel price (gas, coal, etc.) in each operation simulation interval
Generation Build Cost	Cost of building new generators
Generation Commission	Availability of existing generators
Intermittent resource Availability	The hydroelectric power availability (e.g., Wet, dry year, etc.), wind, and solar.
Line Build Cost	Cost of new transmission lines
Line Commission	Availability of existing transmission lines
Load	Load conditions (high/medium/low load growth, etc.)
RPS	State-level RPS policy aggressiveness (higher/lower than the base case requirement)
Storage Build Cost	Cost of new storage facilities
Storage Commission	Availability of existing storages

I explain some useful notation here. The nodes are connected by the branches of the scenario tree, and if a node A can be tracked backward temporally to another node B, the latter will be an *ancestor node* to node A, and the node A is a *descendant node* to node B. The decision made in the ancestor node will affect all its descendant nodes. A pair of an ancestor node and a descendant node that are adjacent in a scenario tree are also called the *parent node* and the *child node*. Scenario tree branches must not cross; thus any node can have only one parent node. In particular, the first node of the scenario tree (the ancestor node to all other nodes) is called the *root node*.

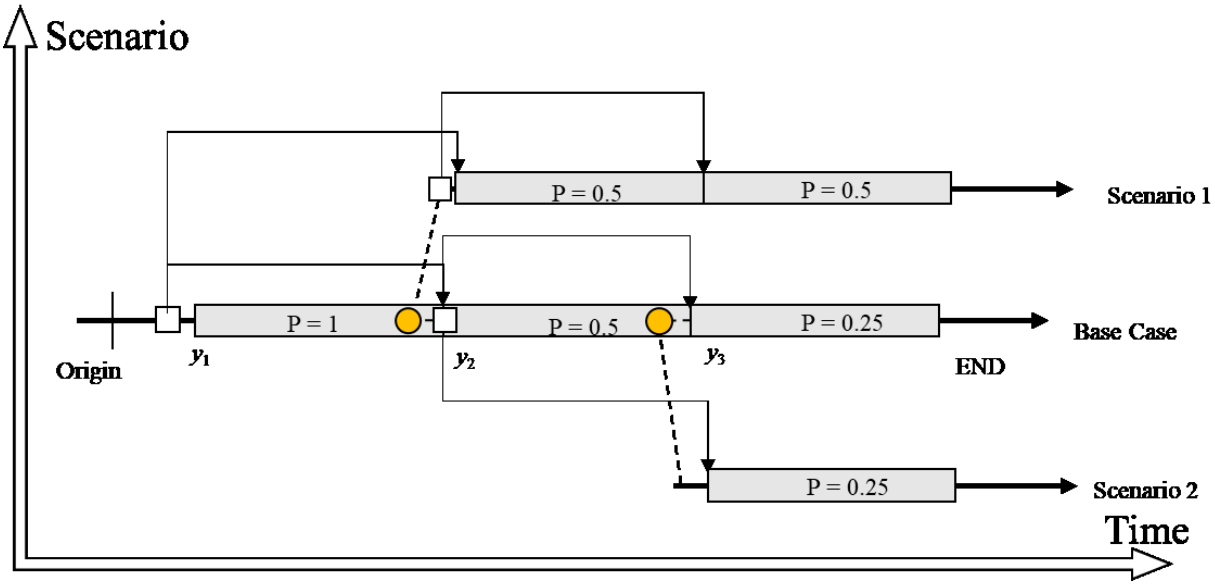

Figure 2.2. Example diagram of the JHSMINE scenario tree.

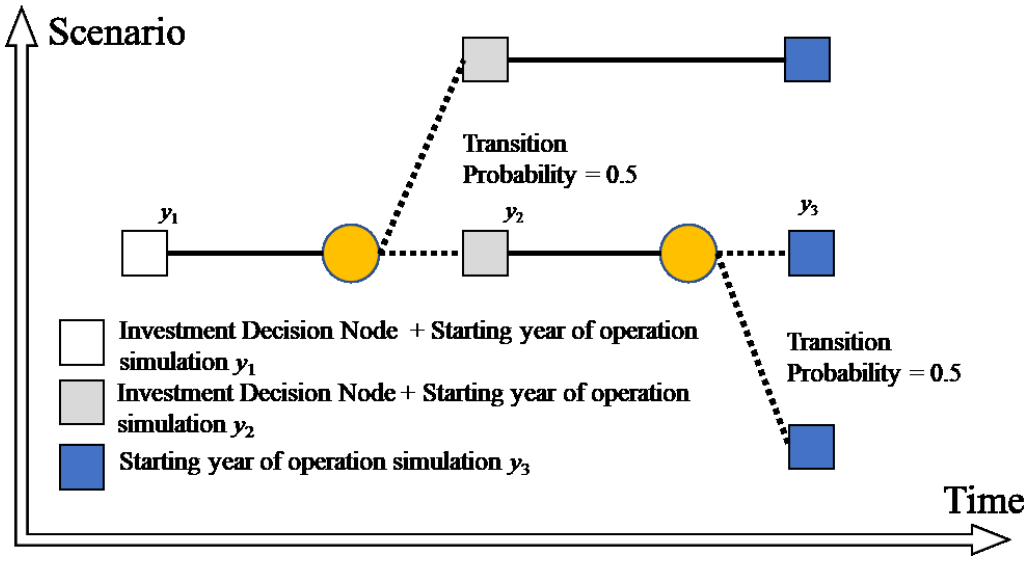

Figure 2.3. Example diagram of the JHSMINE scenario tree (Classic view).

Figure 2.2 shows an example of a JHSMINE scenario tree and Figure 2.3 shows a version of the same scenario tree following the style in Clemen and Reilly (1999): each decision node (square boxes) and each gray box (operation simulation interval) can be viewed as a scenario tree node (there are six in the plots, if the decision-making time points

coincident with the beginning of simulation intervals.) In this example, the base case branches twice where the chance nodes are (yellow circles): the first branch is between y_1 and y_2 while the second branch is between y_2 and y_3. Note that the first decision made in the base case will be realized in all three scenarios, while the second decision made in the base case will only be realized in the base case and scenario 2. This scenario tree structure also prevents the decision made in scenario 1 from affecting scenario 2. The branches of the scenario tree must not cross: for example, there will be no decision affecting arrow of scenarios 1 or 2 that then links back to the base case scenario. The probability of each operation simulation interval is calculated as the product of 1) the probability of the parent node and 2) the transition probability from the parent node to the child node.

With the three major components of JHSMINE discussed, now I am ready to present the detailed formulation of JHSMINE, starting with the nomenclature.

2.3 Nomenclature

2.3.1 Sets

A	Balancing authority areas, index a.
E	Energy storage technologies, index e.
F	Fuel types, index f.
G	Generation technologies, index g.
H	Hours, index h.
I	Buses, index i.
J	Energy storages, index j.
K	Generators, index k.
L	Transmission lines, index l.

P	Path/Flowgates, index p.
R	Reserve sharing groups, index r.
S	Scenarios, index s.
W	States/Provinces, index w.
Y	Years, index y.

2.3.2 Subsets

A_r	Balancing Authority Areas that are members of reserve sharing group r.
I_w	Buses that are geographically in the state w.
I_a	Buses that belong to the balancing authority area a.
J_a	Energy storage facilities that belong to the balancing authority area a.
J_e	Energy storage facilities that belong to the energy storage technology e.
J_f	Energy storage facilities that use fuel f to generate electricity.
J_i	Energy storage facilities that are connected to the bus i.
J_w	Energy storage facilities that belong to the state w.
K_a	Generators that belong to the balancing authority area a.
K_f	Generators that use fuel f to generate electricity.
K_g	Generators that belong to the generation technology g.
K_i	Generators that are connected to the bus i.
K_w	Generators that belongs to the state w.

2.3.3 Parameters

$CTAX_{s,y,w}$	Carbon price or tax of state w in the scenario tree node (s,y), unit: \$/ton.
D_y	Discounting factor of year y to the beginning of the planning horizon.

DA_y	Accumulative discounting factor of year y to the beginning of the planning horizon.
$ECOM_{s,y,j}$	Commission status the storage facility *j*, unitless.
$EECP_j$	Energy capacity of the storage *j*, unit: MWh.
$EELCC_{a,e}$	Expected load-carrying capability specified by balancing area *a* for the energy storage technology *e*, unitless.
EER_j	Emission rate of the storage facility *j*, unit: metric ton CO_2e/MWh.
$EEXC_{s,y,j}$	Expansion cost of the storage facility *j* in scenario tree node (*s,y*), Unit: $.
$EFOM_j$	Fixed O&M cost of the storage *j*, unit: $/MW-year.
$EGCP_j$	Generating capacity of the storage *j*, unit: MW.
$EGEF_j$	Generating efficiency of the storage *j*, unitless.
EHR_j	Heat rate of the storage *j*, unit: MMBTU/MWh.
$ELED_j$	Lead year of investment decision of the storage *j*, unit: year.
$EPCP_j$	Pumping capacity of the storage *j*, unit: MW.
$EPEF_j$	Pumping efficiency of the storage *j*, unit: fraction.
$ESAL_{s,y,j,s',y'}$	Salvage revenue of storage facility *j* if expanded in the scenario tree node (*s',y'*) and retired in node (*s,y*), unit: $.
$EVOM_j$	Variable O&M cost of the storage *j*, unit: $/MWh.
$FC_{s,y,h,f}$	Price of the fuel *f* at hour *h* in scenario tree node (*s,y*), unit: $/MMBTU.
$GCOM_{s,y,k}$	Commission status of the generator *k* in scenario tree node (*s,y*), unitless.
$GELCC_{a,g}$	Expected load-carrying capability specified by balancing area *a* for generation technology *g*, unitless.
GER_k	Emission rate of the generator *k*, unit: MW.

$GEXC_{s,y,k}$	The expansion cost of the generator k in scenario tree node (s,y), unit: \$.
$GFOM_k$	Fixed operating and maintenance cost of the generator k, unit: \$/MW-year.
$GFOR_k$	Forced outage rate of the generator k, unitless.
$GHAV_{s,y,k,h}$	Hourly availability of the generator k, unitless.
GHR_k	Average heat rate of generator k, unit: MMBTU/MWh.
$GLED_k$	Lead year of the investment decision of the generator k, unit: year.
$GMDT_k$	Minimum downtime of the generator k, unit: hour.
$GMIN_k$	Minimum run as a fraction of the capacity, unitless.
$GMUT_k$	Minimum uptime of the generator k, unit: hour.
$GNPL_k$	Nameplate capacity of the generator k, unit: MW.
$GPOR_k$	Planned outage rate of the generator k, unitless.
$GRPR_k$	One-hour ramp rate as a fraction of the capacity, unitless.
$GSAL_{s,y,k,s',y'}$	The salvage revenue of the generator k if it is expanded in scenario tree node (s',y') and retired in the node (s,y), unit: \$.
GSP_k	Spinning reserve cap as a fraction of the capacity, unitless.
$GSUC_k$	Start-up cost of generator k per unit of the capacity, unit: \$/MW.
$GVOM_k$	Variable operating and maintenance cost of the generator k, unit: \$/MWh.
$HW_{y,h}$	# of hours represented by hour h in year y, unit: hour.
$IRPS_{s,y,w}$	Instate RPS of state w, unitless.
LB_l	Line susceptance of the transmission line l, unit: p.u.
$LBI_{l,i}$	Line-bus incidence matrix. 1 if bus i is the to-bus of line l; -1 if bus i is the from-bus of line l; 0 otherwise, unitless.
LBM_l	Big positive number for KVL disjunctive constraints, unit: MW.

$LCOM_{s,y,l}$	Commission status used for the existing transmission line l, unitless.
$LEXC_{s,y,l}$	Expansion cost of the transmission line l in the scenario tree node (s,y), unit: \$.
$LLED_l$	Lead year of investment decision of the transmission line l, unit: year.
$LOAD_{s,y,h,i}$	Bus-level load; i.e., electricity demand, unit: MW.
$LSAL_{s,y,l,s',y'}$	Salvage revenue of the transmission line l if it is built in the scenario tree node (s',y') and retired in the node (s,y), unit: \$.
LTM_l	Line rating (or the thermal limit) of the transmission line l, unit: MW.
$PBASE$	Base power, unit MW.
PBD_p	Existing limit of the path/flowgate p in the backward direction, unit: MW.
$PBDE_{p,l}$	Expansion on the backward limit of path p if the line l is built, unit: MW.
$PEAK_{s,y,r}$	Peak demand of reserve sharing group in the scenario tree node (s,y), unit: MW.
PFD_p	Existing limit of the path/flowgate p in the forward direction, unit: MW.
$PFDE_{p,l}$	Expansion on the forward limit of path p if the line l is built, unit: MW.
$PLI_{p,l}$	Path-line incidence matrix. 1 if the transmission line l is part of the path p and flows in the same direction as p; -1 if the transmission line l is part of the path p and flows in the opposite direction; 0 otherwise, unitless.
$RACP_w$	Alternative compliance penalty for RPS of state w, unit: \$/MWh
$RE_{w,g}$	Renewable eligibility; 1 of the technology g is considered as renewable in the state w, unitless.
$RMSP_r$	Spinning reserve margin of the reserve sharing group r, unitless.
$RMPL_r$	Planning reserve margin of the reserve sharing group r, unitless.

$RPS_{s,y,w}$ Renewable portfolio standards (RPS) of state w in scenario tree node (s,y), unitless.

$RPSO_{s,y,w}$ Other RPS of state w, unitless.

$RPSS_{s,y,w}$ Solar RPS of state w for solar, unitless.

$RPSW_{s,y,w}$ Wind RPS of state w, unitless.

$SDOI_{s,y,s',y'}$ Decision operation incident. 1 if the node (s,y) is a descendant node of (s',y'), unitless.

$SP_{s,y}$ Scenario probability, unitless.

$VOLL$ Value of lost load, unit: $/MWh.

2.3.4 Special Notation

(s_0,y_0) The root node of the scenario tree.

(s_1,y_1) The first operation node.

(s_p,y_p) The previous operation node.

$Pre(y)$ The previous operation year,

2.3.5 Variables

2.3.5.1 Expansion and Retirement Variables

$eexp_{s,y,j}$ Storage expansion decision, 1 if an expansion decision is made for the storage j in (s,y), binary, unitless.

$eincexp_{s,y,j}$ Storage incremental expansion, 1 if the storage j becomes commissioned in (s,y), binary, unitless.

$eincret_{s,y,j,s',y'}$ Storage incremental retirement, 1 if the storage j that became commissioned in (s',y') is decommissioned in (s,y), binary, unitless.

$eret_{s,y,j,s',y'}$ Storage retirement decision, 1 if a retirement decision is made in (s,y) for the storage j that becomes online in (s',y'), binary, unitless.

$estat_{s,y,j}$ Storage commission status, 1 if the storage j is in commission in (s,y), binary, unitless.

$gexp_{s,y,k}$ Generator expansion decision, 1 if an expansion decision is made in the scenario tree node (s,y), binary, unitless.

$gincexp_{s,y,k}$ Generator incremental expansion, 1 if the generator k starts to be commissioned in (s,y), binary, unitless.

$gincret_{s,y,k,s',y'}$ Generator incremental retirement, 1 if the generator k that became online in (s',y') is decommissioned in (s,y), binary, unitless.

$gret_{s,y,k,s',y'}$ Generator retirement decision, 1 if a retirement decision is made for generator k in (s,y) if it is online in (s',y'), binary, unitless.

$gstat_{s,y,k}$ Generator commission status, 1 if the generator k is in commission in the scenario tree node (s,y), binary, unitless.

$lexp_{s,y,l}$ Transmission line expansion decision, 1 if an expansion decision for transmission line l is made in (s,y), binary, unitless.

$lincexp_{s,y,l}$ Transmission line incremental expansion, 1 if the transmission line l becomes commissioned in (s,y), binary, unitless.

$lincret_{s,y,l,s',y'}$ Transmission line incremental retirement, 1 if the transmission line l that becomes commissioned in (s',y') is decommissioned in (s,y), binary, unitless.

$lret_{s,y,l,s',y'}$ Transmission line retirement decision, 1 if a retirement decision is made in (*s,y*) for the transmission line *l* that becomes commissioned in (*s',y'*), binary, unitless.

$lstat_{s,y,l}$ Transmission line commission status, 1 if the transmission line *l* is in commission in the scenario tree node (*s,y*), binary, unitless.

2.3.5.2 Operation Variables

$cpf_{s,y,g,h,w1,w2}$ Energy credit of the technology *g* flowing from the state *w1* to the state *w2* at the hour *h*.

$echg_{s,y,h,j}$ Discharge of the storage *j* at the hour *h*, nonnegative, unit: MW.

$edis_{s,y,h,j}$ Discharge of the storage *j* at the hour *h*, nonnegative, unit: MW.

$elev_{s,y,h,j}$ Energy level of the storage *j* at the beginning of hour *h*, nonnegative, unit: MWh.

$eors_{s,y,h,j}$ Operating (spinning-) reserve provided by the storage *j* at the hour *h*, nonnegative, unit: MW.

$gopt_{s,y,h,k}$ Power output of the generator *k* at the hour *h*, nonnegative, unit: MW.

$gopstat_{s,y,h,k}$ Operating status of the generator *k* is on at hour *h*, binary, unitless.

$gors_{s,y,h,k}$ Operating (spinning-) reserve of the generator *k* at the hour h, nonnegative, unit: MW.

$gpmin_{s,y,h,k}$ Effective minimum run capacity of the generator *k* at hour *h*, nonnegative, unit: MW.

$gsdn_{s,y,h,k}$ Shut-down action of the generator *k* at the beginning of the hour h, binary, unitless.

$gsup_{s,y,h,k}$ Start-up action of the generator k at the beginning of the hour h, binary, unitless.

$pa_{s,y,h,i}$ Phase angle of the bus i at the hour h, unrestricted, unit: rad.

$pf_{s,y,h,l}$ Power flow on the transmission line l at the hour h, unrestricted, unit: MW.

$nload_{s,y,h,i}$ Load shedding at bus i at the hour h, nonnegative, unit: MWh.

$norps_{s,y,h,w}$ Non-compliance with other RPS policy, unit: MW, nonnegative.

$nrps_{s,y,h,w}$ Non-compliance with RPS policy, unit: MW, nonnegative.

$nsrps_{s,y,h,w}$ Non-compliance with Solar RPS policy, unit: MW, nonnegative.

$nwrps_{s,y,h,w}$ Non-compliance with Wind RPS policy, unit: MW, nonnegative.

2.3.5.3 Objective Function Variables

obj Objective function, unit: $.

$invc_{s,y}$ Investment cost occurs at the scenario tree node (s,y), unit: $.

$oprc_{s,y}$ Operation cost occurs at the scenario tree node (s,y), unit: $.

$fomc_{s,y}$ Fixed O&M cost occurs at the scenario tree node (s,y), unit: $.

$fuel_{s,y}$ Fuel cost occurs at the scenario tree node (s,y), unit: $.

$vomc_{s,y}$ Variable cost occurs at the scenario tree node (s,y), unit: $.

$stuc_{s,y}$ Start-up cost occurs at the scenario tree node (s,y), unit: $.

$ctax_{s,y}$ Carbon tax payment occurs at the scenario tree node (s,y), unit: $.

$voll_{s,y}$ Lost load cost occurs at the scenario tree node (s,y), unit: $.

$rpsc_{s,y}$ Cost of renewable portfolio standards non-compliance penalty, occurs at the scenario tree node (s,y), unit: $.

2.4 Formulation

In this section, I demonstrate the formulation of JHSMINE. In Section 2.4.1, I show the objective function of JHSMINE, which is to minimize the probability-weighted system cost. Also, how JHSMINE discounts the investment cost and the operation cost are thereby discussed. In the following Section 2.4.2, I show the expansion constraints of JHSMINE, which keep track of the availabilities of generation, transmission, and storage facilities in the system, and they also keep track of the newly commissioned or retired facilities so that expansion cost can be calculated.

Then, in Sections 2.4.3 to 2.4.7, I show the operation constraints if JHSMINE, which model the generation unit commitment and dispatch, the transmission and storage operation, the fulfillment of renewable portfolio policy, and finally, the fulfillment of reliability obligations such as operating reserves, planning reserves, and flowgate limits. Table 2.3 shows an overview of operation constraints.

Table 2.3. JHSMINE operation constraints and associated market participants

Resolution	Constraints (Section #)	Market Participants/Market Clearing
Hourly	Kirchhoff's Voltage Laws, Thermal limits, (Section 2.4.4), Flowgate limits (Section 2.4.7)	ISO
Hourly	Capacity limits, spinning reserve capacity limits, unit commitment (Section 2.4.3)	Generation Companies
Hourly	Storage charge/discharge capacity limits, state of charge management (Section 2.4.5)	Storage Companies
Hourly	Kirchhoff's Current Laws (Section 2.4.4)	Market Clearing: Electricity
Hourly	Renewable energy credit gathering and distribution (Section 2.4.6)	Market Clearing: REC
Hourly	Spinning Reserve Constraints (Section 2.4.7)	Market Clearing: Spinning Reserve
Yearly	RPS (Section 2.4.6)	Load Serving Entities
Yearly	Resource Adequacy (Section 2.4.7)	Market Clearing: Resource Adequacy

2.4.1 Objective Functions

The objective function of JHSMINE is to minimize Eq. (2.1): the probability-weighted system cost discounted back to the Net Present Value. Two terms constitute the system costs: investment cost *invc*, and operation cost *oprc*, and both realize at the scenario tree node (*s,y*).

$$\text{Minimize} \quad obj = \sum_{(s,y)} SP_{s,y} \cdot \left(D_y \cdot invc_{s,y} + DA_y \cdot oprc_{s,y} \right) \tag{2.1}$$

Notably, the investment cost occurs at the time when the expansion is online, rather than the time when the decision is made and JHSMINE discount the investment cost back to the beginning of the planning horizon using the following parameter:

$$D_y = 1/(1+\delta)^{y-y_{origin}}, \quad \delta \text{ is the interest rate.}$$

Here is an example. Suppose the origin year of the planning horizon is 2018, the interest rate is 5%, and a transmission line cost of \$1 (overnight cost) is online in the year 2034. The present value of the cost of this transmission line is $\$1/(1+5\%)^{2034-2018} = \$0.458$.

The *oprc* of Eq. (2.1) is the operation cost of the operation node (*s,y*); *y* is the first year of each operation simulation interval; JHSMINE assumes that the operation condition (e.g., load, policies, fuel price, etc.) of operation node will repeat until the next operation simulation interval. All cash flows for operations are assumed to be end-of-year flows, and the discounting formulas are defined accordingly as:[4]

$$DA_y = D_y \left(\sum_{t=1}^{Y_y} 1/(1+\delta)^t \right) = D_y P\left(1, Y_y, \delta\right).$$

[4] Here, Y_y is the length of the operation simulation interval and $P(1, Y_y, \delta)$ is the annuity-to-present-value formula. The DA_y formula first discounts all end-of-year operation costs to the beginning of the operation simulation interval *y* and then discounts them back to the origin of the planning horizon using D_y.

Let us look at an example. Suppose one operation simulation interval is from 2034 to 2065 (32 years). A $1 operation cost will happen at the end of each year of this operation simulation interval, and the present value (at 2034) these cash flows is P($1,32,5%) = $15.80; thus the present value discounted at the beginning of planning horizon is $15.80 × 0.458 = $7.24.

In summary, Eq. (2.1) is the expected system cost discounted to the origin of the planning horizon. In the following two subsections, I demonstrate the detailed calculation of the expansion cost and the operation cost.

2.4.1.1 Investment Cost

JHSMINE calculates the investment cost of new facilities using equation Eq. (2.2), which is, in fact, the net of (1) the expansion cost due to facilities that are newly commissioned and (2) the salvage revenue for facilities that are newly retired. Specifically, the salvage cost not only depends on when the retirement happens but also when the facility being retired was firstly built; i.e., it is dependent on both (*s,y*) and (*s',y'*).

$$\begin{aligned} invc_{s,y} = {} & GEXC_{s,y,k} \cdot gincexp_{s,y,k} - \sum_{(s',y')} GSAL_{s,y,k,s',y'} \cdot gincret_{s,y,k,s',y'} \\ & + LEXC_{s,y,l} \cdot lincexp_{s,y,l} - \sum_{(s',y')} LSAL_{s,y,l,s',y'} \cdot lincret_{s,y,l,s',y'} \\ & + EECL_{s,y,j} \cdot eincexp_{s,y,j} - \sum_{(s',y')} ESAL_{s,y,j,s',y'} \cdot eincret_{s,y,j,s',y'} \end{aligned} \tag{2.2}$$

2.4.1.2 Operation Cost

JHSMINE calculates the operation cost using equation Eq. (2.3), which is composed of seven terms: (1) the fixed operation and maintenance (O&M) cost of generation and storage facilities; i.e., Eq. (2.4), (2) the variable O&M cost of generation and storage operations; i.e., Eq. (2.5), (3) the fuel cost of generation and storage operations; i.e., Eq.

(2.6), (4) the start-up cost from generation unit commitment; i.e., Eq. (2.7), (5) the carbon tax/allowance payment due to generation and storage operations; i.e., Eq. (2.8), (6) value of lost load; i.e., Eq. (2.9), and finally, (7) noncompliance penalty of renewable portfolio standards (RPS); i.e., Eq. (2.10).

$$oprc_{s,y} = fomc_{s,y} + vomc_{s,y} + fuelc_{s,y} + stup_{s,y} + ctax_{s,y} + rpsc_{s,y} + voll_{s,y} \quad (2.3)$$

$$fomc_{s,y} = \sum_{k} GFOM_k \cdot GNPL_k \cdot gstat_{s,y,k} + \sum_{j} EFOM_j \cdot EGCP_j \cdot estat_{s,y,j} \quad (2.4)$$

$$vomc_{s,y} = \sum_{h} HW_{y,h} \cdot \left(\sum_{k} GVOM_k \cdot gopt_{s,y,h,k} + \sum_{j} EVOM_j \cdot edis_{s,y,h,j} \right) \quad (2.5)$$

$$fuelc_{s,y} = \sum_{h} HW_{y,h} \cdot \left(\sum_{f} FC_{s,y,f,h} \cdot \left(\sum_{k \in K_f} GHR_k \cdot gopt_{s,y,h,k} + \sum_{j \in J_f} EHR_j \cdot edis_{s,y,h,j} \right) \right) \quad (2.6)$$

$$stuc_{s,y} = \sum_{h} \frac{HW_{y,h}}{[1hour]} \cdot \left(\sum_{k} GSUC_k \cdot GNPL_k \cdot gsup_{s,y,h,k} \right) \quad (2.7)$$

$$ctax_{s,y} = \sum_{h} HW_{y,h} \cdot \left(\sum_{w} CTAX_{s,y,w} \cdot \left(\sum_{k \in K_w} GER_k \cdot gopt_{s,y,h,k} + \sum_{j \in J_w} EER_j \cdot edis_{s,y,h,j} \right) \right) \quad (2.8)$$

$$voll_{s,y} = \sum_{h} HW_{y,h} \cdot VOLL \cdot \left(\sum_{i} nload_{s,y,h,i} \right) \quad (2.9)$$

$$rpsc_{s,y} = \sum_{h} HW_{y,h} \cdot \left(\sum_{w} RACP_w \cdot nrps_{s,y,w,h} \right) \quad (2.10)$$

2.4.2 Expansion Constraints

Constraints (2.11) to (2.25) are investment constraints, which connect the expansion/retirement decisions and the availability of the facilities. Table 2.4 lists different investment modes of the facilities in JHSMINE; facilities with different investment modes are subject to different investment constraints.

Table 2.4. Invest mode of facilities in JHSMINE

Invest Mode	Description
Candidate Facilities	Expandable candidate facilities, expansion variables and retirement variable and status variables are defined
Existing Facilities – Economic Retirement	Existing facilities that can be actively retired by model if they are not economical to be kept commissioned in the system, only retirement variables and status variables are defined
Existing Facilities – Forced Retirement	Existing facilities that are forced to be retired or kept commissioned (specify by the planner), only status variables are defined and fixed using commission status parameters

The logics of expansion constraints for generation, storage, and transmission are identical in structure, and thus, only the generation constraints are explained here. A major characteristic of this modeling approach is that every expansion or retirement decision is modeled through binary variables and can be relaxed if needed; a similar approach was first proposed in Pereira et al. (2005).

Constraint (2.11) states: the status of each generation facility in each operation node equals its availability in the previous operation node (or in short, its previous status) plus any incremental expansion and minus any incremental retirement. Specifically, for the first operation node (s_1,y_1), the previous status is set by the parameter $GCOM_{s0,y0,k}$; in other words, the node previous to the first operation node is the origin of the scenario tree.

The constraint (2.12) is defined for generators that are subject to economic retirement mode, stating that the generator must be retired before the commission schedule provided by the user. Constraints (2.13) and (2.14) calculate the incremental expansion and retirement: the incremental expansion in a scenario tree node (s,y) equals to the expansion decisions that pass the lead time, but are not yet realized; also this decision must be made in an ancestor node to the current node; i.e., $SDOI_{s,y,s'',y''} = 1$. And finally, Constraint (2.15) is only defined for candidate facilities, stating that the accumulative retirement decision

(the sum of all realized retirement decisions since the beginning of planning horizon) cannot be higher than the incremental expansion, in other words, JHSMINE cannot retire a plant that is not built. Note that all investment decision variables can be relaxed as long as the operation constraints allow (see Sections 2.4.3 to 2.4.7.)

2.4.2.1 Generation Expansion Constraints

$$\left.\begin{aligned} gstat_{s_1,y_1,k} &= GCOM_{s_0,y_0,k} + gincexp_{s_1,y_1,k} - \sum_{(s',y')} gincret_{s_1,y_1,k,s',y'} \\ gstat_{s,y,k} &= gstat_{s_p,y_p,k} + gincexp_{s,y,k} - \sum_{(s',y')} gincret_{s,y,k,s',y'} \end{aligned}\right\} \tag{2.11}$$

$$gstat_{s,y,k} \le GCOM_{s,y,k} \tag{2.12}$$

$$gincexp_{s,y,k} = \sum_{\substack{(s'',y'')st.SDOI_{s,y,s'',y''}=1,\\ pre(y)<y''+GLED_k \le y}} gexp_{s'',y'',k} \tag{2.13}$$

$$gincret_{s,y,k,s',y'} = \sum_{\substack{(s'',y'')st.SDOI_{s,y,s',y'}=1,\\ pre(y)<y''+GLED_k \le y}} gret_{s'',y'',k,s',y'} \tag{2.14}$$

$$\sum_{\substack{(s'',y'')st.SDOI_{s,y,s'',y''}=1,\\ y''+GLED_k \le y}} gret_{s'',y'',k,s',y'} \le gincexp_{s',y',k} \tag{2.15}$$

2.4.2.2 Transmission Expansion Constraints

$$\left.\begin{aligned} lstat_{s_1,y_1,l} &= LCOM_{s_0,y_0,l} + lincexp_{s_1,y_1,l} - \sum_{(s',y')} lincret_{s_1,y_1,l,s',y'} \\ lstat_{s,y,l} &= lstat_{s_p,y_p,l} + lincexp_{s,y,l} - \sum_{(s',y')} lincret_{s,y,l,s',y'} \end{aligned}\right\} \tag{2.16}$$

$$lstat_{s,y,l} \le LCOM_{s,y,l} \tag{2.17}$$

$$lincexp_{s,y,l} = \sum_{\substack{(s'',y'')st.SDOI_{s,y,s'',y''}=1,\\ pre(y)<y''+LLED_l \le y}} lexp_{s'',y'',l} \tag{2.18}$$

$$lincret_{s,y,l,s',y'} = \sum_{\substack{(s'',y'')st.SDOI_{s,y,s',y'}=1,\\ pre(y)<y''+LLED_l \le y}} lret_{s'',y'',l,s',y'} \tag{2.19}$$

$$\sum_{\substack{(s'',y'')st.SDOI_{s,y,s'',y''}=1,\\ y''+LLED_l \le y}} lret_{s'',y'',l,s',y'} \le lincexp_{s',y',l} \tag{2.20}$$

2.4.2.3 Storage Expansion Constraints

$$\left.\begin{aligned} estat_{s_1,y_1,j} &= ECOM_{s_0,y_0,j} + eincexp_{s_1,y_1,j} - \sum_{(s',y')} eincret_{s1,y1,j,s',y'} \\ estat_{s,y,j} &= estatus_{s_p,s_p,j} + eincexp_{s,y,j} - \sum_{(s',y')} eincret_{s,y,j,s',y'} \end{aligned}\right\} \quad (2.21)$$

$$estat_{s,y,j} \le ECOM_{s,y,j} \quad (2.22)$$

$$eincexp_{s,y,j} = \sum_{\substack{(s'',y'')st.SDOI_{s,y,s'',y''}=1, \\ pre(y)<y''+ELED_j \le y}} eexp_{s'',y'',j} \quad (2.23)$$

$$eincret_{s,y,j,s',y'} = \sum_{\substack{(s'',y'')st.SDOI_{s,y,s',y'}=1, \\ pre(y)<y''+ELED_j \le y}} eret_{s'',y'',j,s',y'} \quad (2.24)$$

$$\sum_{\substack{(s'',y'')st.SDOI_{s,y,s'',y''}=1, \\ y''+ELED_j \le y}} eret_{s'',y'',j,s',y'} \le eincexp_{s',y',j} \quad (2.25)$$

2.4.3 Generation Operation

2.4.3.1 Generation Dispatch

$$gopt_{h,k} + gors_{h,k} \le GHAV_{h,k} \cdot (1 - GPOR_k) \cdot (1 - GFOR_k) \cdot GNPL_k \cdot gstat_k \quad (2.26)$$

$$gors_h \le GSP_k \cdot (1 - GPOR_k) \cdot (1 - GFOR_k) \cdot GNPL_k \cdot gstat_k \quad (2.27)$$

The constraint (2.26) is the capacity limit of generators and (2.27) is the spinning reserve capacity limit. The capacity limit of the spinning reserve is usually defined as the 10-min ramp rate since the spinning reserve requires a 10-min response time.

2.4.3.2 Generation Unit commitment

The unit commitment constraints in JHSMINE are expanded based on the "Tight Relaxed Unit Commitment" (TRUC) Constraints in Kasina (2017); for classic unit commitment without generation expansion, I refer readers to some seminal articles as Baldick (1995) and Morales et al. (2013). Under TRUC, unit commitment variables, i.e., operating

status, start-up, and shut-down variables, can be relaxed; in the meanwhile, each unit commitment constraint is still physically meaningful. In this subsection, for each constraint, I first discuss the meaning of this constraint if unit commitment variables are binary, and then explain the physical meaning of it if unit commitment variables are relaxed. I made two assumptions in this subsection: 1) I assume start-up and shut-down movements happen at the beginning of the hour specified by the subscript (referred as the *current hour* in this section), and 2) unit commitment is modeled as an ouroboros (snake-biting-it-tail) style: if the cycle length one day, the hour after the 24th hour of the day is the 1st hour of the same day.

Constraints (2.28) to (2.33) are operating status constraints of generators that are subject to unit commitment. Constraint (2.28) states that the generator cannot be "on" if it is not built. Constraint (2.29) calculates the start-up and shut-down variables and (2.30) calculates the minimum running capacity. Constraint (2.31) states the output of the generator must be higher than the minimum running capacity. And finally, constraints (2.32) and (2.33) limit the total output and the spinning reserve at the current hour.

The relaxation of Constraints (2.28) to (2.33) is intuitive: the meaning of the operating status variable expands to "how much fraction of the nameplate capacity is on"; similarly, the relaxed start-up and shut-down variables mean "how much fraction of the nameplate capacity is started-up and shut-down." In a relaxed context, the nameplate capacity can be "on" up to the expanded amount (Constraint (2.28)). The minimum run limit, which is a continuous variable now, is calculated in (2.30).

$$gopstat_{h,k} - gstat_k \leq 0 \tag{2.28}$$

$$gopstat_{h,k} - gopstat_{h-1,k} = gsup_{h,k} - gsdn_{h,k} \tag{2.29}$$

$$gpmin_{h,k} = GMIN_k \cdot (1 - GFOR_k) \cdot (1 - GPOR_k) \cdot GNPL_k \cdot gopstat_{h,k} \tag{2.30}$$

$$gpmin_{h,k} \le gopt_{h,k} \tag{2.31}$$

$$gopt_{h,k} + gors_{h,k} \le (1 - GFOR_k) \cdot (1 - GPOR_k) \cdot GNPL_k \cdot gopstat_{h,k} \tag{2.32}$$

$$gors_{h,k} \le GSP_k \cdot (1 - GFOR_k) \cdot (1 - GPOR_k) \cdot GNPL_k \cdot gopstat_{h,k} \tag{2.33}$$

Constraints (2.34) and (2.35) are the ramp rate up and down limit constraints. Specifically, the constraint (2.34) states: If the generator is just started-up at (the beginning of) the current hour, the ramp-up limit at this hour is zero because the operating status in the previous hour was "off." Similarly, if a generator is going to be shut-down at the current hour, the constraint (2.35) will limit the output in the previous hour to be at the minimum run; in other words, the generator must be ready for such a shut-down move.

The relaxation of these two constraints is also intuitive. Constraint (2.34) states the ramp-up limit of the current hour is set by the ramp capacity of the previous hour because the newly started up (if any) capacity is not yet ready to ramp-up. Please note that there can be a difference between the minimum runs of these two consecutive hours because of the variable relaxation. Similarly, constraint (2.35) states the ramp-down limit is set by the ramp capacity of the current hour because the newly shut-down capacity (if any) was already at the minimum run in the previous hour and cannot provide the ramping capability.

$$\begin{aligned} &\left(gors_{h,k} + gopt_{h,k} - gpmin_{h,k}\right) - \left(gopt_{h-1,k} - gpmin_{h-1,k}\right) \\ &\le GRPR_k \cdot (1 - GPOR_k) \cdot (1 - GFOR_k) \cdot GNPL_k \cdot gopstat_{h-1,k} \end{aligned} \tag{2.34}$$

$$\begin{aligned} &\left(gopt_{h,k} - gpmin_{h,k}\right) - \left(gors_{h-1,k} + gopt_{h-1,k} - gpmin_{h-1,k}\right) \\ &\ge -GRPR_k \cdot (1 - GPOR_k) \cdot (1 - GFOR_k) \cdot GNPL_k \cdot gopstat_{h,k} \end{aligned} \tag{2.35}$$

Constraints (2.36) and (2.37), respectively, limit the output during the start-up and shut-down hours. For example, the constraint (2.36) states that if the generator is "off" in the previous hour, the output above minimum run in the current hour is zero (0); in other words, the output of the just started generator must be at the minimum run capacity.

Similarly, constraint (2.37) states if the generator is "off" in the current hour, the output of the previous hour must be at minimum run capacity.

$$\begin{aligned}&\left(gors_{h,k} + gopt_{h,k} - gpmin_{h,k}\right)\\&\leq \left(1 - GPOR_k\right)\cdot\left(1 - GFOR_k\right)\cdot\left(1 - GMIN_k\right)\cdot GNPL_k \cdot gopstat_{h-1,k}\end{aligned} \tag{2.36}$$

$$\begin{aligned}&\left(gors_{h-1,k} + gopt_{h-1,k} - gpmin_{h-1,k}\right)\\&\leq \left(1 - GPOR_k\right)\cdot\left(1 - GFOR_k\right)\cdot\left(1 - GMIN_k\right)\cdot GNPL_k \cdot gopstat_{h,k}\end{aligned} \tag{2.37}$$

In a binary context, it is noticeable that (1) constraints (2.34) and (2.36) are identical if there is a start-up at the current hour since the right-hand sides are both zero; (2) if there is a shut-down at the current hour, constraint (2.34) and (2.36) will not be active; (3) if there is no start-up (or shut-down) movement, constraint (2.36) will not bind. A similar relationship between constraints (2.35) and (2.37) can be found: (1) if there is a shut-down at the current hour, constraints (2.35) and (2.37) are identical because the right-hand sides are both zero; (2) if there is a start-up, both constraints will not be active; (3) if there is no start-up or shut-down movement, constraint (2.37) will bind. In summary, in a binary context, constraints (2.36) and (2.37) are "redundant" in the optimal solution, but they serve as tight constraints (or cuts) in the branch-and-cut algorithm of solving mixed-integer programming to reduce the distance between the convex hull and the linear searching space.

However, constraints (2.36) and (2.37) bear physical meaning if unit commitment variables are relaxed. Constraint (2.36) states: in the current hour, the output above the minimum run is limited by the "variable output range" in the previous hour. The variable output range is defined as:

$$\left(1 - GPOR_k\right)\cdot\left(1 - GFOR_k\right)\cdot\left(1 - GMIN_k\right)\cdot GNPL_k \cdot gopstat_{h,k}$$

In other words, the newly started-up capacity, if any, cannot contribute to the "variable range": it must be operated at the minimum run. On the other hand, Constraint (2.37)

tells a similar story: in the previous hour, the output above the minimum run is limited by the "variable output range" in the current hour; in other words, the newly shut-down capacity will be operated at minimum run already in the previous hour.

Constraints (2.38) and (2.39) are, respectively, the minimum uptime and minimum downtime limits. If any start-up or shut-down decision is made within the minimum down/uptime window, the generator must stay "on" or "off" in correspondence. The relaxation meaning of these two constraints are as follows: Any fractional start-up decision that is made within the minimum uptime window will move up the lower limit at which the generator can be operated; any fractional shut-down decision that is made within the minimum downtime window will move down the upper limit at which the generator can be operated.

$$gopstat_{h,k} \geq \sum_{h'=h-GMUT+1}^{h} gsup_{h',k} \tag{2.38}$$

$$gopstat_{h,k} \leq gstatus_k - \sum_{h'=h-GMDT+1}^{h} gsdn_{h',k} \tag{2.39}$$

2.4.4 Transmission Operation

This subsection discusses the transmission operation constraints. The constraint (2.40) is the power flow upper limit; naturally, if a transmission line is not commissioned, the power flow on this line is fixed to zero.

$$\left| pf_{h,l} \right| \leq LTM_l \cdot lstatus_{h,l} \tag{2.40}$$

Constraint (2.41) is the B-theta version of Direct Circuit Optimal Power Flow (DCOPF) constraint: if a transmission line is close in the network, its power flow must be equal to the product of (1) the phase angle difference between both ends of the transmission line, (2) the per unit of line susceptance, and (3) the base power of the transmission network;

this DC OPF is a linearized version of Kirchhoff's Voltage Law (Glover et al., 2011). This constraint is also known as the disjunctive constraint of DC OPF proposed in Bahiense et al. (2001); for a detailed explanation of the disjunctive constraint, see Winston et al. (2003).

$$\left| pf_{h,l} + PBASE \cdot LB_l \cdot \left(\sum_i LBI_{l,i} pa_{h,i} \right) \right| \leq LBM_l \cdot (1 - lstatus_l) \tag{2.41}$$

Constraint (2.41) deserves extra attention: if a transmission line is open, then this constraint becomes the limitation on the phase angle difference of both ends:

$$\left| \sum_i LBI_{l,i} pa_{h,i} \right| \leq \frac{LBM_l}{PBASE \cdot LB_l}.$$

To avoid selecting overly large Big-M parameters, which will, in turn, results an ill-conditioned coefficient matrix of the problem, JHSMINE selects Big-M parameters using the following formula, which utilizes one of core assumptions of DC OPF[5]: the phase angle differences between two ends should not be overly large; in this case, limited at π/6.[6]

$$LBM_l = \frac{\pi}{6} PBASE \cdot LB_l.$$

And. finally, the constraint (2.42) is the node electricity balance, also known as Kirchhoff's Current Law. This constraint requires the total injection into the node equals the total load withdrawal.

$$\sum_{k \in K_i} gopt_{h,k} + \sum_{j \in J_i} \left(edis_{h,j} - echg_{h,j} \right) + \sum_l LBI_{l,i} pf_{h,l} + nload_{h,i} = LOAD_{h,i} \tag{2.42}$$

[5] Assumptions of the DC OPF include negligible resistance, stable voltages at both ends measured at a per unit system, and the small phase angle difference between two ends of the transmission line.

[6] Nevertheless, using this formula also means to limit the phase angle between nodes even if no line is built, which is benign if there is an existing line in the corridor; i.e., JHSMINE is performing reinforcement expansion. If there is no existing line in between (JHSMINE is planning for new lines), this formula might be overly limiting.

2.4.5 Storage Operation

This section demonstrates the storage operation constraints; similar approaches can be found in Wogrin and Gayme (2015). Constraints (2.43), (2.44), and (2.45) are the charging, discharging capacity limits, and the energy capacity limit of the storage.

$$echg_{h,j} \leq EPCP_j \cdot estat_j \tag{2.43}$$

$$edis_{h,j} + eors_{h,j} \leq EGCP_j \cdot estat_j \tag{2.44}$$

$$elev_{h,j} \leq EECP_j \cdot estat_j \tag{2.45}$$

Constraint (2.47) combines constraints (2.43) and (2.44) into one, and it limits the possibility of charge and discharge happens simultaneously. For example, if the charge is zero, this constraint becomes (2.46); if the discharge and spinning reserve is zero, this constraint becomes (2.44); and finally, if in any case, discharge and charge are both non-zero, they will limit each other.

$$EGCP_j \cdot echg_{h,j} + EPCP_j \cdot \left(edis_{h,j} + eors_{h,j}\right) \leq EGCP_j \cdot EPCP_j \cdot estat_j \tag{2.47}$$

The constraint (2.48) is the energy transition constraint and constraint (2.49) requires that the energy in the storage is able to serve one hour of discharge and a half-hour of spinning reserve activation.

$$elev_{h+1,j} = elev_{h,j} - \left(\frac{edis_{h,j}}{EGEF_j}\right) \cdot \left[1\,hour\right] + EPEF_j \cdot echg_{h,j} \cdot \left[1\,hour\right] \tag{2.48}$$

$$elev_{h,j} - \left(\frac{edis_{h,j} \cdot [1\,hour] + eors_{h,j} \cdot [0.5\,hour]}{EGEF_j}\right) \geq 0 \tag{2.49}$$

2.4.6 Interstate Energy Credit Trading and Renewable Portfolio Standards

This subsection demonstrates the modeling of interstate energy credit trading, and this modeling is critical to the accounting of the RPS requirement. An early version of

renewable energy trading modeling can be found in Ho et al. (2016) and Xu and Hobbs (2017). In the current version of JHSMINE, the energy credit trading is on the state-level, hourly-level, and per technology. For example, there can be 1 MW Biomass energy credit flow from Oregon to California at the hour *h*.

Constraint (2.50) aggregates the energy credit of technology *g* generated at hour *h* to the state-level (*w*) and then distributes the aggregated energy credits to different states (*w'*). For instance, if *w* = *w'*, the value of $cpf_{solar,1,w,w'}$ is the amount of solar energy credit sold from generators in state *w* to local LSEs.

$$\sum_{k \in K_g \cap K_w} gopt_{h,k} = \sum_{w'} cpf_{g,h,w,w'} \tag{2.50}$$

Many states of the U.S. have adopted the Renewable Portfolio Standards (RPS) policy on the demand side, requiring the LSE to serve its load with a minimum share of renewable energy. Since LSEs are not the owners of renewable generation, they buy energy credit from the generators through variable *cpf*.

The constraint (2.51) is the general RPS requirement: it requires that the amount of purchased renewable credits has to be higher than the RPS requirement of each state. Importantly, the renewable energy credits that are used to comply with the RPS requirement must be identified as renewable by the government. For example, the hydropower from large dams is not considered as renewable in California, and the hydropower imported in California cannot be used for California RPS compliance; in the JHSMINE, this is by specifying $RE_{CA,Hydro} = 0$. Furthermore, not any imported renewable credit is eligible to fulfill the RPS requirement: for instance, in JHSMINE, the default assumption is that energy credits imported from a state without RPS are not eligible to fulfill the RPS of other states; this is controlled by parameter $TD_{w',w} = 0$.

$$\sum_h HW_h \left(\sum_{g,w'} RE_{w,g} \cdot TD_{w',w} \cdot cpf_{g,h,w',w} + nrps_{w,h} \right) \geq$$
$$RPS_w \cdot \sum_h HW_h \cdot \left(\sum_{i \in I_w} \left(LOAD_{h,i} - nload_{h,i} \right) \right) \tag{2.51}$$

The constraint (2.52) is the instate RPS requirement. Some states require that the part of the RPS requirement needs to be satisfied using the in-state generation, where the energy credit from outside does not count.

$$\sum_h HW_h \cdot \left(\sum_{g,w'=w} RE_{w,g} \cdot cpf_{g,h,w',w} + nrps_{w,h} \right)$$
$$\geq IRPS_w \cdot \sum_h HW_h \cdot \left(\sum_{i \in I_w} \left(LOAD_{h,i} - nload_{h,i} \right) \right) \tag{2.52}$$

Constraints (2.53) to (2.55) are the RPS carve-outs modeled in JHSMINE. RPS carve-out is the special RPS requirement set aside for particular technologies, such as wind, solar, and other renewables.

$$\sum_h HW_h \cdot \left(\sum_{g \in Solar, w'} RE_{w,g} \cdot TD_{w',w} \cdot cpf_{g,h,w',w} + nsrps_{w,h} \right)$$
$$\geq SRPS_w \cdot \sum_h HW_h \cdot \left(\sum_{i \in I_w} \left(LOAD_{h,i} - nload_{h,i} \right) \right) \tag{2.53}$$

$$\sum_h HW_h \cdot \left(\sum_{g \in Wind, w'} RE_{w,g} \cdot TD_{w',w} \cdot cpf_{g,h,w',w} + nwrps_{w,h} \right)$$
$$\geq WRPS_w \cdot \sum_h HW_h \cdot \left(\sum_{i \in I_w} \left(LOAD_{h,i} - nload_{h,i} \right) \right) \tag{2.54}$$

$$\sum_h HW_h \cdot \left(\sum_{g \in Other, w'} RE_{w,g} \cdot TD_{w',w} \cdot cpf_{g,h,w',w} + nsrps_{w,h} \right)$$
$$\geq ORPS_w \cdot \sum_h HW_h \cdot \left(\sum_{i \in I_w} \left(LOAD_{h,i} - nload_{h,i} \right) \right) \tag{2.55}$$

Constraints (2.56) and (2.57) set the upper limits of the alternative non-compliance credit can be brought from the government.

$$nrps_{w,h} \le \sum_{i \in I_w} \left(LOAD_{h,i} - nload_{h,i} \right) \tag{2.56}$$

$$nsrps_{w,h} + nwrps_{w,h} + norps_{w,h} \le nrps_{w,h} \tag{2.57}$$

2.4.7 Reliability Modeling

In this section, I demonstrate the reliability requirements modeled in JHSMINE: the spinning reserve, the resource adequacy requirement (also known as the planning reserve), and the transmission flowgate limits. In JHSMINE, the spinning reserve and resource adequacy are modeled at the reserve sharing group level, which is constituted by different balancing authority areas.[7]

Constraint (2.58) modeled the hourly spinning reserve requirement. In JHSMINE, I assume that the storage can provide additional spinning reserves by stopping charging. Constraint (2.59) models the resource adequacy requirement.

$$\sum_{a \in A_r} \left(\sum_{k \in K_a} gors_{h,k} + \sum_{j \in J_a} \left(eors_{h,j} + echg_{h,j} \right) \right) \ge RMSP_r \cdot \sum_{a \in A_r} \left(\sum_{i \in I_a} LOAD_{h,i} \right) \tag{2.58}$$

$$\begin{aligned} &\sum_{g} GELCC_{g,r} \cdot \left(\sum_{a \in A_r} \left(\sum_{k \in K_g \cap K_a} GNPL_k \cdot gstat_k \right) \right) \\ &+ \sum_{e} EELCC_{e,r} \left(\sum_{a \in A_r} \left(\sum_{j \in J_a \cap J_e} EGCP_j \cdot estat_j \right) \right) \ge \left(1 + RMPL_r \right) PEAK_r \end{aligned} \tag{2.59}$$

Constraints (2.60) and (2.61) are the flowgate limit (also known as the path limit) in the forward and backward directions. Note that a transmission line expansion can make the flowgate limits larger.

$$\sum_{l} PLI_{p,l} pf_{h,l} \le PFD_p + \sum_{l} PFDE_{p,l} lstat_l \tag{2.60}$$

[7] For instance, there are more than 30 balancing authority areas in WECC and they modeled them as 4 reserve sharing groups, where 3 of them are NREC registered groups: Northwest Power Pool (NWPP), Rock Mountain Reserve Sharing Group (RMPG), and Southwest Reserve Sharing Group (SRSG).(WECC, 2014b).

$$\sum_{l} PLI_{p,l} pf_{h,l} \geq -\left(PBD_{p} + \sum_{l} PBDE_{p,l} lstat_{l} \right) \tag{2.61}$$

2.5 Conclusions

In this chapter, I provided the rationale, development history, general overview, and, most importantly, the detailed formulation of JHSMINE. In short, the demonstration here serves as a mathematical foundation of the following chapters, where I generated the respective results using JHSMINE with different settings or minor modifications. Thus, in the remainder of this thesis, I will frequently refer readers to this Chapter for detailed formulation.

Chapter 3 Value of Model Enhancements: Quantifying the Benefit of Improved Transmission Planning Models[8]

3.1 Chapter Summary

This chapter, as aforementioned in Chapter 1, focuses on answering the following questions: *What, exactly, is a better planning model? How can we value, in economic terms, the extent to which one planning model performs better than another?* As an attempt to answer these questions, in this chapter, I propose a framework to quantify the value of model enhancements (VOME) in transmission planning models; as an illustration, I applied it to a case study of the large-scale, long-term planning of the Western Electricity Coordinating Council (WECC) system.

The VOME, which is closely related to the concept of the value of information from decision analysis, quantifies the probability-weighted improvement in the system performance resulting from changes in decisions that result from model enhancements. The WECC case study, in this chapter, shows the practicality to quantify VOME and illustrates the type of insights that can be obtained. I compare the values of four types of model enhancements. The results show major benefits from considering long-run uncertainty using multiple scenarios of technology, policy, and economics; these benefits are as much as 14% of total benefits of new transmission built in the first ten years. But less benefit (< 2%) is obtained from more temporal granularity within the year (24 to 48 time-slices), more complex transmission network representations (from transshipment to DC OPF power flow modeling), and inclusion of generator unit commitment constraints and costs. Power

[8] This chapter is an expansion of Xu and Hobbs (2019).

system planners can apply this framework to quantify the value of model enhancements in any planning context, such as integrated resource planning.

3.2 Special Notations

$C(x)$ Expected present worth of system cost of making decision x, based on the model with all enhancements.

$E_i(\omega)$ Binary parameter: if $E_i(\omega^*) = 1$, then enhancement i is included in the model with setting ω^*; if zero, then the enhancement is excluded. For instance, if there are three candidate enhancements, then $E_1(\omega^*) = 1$, $E_2(\omega^*) = 0$, $E_3(\omega^*) = 1$ indicates a model with only Enhancements 1 and 3 implemented.

I Set of enhancements, index by i and j.

x_ω Optimal first stage transmission investments ("decision") from a model with enhancements setting specified by ω; E.g., x_{ω^*}, where $E_1(\omega^*) = 1$, $E_2(\omega^*) = 0$, $E_3(\omega^*) = 1$ indicates investments from a model with only Enhancements 1 and 3 implemented.

x_0 Decision of no transmission investments in the first stage.

x_1 Optimal decision from the model with all enhancements; i.e., $E_i(\omega^*) = 1$ for all i.

ω Model enhancement setting, describing what enhancements are included in the model formulation.

Ω_i Set of all possible permutations of enhancements other than i.

3.3 Introduction

Grid reinforcements are a large part of the cost of integrating renewable energy (Kahn, 2010). This cost is often justified by the contributions those reinforcements make to a cost-efficient, reliable, and sustainable power system by delivering renewables and reducing congestion. But they should be planned carefully to maximize those benefits and avoid unnecessary expenses.

Planning processes for transmission are necessarily complex. Permitting and construction take on the order of a decade. This fact, together with the long life of transmission assets and large policy, technology, and economic uncertainties, means that benefit calculations must analyze how grid investments will perform under many different scenarios (Gorenstin et al., 1993). Also, planning should consider the entire system and all alternatives for an entire region at once, because a network reinforcement in one location can strongly affect the benefits of new lines elsewhere. Further, although many power markets have unbundled transmission from generation, grid planners need to consider how generation mix and siting are affected by where and when lines are added. This is called "proactive" transmission planning (Sauma and Oren, 2006).

In summary, transmission expansion planning (TEP) models are complex because they need to consider entire regions, multiple decades of costs (Sawey and Zinn, 1977), generation-transmission investment interactions (Sauma and Oren, 2006), and uncertainty in fundamental drivers (Gorenstin et al., 1993; Hobbs et al., 2016), as well as numerous technical and economic details.

However, models for transmission planning cannot be arbitrarily complex because computation capabilities limit the size of models that can be solved. As solvers and

hardware improve, planners can add features to planning models to make them more realistic, but not all desired features can be accommodated. Thus, planners always face tradeoffs when they consider which model enhancements to implement. For instance, if a model has 8760 operating periods/yr, a 40-yr horizon, 10 long-run scenarios, 1000 candidate generators, and 500 candidate transmission lines, model size can easily grow to several billions of variables and constraints. Thus, a planner must choose which features of the real system to represent, which to omit, and what approximations to use. Choosing which features to include in a model is difficult and should ideally consider how much transmission plans would improve as a result of alternative model enhancements.

On the other hand, the need for TEP model enhancements has motivated the development of an extensive rich literature on the topic (see the review in Section 3.4.) But which model enhancements would most improve transmission plans? This paper is concerned with the question: *Can we quantify an economic index to meaningfully compare the value that alternative model enhancements might provide to transmission planning?* To the best knowledge of my knowledge, a systematic and quantifiable framework to provide such information has not been proposed.

The purpose of this chapter is to provide a general, systematic framework for quantifying the economic value of model enhancements (VOME). The goal is not to propose new technical or economic enhancements *per se* to TEP models; rather, the framework is intended to provide a meaningful economic index to enable planners to systematically compare and select possible enhancements, considering how they would improve the cost of the resulting plans. This is the first time that an index has been proposed for comparing

the economic value of alternative enhancements of models for energy investment planning together with a practical procedure for quantifying that value.

As an illustration, I apply this framework to the Western Electricity Coordinating Council (WECC) using a realistic 300-bus network (Ho et al., 2016) based on WECC's 2024 Common Case database (WECC, 2014a). For the first time, the benefits of considering improved representations of long-term uncertainty and short-term variability are systematically quantified and compared. Two other enhancements are also valued in economic terms: alternative network representations and inclusion of unit commitment constraints and costs. The case study illustrates, in concrete terms, the types of useful insights and recommendations that can be obtained from applying the framework.

The chapter is organized as follows. Initially, in Section 3.4, I briefly review some enhancements that have been proposed for transmission planning models and related models. Then in Section 3.5, a systematic framework for calculating the value of model enhancements (VOME) is presented. In Section 3.6, I describe the base planning model, the WECC case study environment, and the tested enhancements. In Section 3.7, I summarize illustrative insights regarding which enhancements have the most value in order to demonstrate the usefulness of VOME, and Section 3.8 concludes this chapter.

3.4 Background

Researchers and software vendors have recommended various enhancements to power system planning optimization models (Table 1) with the goal of providing useful information and better performing plans. In this section, I summarize some of the enhancements that have been proposed in recent years (detailed reviews can be found in Krishnan et al. (2015), Lumbreras and Ramos (2016)). These can be roughly grouped into eight

categories ranging from uncertainty treatment to the consideration of generation and transmission coordination. While the surveyed literature offers theoretical and case study-based arguments for the value of individual enhancements, careful comparisons across categories are rare. For example, no one has quantified whether transmission plans would be more improved by consideration of a wider range of long-term uncertainties (load-growth, etc.) or by including finer short-term variability resolution (wind and solar availability). This review highlights the need for a practical framework to make this type of comparison.

3.4.1 Long-term uncertainties

This enhancement recognizes long-run uncertainties in the fundamental drivers of the economic value of transmission additions, such as generation capacity mix, load growth, technology improvements, or policy, rather than considering just one "deterministic" or "base case" scenario (Munoz et al., 2014). Since restructuring has separated the responsibilities for expansion and transmission planning in many markets, some researchers have demonstrated that the generation mix can be usefully treated as uncertainties faced by transmission planners, such as in de la Torre et al. (2008). However, others have argued that generation siting and the mix should not be defined as scenarios, but rather as variables in a co-optimization that respond to the transmission grid configuration (Sauma and Oren, 2006). A rich pool of tools has been developed to enable consideration of uncertainty within TEP. Many of these tools are applicable both to long-run uncertainties and short-run variability, discussed next. Two of the most widely cited methods are scenario-based stochastic programming (Baringo and Conejo, 2012; de la Torre et al., 2008; Ding et al., 2018; Gu et al., 2012; Majidi-Qadikolai and Baldick, 2016; Munoz et al., 2014; Sun et al., 2018) and uncertainty-budget-based adaptive robust optimization (Chen et al., 2014; Chen

and Wang, 2016; Jabr, 2013; Moreira et al., 2017; Ruiz and Conejo, 2015). Other tools for modeling long-run uncertainties in planning include chance-constrained programming (Sharaf and Berg, 1984), conditional value at risk (CVaR) constraints (Munoz et al., 2017), adaptive programming (Mejia-Giraldo and McCalley, 2014), and most recently, robust (data-driven) stochastic programming (Bagheri et al., 2017). Simpler heuristic methods also attempt to identify plans that are "robust" to an uncertain future. Examples are MISO's "Multi-Value Projects" (MISO, 2010) and the CAISO's "least regret investments" (CAISO, 2004), which identify network investments that are attractive under most scenarios.

Table 3.1. Some Proposed Enhancements to Transmission Models

Category	Examples
1. Long-term uncertainty considera-tion	Deterministic; multiple scenarios concerning genera-tion capacity; load growth, policy, fuel prices, etc.
2. Short-term uncertainty/variability consideration (operating hours)	More hours/yr; load duration curve vs. chronological hours
3. Long-term temporal granularity (investment stages)	Static; dynamic: more than one investment stage over the planning horizon
4. Generation representation	Generation dispatch, with/without unit commitment
5. Spatial granularity	Number of nodes in the network; bus aggregation level
6. Network representation	Pipes-and-bubbles; hybrid DC; DC OPF; linearized AC; AC OPF; line losses
7. Transmission-generation-storage investment coordination	Reactive; proactive
8. Security and others	N-K security, extreme events

3.4.2 Short-term uncertainty/variability (operating hours)

I define short-term uncertainties as uncertain variables with a time scale of minutes to months. For example, with the increasing penetration of the hard-to-predict intermittent power, e.g., wind and solar, researchers have treated their availability as uncertainties, as in Baringo and Conejo (2012) and Gu et al. (2012). Finer modeling of short-term

uncertainty/variability means more operating hours (or time slices) in the power flow simulation; equivalently, it means more short-term scenarios.

It has been argued that having more operating hours per year in a transmission model is more important than representing Kirchhoff's voltage law (Ventyx Corporation, 2005). However, others who have studied the impact of more temporal granularity on generation expansion (Mai et al., 2015) have concluded that adding dispatch periods slows down computations while having a little apparent effect on generation expansion decisions.

3.4.3 Long-term temporal granularity

Though many TEP models are based on a single investment decision stage ("one-shot" or "static" planning) (Fang and Hill, 2003), dynamic TEP models (Sawey and Zinn, 1977) have gained increasing popularity due to improved computational abilities and the need for plans to include timing of investments. For readers who are interested in dynamic TEP models, a graphical illustration is provided in Chapter 2, Section 2.2.

3.4.4 Generation representation

Planning models can also be enhanced by more realistic models of generator costs and constraints. Notably, unit commitment modeling can be added to expansion models, replacing traditional load-duration curve/merit-order methods. In the context of generation expansion planning, representations of commitment, and ramp constraints, which limit generation flexibility, can improve estimates of the cost of integrating variable renewables (Palmintier and Webster, 2011). TEP models typically drop unit commitment constraints, and generators are only limited by their capacity or resource availability, e.g., wind, solar, and hydro. As one exception, Ho et al. (2016) implemented linearized unit commitment constraints (Kasina et al., 2013) in transmission optimization; their results indicate that

limiting the flexibility of generators has more impact on transmission economics in systems with slow baseload units.

3.4.5 Spatial granularity

Finer geographical representation or more network nodes is another potential enhancement. Krishnan and Cole (2016) showed that more spatial aggregation could penalize photovoltaics since it mixes solar resources of good and bad quality; such fidelity loss may introduce the loss of the benefit from diversifying the solar or wind resource within an area. Most recently, Lumbreras et al. (2017) used a zonal model to guide nodal transmission expansion; however, the loss of fidelity was not discussed.

3.4.6 Network representation

The "pipes-and-bubbles" (transshipment) networks used in many planning models have been proposed to be replaced by more realistic but practical to solve approximations of power flow, such as the DC OPF (Bahiense et al., 2001); for a mathematical representation, see Section 2.4.4. However, as Mai et al. (2015) show, in a large-scale system, DC OPF modeling can dramatically slow solution times and may have little impact on investment recommendations, compared to transshipment networks that lack Kirchhoff's voltage law. An intermediate level of complexity is the hybrid power flow (Romero et al., 2002); there, existing AC line flows are modeled using angle difference/flow relationships (as in the linearized DC load flow), but all new lines are modeled as if they are DC circuits whose flows are controllable (as in pipes-and-bubbles models) and whose capacity can be added in continuous amounts. Other improvements could include linearized AC power flow (Zhang et al., 2013), high-voltage DC power flow (Torbaghan et al., 2015), and consideration of losses (Ozdemir et al., 2016; Zhang et al., 2013). With present computational

capabilities, TEP optimization models with full AC power flow can only be solved by meta-heuristic (Zhao et al., 2011) or constructive heuristic methods (Rider et al., 2007).

3.4.7 Transmission-generation-storage investment coordination

Transmission optimization models traditionally treat generation investment locations and types as exogenous "build-out" scenarios (Chen et al., 2014; Chen and Wang, 2016; Fang and Hill, 2003; Garces et al., 2009; Jabr, 2013; Ruiz and Conejo, 2015; Sharaf and Berg, 1984). This is termed "reactive" planning. However, proactive transmission planning (Sauma and Oren, 2006), which considers how generation investment decision might be affected by grid reinforcements, can lead to less costly plans because they consider how grid reinforcements can lead to savings in both capital and operating costs of generation (Spyrou et al., 2017).

In the simplest proactive models, generation markets are assumed to be perfectly competitive, which allows proactive transmission planning to be modeled using a single "co-optimization" model (Munoz et al., 2014; Sauma and Oren, 2006; Spyrou et al., 2017). If instead, generators behave strategically, multi-level transmission planning models[9] can be used (Baringo and Conejo, 2012; Jenabi et al., 2013; Maurovich-Horvat et al., 2015; Pozo et al., 2013; Sauma and Oren, 2006), but are much more computationally intensive.

Recently, researchers started to add storage investment as an option into TEP in order to capture the interactions (substitution and complementary relationships) between

[9] A multi-level problem usually adopts the rationale that the upper-level player(s) optimize its own objective with the knowledge of lower-level problems: optimality conditions, or more generally, the reaction strategies of lower-level players given the value of the upper-level decision. For instance, in a three-level TEP problem proposed by Pozo et al. (2013), the third (lowest) level player is the ISO who maintains market clearing given the transmission topology and generation capacities; the second (middle) level is composed of the generation companies that are maximizing profits by expanding capacities; the first (top) level player is the transmission expansion planner.

transmission and storage investment (Qiu et al., 2017; Xu and Hobbs, 2020). Researchers have also expanded the scope of TEP beyond the electricity sector to include the representations of upstream gas network constraints (Ding et al., 2018; Hu et al., 2016); for instance, Barati et al. (2015) showed the inclusion of upstream gas network and its expansion decisions could introduce more transmission expansion.

3.4.8 Security and Other Enhancements

These include proposals to incorporate N-1 security constraints (Majidi-Qadikolai and Baldick, 2016), N-K security constraints[10] (Moreira et al., 2015), and extreme events such as blackouts (Shortle et al., 2014) and earthquakes (Romero et al., 2013).

3.5 Value of Model Enhancements (VOME)

For the enhancements mentioned in Section 3.4, their impacts on solutions to TEP optimization models have often been assessed through sensitivity analyses (Ho et al., 2016; Krishnan and Cole, 2016; Mai et al., 2015; Shawhan et al., 2014). These analyses usually focus on changes in decisions (such as locations or amounts of investments) rather than on the improvement in the economic performance of recommended plans, i.e., the improvement in expected costs if solutions from the more sophisticated model were to be implemented. In one exception, the cost savings resulting from proactive transmission planning were investigated in (Spyrou et al., 2017), but they were not compared to the value of other kinds of enhancements.

[10] These problems model N-K (including N-1 or N-1-1) as constraints to maintain the operation feasibility under N-K contingencies, which refer to the contingencies where the system suddenly loses K facilities (generators or transmission lines) because of equipment failure or any other reason.

To the best of my knowledge, a systematic framework for researchers and planners to compare the economic value of alternative modeling enhancements has not been proposed previously. The contribution of this work is to present such a framework to prioritize model improvement efforts and to illustrate its potential usefulness through a realistic case study.

In this section, I first define the value of model enhancements. I then propose a framework for implementing this idea in transmission optimization modeling. Finally, a metric is proposed that compares VOME to the overall benefits of transmission expansion, which is useful for gauging the practical significance of VOME.

3.5.1 Definition of VOME

VOME is a close analogy to the idea of the "expected value of perfect information" (EVPI) from decision analysis. EVPI is the most that a planner is willing to pay for perfect information, equal to the probability-weighted (expected) improvement in the performance of the optimal solution if perfect information is provided about future conditions.

Here is a simple example of EVPI. Suppose a decision-maker (DM) needs to select one from two choices, A and B, to prepare for an uncertain future of two equally possible scenarios S1 and S2. A cost of 1 will occur if the DM chooses A while S1 happens, and we note this as $C_{S1,A} = 1$. Then, suppose we have $C_{S2,A} = 1$, $C_{S1,B} = 0.5$, $C_{S2,B} = 2$. Naturally, choice A will invoke an expected cost of 1, and choice B an expected cost of 1.25; if DM is risk-neutral, he will choose A as it costs less. However, if a fortune teller can tell DM what will surely happen before DM making a choice, DM will choose A while he knows S2 will happen, and B for S1; this will invoke an expected cost of 0.75. The maximum

amount of money that this DM is willing to pay for this fortune teller, i.e., perfect information, is thus 1.25 – 0.75 = 0.5.

Similarly, VOME can be stated as: *what are we willing to pay for elaborating a planning model in a specified way?* This is the expected improvement in the performance of the resulting decision. Another way to look at VOME is the deterioration in the solution if the model is simplified, i.e., how much solution performance is sacrificed, in expectation, if a particular simplification is made, i.e., an enhancement is omitted.

The idea as follows. Imagine a DM builds a model, and the model indicates that some plan x_A is optimal. Then, the DM enhances the model by improving the realism of the constraints or objective and then gets a different plan x_B back instead. Finally, imagine for now that the DM can test the performance of alternative plans before implementing them by using a sophisticated and highly realistic simulation model. This simulation shows x_A would have a "true" expected cost of $C(x_A)$, while decision x_B's "true" cost is $C(x_B)$ (I put the "true" into quotes because the actual expected cost cannot be known, but this is the best estimate that can be obtained. These "true" costs are, of course, subject to uncertainty because of the inability to consider all possible scenarios and because the probabilities used are themselves uncertain. Further, any estimate of such costs is itself subject to error because of model and data limitations even in the most sophisticated model.) The VOME of this enhancement (more constraints) is then calculated as $C(x_A)$ - $C(x_B)$, which is the decrease in "true" cost resulting from using the enhanced model to make decisions.

However, we must overcome at least three conceptual difficulties to calculate the VOME successfully.

1) Sometimes an enhancement involves combining information from several sources. For example, we can have a model A1 based on one set of n operating hours/yr, and a model A2 based on a different set of n hours/yr. Combining the information, we have model B with $2n$ hours. Then the cost improvement can be calculated in two ways: ($C(x_{A1})$ - $C(x_B)$) and ($C(x_{A2})$ - $C(x_B)$). Which should we use?
2) There are usually multiple enhancements available. For instance, if there are 2 kinds of enhancements, from A to B (e.g., fewer to more operating hours) and from C to D (e.g., from a simple to a more sophisticated network), then there are 4 types of models (what we call "enhancement settings" ω): AC, BC, AD, BD. This also means that there are at least two ways of calculating the savings of using B rather than A: ($C(x_{AC})$ - $C(x_{BC})$) and ($C(x_{AD})$ - $C(x_{BD})$). Which should we use?
3) The "true" cost $C(x)$ may be hard to evaluate, involving a complex or difficult to compute model, as it should ideally be capable of simultaneously evaluating all enhancements under investigation. How should $C(x)$ be estimated?

To address these difficulties, I propose the approach below:

1) When the enhancement involves combining information from more than one source, we can calculate a weighted average of the improvements. For instance, consider the enhancement mentioned above, in which two sets of hours, each of size n, are combined into a $2n$ hour set. Since each set contributes half of the information, we set the weights to 0.5. In that case, the value of this enhancement is $((0.5C(x_{A1}) + 0.5C(x_{A2}))-C(x_B))$. A similar idea is applied to assess the enhancement from deterministic to stochastic planning. For example, consider two possible scenarios with probability p_1 and p_2, resulting in plans x_1 and x_2. A stochastic model considering

both scenarios and their probabilities gives a plan x_s. Then, the value of this enhancement is $((p_2C(x_1) + p_2C(x_2))-C(x_s))$. This is the same as the definition of the expected cost of ignoring uncertainty (ECIU) (also known as the value of the stochastic solution) in classical decision analysis (Birge and Louveaux, 2011).

2) When calculating the VOME for one enhancement when others are also under consideration, we calculate the incremental impact given every possible combination of the other enhancements. That is, we compare solutions from two models at a time, where only the enhancement of interest i is changed, and all other model features are the same. This results in N_i pairs of decisions (thus N_i cost differences), where N_i equals the number of all possible permutations of other enhancements; e.g., if there are 3 other possible enhancements, each either being present or absent, then there are $N_i = 2^3 = 8$ possible combinations of those features. Then we average these N_i cost differences.

3) We define the "true" system cost $C(x)$ as the best obtainable estimate of the cost of making decision x. This can be done by fixing x in the most sophisticated model that can be solved and optimizing over other variables again.

With these assumptions, VOME can be formulated as follows:

$$VOME_i = \frac{1}{N_i} \sum_{(\omega_0,\omega_1)\in\Omega_i} \left(E\left[C\left(x_{\omega_0}\right)\right] - E\left[C\left(x_{\omega_1}\right)\right]\right) \tag{3.1}$$

In this formulation, x is the decision (here, the immediate or first-stage transmission investment) obtained by a model with formulation setting ω. The set Ω_i is composed of all the pairs of model formulations (ω_0, ω_1) in which:

1) $E_i(\omega_0) = 0$, $E_i(\omega_1) = 1$; i.e., the two model formulations being compared are without and with enhancement i, respectively, and

2) $E_j(\omega_0) = E_j(\omega_1)$, for all j ≠ i; i.e., enhancements other than *i* are the same in the two models whose costs are compared.

In other words, Ω_i is the set of all possible pairs of models involving permutations of enhancements other than *i*. N_i is the number of model pairs within Ω_i. The expectation operator accounts for both the possibility of multiple long-run scenarios (each with an assumed probability) and the weighting of multiple sets of information, as described under the first difficulty above.

Note that this section has focused on the theoretical calculation of the VOME, which in general requires that models with every possible combination of enhancements need to be solved. For instance, if one has three (3) candidate enhancements for his model and they are not mutually exclusive, he will need to solve the model and test the solution at least 8 times to fully calculate the VOME for each enhancement; 16 if he has four (4) enhancements. In practice, this might not be practical. Thus, I provide suggestions for the practical utilization of VOME in transmission planning in the conclusion discussion of Section 3.8.

3.5.2 VOME calculation in Transmission Planning

Before I implement VOME for transmission planning models, I lay out three basic assumptions of the VOME calculation procedure.

First, all my *transmission planning models are in the form of transmission-generation co-optimization* (Sauma and Oren, 2006). Thus, the optimal transmission plan anticipates how generator investment and spot markets will react to grid changes, under the assumption that generation decisions take place under competitive conditions.

Second, I take the viewpoint of a transmission planner and am interested in *the cost of making mistakes in the first stage (immediate or "here and now") transmission investment decisions*. I define x, for the application in this chapter, as the first stage *transmission* investments, and when calculating $C(x)$, I allow the most sophisticated model to choose the second stage transmission investments, as well as all generation decisions. This assumption is based on the recognition that a transmission system only commits to first stage (immediate) decisions and has the flexibility to deviate from the solution's second stage recommendations later when there is better information. Thus, this VOME is the value of the model enhancement just for immediate transmission investments.

Finally, in calculating $C(x)$, I assume that *generation investors make decisions with full information on how the grid design would affect prices*, based on the information that would be provided by a model with all enhancements, even if transmission plans x are based on more naïve assumptions from a simpler model. This can be viewed as the competitive energy market's reaction to grid reinforcements x, in which generators use the most sophisticated possible model to project prices, even if the transmission planner is naive.

Alternative assumptions are possible when calculating VOME. For instance, oligopoly could be assumed instead of competitive energy markets. Or first stage generation investments could also be included in x, in which case VOME would quantify the value of better models for combined transmission-generation planning.

Combining all three assumptions, I calculate VOME following the procedure in the flowchart in Figure 3.1, where:

1) x is the first-stage transmission investment from a model with an assumed set of enhancements. For example, a TEP model with transshipment power flow

modeling generates a plan x showing lines A and B are to be built in the first ten years; a TEP model with DC OPF generates a plan x' showing C and D are to be built.

2) $C(x)$ is the "true" system cost obtained by simulating the optimal generation decisions and second-stage transmission investments in response to x. Following the example above, in the model with DC OPF, I fix the first-stage decision as building A and B and re-run the model; I record the resulted objective function as $C(x)$. This simulates the reaction of the markets toward the expansion decision of building A and B. Then, I plug in the plan x', C and D, and re-run the model to get $C(x')$.
3) VOME for an enhancement is then obtained by (3.1). In the simple example above, the value of adding DC OPF to a TEP model is thus $C(x) - C(x')$.

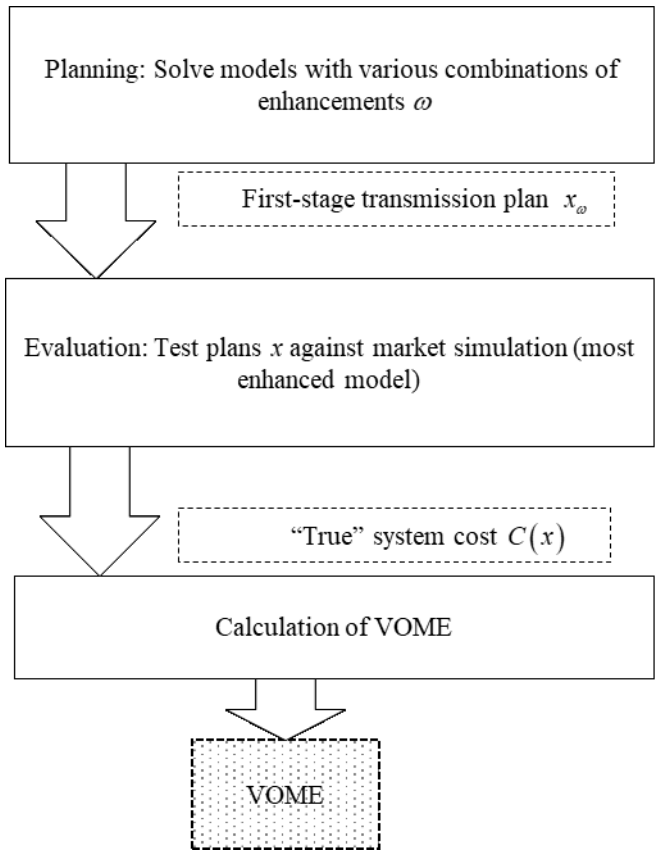

Figure 3.1. Procedure for calculating VOME in multistage transmission planning

3.5.3 A Benefit Metric for Transmission Planning

To place VOME in context, I compare it to the overall benefit of building new transmission. If VOME for one model feature is a significant fraction of the total benefit of adding transmission, then I conclude that such enhancement is potentially important to include in the model.

The benefit of the additional transmission capacity is calculated as follows. Assume that it is feasible to build no lines at all in the first stage and let x_0 stand for this null plan. The resulting null plan cost (*NPC*) will be $C(x_0)$. Then I can define any other plan x's net benefit ($NB(x)$) as the reduction in system cost relative to the null plan: $NB(x) = NPC - C(x)$.

For example, if building no lines in the near term will result in a system cost of \$790B, and an alternative plan A will result in a cost of \$770B, the benefit of this plan is \$790B – \$770B = \$20B.

By defining "true" cost $C(x)$ as the cost from the most sophisticated model, i.e., with all enhancements, I can define the best possible plan cost (OPC) as $C(x_1)$, where x_1 is the optimal first stage transmission solution from that model. I can then define the upper bound of economic benefit (UPB) from new lines as $UPB = NPC - OPC$. For example, if building the optimal plan from the most enhanced model will result in a present worth of \$750B, the upper bound of the economic benefit from building transmission in the first stage is UPB = \$790B – \$750B = \$40B. Assuming that the most sophisticated optimization model correctly solves, no other first stage plan x can yield a lower value of $C()$ than $C(x_1)$, since, by definition, x_1 is the optimal solution of that model.

Any plan x, other than the optimal plan x_1, might achieve some but not all possible benefits. Thus, I can define the proportion of possible benefits that are realized by building x ("economic benefit recovery") as $BR(x) = NB(x) / UPB$. For example, plan A would realize \$20B/\$40B = 50% of the total possible benefit. Of course, a better plan (thus a better TEP model) should result in more net benefits.

The $BR(x)$ is intended to be a relative metric that is useful to compare different transmission plans. One reason for normalizing it with respect to transmission benefits is because the change in the overall objective function resulting from transmission investment is usually a small part of total system cost, which is typically one to two orders of magnitude larger in actual power systems because it also includes all generation capital and

operating costs. Such a relative index is also useful for comparing VOME across different planning problems.

However, the calculation of VOME, which can be undertaken by following the flow chart Figure 3.1, does not require the use of the benefit recovery metric defined here. Rather, this metric is a simple means to help the reader interpret the significance of the benefits of enhancement, i.e., VOME.

3.6 Experimental Design

3.6.1 Overview

I now describe how I implemented VOME in a realistic transmission planning study. I provide results from this study in Section 3.7; these results illustrate the types of insights that can be obtained concerning the economic value of improved model features and identify long-run uncertainties as the most beneficial enhancements among those considered here. First, I briefly describe the basic model for the VOME calculation, and then I give an overview of the enhancements I investigated. I then summarize the case study environment, which is a 300-bus network for WECC. Finally, I describe how the four enhancements are added to the model.

3.6.2 Summary of Basic Planning Model

The basic planning model is the Johns Hopkins Stochastic Multi-Stage Integrated Network Expansion (JHSMINE), whose mathematical formulation can be found in Chapter 2. In this chapter, a two-stage version of JHSMINE is used (Xu and Hobbs, 2017) (Figure 3.2, where one of the scenarios is explicitly shown), in which first-stage (here-and-now) decisions made today (year 0) include immediate transmission and generation

investments that will be online in year 10, while recourse decisions are new transmission/generation investments that come online in year 20, as well as optimal generation dispatch and power flows in years 10 and 20, the latter being used to estimate costs in years after 20.

The objective function is the net present value of the system cost, which is composed of discounted cash flow in each operating year (year 10 and year 20 in Figure 3.2). The cash flows include the overnight cost of building generation and transmission assets, as well as the system operating cost, including unit commitment and dispatch expenses. These decisions are subject to network, unit commitment, and other constraints. Renewable portfolio standards and renewable credit trading are also modeled. Uncertainties can be handled through multiple scenarios, each with a different set of year 10 and year 20 model parameters. Examples include capital cost uncertainties caused by technology advances (i.e., scenarios of objective function coefficients), load/peak growth uncertainty (represented by scenarios of right-hand sides of constraints), and policy uncertainties, such as carbon prices.

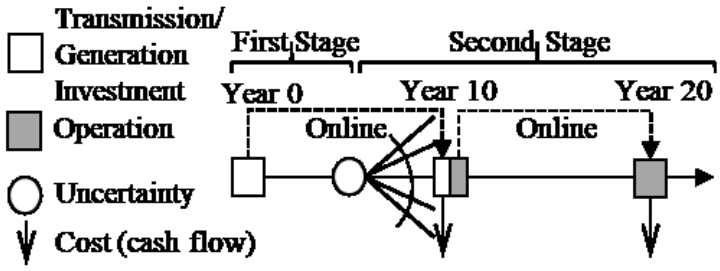

Figure 3.2. Diagram of JHSMINE chronology in Chapter 3

3.6.3 Case Study Environment: 300-bus WECC system

Here, I discuss four sets of assumptions: network reduction, existing generation mix, new generation investments, and network investment possibilities.

First, the system is a reduction I performed of the WECC Common Case 2024 network, generators, and loads (WECC, 2014a) (details in Ho et al. (2016), Zhu and Tylavsky (2018), and I abstractly reproduced the method in Appendix B). The reduced network includes 328 nodes and 530 lines (Figure 3.3), in which 249 of the nodes are preserved existing nodes in the original network (230 kV or above), while 244 lines (red lines in Figure 3.3) are preserved existing lines from the original network. The preserved paths divide the whole network into 26 regions (WECC, 2013b).

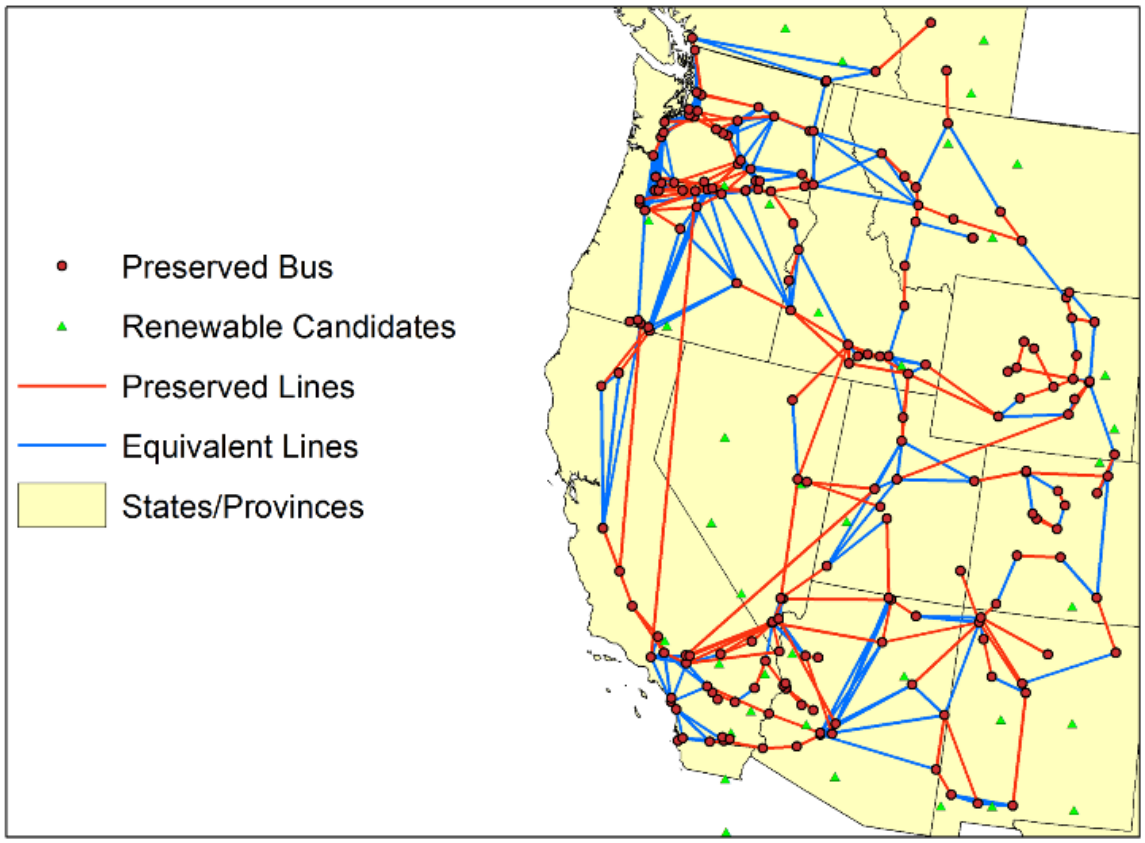

Figure 3.3. WECC case study network reduction

Second, the system includes 544 existing generators of 16 types distributed among 249 existing nodes (for the generation aggregation procedure, see Appendix C). Third, the other 79 nodes are designed as candidate sites for generation expansion. 26 of the 79 nodes are location-irrelevant conventional generation expansion sites in each of the 26 regions just mentioned. The remaining 53 nodes in the network are candidate sites for renewable investment (green triangles in Figure 3.3). Their locations and potential capacities are derived from data from Western Governors' Association and U.S. Dept. of Energy (2009). Four types of renewables (wind, utility-level solar, geothermal, and biofuels) can be constructed along with two types of conventional generation (gas combined cycle and combustion turbines). Capital costs assumptions vary based on the location of candidate sites (which state each candidate is located); they are available at E3 and WECC (2014).

Finally, transmission investment candidates can be divided into two categories: backbone reinforcements and renewable access. Backbone reinforcements are defined as having the characteristics of the existing line with the largest capacity in a given WECC transmission path; the path data are at WECC (2013b). Such lines relieve congestion and path limits: the amount of increased path limit is identical to the line that the candidate is mirroring. Here is a simple example, suppose a path with a 1000 MW limit be composed of two lines with 900 MW and 300 MW thermal limits, respectively. I will design a candidate mimicking the line with 900 MW, the larger of the two; if built, this candidate will increase the path limit by 1000 MW · 900 MW /(900 MW + 300 MW) = 750 MW. Radial renewable access lines connect renewable developments to the closest nodes in the existing network. Since I assumed all reinforcements in the WECC "Common Case" (WECC,

2014a) have been brought online by 2024, all transmission investment variables in my model are incremental over and above the Common Case.

3.6.4 Candidate Model Enhancements

I compare the economic value of four possible model enhancements using VOME: adding generation unit commitment constraints, adding more hours (i.e., load slices) into operation simulation, adding DC OPF modeling in the power flow modeling, and finally, adding stochasticity by considering multiple long-run scenarios.

3.6.4.1 Generating Unit Commitment

This enhancement consists of replacing the basic load-duration-curve-based representation of system dispatch (in which a year's hourly loads are grouped into nonchronological "load slices" of similar hours, and no operating constraints link generation dispatch variables in different slices.) This enables the model to consider limits upon generation flexibility, such as start-up costs, minimum running capacity, and ramp limits, which I collectively refer to as unit commitment constraints. This enhancement would penalize slow-moving steam generators relative to single and combined cycle plants. Such limits are relevant to transmission planning because, for example, delivery of distant renewables will be less valuable if their fluctuating output cannot be fully used by the grid.

In my model, this enhancement is modeling by defining a new continuous decision variable as the in-operation minimum run capacity (in MW), and linearizing every set of unit commitment constraints (start-up, shut-down, ramp rate limit and minimum start-up

and shutdown time) around it (Kasina et al., 2013).[11] The effect of linearized unit commitment is two-fold: fewer binary variables, thus speeding up solution times; and enabling the model to include generation capacities as decision variables. Only thermal generation technologies are subject to these flexibility constraints.

3.6.4.2 Network Modelling

More physically realistic models of power flows will help the TEP model to characterize better how grid reinforcements affect transmission capability, dispatch, and, ultimately, costs.

The basic model is a pipes-and-bubbles (P&B, or transshipment) power flow model that does not enforce Kirchhoff's voltage law; to wit, only constraints (2.40) and (2.42) of Section 2.4.4 are implemented. This model can be enhanced by implementing a linearized DC power flow model using a "B-theta" formulation, which includes the voltage law by explicitly modeling phase angles, but assumes unit voltage and negligible resistance (Glover et al., 2011). Flow on a line equals the phase angle difference across the line divided by impedance; I enforce this for new lines by disjunctive constraints (Bahiense et al., 2001) that use 0-1 variables to represent absence/presence of the line; to see the constraint, I refer readers to the constraint (2.41) of Section 2.4.4. An intermediate level of enhancement is hybrid flow modeling (Romero et al., 2002), as defined in Section 3.4, above. I evaluate both enhancements: from "Pipes and Bubbles" to "Hybrid power flow" and from "Hybrid power flow" to "DC OPF."

[11] This unit commitment formulation is documented in Ho et al. (2016) and Xu and Hobbs (2017), while the one presented in Chapter 2 is an refined version based on Kasina (2017), where the unit commitment variable can be binary or continuously in [0, 1]. There is no apparent deviation between these two versions.

3.6.4.3 More Short-Run (Within-Year) Temporal Granularity

This enhancement consists of increasing the number of load slides or distinct hours considered in the operating model from 24 to 48.

Computational limits mean that it is not possible to model 8760 hours/year in a multi-decadal transmission optimization model, even without any other enhancements; this necessitates the aggregation of hours into a smaller number of distinct operating periods. More periods/year can yield a better representation of load and renewable temporal distributions and correlations.

The two 24-hour sets are generated using a methodology combining clustering (James et al., 2013) and random sampling. First, based on the 8760-hourly profiles of load and intermittent resources availability (e.g., hydroelectricity, wind, solar, etc.), the 8760 hours are grouped into 24 clusters, each of which has a different size (N_c, c = 1 … 24). Second, one hour from each cluster is randomly selected to generate a single sample hour-set, and this step is repeated 80,000 times. When using a 24-hour sample in the TEP model, each hour is assumed to be repeated N_c times. Finally, two mutually exclusive 24-hour samples are selected. Each sample set of hours is chosen by minimizing the deviation of first and second moments of all profiles between the 24-hour sample sets and the original 8760-hourly data while constraining the sampled coincident peak to be at least 85% of the peak of 8760-hourly data. The 48-hour set is the union of these two 24-hour sets, with the duration of each hour halved. Examples of the resulting load duration curves are shown in Figure 3.4.

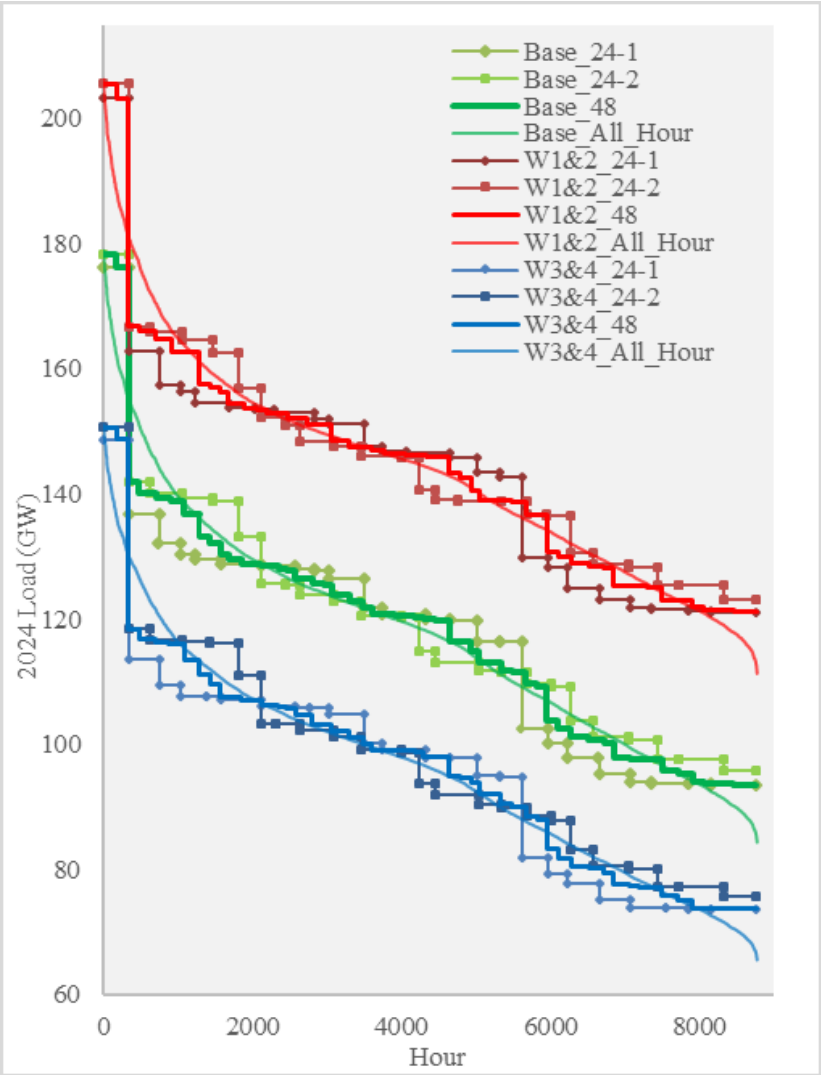

Figure 3.4. WECC-wide load duration curves (LDCs) for different hour sets in the year 2024

3.6.4.4 Stochasticity: Multiple Long-Run Scenarios

This enhancement consists of extending the JHSMINE from a deterministic TEP planning to a stochastic TEP planning by adding five (5) long-run scenarios.

Reasons for considering long-run uncertainty are discussed in the introduction and the literature review (Sections 3.2 and 3.3, above) and in more detail in Lumbreras and Ramos (2016). Here, I take stochasticity into consideration by two-stage stochastic

programming (Birge and Louveaux, 2011). This method uses an expected cost objective to decide which the first-stage investment commitments ("here-and-now" decisions) to make before it is known how uncertainties such as load growth will be resolved while making "wait-and-see" (or second-stage) decisions afterward. Although, as mentioned in the literature review, there are other uncertainty planning methods, stochastic programming has the advantage of representing system adaptations over time as well as the state-of-knowledge when commitments are made. Further, the objective (MIN expected cost) is consistent with the definition of $C(x)$ used by VOME.

I quantify the value of considering long-run uncertainties in the case study by considering the first stage transmission decisions x that are made considering either each of 5 scenarios separately (deterministic model) or jointly in an enhanced model (stochastic programming, with 5 second-stage scenarios). In the latter model, I assume the 5 scenarios are equally likely. Parameters values for these five scenarios (

Table 3.2) are either directly from WECC's 2013 study cases (WECC, 2013a) or developed with the help of a WECC technical advisory group (Ho et al., 2016). As an example of the long-run scenario definitions, the load duration curves of different hour-sets in different scenarios in 2024 is shown in Figure 3.4. Note that the 48-hour approximations are visibly better approximations of the full 8760-hour LDCs, which are also shown in Figure 3.4.

Table 3.2. Values of Uncertain Variables by Scenario

Scenario:	Base	W1	W2	W3	W4
Gas Price (% change from base)	0	+86	0	0	-51
Carbon Price ($/ton)	58	58	113	33	113
Load Growth (%/year)	1.13	3.20	3.20	-0.91	-0.91
Peak Growth (%/year)	1.28	2.64	2.64	-0.37	-0.37
State RPS (% change)	0	0	+50	0	+50
Federal RPS (% of Load)	0	0	+15	0	+15
Wind Capital Cost (% change)	0	+7.5	-18.3	+7.5	-18.3
Geothermal Capital Cost (% change)	0	0	-15	0	0
Solar Capital Cost (% change)	0	0	-28.7	+30	0

3.6.4.5 Summary of Experimental Design

For the above four enhancements, two groups of experiments were undertaken as follows. In the first group, the effect of generator unit commitment (the first enhancement) is investigated by itself, with the model including stochasticity (5 scenarios) but only the pipe-and-bubbles network. Then, in the second group of experiments, the other three enhancements (temporal granularity, network representation, and stochasticity) are compared together. Unit commitment is analyzed in a separate experiment, mainly because it requires sequential hourly data. This requirement, which requires representative days instead of hours, renders the planning model with other features, especially DC OPF, computationally intractable. On the other hand, the three days (72 hours) I used in the unit commitment analysis are not as accurate a representation of cross-region load and renewable output correlations as the sets of hours investigated in the second experiment.

3.7 Results

In this section, I show the outcomes of the VOME experiments for the case study WECC system. First, I summarize model sizes and computation times to help the reader appreciate the "curse of dimensionality" that arises from attempts to include all possible enhancements. Then I show the VOME for adding unit commitment variables, costs, and constraints to the planning model and, finally, compare the values of VOME across the enhancements of increased temporal granularity, improved network representation, and inclusion of long-run uncertainties via multiple scenarios.

3.7.1 Model Size and Computation Time Comparison

First, in Table 3.3 and

Table 3.4, I display the change in model size and solution times under alternative enhancements.

Table 3.3. Model Size and Solution Time with Various Enhancements (Deterministic / Single Scenario Cases)

	Deterministic (14 candidate backbone lines x 2 stages)					
Network	P&B	Hybrid	DC OPF	P&B	Hybrid	DC OPF
# Hours (Load Slices)	24	24	24	48	48	48
# Constraints (million)	0.23	0.26	0.26	0.46	0.51	0.52
# Variables (million)	0.18	0.19	0.19	0.36	0.36	0.36
Solution Time (minutes)	0.5	6.67	13.94	1.17	23.19	51.79

Table 3.4. Model Size and Solution Time with Various Enhancements (Stochastic / Five Second Stage Scenarios)

	Stochastic (Same Candidates, 5 WECC scenarios)							
Network	P&B	Hybrid	DC OPF	P&B	Hybrid	DC OPF	No UC	With UC
# Hours (Load Slices)	24	24	24	48	48	48	72	72
# Constraints (million)	1.15	1.25	1.26	2.25	2.49	2.51	4.97	17.5
# Variables (million)	0.90	0.93	0.93	1.74	1.86	1.86	4.19	7.61
Solution Time (Hours)	0.06	1.97	15.46	0.25	13.49	34.67	0.77	25.8

All these models are mixed-integer linear programs (MILPs) and are solved to a MILP gap of 10^{-4} (relative to the objective function value) to avoid possible biases in my conclusions introduced by large gaps. All models were solved on a workstation with an Intel® Core™ i7-5930K CPU and 32 GB of core memory using solver CPLEX 12.6.3. All solution times shown here are averages, since, for example, there are 10 deterministic runs using the P&B network together one of the two 24-hour sets (5 scenarios times 2 sets of 24 hours), for which the average solution time is 30 seconds.

In summary, model size dramatically affects solution times. Only about 30 seconds are needed to generate an optimal plan for the most simplified model, while more than one day was required to solve a model with the most enhancements.

3.7.2 First Group of Experiments: VOME of Unit Commitment

In this part of the analysis, first-stage plans are generated from two planning models, both with the stochasticity enhancement (5 scenarios, see Section 3.6.4.4), but one without linearized unit commitment constraints and costs, and the other with those features. The

network was assumed to be P&B for computation tractability. The same three days were considered per year (72 hours/year) in both models.

Since the planning model that includes unit commitment is closer to reality, the calculation of $C(x)$ is performed with both unit commitment and stochasticity. That is, "true" cost $C(x)$ for a given set of first-stage transmission investments, x, is calculated by optimizing all the other decision variables while including first-stage generation investments, unit commitment, and 5 second-stage scenarios and associated second-stage generation and transmission investment and operating variables. The resulting cost of transmission plans and their benefits is shown below in

Table 3.5. The "true" cost $C(x_0)$ of the null plan x_0 (no first stage transmission other than the WECC Common Case lines) is *NPC* = \$890.38B (2014 present worth). In contrast, with about \$3.18B of first-stage transmission investment x resulting from the unit commitment model with 5 scenarios, the system's "true" cost $C(x_1)$ is \$35.39B lower, which I treat as the upper bound *UPB* of the net benefit of transmission.

In contrast, if unit commitment is *not* included, more renewable interconnection transmission is constructed, with a higher total first stage transmission investment (\$3.52B), and a $C(x)$ that is \$35.28B lower than *NPC*. Thus, the model enhanced with unit commitment gave a more conservative plan x, whose benefits are \$0.11B billion higher (= \$35.39B-\$35.28B) than the x resulting from the model without unit commitment. This is my estimate of VOME for including the unit commitment in the WECC-wide transmission planning model.

Table 3.5. First Experiment Group: Costs and Expected Benefits of First Stage Transmission Plans Generated by Model without/with Unit Commitment Enhancement (billion 2014 US$).

Planning Model	No Unit Commitment	With Unit Commitment
Backbone Transmission	0.80	0.80
Renewable Transmission	2.72	2.38
"True" Cost $C(x)$	855.11	854.99
Net Benefit ($NB(x)$) relative to null plan	35.28	35.39
Benefit recovery $BR(x)$	99.7%	100%
Null plan cost (NPC)[12]	890.38	

3.7.3 Second Group of Experiments: VOME of Temporal Granularity, Power Flow Representation, and Stochasticity

While estimating the VOME of the three other enhancements, the impracticality of solving a unit commitment model together with all three other enhancements means that each model in this section omits unit commitment (i.e., assumes that generators can be ramped up and down without restriction and can be freely started up or shut down).

Also, for the same reason, requirements for spinning reserves, which would double the number of operating variables for conventional generators, are not modeled in this section;[13] for the formulation, I refer readers to Section 2.4.7 of Chapter 2. Nevertheless, the inclusion of generation spinning reserves can be viewed as an enhancement of TEP, and therefore can be investigated by VOME as well. The results showed a nearly negligible VOME of $0.007B (0.02% of the $35.39B benefit of transmission) for including spinning reserves compared to the VOME for UC of $0.11B (0.32%). In summary, the unit

[12] This null plan cost is based on the three days modeled in the first group of analyses; as these three days are different from the 24/48 load slices used in the second group of analyses, the null plan cost and other cost values of the latter are thus different from the first group.

[13] It was in the first group of analyses.

commitment modeling and the spinning reserve modeling are not modeled in the second group of analyses.

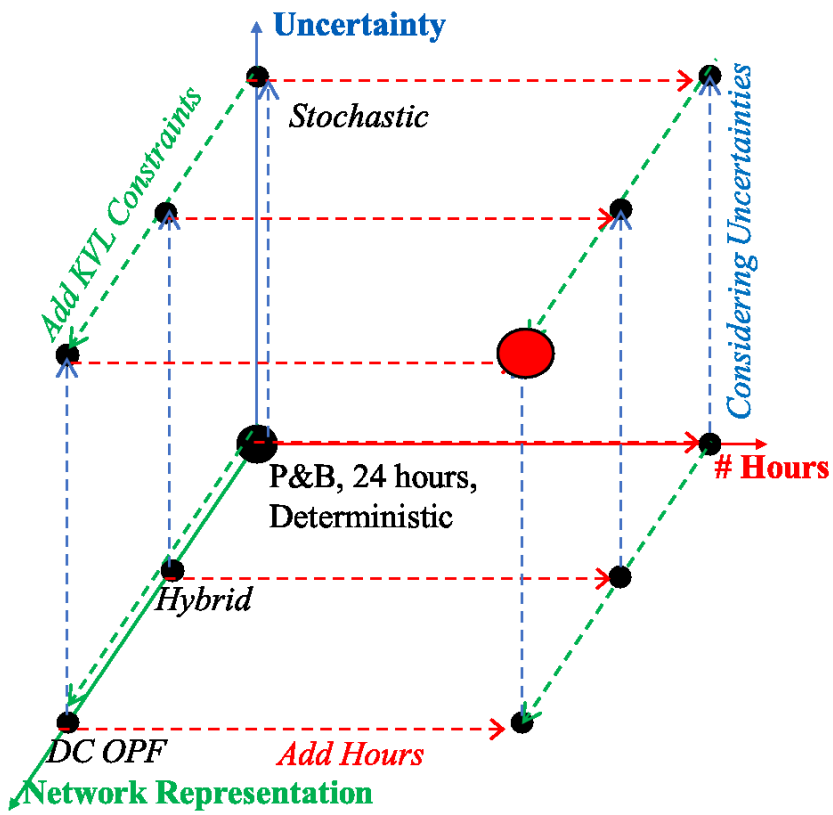

Figure 3.5. The conceptual framework for VOME calculation of Temporal Granularity, Network Representation, and Stochasticity

Figure 3.5 is a visualization of how I implemented the definition of VOME from Section 3.5 in this experiment. Let the origin of the three-dimensional plot represent the outcome of a highly simplified model with just a P&B network, 24 operating hours/year, and a single long-term scenario. Then one can imagine enhancing the planning model along any or all of three dimensions, anticipating that the enhancement(s) will generate a more beneficial first-stage transmission plan x. Each node in the diagram represents one possible model formulation (a combination of enhancements), for which I obtain the first-stage transmission plan x whose "true" cost $C(x)$ is calculated using the most sophisticated

set of assumptions (linearized DC network, 48 hours/year, and stochasticity with 5 scenarios). Then I calculate the differences between adjacent nodes, which is equivalent to calculating the cost savings resulting from enhancing the model in one direction. The average of cost differences (across the four to six arrows with the same color) is the VOME for the enhancement represented by the direction of the arrow, i.e., Eq. (3.1), above.

Table 3.6 shows the benefits achieved by different plans obtained by comparing their "true" cost $C(x)$ to that of the null plan $C(x_0)$; Figure 3.6 is a visualization of Table 3.6 by adding results on Figure 3.5. The upper bound of benefit is UPB = \$40.58B (the value of the plan from the model with all enhancements, last entry in the next-to-last row). (Note that this differs slightly from the UPB for the model with unit commitment in the previous section.)

Several trends are noticeable in Table 3.6. First, deterministic models (especially based on scenario W3) often perform poorly relative to stochastic models. The benefits of plans generated by stochastic models are consistently higher than plans from the five deterministic models (one per scenario) in the same row. The large variation among the five deterministic models in each row shows that choosing the wrong scenario for planning can result in large regret. On average, stochastic plans achieved \$5.59B more benefits compared to deterministic plans, which represents 13.8% of the maximum benefits of first-stage transmission investments UPB.

Table 3.6. Net Benefits NB(x) of First-Stage Transmission x Generated by Different Models (Billion 2014US$)

Power Flow/ Hour Set	Deterministic (Single Scenario) Plans						Stochastic
	Base	W1	W2	W3	W4	Avg.	
P&B/24-Set 1	36.84	37.91	38.40	21.93	34.75	33.97	39.67
P&B/24-Set 2	38.56	38.53	38.94	22.39	36.28	34.94	39.74
P&B/48 hours	38.45	38.19	38.60	23.48	35.89	34.92	39.87
Hybrid/24-Set 1	37.54	38.47	38.81	19.60	35.71	34.03	39.66
Hybrid/24-Set 2	38.98	38.81	39.17	17.44	35.95	34.07	40.17
Hybrid/48 hours	39.43	38.59	38.94	20.36	36.30	34.72	40.46
DCOPF/24-Set 1	37.69	38.87	38.92	19.64	35.17	34.06	39.79
DCOPF/24-Set 2	39.02	39.19	39.30	17.40	36.16	34.21	40.24
DCOPF/48 hours	39.48	39.04	39.06	19.79	36.32	34.74	40.58
Null Plan (x =0) Cost (*NPC*)						788.93	

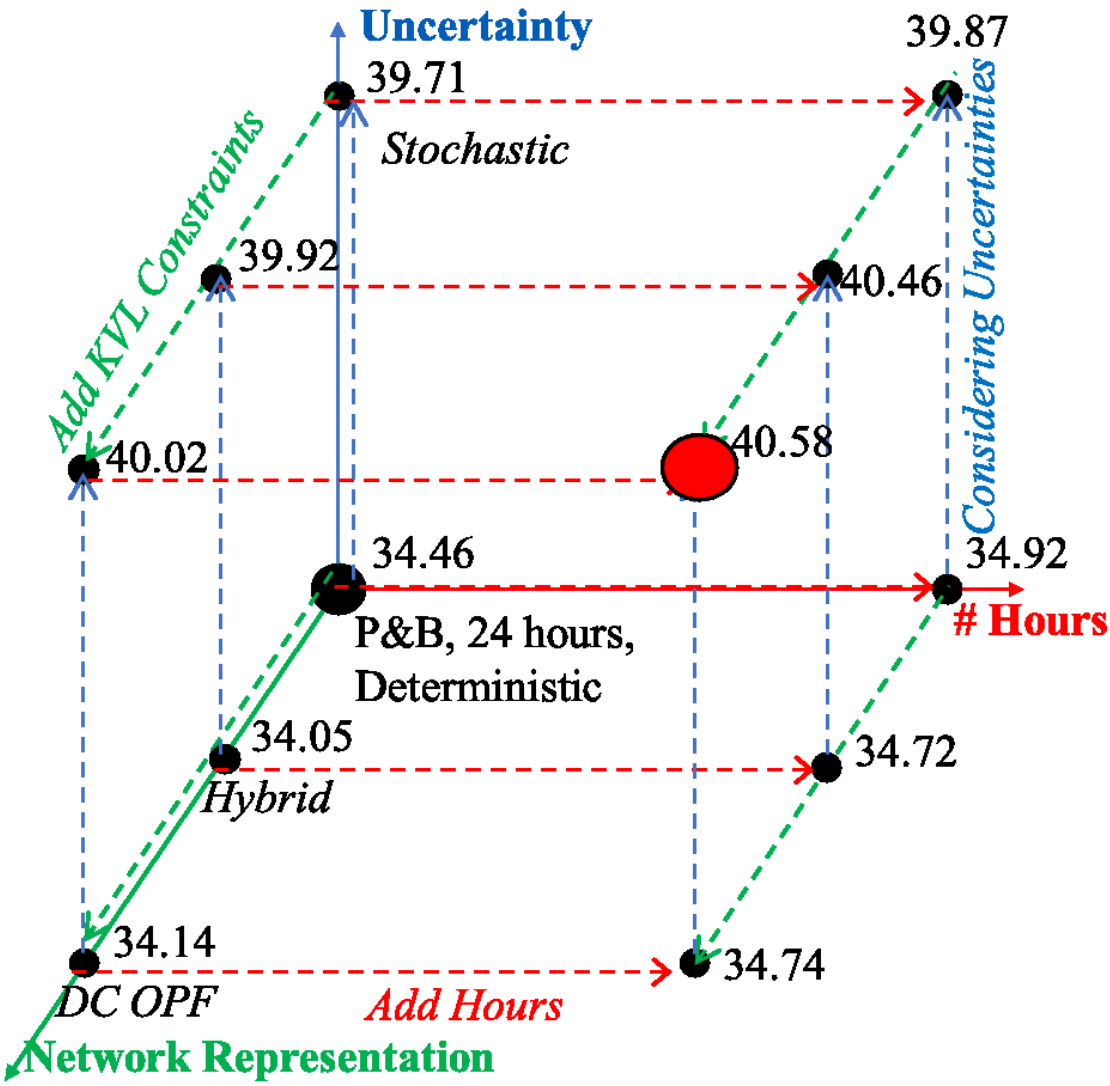

Figure 3.6. VOME Results of Temporal Granularity, Network Representation, and Stochasticity

Second, for the enhancements of temporal granularity and power flow representation, the improvements in "true" cost are consistently small, and their sign can vary. For example, on average, for a model with deterministic and 48-hour enhancement, "true" benefits *decrease* when hybrid power flow is modeled instead of P&B power flow, resulting in a negative number in column 4, last row of Table 3.7.

An individual model enhancement can result in negative benefits (worse plans) because (1) plan x is only part of the solution, and (2) adding just some of a set of missing constraints does not necessarily lead to better values of a subset of the decision variables (e.g., x). To visualize, see Figure 3.7 for a two-variable optimization. Initially, imagine two models: a full model, of which the feasible region is colored grey in Figure 3.7, and a base model with two missing constraints, Con_1 and Con_2; furthermore, imagine an objective function with a maximizing direction indicated by the blue arrow. The first observation is intuitive: the optimal solution is (x^*, y^*), and the objective function is $O(x^*)$. The base model, however, yields a different solution of (x_a, y_a); by fixing $x = x_a$ and solving the full optimization again, I obtain a solution of $(x_a, \underline{y}_a)$ and an objective function $O(x_a)$.

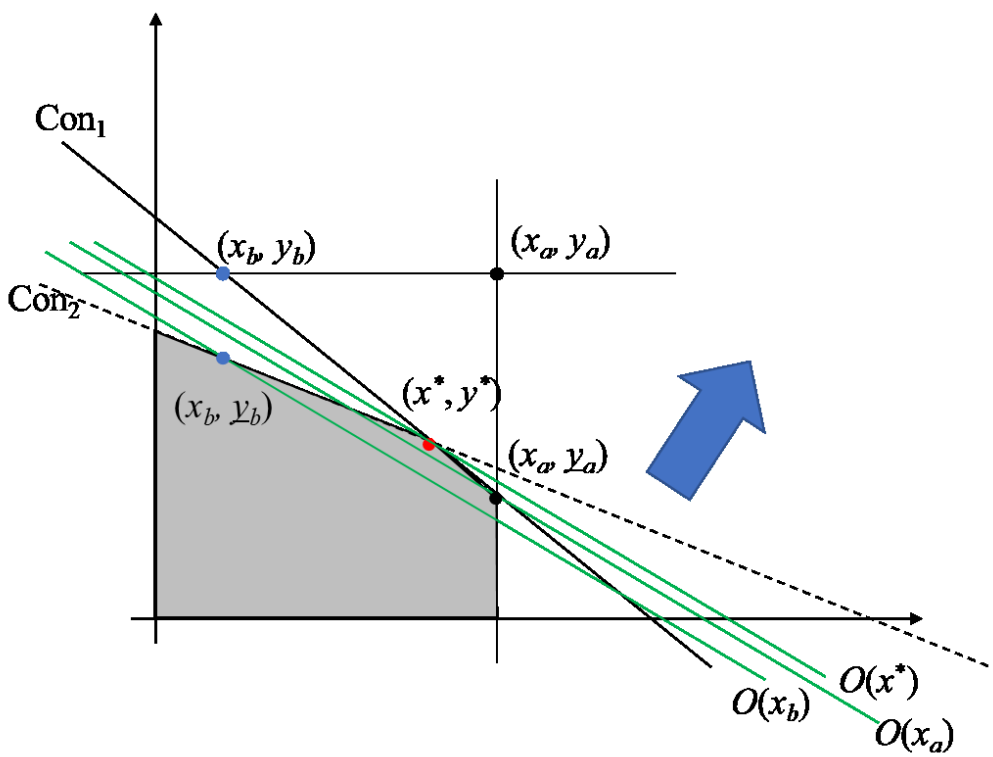

Figure 3.7. Example of Negative Value of Model Enhancement

Suppose that I enhance the model by adding Con_1, and this new model yields an "enhanced" solution of (x_b, y_b); by fixing $x = x_b$ and solving the full optimization again, I gain a solution of $(x_b, \underline{y}_b)$ and an objective function of $O(x_b)$. Apparently, $O(x_b)$ is worse than $O(x_a)$: this enhancement has a negative value.

Hybrid transmission modeling provides an example of negative VOME: it may distort plans by exaggerating the benefits of new lines (which are modeled as controllable DC lines whether or not they are actually AC) relative to existing AC circuits that are subject to Kirchhoff's voltage law; On the other hand, however, when stochasticity is considered, the benefit of adding hours is always positive. The third trend is that a simple stochastic model (P&B network/24 hours) can achieve most (98%) of the potential benefit.

Table 3.7. VOME for Three Enhancements (Stochasticity, Hours, Network) and Associated Ranges (Billion 2014US$)

Enhancement	Stochasticity	Temporal Granularity	Transmission: P&B to Hybrid Network	Transmission: Hybrid Network to DCOPF
VOME ($)	5.59	0.50	0.049	0.080
Fraction of total benefit	13.8%	1.24%	0.121%	0.198%
Max ($)	5.88	0.68	0.59	0.12
Min ($)	4.95	0.17	-0.41	0.014

The results from Table 3.6 are used to derive the VOME values (Table 3.7). Consistent with the trends just discussed, the inclusion of multiple scenarios (stochasticity) is the most valuable enhancement by over an order of magnitude. Its value of $5.59B (present worth) is also far greater than the VOME of including unit commitment ($0.11B) and spinning reserves ($0.007B), calculated earlier.

Of course, for other planning problems, the relative value of these enhancements may be quite different; for instance, for a system with many slow-moving coal plants and a much higher renewable penetration, the number of hours and inclusion of unit commitment would likely have a significantly increased VOME. The conclusion of this section is not that long-run stochasticity is necessarily more important than other enhancements, but that TEP model improvements can have large tangible benefits in general, and that those benefits can be estimated.

3.8 Conclusions and Limitations

This paper has presented a framework to calculate the economic value of model enhancements (VOME), in terms of the expected improvement in the probability-weighted present worth of system costs resulting from changes in immediate transmission investments. I apply the concept to a large-scale, long-term planning model for the WECC transmission network. Four types of enhancements, including stochasticity (multiple long-run scenarios), finer temporal granularity (operating hours), improved network modeling, and inclusion of unit commitment costs and constraints, are compared.

I now return to the question raised at the beginning of this chapter: *Can we quantify an economic index to meaningfully compare the value that alternative model enhancements might provide to transmission planning?* The answer, provided by the VOME methodology, is yes. The results for this particular case show major benefits from considering long-run uncertainty using multiple scenarios of technology, policy, and economics, but less benefit from the other potential enhancements. These benefits are as large as 13.8% (approximately $5.59B) of the overall benefit of building new transmission lines between

2015 and 2024 over and above the lines already included in the WECC Common Case (WECC, 2014a).

These results imply that considering long-run uncertainties is potentially highly beneficial in transmission planning. To the best of knowledge of the authors, this is the first time that the benefits of considering long-term uncertainty versus short-term variability or other model enhancements have been systematically quantified and compared in the context of transmission planning or in any physical infrastructure planning model, for that matter. This quantification framework and its result is particularly important in power systems with rapidly increasing renewable penetration and can be informative for planners who must trade off the number of futures and the number of hours to consider. However, only the stochastic programming technique for representing long-run uncertainties is discussed in this paper. Therefore, applying the VOME framework to compare and evaluate plan improvements resulting from other uncertainty-based planning techniques, e.g., robustness optimization, is a desirable extension of this research.

The results also imply that a simple model with a small set of hours and a pipes-and-bubbles power flow simulation can potentially yield a plan that achieves most of the potential economic benefits. On the other hand, deterministic (single scenario) planning based on the wrong scenario concerning future policy, economics, or technology can result in a huge economic regret. These results suggest the following practical approach to optimizing network reinforcements: start with a plan generated by optimizing a simple stochastic model and then use it as a starting point for a heuristic search for a better set of first-stage network reinforcements, using the most sophisticated model available to test the solution.

However, these VOME results do not necessarily apply to other regions or planning problems. Furthermore, they may become outdated even for WECC as conditions and computational capabilities change over the next few years. Inherently, VOME calculated today depends on the planning alternatives available (generation and transmission candidates); it also depends on the current view of the technological, economic, and policy developments in the future, and what model enhancements are feasible also play has a factor of VOME. And all of these are likely to change rapidly in the future, just as they have in the recent past. Thus, several years from now, the system and our models of it can be very different from now. Since VOME depends on the system and modeling assumptions, this implies that the VOME calculated in the next planning cycle can depart significantly from today's values. For example, if several WECC states adopt California's 100% renewables target, a VOME calculation in the future might show a much higher value for adding representative hours than what we would calculate today.

Nonetheless, the results indicate that systematically quantifying the economic value of model improvements is practical. The applications of VOME are not limited to the enhancements discussed in this work. For example, enhancement of TEP models by considering distributed energy resources (including generation, demand response, and storage) is appealing, given the increasing importance of those resources. Other potential enhancements might result in significant improvements of plans; examples include improved network reductions or explicit N-1 (or N-K) contingency constraints. Although some papers have shown how such network model enhancements can change operations or investment plans as well as cost estimates, and compared those changes to other model enhancements (Shayesteh et al., 2016), their VOME has not been calculated or compared to that of other

enhancements. Finally, VOME can provide useful insights not only for users of transmission planning models but also for other types of planning optimization problems in power and other infrastructure systems.

VOME can also be a very beneficial tool in transmission expansion processes that regularly update plans, e.g., the CAISO's annual transmission expansion planning process (CAISO). To provide guidance on improving planning models, a VOME analysis could be conducted after planning is complete each year, in which an optimal plan has been generated from some model with some enhancements. Such a VOME analysis can help planners gain insights on the current plan and its robustness to assumptions, while at the same time providing information on how to improve TEP models for the next plan update. In other words, VOME can show which enhancements would be beneficial to the current TEP and, therefore, should be considered for inclusion in the next planning cycle. For example, if the consideration of the long-run scenarios has significantly higher VOME than other candidate features in, say, the year 2019 plan, planners should put more effort into defining and enriching long-run scenarios in subsequent plans while preparing for the next planning cycle, say, 2021.

As explained in Section 3.5, VOME is, in theory, best quantified by developing and solving a TEP model for every combination of investigated enhancements. This would generally require a great deal of effort, and it may not even be feasible to solve some of the more complex models. However, a useful and meaningful indication of the VOME can be obtained by considering a subset of the possible combinations of enhancements. For example, if the solution for the red dot in Figure 3.5 (representing the model with all possible enhancements) is unobtainable, this implies that the incremental cost savings associated

with the three arrows connected to the red dot will also be unobtainable (each representing adding one individual enhancement to the TEP). Nonetheless, we can still obtain an estimate of VOME using the other model runs (i.e., the other arrows), albeit with a possible sacrifice of accuracy. For instance, the value of including KVL constraints relative to the hybrid load flow model can be quantified through comparisons of three pairs of runs (three arrows shown in Figure 3.5), omitting the fourth arrow that connects a hybrid model with the red dot. Thus, calculating VOME can be practical even if the most complex models cannot be solved.

Chapter 4 Transmission Planning and Co-optimization with Market-Based Generation and Storage Investment[14]

4.1 Chapter Summary

I enhanced the JHSMINE used in Chapter 3 by adding the storage expansion and operation module to recognize how storage investments, as well as supply investment, will respond to the changed network. I formulated the model as a mixed-integer linear program that co-optimizes transmission-generation-storage expansion (see Section 2.4.5 of Chapter 2 for detailed formulation); in an unbundled market context, the usage of such a model by transmission owners is termed "proactive" or "anticipative" transmission expansion planning (TEP). Using a case study of planning for the Western Electricity Coordinating Council (WECC) in the U.S., I demonstrate how the inclusion of battery storage co-optimization will change the TEP solution, and I quantify the economic benefit of such co-optimization; such quantification is based on the VOME framework that I proposed in Chapter 3. The results show, first, that optimizing while accounting for storage expansion will help TEP avoid overbuilding lines in some cases and underbuilding lines in others, while generation and storage are sited and sized more efficiently. This implies that storage and transmission sometimes are substitutes, and sometimes are complements in the WECC region. Second, the results indicate that proactive recognition that storage siting will react to network expansion will result in additional transmission benefits. This benefit increases as the cost of battery storage is reduced, but changes nonmonotonically with respect to the assumed cost

[14] A condensed version of this chapter will appear in Xu and Hobbs (2020), the formulation part of which is reformatted and moved in Chapter 2 of this thesis.

of carbon emissions. Finally, my results show that transmission planning process can considerably impact the total value brought by battery storage installation to the system; to wit, compared to the transmission expansion plan with the anticipation of storage expansion, the naïve transmission expansion plan generated without such an anticipation will lower the value of storage to the system by up to 27%, with an average of 14%.

4.2 Chapter Introduction

The benefits of optimal transmission expansion planning (TEP) are not limited to adding lines to already congested corridors in order to lower fuel costs through a more efficient dispatch of the existing generation fleet. This is because the amount and location of generation *investment*, as well as its dispatch, might shift to take advantage of changes in network capabilities, and these shifts will, in general, unfold over the multidecadal lifetime of the transmission assets. In sum, transmission investment will change not only operating costs of generation, but also investment costs. Thus, a TEP planner should anticipate changes in generation plant siting, amounts, and mixes, as discussed in Chapter 3. The traditional approach of evaluating the economic benefits of transmission just by valuing the resulting savings in operating costs results in distorted estimates of the benefits of transmission reinforcements and potentially suboptimal grid expansion decisions (CAISO, 2004; MISO, 2010; Spyrou et al., 2017).

Transmission generation expansion co-optimization tools (also called "proactive" planning methods) are designed for this job: they help TEP planners to plan transmission in a proactive manner so that transmission planners are able to select the lines anticipating the market reactions of generation investors and any resulting changes in generation

investment costs (Krishnan et al., 2015; Liu et al., 2013b; Sauma and Oren, 2006; Sauma and Oren, 2007).

Several generation-transmission co-optimization models have been published and are being tested by regional transmission agencies. Most are formulated as optimizations that minimize the total capital and operating cost of the joint transmission-generation system, or as maximizing net market benefits (value of energy consumption minus those costs). The assumption of most such models is that the underlying generation market is perfectly competitive with no major market failures (which is equivalent to net market benefits maximization for just generation,) and that the transmission planner's objective is also to maximize net market benefits (van der Weijde and Hobbs, 2012). Thus, the bi-level structure of decision making in the market (transmission acting as a "Stackelberg leader" with respect to generation followers) reduces to a convenient-to-solve single-level optimization.

Other co-optimization models, however, recognize that serious imperfections exist in the generation market (externalities, subsidies, market power, regulated prices), so that instead, an explicitly bi-level optimization approach is called for. Such problems are inherently more difficult to solve, but progress has been made recently (Pozo et al., 2013; Tohidi et al., 2017).

In addition to market failures in generation markets, another challenge (or opportunity) to TEP is the rise of new types of supply technologies, as well as storage and demand response. The challenges of a load growth together with renewables could be met with a greatly expanded grid, but storage and demand technologies hold the promise of lowering the cost of renewables integration and also being less costly in at least some cases than new transmission facilities. Following this logic, people can argue that transmission

and storage seem functionally compete and substitute each other. This substitution relationship was identified by Bustos et al. (2018), Neetzow et al. (2018), and Xu and Hobbs (2018), however, the relationship can also be complementary. A proactive TEP should, therefore, anticipate the response of investments in new technologies. This is the focus of this chapter; in particular, I expand least-cost types of co-optimization models to include storage as well as transmission and generation. With the cost of energy storage plummeting rapidly, consideration of storage might greatly affect TEP.

As mentioned above, as definite yes-or-no answer to the question *whether the relationship between transmission and storage is complementary or substitutive* is not available and it depends on the system characteristics (Bustos et al., 2018; Neetzow et al., 2018; Xu and Hobbs, 2018); thus it may be more appropriate to ask this question: *How will decreasing costs of storage technology affect the transmission expansion planning? How much benefit can we get in transmission expansion planning by anticipating how storage will be expanded in response?* From the point of view of potential storage investors, the reversing question is also intriguing: *How will the transmission expansion planning affect the profitability of the storage technology? How much potential benefit is lost because the transmission planner naively ignores the possibility of storage expansion?* These questions, to the best of my knowledge, have never been raised nor answered, and I will provide my approach and answers to these questions in this chapter.

I organize the remainder of this chapter as follows. In Section 4.3, I provide some background: First, the interactions of transmission and generation and the complications posed by storage; second, a historical view of co-optimization of transmission and generation expansion; and finally, a procedure to calculate the economic value of considering

storage expansion in TEP. In Section 4.4, I present a case study for the WECC regions. I then conclude this chapter in Section 4.5. For the formulation of this work, I refer readers to Chapter 2 of this thesis, for specifically the storage formulation, see Section 2.4.5.

4.3 Background

4.3.1 Interactions among Transmission, Generation and Storage

In classic microeconomics, e.g., (Varian, 2009), people characterize interactions between two goods with the words "complementary" or "substitutive," which is, in turn, formally defined by the cross-price elasticity. The cross-price elasticity of two goods is calculated as the relative increase of consumption of one good divided by the relative increase in the price of another, *ceteris paribus*. Intuitively, the sign of cross-price elasticity tells us a story: a negative cross-price elasticity means an increase of the price of one will decrease the consumption of another, and they are complementary; they are thus substitutive if the cross-price elasticity is positive. The definition of complements and substitutes can also extended to the power system planning context: if the drop of capital cost of one asset (e.g., storage technology) will encourage the market to build more transmission line capacity, I can say that they are substitutes to each other.[15] The reason behind the number can be that they are functionally competing each other.

Generation and transmission expansions interact in complex ways. Fundamentally, they can be complements (investment in one increases the market value of the investment in another) or substitutes (investment in one lowers the market value of the other). Transmission is valuable just because of its capability to deliver electricity from a cheap resource

[15] There may exist other definitions, for example, a quantity-to-quantity ratio defined in Neetzow et al. (2018).

to the demand, avoiding turning on an expensive local generation; thus, transmission investment is a complement to the remote resource, but a substitute for the local one. As specific examples, transmission and generation complement each other in cases such as mine-mouth coal power plants and wind farms that are distant from load centers: cheap power is only valuable when deliverable. The opposite can also be true: when local generation, such as gas turbines or rooftop solar panels, became cheap, it diminishes the value of new transmission into a load pocket, and thus generation and transmission become substitutes.

The rise of electricity storage, especially distributed storage in the form of batteries, is making this story more complicated. First, storage can both compete with and complement generation. Storage can compete with conventional generation, for instance, in meeting peak loads. Regulators encourage this competition: Order No. 841 (FERC, 2018) from the U.S. Federal Energy Regulatory Commission requires that independent system operators adjust their rules and market software so that storage can compete with the generation in the energy, ancillary service, and installed capacity markets. The fast ramping response of electric storage implies that storage and generation may compete fiercely in reliability markets as the cost of storage decreases. However, storage, because of its fundamental ability to shift supply from one time period to another, can be a complement to generation with less operational flexibility (e.g., base-loaded thermal plants) or intermittent availability (e.g., variable renewable energy, VRE). Indeed, pumped storage plants were often justified in the 1960s and 1970s because of this complementarity with nuclear plants, which are most efficient when running flat out for all hours (Rehman et al., 2015). Nowadays, however, the focus is on storage's complementarity with VRE; such storage will be

essential to achieving the very high renewable penetrations that are the targets in some jurisdictions (e.g., 100% in Hawaii and California).

Storage also interacts with the transmission, but in a somewhat subtler way: they are both arbitragers of the energy, with the transmission arbitraging over space and storage doing so over time. They can both facilitate higher penetrations of VRE (Bustos et al., 2018; Neetzow et al., 2018). A better interconnection can help in the following way: at a certain point in time, unexpected under-generation of VRE in one place can be made up by transmission delivering available production from another plant (e.g., another VRE) from hundreds of km away. This may, for instance, avoid starting-up or ramping of local generators that is perhaps both costly and polluting. On the other hand, storage can also resolve local shortfalls by, in effect, delivering cheap output of a plant that was produced several hours or even days or months ago (e.g., from wind or hydro energy that would have otherwise been curtailed or "spilled").

Transmission and storage are not always competing. As a simple case, we can imagine a distant wind farm might be more economical because of a bundled storage facility, and hence a transmission project also becomes valuable. On the other hand, this nearby storage could enable a transmission facility to be downsized and still deliver the same amount of VRE production (Neetzow et al., 2018; Xu et al., 2018b).

Overall, the interactions between transmission, generation, and storage will strongly affect the economic value of transmission reinforcements. Hence, from the perspective of the transmission planner, a planning model with the ability to capture the above substitutive and complementary interactions becomes valuable and informative. We shall next discuss co-optimization tools that have this capability.

4.3.2 Using Co-optimization to Support Transmission Expansion Planning

Co-optimization of transmission and generation planning is not a new topic. The mathematics problems describing siting generation and transmission together can be dated back at least to the 1970s (Anderson, 1972; Sawey and Zinn, 1977; Turvey and Anderson, 1977). However, the meaning of co-optimization of transmission and generation expansion changed with time went by, and a major milestone was the deregulation of the power sectors in Europe and the U.S.

"*Co-optimization*" used to mean co-planning of just generation and transmission. When most of the power industry was still vertical integrated, generation planners and transmission planners were able to work together: generation expansion plans were first developed and handed to the transmission planners, transmission plan was then developed, and may or may not be handed back to the generation planners for more iterations. In this iterative manner, the interaction between generation and transmission and was at least partially accounted for by these vertically integrated monopolies; in the work of Spyrou et al. (2017), authors quantified the value of such iteration.

The meaning of co-optimization has enriched since the deregulation of the power industry in Europe and the U.S in the 1990s. In the newly established markets, the planning of transmission and generation expansions are separated and respectively performed by grid owners/transmission system operators (TSOs)/regional transmission organizations (RTOs) and generation companies. Without the full co-operation of the generation planners and, at the same time, lacking tools to anticipate how generation siting would respond to grid changes, many transmission planners have been forced to treat the locations and amounts of generation capacity as purely exogenous "boundary conditions": they would

have to assume scenarios in which the generation siting is known and then plan the transmission expansion based on the scenarios. This is called "*reactive*" transmission expansion planning: transmission planners react to generation expansion.

In contrast to "reactive" transmission expansion planning, "*proactive*" transmission expansion planning anticipates how generation investors will choose the sites, types, sizes, and timing of changes in their assets in reaction to the network plan, and then chooses the best set of transmission expansion projects (Hirst and Kirby, 2002; Sauma and Oren, 2006; Sauma and Oren, 2007). From the point of view of game theory, the game between transmission and generation is a bi-level or "Stackelberg" game. The transmission planner is a leader who optimizes subject to the anticipated reactions of a set of generation investors who are competitive or Nash players who do not anticipate how the grid plan would change in response to generation decisions. It is natural to place the transmission in the role of a leader because transmission assets generally take much longer to plan and build than the natural gas-fired or renewable generating assets that constitute most or all of the generation additions in North America and Europe today. Although outside of the scope of this chapter, I refer readers that are interested in "proactive" transmission expansion models formulated explicitly as bi-level or multi-level games to Gonzalez-Romero et al. (2019); Jenabi et al. (2013); Jin and Ryan (2014a, 2014b); Pozo et al. (2013); Sauma and Oren (2006); Tohidi et al. (2017).

Transmission and generation co-optimization models can be seen as one of several types of "proactive" transmission expansion planning models if planners make the strong assumptions listed below (Liu et al., 2013b; Sauma and Oren, 2006; Spyrou et al., 2017):

- The transmission expansion planner has the objective of maximizing market surplus (what the economists call "market efficiency" or "societal welfare").[16] This is defined as the sum of surpluses accrued by all market parties, including profits earned by each resource and storage, transmission congestion surplus minus incremental grid costs, and consumer surplus. If demand is perfectly inelastic (fixed), this objective is equivalent to minimizing the sum of resource, storage, and transmission costs.
- Short-run (spot) electricity markets, including energy, ancillary service, and capacity markets, are perfectly competitive. All suppliers are price takers and profit maximizers.
- Similarly, in the long run, generation expansion planners are siting optimally and competitively to maximize their profits, given the cost of transmission as reflected in locational marginal prices, which depend on the grid and all suppliers' decisions.

Of course, this basic proactive model simplifies reality but then do all models. These assumptions enable the bi-level game to be solved as a single optimization model since the TEP objective of maximizing market surplus is consistent with perfect competition on the lower level, which can be modeled by maximizing total market surplus as well. (See proof in Appendix A.) Relaxing any of those three assumptions will generate a new type of "proactive" transmission planning model that in general, will have a difficult to

[16] Evaulate, planning, build infrastructures aiming to maximize societal welfare are can be seen in some classic works, such as Barron et al. (1998).

solve bi-level structure in which the leader and follower objectives are not aligned, as mentioned above.

Besides relaxing the three assumptions, another way in which co-optimization models can be broadened is by including more types of market players, including consumers (i.e., demand response) and storage. As mentioned before, in Feb. 2018, the FERC issued Order No. 841 to urge the U.S. markets under its purview to modify their tariffs to make sure that electric storage can compete with the conventional generators in the energy, ancillary service, and capacity markets, so that energy storage can participate fully in spot markets and are able to set prices (FERC, 2018).

With electricity storage coming into play, co-optimization models must now co-optimize (or anticipate) the siting and operation of storage. As a result, additional assumptions are needed, namely that storage owners are competitive. They, therefore, choose the timing, type, size, and location of storage facilities to maximize their profit subject to locational commodity prices that they assume they cannot alter. Reflecting the new FERC rules (FERC, 2018), practical co-optimization models usually assume that storage owners can either let the ISO dispatch their facilities optimally or, equivalently, they self-schedule with perfect foresight of the time-varying prices they will receive.

4.3.3 Quantify the Economic Value of Considering Storage Expansion in Transmission Expansion Planning

As battery costs continue to decline, batteries, flywheels, compressed air, and other storage devices will achieve more penetration in power markets and thereby interact with and change the value of transmission and generation. Traditional vertically integrated utilities will likely adapt their generation and transmission planning methods to consider how

possible investments in storage might change optimal investments in other assets. In restructured, vertically disintegrated markets, on the other hand, storage is another player, of whom the operating and investment decisions will need to be anticipated by transmission planners in the proactive paradigm. If the effects of grid reinforcements on the siting, sizing, and timing of storage investment is disregarded in TEP, the result might be a different—and economically inferior—transmission plan. I now address the question: how can we quantify the value of considering storage in a proactive TEP? I propose and demonstrate a procedure for quantifying this value in the remainder of this chapter. The demonstration is for the western US and Canada system (WECC) for the year 2034.

Previous work (Liu et al., 2013a; Spyrou et al., 2017) has quantified the value of anticipating how grid reinforcements affect generation expansion in TEP (i.e., the "value of generation-proactive TEP") for the eastern US and Canada system. There, authors show that iterating between (1) solving a TEP subject to a fixed generation build-out and (2) solving a generation expansion problem (GEP) subject to a fixed network can realize only part of the value of generation-proactive TEP.

In summary, the quantification of the value of considering storage in proactive TEP involves three steps:

1) planning with co-optimization of storage, generation, and transmission;
2) planning while disregarding the possibility of the storage installation and how it reacts to network expansions; and
3) evaluation of the latter, potentially flawed plan by modeling the "actual" reaction of storage and generation to that plan.

This process is presented in a more formal, rigorous way later in this section. The first step is the full co-optimization, where the transmission expansion planner makes an expansion plan anticipating the reactions of both generation and storage installations. The results of this step are the optimal plan (a set of selected transmission projects) and a minimized system cost. In the second step, a transmission expansion plan is obtained from a "flawed" planning model, where the transmission expansion planner ignores the possibility of storage installation, and only generation is considered in such a "flawed" co-optimization framework. Finally, I evaluate this "flawed" plan by plugging it into the co-optimization model (fixing the network decision variables at their flawed values) and getting a new minimized cost for the generation and storage followers, which may involve the installation of storage but at potentially different locations and in different amounts than the full co-optimization. The difference in the costs between steps 1 and 3 is the value of considering storage in transmission expansion planning. Because step 3 is more constrained than step 1, its cost will be no lower than the full co-optimized model and is potentially higher. I call this increase in cost the "*value of model enhancement for storage*" (VoMES).[17] I define another closely related term, *"value of storage"* (VoS), as the objective function improvement if storage is allowed to be expanded in the system, i.e., the differences in the objective function values resulting from step 1 and 2. For example, the VoS under alternative incentive mechanisms for merchant transmission expansions is calculated for IEEE test-systems in Khastieva et al. (2019). These results show that the VoS is relatively small compared to system cost ($2 million compared to $442 million) but can be more than three times higher than that amount if transmission expansion incentives are provided. The

[17] Reader should find this name familiar: yes, this is another application of VOME in Chapter 3.

conceptual differences and relationship between VoMES and VoS will be discussed in a more formal, mathematical way below.

I now present the details of each step, including the TEP co-optimization models that we apply.

Step 1. Planning with Co-optimization (Benchmarking): Imagine we have a TEP tool which can select the best set of new transmission lines (T) by anticipating the construction of new generation (G), the installation of new storage (S), and the system operation (P) to minimize annualized system cost $C(T, G, S, P)$ (in \$/yr) for some future scenario year. (Existing facilities are implicitly in the model as well.) All the decision variables are subject to the feasible region (F) which is defined by the physical operating constraints for the network as well as individual resources (e.g., Kirchhoff's laws, line and resource capacity limits, ramp limits, state-of-charge relationships etc.) and policy constraints such as renewable portfolio standards or emissions limits. An abstract mathematical programming problem (MP1) can be shown as follows, the formulation of which is shown in Chapter 2:

$$\begin{aligned} \text{Minimize}_{T,G,S,P} \quad & C(T,G,S,P) \\ \text{s.t.} \quad & (T,G,S,P) \in F \end{aligned}.$$

If this is solved to optimality, it will return a solution of (T^*, G^*, S^*, P^*) and a system cost of $C(T^*, G^*, S^*, P^*)$. (Note that if demand is elastic, instead of minimizing cost, we would instead be maximizing net market surplus, recognizing the value of benefits associated with different levels of consumption as captured by the integrals of demand curves.)

By definition, $C(T^*, G^*, S^*, P^*)$ is the lowest cost that the model can achieve, and T^* is the optimal transmission plan provided by the model. In other words, any

transmission plan other than T^* will leads to a system cost no lower than $C(T^*, G^*, S^*, P^*)$, and hence that network configuration and the associated cost can be used as a benchmark.

Step 2. Planning without storage anticipation: Imagine the planner chooses to ignore the storage installation in the TEP. Mathematically, it means forcing $S = 0$ in the formulation above (MP1). Thus, we are solving the following problem (MP2) instead:

$$\begin{aligned} \text{Minimize}_{T,G,P} \quad & C(T,G,0,P) \\ \text{s.t.} \quad & (T,G,0,P) \in F \end{aligned}$$

Let the solution of this TEP model be $(\hat{T}, \hat{G}, 0, \hat{P})$ and the associated system cost be $C(\hat{T}, \hat{G}, 0, \hat{P})$. $\hat{T}$, therefore, stands for the optimal transmission expansion plan that the planner can get if they ignore the possibility of installing storage.

Step 3. Plan Evaluation: Imagine the transmission expansion plan from Step 2 is implemented. Mathematically, it means forcing $T = \hat{T}$ in MP1; equivalently, we are solving the following problem (MP3):

$$\begin{aligned} \text{Minimize}_{G,S,P} \quad & C(\hat{T},G,S,P) \\ \text{s.t.} \quad & (\hat{T},G,S,P) \in F \end{aligned}$$

Let $(\hat{T}, \bar{G}, \bar{S}, \bar{P})$ be the solution of MP3 and $C(\hat{T}, \bar{G}, \bar{S}, \bar{P})$ be the associated objective function. By definition, $C(\hat{T}, \bar{G}, \bar{S}, \bar{P})$ is no lower than $C(T^*, G^*, S^*, P^*)$, since the former is the system cost resulted from choosing a transmission plan $\hat{T}$ other than the optimal T^*. One can thus naturally conclude that the cost of ignoring storage installation leads to a different plan and a cost no lower than the optimal. And the difference between $C(\hat{T}, \bar{G}, \bar{S}, \bar{P})$ and $C(T^*, G^*, S^*, P^*)$ is the "*value of model enhancement to consider storage*" (VoMES) in TEP:

$$\text{VoMES} = C(\hat{T}, \bar{G}, \bar{S}, \bar{P}) - C(T^*, G^*, S^*, P^*).$$

In a sense, this is the value of "smart" planning that proactively anticipates how storage will be installed and used, versus a naïve plan that overlooks storage.

This value of smart planning is distinct from the overall "*value of storage*" VoS to the system, as in Khastieva et al. (2019), which is the cost improvement from a co-optimized plan that only includes transmission and generation to a plan that co-optimized storage as well; i.e., the reduction in cost from MP2 (no storage) to MP1 (all options):

$$\text{VoS} = C(\hat{T}, \hat{G}, 0, \hat{P}) - C(T^*, G^*, S^*, P^*).$$

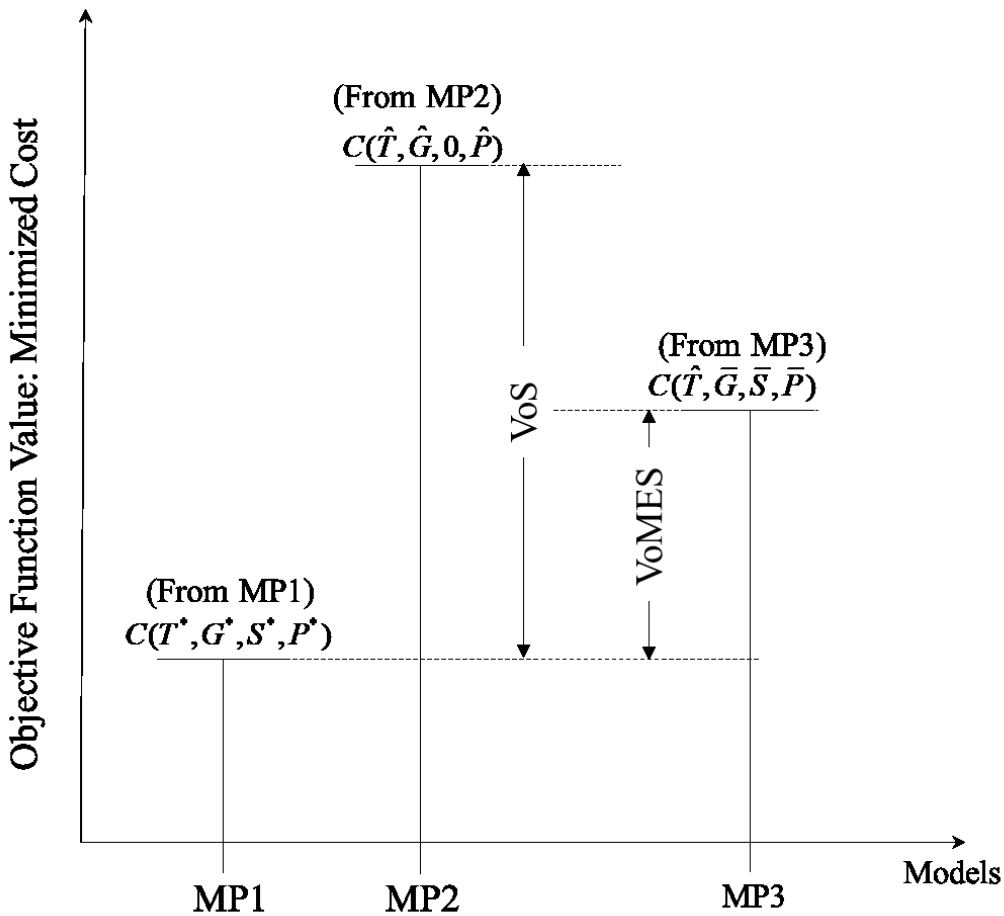

Figure 4.1. Diagram of Value of Model Enhancement to consider Storage (VoMES) and the Value of Storage (VoS)

Note that VoMES ≤ VoS in that the cost of MP3 will necessarily be no higher than MP2's cost. More specifically, this is because MP2 and MP3 have the same value of T, but MP3 is free to choose both G and S, while MP2 can only choose G as S is constrained to zero. Their relationship is shown in Figure 4.1. One implication of this inequality is that the economic value that storage can potentially provide to the system can be offset by TEP's naive disregarding storage expansion and its response to transmission expansion, in which case the net benefit will be the remainder of (VoS – VoMES). Thus, the larger VoMES is (as a proportion of VoS), the greater the loss of storage benefits will be if naïve rather than proactive transmission planning is undertaken; in other words, the benefits of storage to the system is more dependent on transmission expansion planning.

In this chapter, my focus is on the value of modeling to implement proactive TEP, and my major interest is, thus, in the calculation of VoMES to show what can be gained from proactive planning. But the calculation of VoS is also useful as it illustrates one of the many types of insights that can be obtained from applying TEP models. Readers should also bear in mind that the terms VoMES and VoS are not limited to the anticipated storage expansion, and they can easily extend such concepts to other aspects of the electricity system. The value of enhancing a model with generation-transmission co-optimization is calculated by Spyrou et al. (2017); i.e., VoME of co-optimization, showing that co-optimization can double the net cost savings from transmission expansion, comparing to purely reactive TEP; iterative planning (alternating between transmission and generation capacity expansion models) can partially but not fully realize these benefits. For a review of enhancements that have been implemented in transmission expansion models, readers are referred to (Xu and Hobbs, 2019) or Chapter 3 of this thesis.

4.3.4 Detailed Formulation Discussion

The general formulation of MP1 is shown in Chapter 2 of this dissertation, and here, I provide some additional details specific to the model used in this Chapter. Also, for a review of literature on co-optimization transmission and storage but omitting generation expansion, I refer the reader to works of Khastieva et al. (2019); Qiu et al. (2017). Some general assumptions include the following.

In general, TEP models need to consider both short- and long-run uncertainties, since in Xu and Hobbs (2019) and Chapter 2 I have shown that considering a range of long-run economic, regulatory, and technological scenarios in a two-stage stochastic programming framework can make a significant and economically important difference in transmission plans. However, for the sake of simplicity in this chapter, the consideration of uncertainty will be limited to short-term variability, namely load, wind, solar, and hydro conditions. For reviews of TEP models that consider long-term uncertainties, readers are referred to works of Ho et al. (2016); Munoz et al. (2014); Park et al. (2019); van der Weijde and Hobbs (2012).

The operating constraints and costs of this model include the linearized unit commitment formulation that was proposed in Kasina et al. (2013), in which start-up costs are included in the cost objective, while ramp rates, start-ups, and minimum output levels constrain generation levels. A more comprehensive version of this formulation with long-term planning and long-run uncertainties can be found in Chapter 2. Meanwhile, classic unit commitment formulations that use binary variables to represent generator commitment status is given by Morales et al. (2013); Takriti et al. (1996); such variables are difficult to include in long-term planning models due to the desire to avoid nonlinearities and

impractically large MILP models, and so transmission planning models tend to use simpler operating models.

The network formulation is based upon a combination of a linearized DC load flow (DCOPF), which represents how Kirchhoff's voltage law induces parallel flows in the network (Glover et al., 2011), and disjunctive constraints that utilize the Big-M formulation (Winston et al., 2003). Only high voltage facilities are represented. For more advanced power flow modeling that includes transmission losses and reactive power, readers are referred to Ozdemir et al. (2016); Zhang et al. (2013).

Renewable portfolio standards by states are represented, including rules allowing one state to use renewable energy credits generated in other states to meet renewable obligations as implemented in Ho et al. (2016) and Xu and Hobbs (2017). Carbon policy is represented by a tax on carbon emissions.

4.4 Numerical Example: Analysis of Value of Model Enhancement to Consider Storage

4.4.1 Overview

In this section, I present an example of co-optimization of transmission, generation, and storage is presented, which is based on a 54-node network aggregated from the system of Western Electricity Coordinating Council (WECC) in the U.S. and the planning target year is 2034. The network data are from the WECC 2026 Common Case (WECC, 2017), and I plan for the year 2034 based on the load, fuel cost, and policy data that are specified by WECC's Long-Term Planning Tool (WECC, 2013a). With this example, I will answer the questions that I raised in the introduction of this chapter (Section 4.2), they are: *How*

will decreasing costs of storage technology affect the transmission expansion planning? How much benefit can we get in transmission expansion planning by anticipating the storage expansion? From the point of view of potential storage investors: *How will the transmission expansion planning affect the profitability of the storage technology? How much potential benefit is lost because the transmission planner naively ignores the possibility of storage expansion?* After reviewing the test system in the next section, I will further decompose the questions in Section 4.4.3.

4.4.2 Test Case Description: 54-node System for WECC

In this subsection, I summarize the test system, a 54-node system for WECC.[18] All 54 nodes are further aggregated from the network that appeared in Xu and Hobbs (2018), which in turn, is a reduced network using the 2026 Common Case of WECC (WECC, 2017).

Each node of this 54-node system stands for one or part of a single Transmission Expansion Planning Policy Committee (TEPPC) subarea of WECC. When one TEPPC subarea is totally within one state, one node will be designated; when one TEPPC area has assets spanning several states, e.g., the Los Angeles Department of Water and Power (LADWP), several nodes will be designated and one node will be defined for each state (see Figure 4.2, where LADWP has nodes in states of California, Nevada, and Utah). All inter-area transmission lines are aggregated within each corridor by dropping the impedances and summing the thermal limits; in other words, only thermal limits are preserved, which is shown on the arcs of Figure 4.2 (Next Page).

[18] This is a different and more aggregated system compared to the test-system in Chapter 3.

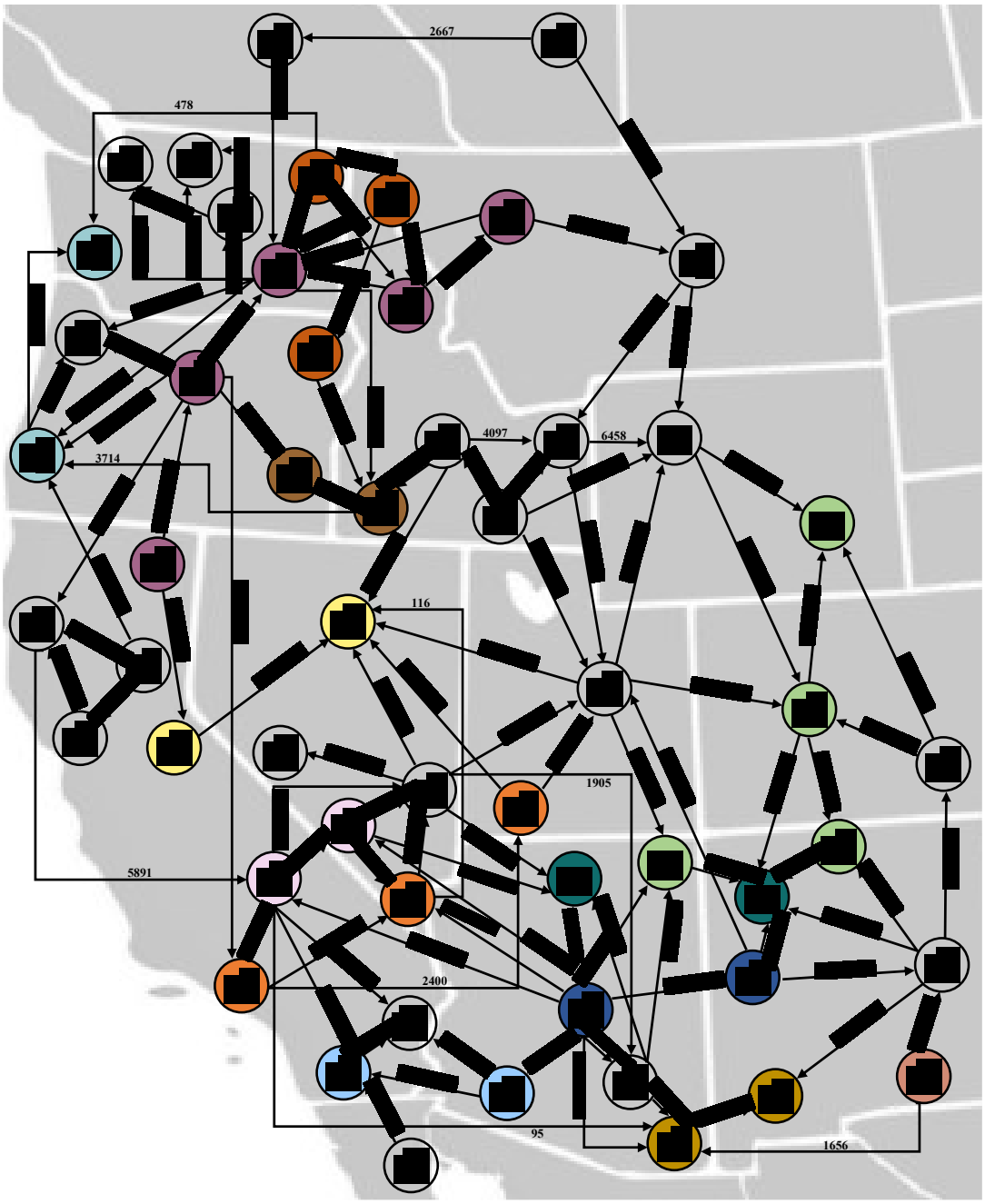

Figure 4.2. Map of the test system. Colors represent different TEPPC subareas.

There are 519 aggregated existing generators and 238 generator candidates in this network. These generators span 25 technologies, including different types of Coal, Gas, Nuclear, Hydro, Wind, Solar, Geo, and Biomass generation.

As for generation candidates, on each node, two types of generation can be invested without limit: Gas Combustion Turbine and Gas Combined Cycle. On the other hand, the renewables, i.e., Wind, Solar, Bio, and Geothermal, can only be expanded at 53 candidate sites and will need new transmission lines to be interconnected with the existing grid. The 53 candidate sites (not the same as nodes) and their maximum installed capacity are identified in (Western Governors' Association and U.S. Dept. of Energy, 2009). A system-wide view of the building cost and the expandable capacity is shown in Table 4.1.

Table 4.1. System-wide Expansion Cost Assumptions for Generation in Year 2034

Gen. Type	Fixed O&M ($/kW-year)	Overnight Build Cost ($/kW)	Life-time (year)	Annualized Build Cost ($/kW-year)*	Potential Capacity (MW)**	Capacity Factor***
Biomass	120	4300	20	345.04	3272	-
Combined Cycle	10	1213	20	97.33	-	-
Combustion Turbine	9	825	20	66.20	-	-
Geothermal	120	5000	25	354.76	4719	-
Solar PV	20	1471	35	89.82	85144	26.0%
Onshore Wind	40	1355	20	108.72	95288	30.6%

*: Assumes a 5% discount rate
**: Summation over all candidate sites
***: Weighted average over all candidate sites, weights are the potential capacity

There are two types of transmission lines: backbone reinforcements and renewable connections. Backbone reinforcement candidates, which are 39 in number, expand capacity on the arcs shown in Figure 4.2. In addition, there are 53 renewable connection

candidates corresponding to the 53 renewable candidate sites. All of the transmission capacity expansion costs are calculated based on the length and the voltage level of the buses in the original network. The average line cost is 640 Million $/line, with a lifetime of 60 years. Assuming a 5%/year discount rate, the average annualized cost of transmission lines is about 34 million$/line-year.

The type of storage we consider is a battery electric-storage system (BESS), and the cost and operation data are based on WECC's generation capital cost tool (WECC and Energy and Environmental Economics, 2017). I assume that a BESS will have 4-hours of storage using Li-ion technology with a round-trip efficiency of 92%. The build cost is assumed to be $440/kWh in the year 2034 (i.e., $1760/kW); with assumptions of 15-year lifetime and 5% discount rate, this corresponds to an annualized cost of $42.5/kWh-year. Storage can be sited (1) at any of the 54 existing nodes in the system or (2) co-sited with the renewables at the 53 candidate renewable sites. Different siting locations will incur different fixed operation and maintenance costs (FOM cost), with the average being $30/kW-year. More details on the cost assumptions can be found in WECC and Energy and Environmental Economics (2017), where shows a dramatic decreasing of the storage installation cost up to the year 2029 with a 38% decrease compared to the year 2016.[19] Storage is expandable up to a capacity of 1000 MW at each location.

[19] Also see Lazard (2018) for a projected decrease of 8%/year of Li-ion battery capital cost decrease, from 2018 – 2022; see NREL (2019) for several projections of Li-ion battery capital cost decrease, e.g., mid-level decrease at a pace of 5.5%/year from 2018 – 2030, starting with $1484/kW. Overall, existing researches agree upon the fact that capital cost of battery is plummeting but with great uncertainty. This particularly motivates my approach here: instead of solving one scenario for one capital cost of battery, I solved ten of different capital cost scenarios.

There are 4 representative days that are selected, and each day is composed of 24 hours. Thus, 96 hours are simulated to represent the variability of load and renewable output conditions.

I assume that future policies in the WECC region will incentivize significant increases in renewable generation. There are two types of environmental policies that are assumed to affect the system in the year 2034: *Renewable Portfolio Standards* (RPS) and *Carbon Pricing*. The RPS data for the year 2034 are from the DSIRE (Database of State Incentives for Renewables and Efficiency, (DSIRE, 2018)), and the demand data are from LTPT (WECC, 2013a) from WECC. RPS policies are implemented on the State-level, and I consider the fact that some states have in-state requirements. For example, in 2034, California requires 60% of its demand to be supplied by renewables and 90% of the renewables should come from within the State. Overall, in 2034, the WECC system requires 38% of its demand (1091 TWh/year) to be supplied by renewables; and for the U.S. part of the WECC, this requirement is 34% of the total energy demand of 854 TWh/year. The non-compliance penalty is assumed to be $100/MWh, which is imposed in the objective function if a given state's RPS is not met.

For carbon pricing policy, I assume a universal carbon tax will be implemented upon the WECC system (or equivalently, a carbon cap-and-trade system is implemented within WECC, and the carbon price reaches the assumed equilibrium level.) The carbon tax varies among the different study cases I consider in this chapter. For current carbon policy implementations in WECC, I refer readers to Chapter 5 of this thesis.

In the application of this chapter, I omit the DC load flow's voltage law constraint in the network representation in order to accelerate solution times. My numerical

experiments indicate that this assumption results in a minor overstatement of the network's transfer capability and results in only minor distortions in near-term transmission investments (Xu and Hobbs, 2019); for more details, I also refer readers to Chapter 3. Thus, the power flow is a "pipe-and-bubbles" (transshipment) formulation. Furthermore, binary variables for both transmission and storage expansion are relaxed (i.e., are continuous in the range [0,1] rather than binary), again in the interest of faster computation times. In its use of continuous variables, the model resembles classical generation expansion planning models, which are formulated as linear programs. More realistic models can be used in actual planning, but this model suffices for the purpose of this chapter, which is to illustrate the use of co-optimization and the calculation of VoMES.

4.4.3 Questions to be Answered and the Experimental Design

With the numerical results from the application of the above model and data, I shall answer the following questions:

1. Would the anticipation of the amount and siting of battery storage change the transmission expansion decisions and how? Will the electric storage incentivize more or less capacity expansion of transmission? Less transmission indicates that, overall, batteries and transmission are substitutes; more would indicate that they are complements.
2. What is the economic value of enhancing the TEP model to include storage (VoMES)? And how will the VoMES change with the build cost of the storage? Note that this is the not, per se, the benefit of storage itself, which is VoS, equal to the difference in cost between MP1 and the naïve model without any storage at all MP2. Rather, VoMES is the benefit of "smart TEP with storage," anticipating where

storage will be sited and adjusting transmission decisions to take advantage of that; as explained at the end of Section 2, this is the difference between MP1 and MP3's objective function values.

3. Will the stringency of carbon prices that impact electricity markets change VoMES? I.e., if the carbon price is applied to the system, will the anticipation of the siting of storage be more or less valuable to the TEP?
4. What are the sources of cost savings from proactive TEP? In particular, when there is a positive VoMES, were the cost savings from investment in transmission or generation, or from reduced fuel or carbon costs? Ignoring the storage in transmission expansion planning will change the transmission expansion plan, and may consequently incentivize investors to make suboptimal siting and the operating decisions—which of those will be distorted more? It is also conceivable that transmission costs will also increase; perhaps disregarding the possibility of storage in model MP2 will result in overbuilding of transmission versus that optimal TEP from model MP1, which might find that transmission and storage substitutes. That would indicate that, overall, transmission and storage are substitutes. On the other hand, reduced investment in T in MP2 (no storage S) would indicate that T and S are instead complementary.

I design the experiments shown in Table 4.2 to answer the questions above.

Table 4.2. Experimental Design for Value of Storage in TEP: Sets of model runs

Set ID	Set Name	Planning Model Description
MP1	TEP with Storage and Generation Expansion	10 levels of build cost of storage (from 100% of base-level $42.5/kWh-year to 10% of base-level); 10 levels of WECC-wide carbon tax from $0/Metric ton to $90/Metric ton. There are 10×10=100 runs.
MP2	TEP with Generation Expansion	10 levels of WECC-wide carbon tax from $0/Metric ton to $90/Metric ton. There are 10 runs.
MP3	Storage and Generation Expansion	Same as Set MP1, except that the transmission expansion plan is fixed at the levels selected in MP2 with the same carbon tax. There are 10×10 =100 runs.

4.4.4 The Impact of Storage on Transmission Expansion Plans

In this section, I show how the storage expansion would affect the transmission expansion plan. Below, I summarize some conclusions that I can draw from the detailed results presented later in this section:

1) The anticipation of storage siting/sizing will change the transmission expansion plan. An example is given in Figure 4.3, where cheaper storage results in more line construction in some places (substitution relationship) and less in others (complementary relationship); that is, blue lines represent the expansion plan at a battery cost level of 100%, and solid red lines are additional lines included in the expansion plan when the battery cost level becomes 10%. Note the additional lines expanded between Idaho and Oregon, Northern and Southern California, and within Southern New Mexico when the battery cost is decreased; meanwhile, one line between Arizona and New Mexico is canceled (dashed line).
2) The greater the level of the carbon tax that is applied to the system, the more the storage expansion anticipation will change the transmission expansion plan;

3) Storage expansion anticipation can both encourage and discourage transmission expansion, with complementary effects dominating under some assumptions and substitution effects in other; and finally,
4) The way that the transmission expansion plan changes differs between types of transmission candidates, i.e., backbone reinforcement and renewable interconnectors. While the interactions between the backbone reinforcement and storage expansion are mixed, and location-dependent, the interaction between the renewable interconnectors and the storage expansion is more clear and is larger in magnitude: (a) while carbon cost is low, storage substitutes for renewable interconnectors, while (b) when carbon cost is high, then as the BESS cost is decreased, storage first substitutes for renewable interconnectors and then complements them.

Now I will examine the numerical results more closely.

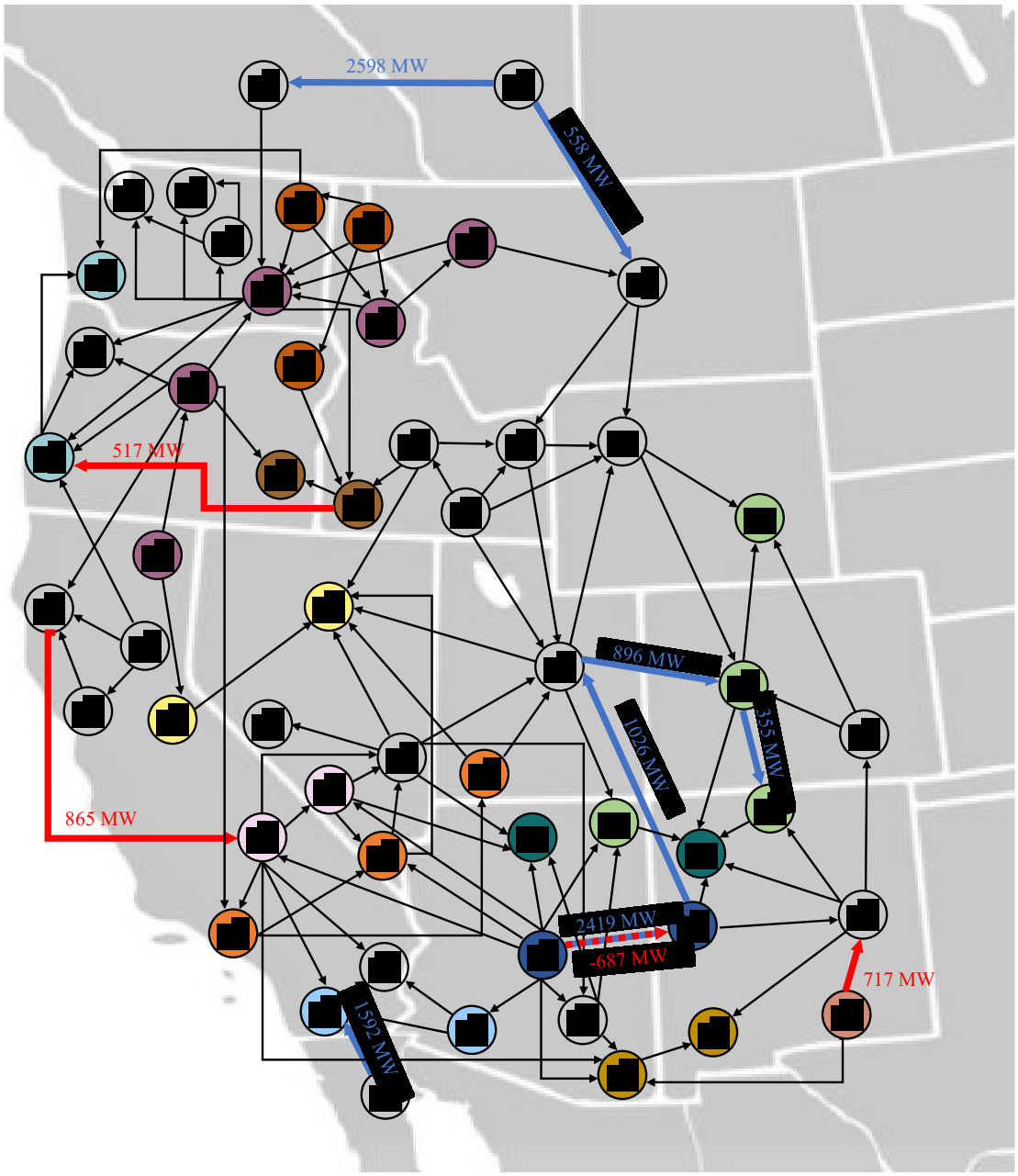

Figure 4.3. Map of Backbone Reinforcement Expansion: Comparison between battery costs of 100% of the base case level ($42.5/kWh-year) and 10% of that level. Carbon Tax is $80/Metric Ton CO_2e.

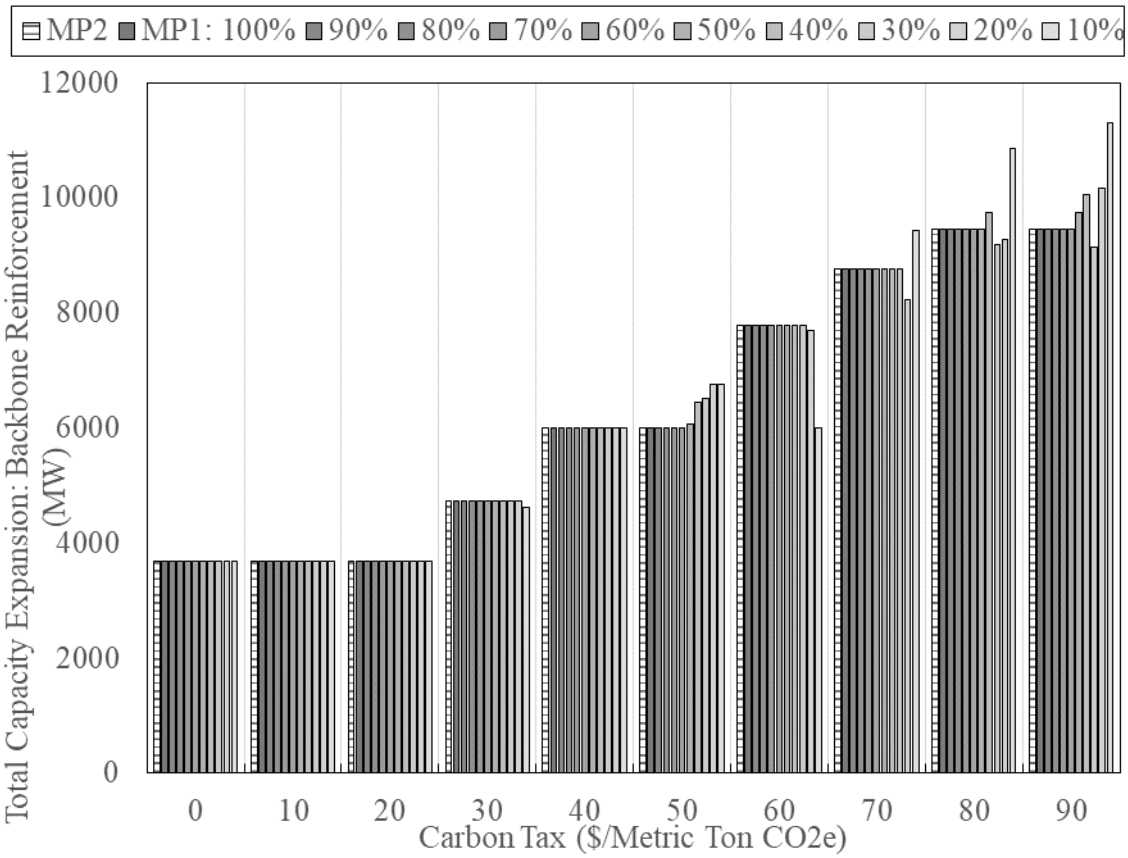

Figure 4.4. Transmission capacity expansion (backbone reinforcements only) by proactive TEP models MP1 with different BESS costs compared to the result of the TEP model with "No BESS" MP2 (Energy Storage Cost at 100% = $42.5/kWh-year).

Figure 4.4 shows the difference between MP1 and MP2's investment in the backbone reinforcements (on inter-regional lines) in 33 (out of 110) study cases: carbon tax = $0, 60, 80/Metric ton CO_2e, and battery cost ranging from $42.5/kWh-year to $4.25/kWh-year. The capacity of all new backbone lines, in MW, is added up to create this index. The figure shows that in cases where carbon tax = $0/Metric ton, anticipating storage expansion does not change the total backbone reinforcements from the "No BESS" case. The locations of additions do not change either. On the other hand, the results show some impact when the carbon price is high, and the battery cost is lower, in particular, when the carbon

price is set to \$80/Metric ton CO_2e, considering storage expansion can cause both the addition and the cancellation of lines, depending on the cost of batteries. As a result, whether backbone lines and storage or complements depends on battery cost assumptions, and surprisingly, this effect is nonmonotonic. Under the highest carbon cost, the magnitude of the effect does not increase uniformly as battery cost falls, and the direction of the effect changes twice as that cost is adjusted.

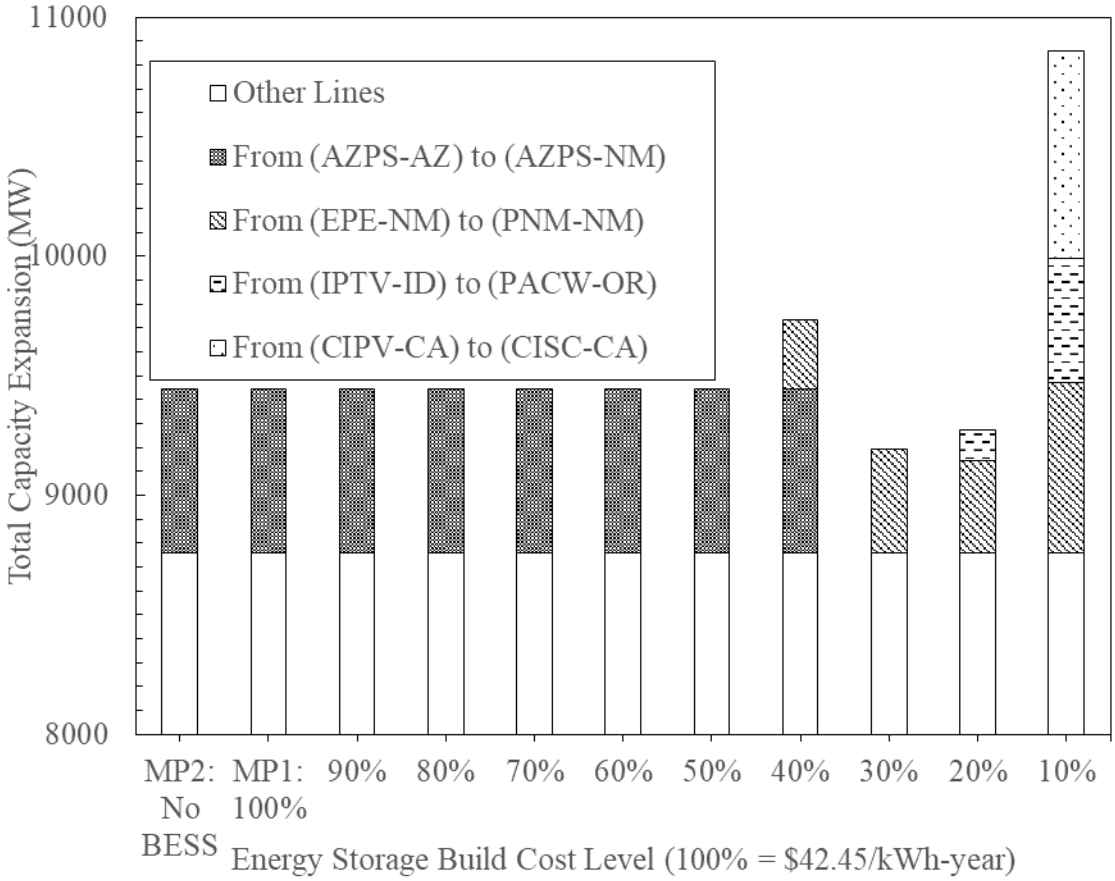

Figure 4.5. Transmission capacity expansion of backbone reinforcements selected by models with carbon tax = \$80/Metric Ton CO_2e in the year 2034

I now turn my attention to locational effects. Figure 4.5 is a zoom-in for the case of carbon tax = \$80/Metric Ton CO_2e in Figure 4.4. When the 4-hour battery cost dropped

from 40% to 30% (corresponding to $16.98/kWh-year and $12.74/kWh-year, respectively), one line from Arizona to New Mexico is canceled; while the battery cost goes lower, several line capacities are added to the system, encouraged by the storage expansion. The locations of those additions are scattered throughout the west, some near load centers (California) and others closer to renewable solar resources (New Mexico). This is essentially showing that the storage system can both substitute (in cases where lines are canceled because of lower storage cost) and complement (in cases where lines are built because of lower storage cost) the transmission expansion.

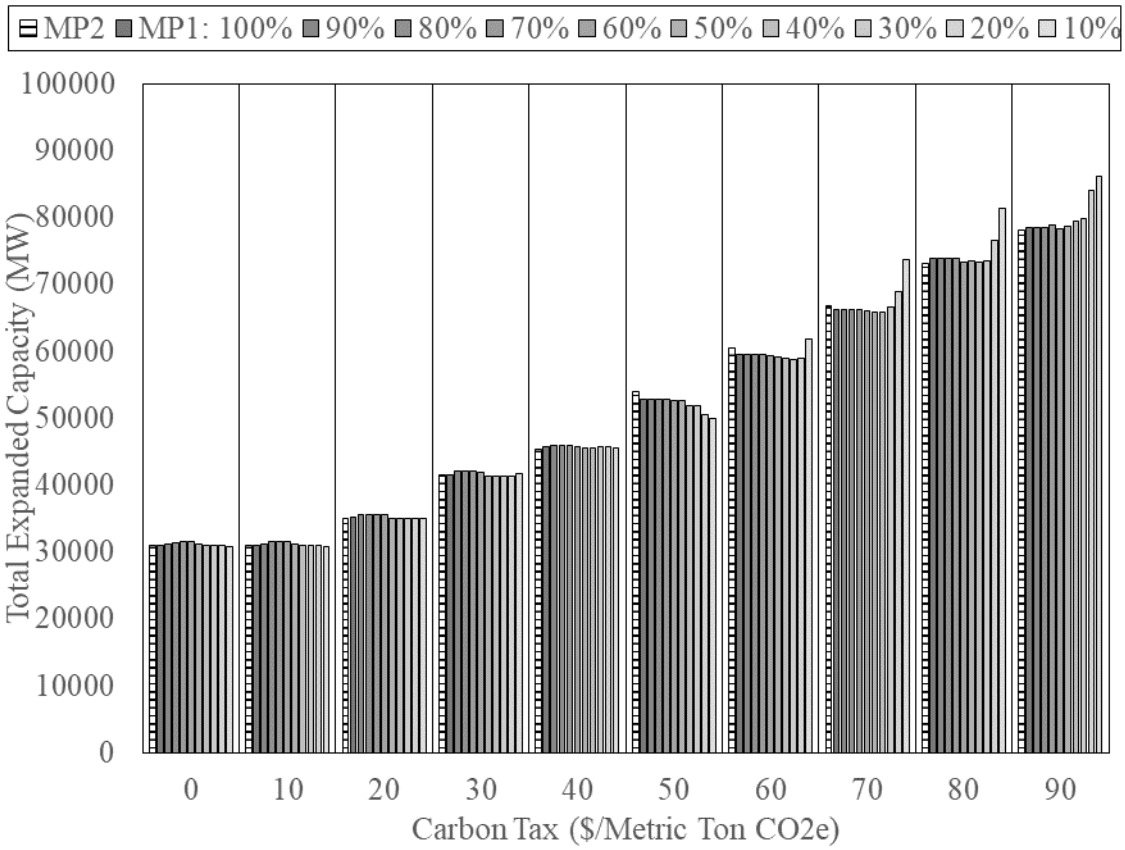

Figure 4.6. Transmission capacity expansion of renewable interconnectors by proactive TEP models MP1 with different BESS costs compared to the result of the TEP model with "No BESS" MP2 (Energy Storage Cost at 100% = 42.5/kWh-year).

When I turn from backbone line expansion to renewable interconnections, the story goes in a similar direction but with a much larger magnitude. A reminder: renewable interconnectors are the lines necessary to deliver new renewable developments to the grid. The expanded capacity of those interconnectors is much higher than the backbones. For instance, backbone reinforcements range from 3.7 to 11 GW, while for renewable interconnectors, the range of additions is 31 to 86 GW. This much higher expansion of interconnectors reflects the impetus towards renewable development throughout the west resulting from our assumed renewable and carbon policies as well as declining costs of renewables. Figure 4.6 shows that anticipation of the storage expansion can both discourage or encourage interconnector expansion. I highlight that in both cases with carbon tax = \$60 and \$80/Metric Ton CO_2e, lower battery costs will first slightly complement the renewable interconnector expansion (expanded capacity is slightly higher when battery costs go lower) and then substitute for expansion (expanded capacity is lower with battery cost goes lower), and then reverses again, returning to a complementary effect.

We can intuitively understand how the storage can substitute for interconnector expansion: you either transport the excessive energy out for consumption, i.e., transmission expansion, or save it for later; i.e., storage expansion and the model (and assumedly the market) will choose the most economical approach. Meanwhile, in cases where the storage expansion encourages renewable interconnectors, the reason is basically that the cheaper storage makes some originally uneconomical intermittent power become economical and worthwhile to be connected. An example is solar in New Mexico that is only available but very strong in the middle of the day; it is not developed at all in high battery cost cases, but at some levels of battery costs, I see an expansion of that renewable source. In one case

where carbon price is at \$80/Metric Ton CO_2e, and battery cost is at 10% of the base level, a 1000 MW BESS is co-sited with a 1575 MW Solar PV facility at a renewable candidate site at Southwestern New Mexico and a transmission line with 850 MW capacity connects both of them to the main grid node at El Paso Electric (EPE) at New Mexico; however, none of these lines are invested in when battery cost is above 20% of the base level.

Overall, I observe from the results that anticipation of storage expansion will change the transmission expansion plan from our TEP model, sometimes encouraging it, and at other times the opposite. How much does this anticipation, with the resulted expansion change, benefit us? Or equivalently, if we transmission planners ignore storage siting/sizing while making the plan, what is the cost we will bear? As was explained in Section 4.3.3, this benefit/cost is called VoMES, the value of TEP model enhancement to proactively anticipate storage and will be discussed next.

4.4.5 Value of Considering Storage in Co-optimized Transmission Expansion Planning

In this subsection, I calculate the value of storage in transmission expansion planning VoMES. To restate the framework defined in Section 4.3.3 above, I first plan transmission expansion T anticipating both generation G and storage S investments (MP1); second, I naïvely plan the transmission expansion without considering storage (MP2, having only T and G as variables); finally I plug the resulting naïve plan from MP2 into a co-optimization model that includes storage expansion to simulate the reaction from the market to the naïve transmission plan (MP3, optimizing S and G, but freezing T at MP2's levels). The intent of VoMES is to simulate the efficiency loss resulting from the situation that transmission expansion planner naively ignores the possibility of storage investment,

as well as the reaction of storage siting and operation to transmission reinforcements, but the storage investors still have the chance to react. The difference between the objective function values of MP1 and MP3 is this index.

The VoMES in TEP in all 100 test cases are shown in Figure 4.7, and the amount of investment for new lines is shown in Figure 4.8. Two basic observations can be made concerning the trends in these figures.

Initially, with the carbon tax fixed at a certain level, VoMES is monotonically increasing as the battery cost goes lower. In other words, the lower the battery cost is, the greater the value of storage expansion anticipation is the transmission planners. The value is zero for the highest battery costs and lowest carbon costs because no storage is added by model MP1 in those cases, so the MP1 and MP3 solutions are identical. Unsurprisingly, the highest values of VoMES are associated with solutions that install the most battery capacity.

Second, the carbon tax is a factor in the value of anticipating storage, but the effect is not monotonic. In other words, a higher carbon tax does not necessarily make VoMES higher. For example, when the battery cost is half the base level (50% case), as the carbon tax goes higher, the VoMES will first go down then up.

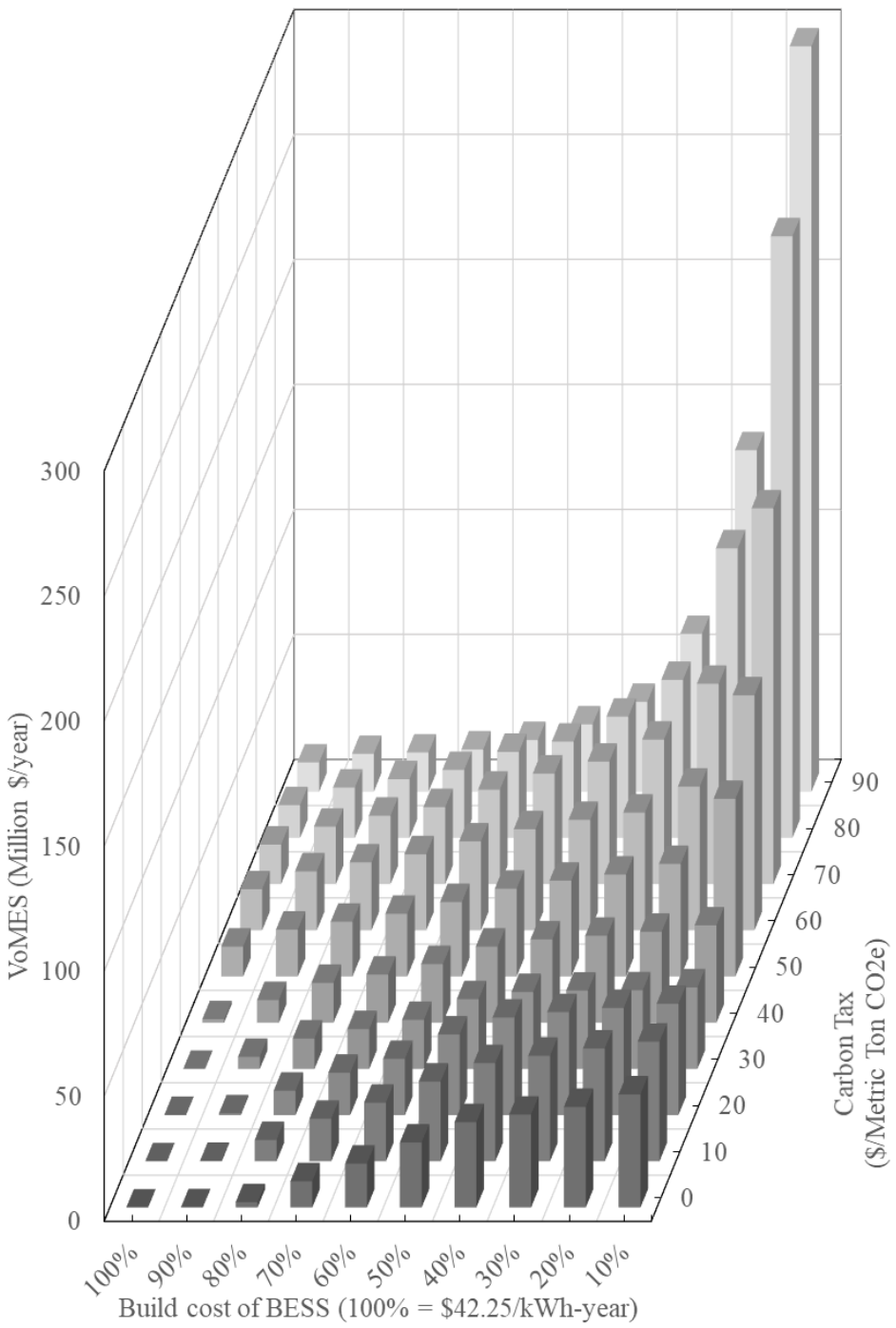

Figure 4.7. VoMES in TEP in different test cases

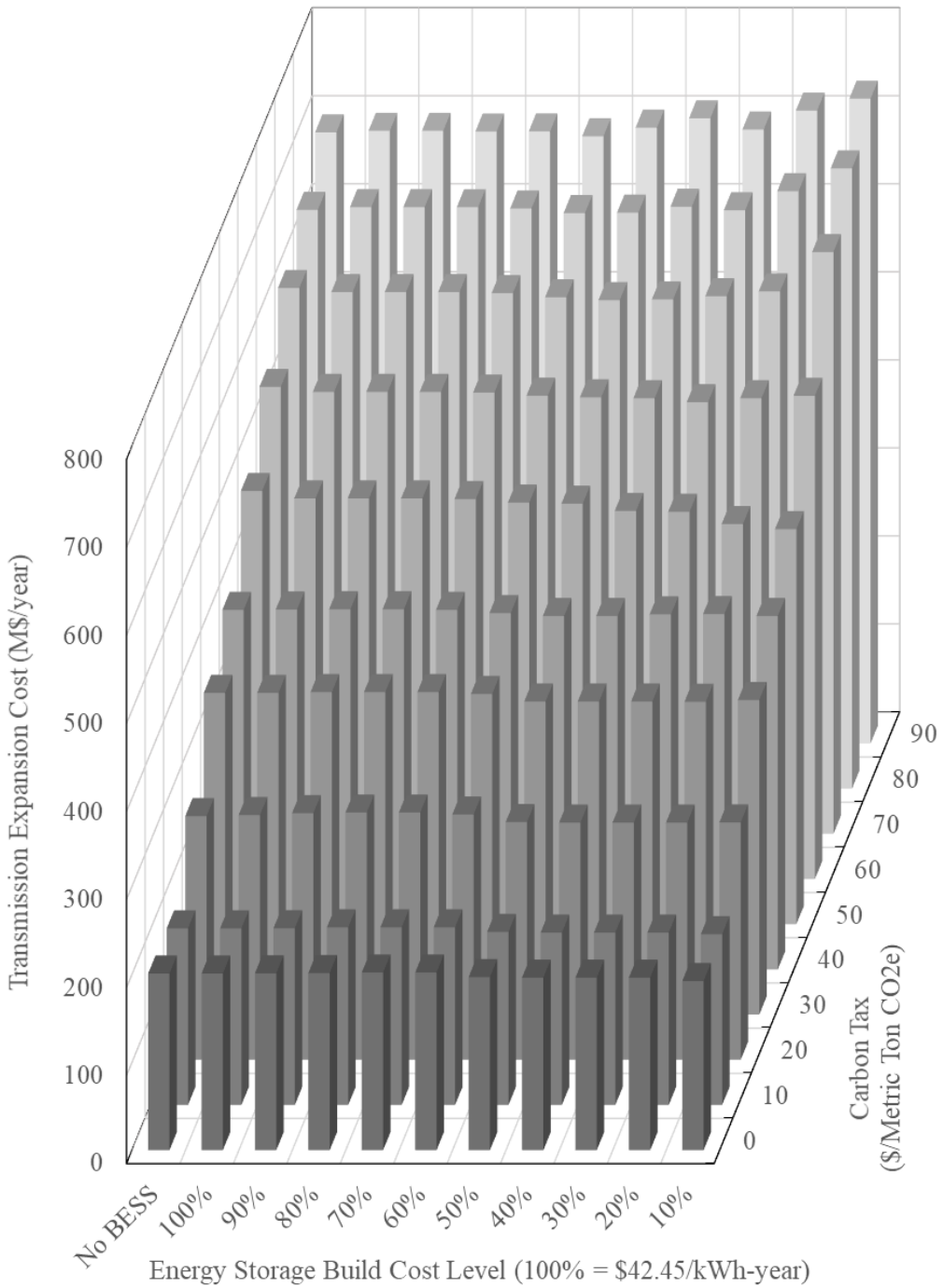

Figure 4.8. Backbone and Renewable Interconnection Transmission Investment Cost in TEP in different test cases

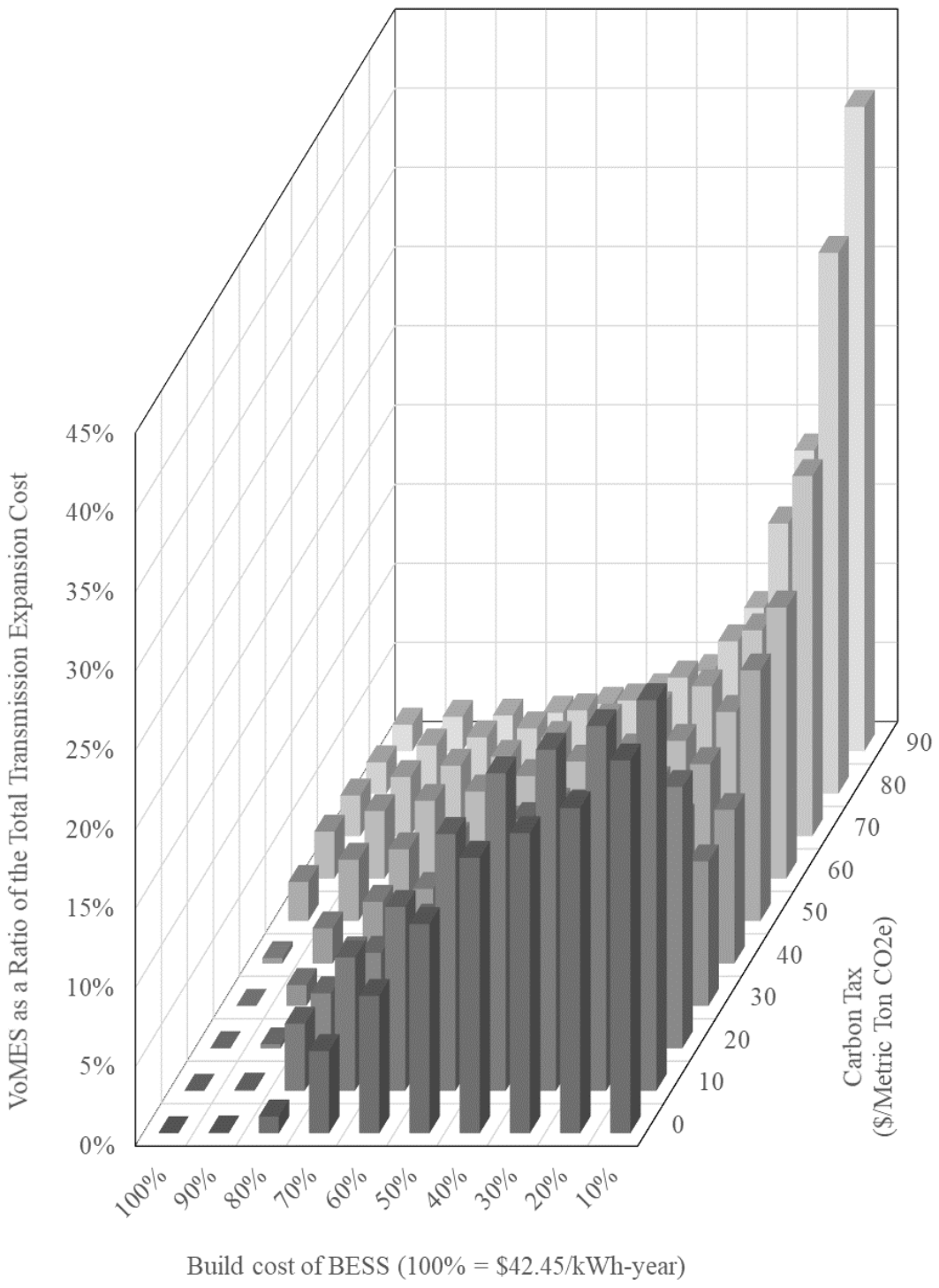

Figure 4.9. VoMES as a Ratio of total Transmission Expansion Cost

To help interpret the magnitude of VoMES, first, I compare it to the incremental transmission investments. Their ratio gives an indication of the relative importance of incorporating the proactive/anticipative perspective in planning. Figure 4.8 shows the transmission expansion cost in all 100 MP1 test cases as well as the 10 MP2 cases that is without the storage siting. In 68 out of 100 MP1 test cases, I see that lower transmission expansion investment costs result compared to the corresponding "No BESS" case, implying that anticipating storage results in less transmission investment (substitution effect). In the remaining 32 cases, proactive planning, including storage results in more transmission (complementary effect). The ratios of VoMES to the MP1 transmission investments are shown in Figure 4.9. This shows that the value of proactive planning that recognizes storage is a significant fraction of total transmission investment under the higher carbon cost assumptions and lower battery costs, which are the runs that have the most battery investment.

Although how carbon policy will affect the transmission is largely out of the scope of this chapter, Figure 4.8 also shows that carbon policy has more impact on the transmission expansion than the storage expansion, the major topic here.

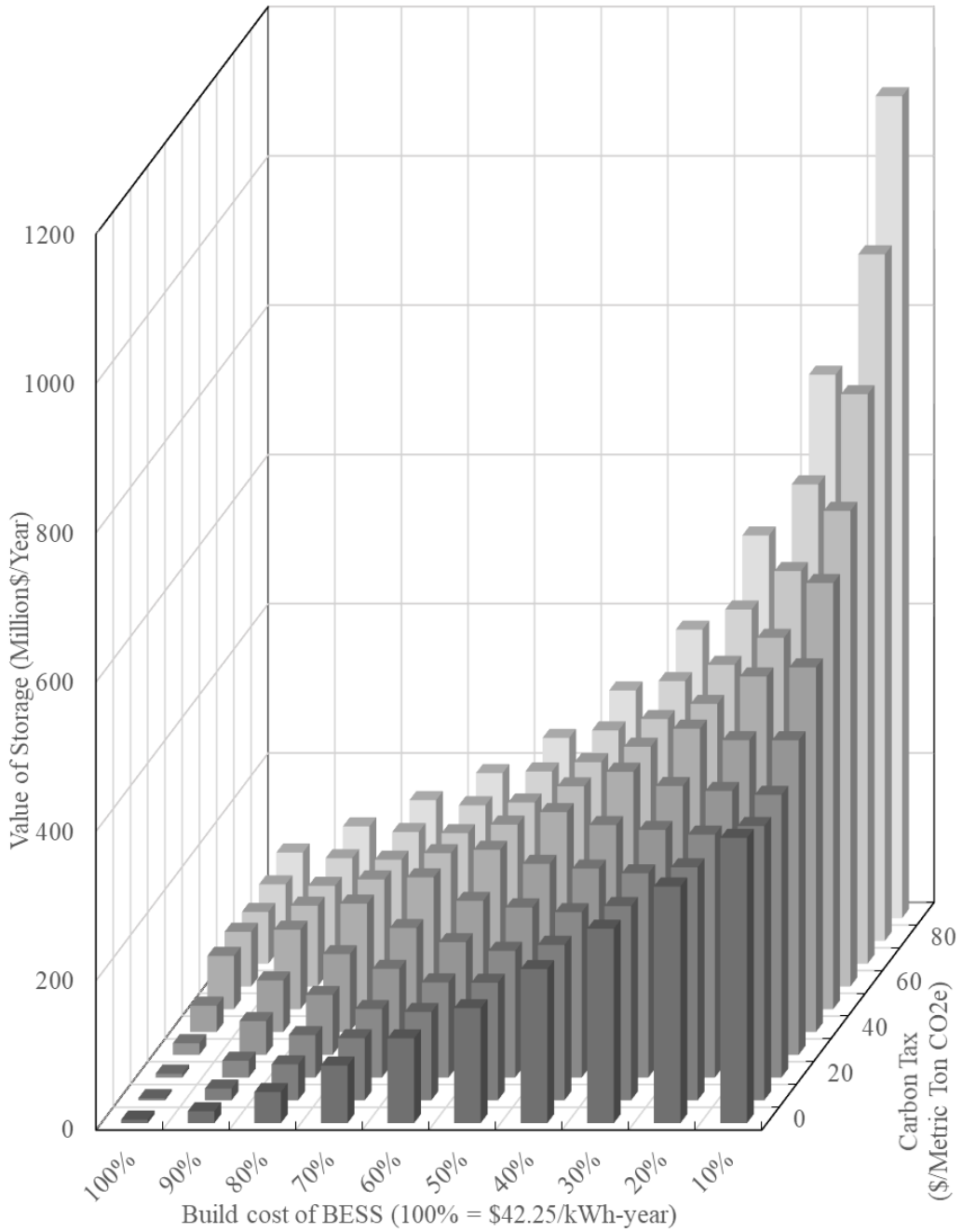

Figure 4.10. VoS in TEP in different test cases

The overall value of storage to the system (VoS) results are shown in Figure 4.10. As pointed out in Section 2, the larger VoMES is (as a proportion of VoS), the stronger the impact that naïve transmission expansion decisions (which disregard storage reactions) will have upon the final realization of the economic value of storage. Among all the test cases, VoMES is about 0-27% of the VoS, and the average is about 14%. Thus, anticipating how storage siting and amounts will react to grid expansion can significantly enhance the value of storage.

4.4.6 Sources of VoMES in Transmission Planning

We have seen that anticipating the sizing/siting of the storage will change the transmission expansion, and this change will provide an economic benefit (VoMES in TEP) to transmission expansion planners. To understand why, it is important to examine the sources of the VoMES, in terms of whether it is reduced investment (and if so, of what type) or reduced operating costs. Is VoMES positive because given the changed transmission plan, the market will react with different generation/storage expansion, or are those investments relatively unchanged and it is transmission investments that shift? Is most of VoMES comprised of fuel and carbon cost savings, or do capital cost savings contribution a large portion? I will identify the primary sources of VoMES in the WECC case study as follows.

Figure 4.11 to Figure 4.13 show the components of VoMES for 60 different test cases (one figure per carbon price = \$0, 60, 80/Metric ton CO_2e, and within each figure BESS costs from 100 % level to 10 %). As a reminder, I calculate VoMES by taking the difference between two objective functions: (1) the objective of MP1, i.e., TEP with generation storage anticipation and (2) the objective of MP3, i.e., generation/storage expansion

simulation with transmission expansion fixed from the "No BESS" case (MP2). Here, I now consider the differences in individual sets of objective function terms, shown in Section 2.4.1 of Chapter 2. The five components I break out are the separate investments in transmission, generation, and storage; fuel and variable O&M costs of generation (excluding carbon costs); and environmental terms, namely the carbon tax and any penalties ("ACP") associated with noncompliance with the state-level renewable portfolio standards.

All three figures show the same pattern:

1) The proactive transmission plan (MP1, which anticipates storage in TEP) is introducing more generation and storage expansion than the naïve plans (MP2, without storage anticipation), and thus the VoMES components associated with generation and storage investments are negative. Thus, by proactively planning, transmission planners also encourage investment in generation and storage.
2) VoMES arises mostly from savings in operating costs and policy compliance: the additional *G* and *S* investment just discussed more than pays for itself in terms of lower fuel costs, variable operation & maintenance costs, start-up and shutdown costs, carbon taxes and the RPS alternative compliance penalty.
3) Consistent with the changes in transmission expansion cost discussed in Section 4.4.5, most scenarios have slightly more transmission investment, but about a third have less investment. However, the changes in transmission investment itself is not a significant portion of VoMES.

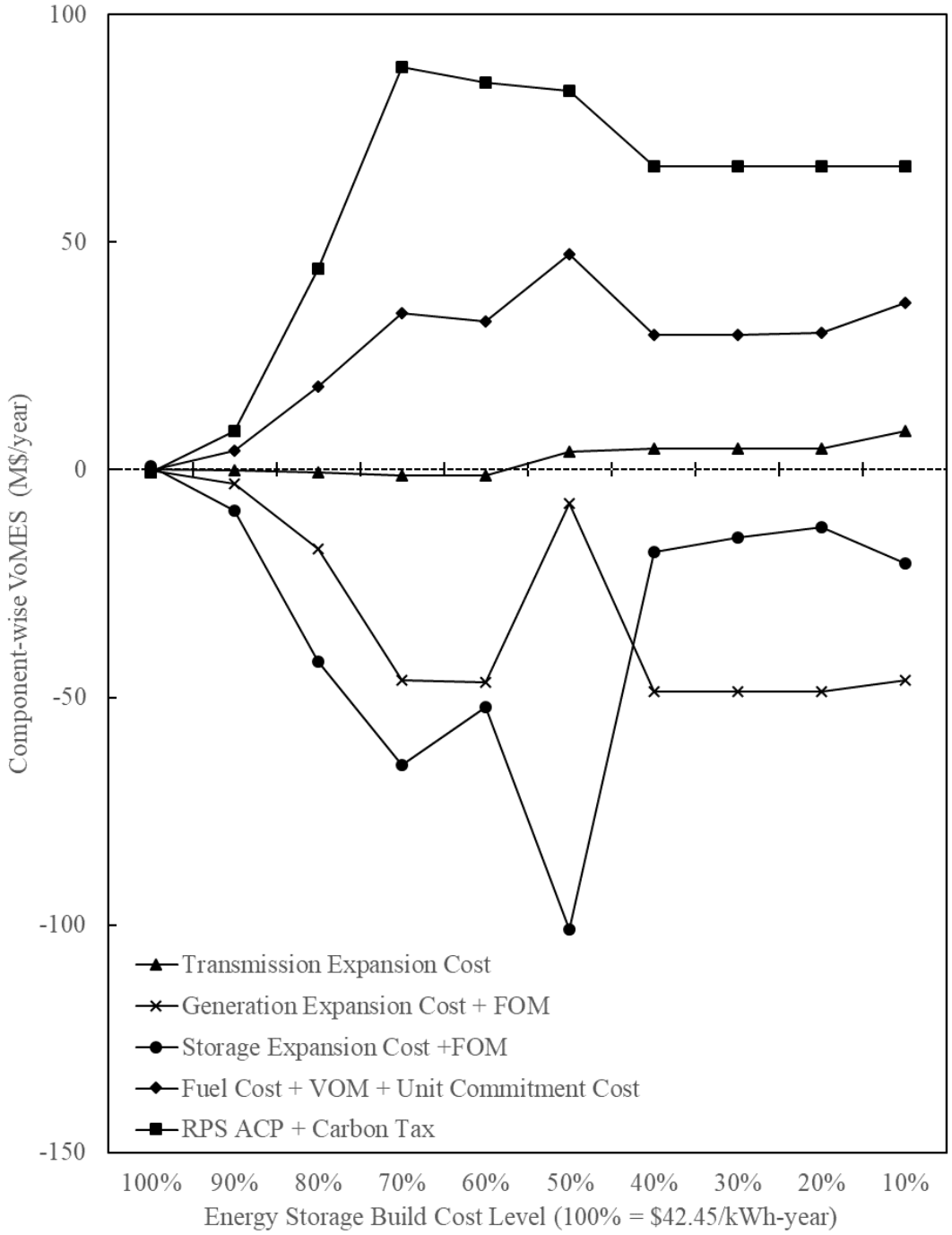

Figure 4.11. Component-wise VoMES in TEP, carbon tax = $0/metric ton

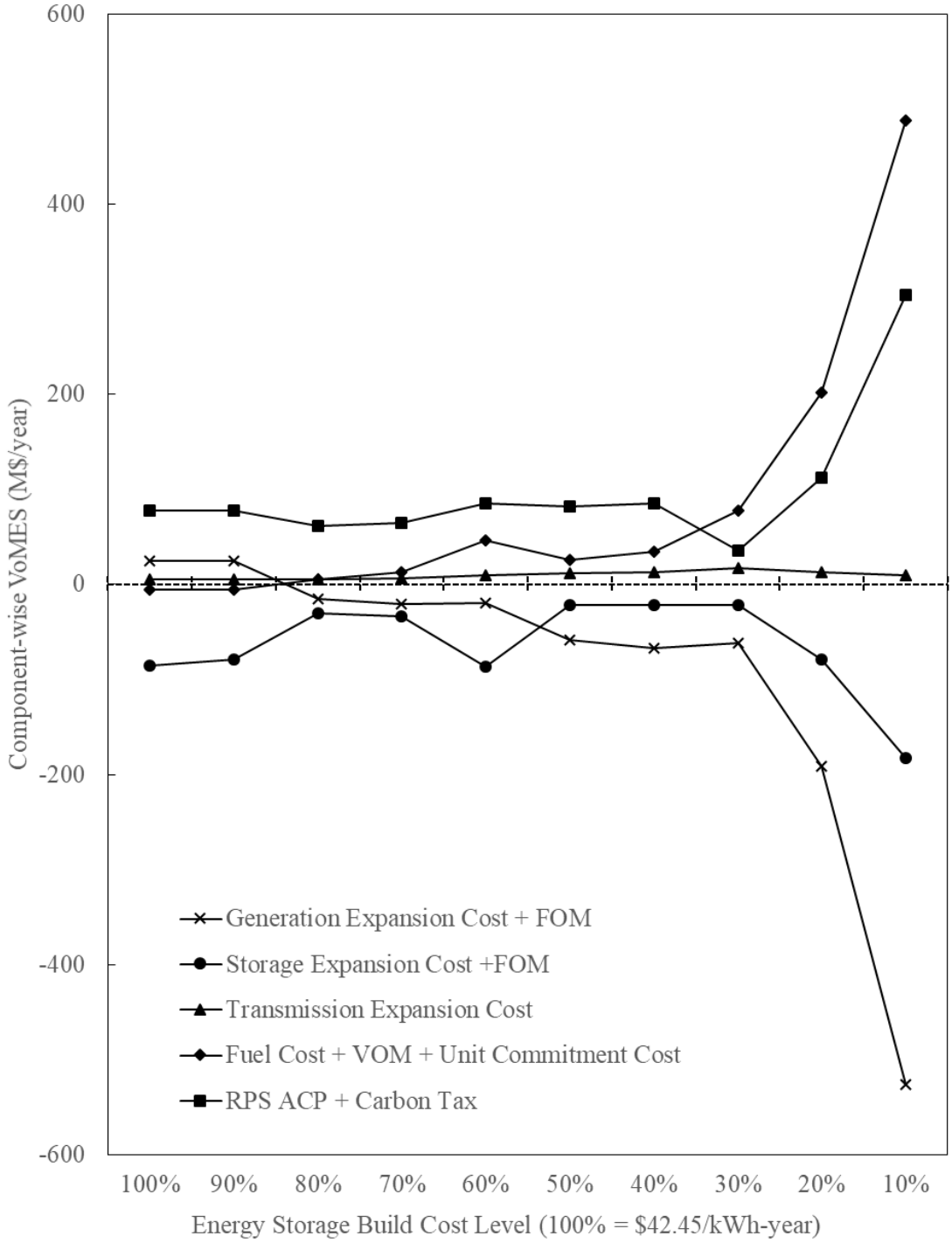

Figure 4.12. Component-wise VoMES in TEP, carbon tax = $60/metric ton

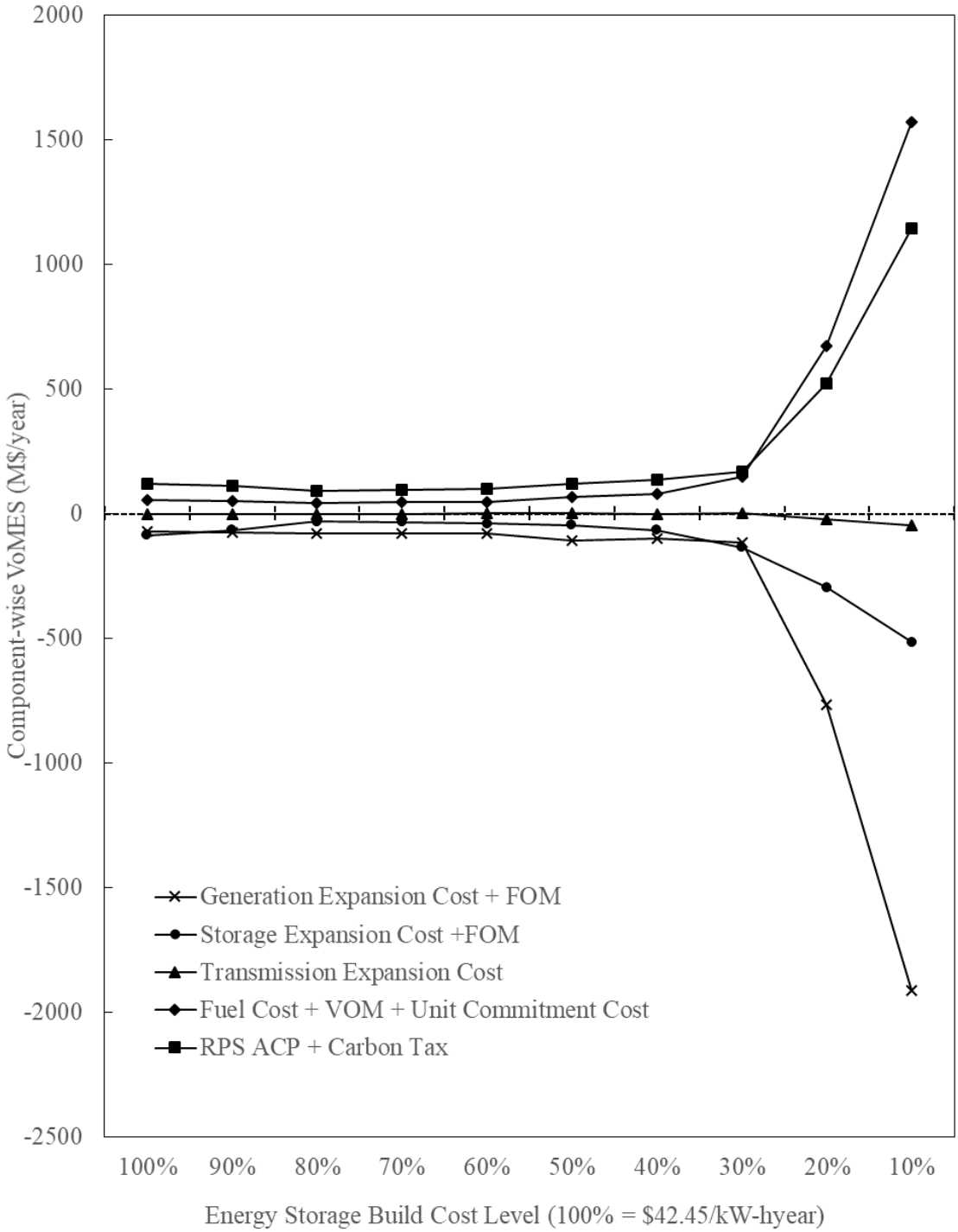

Figure 4.13. Component-wise VoMES in TEP, carbon tax = $80/metric ton

Interestingly, these results imply that although the total amount of transmission investment doesn't change greatly, there is a magnification effect in which the changes that do occur in amount and location induce much larger changes in generation and storage investment.

Please see an example of this impact in Figure 4.14. There, the generation expansion and storage expansion gave different transmission plans. (Only Wind and Solar are shown in the figure because other generation expansions are minor.) Model MP1 is showing the optimal expansions, and while MP3 is the reaction of the market if instead the naïve transmission plan is implemented. The results first show that in both MP1 and MP3, solar is more impacted than wind by battery installations spurred by low battery prices. Second, they show that the effect of naïve TEP is correspondingly greater on solar investments than wind investments. Proactive TEP that anticipates storage will facilitate a roughly doubling of the amount of storage installation under low battery prices, and up to a 30% increase in solar installations. There are much smaller increases in wind capacity. The reason is that solar is only available during the day, and the storage is potentially more valuable to it than the wind resource, which is distributed more evenly over all 24 hours. Thus, ignoring storage expansion in TEP will undervalue the combination of solar and storage, resulting in less transmission being built for solar and, ultimately, less solar development since the ability to convey remote inexpensive solar to markets is reduced.

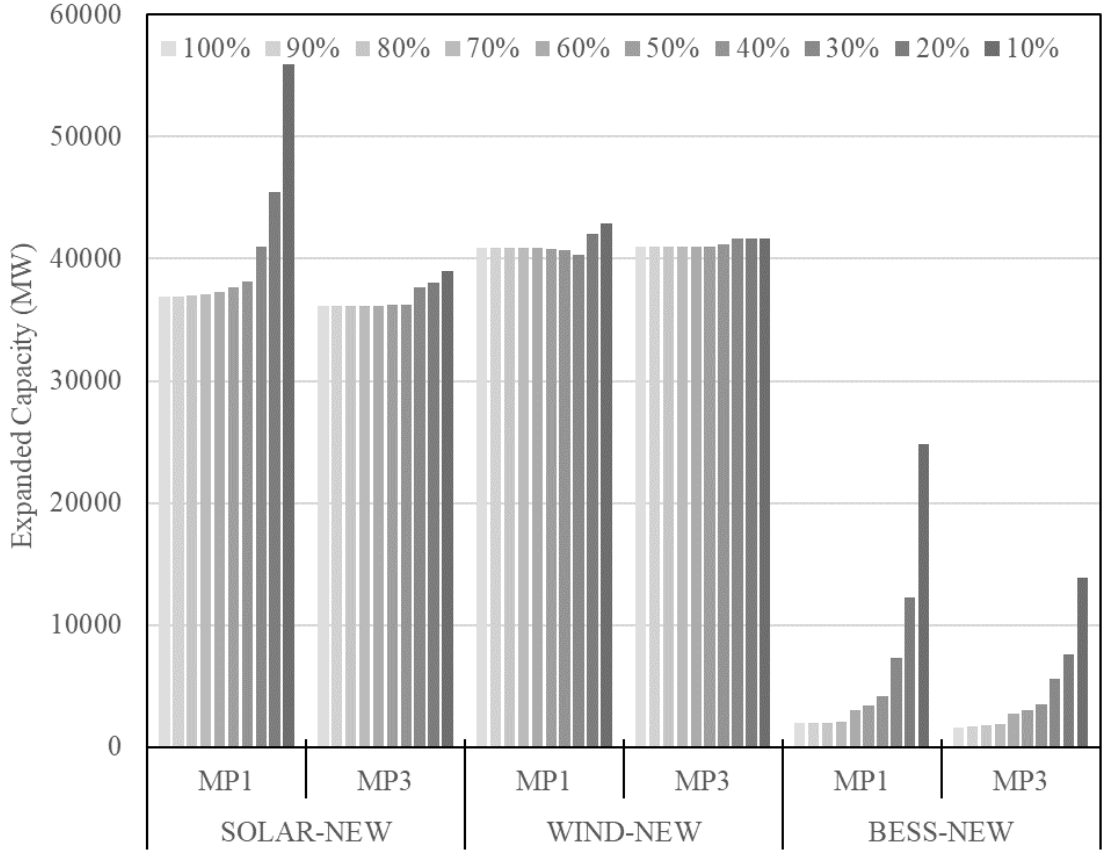

Figure 4.14. Solar, Wind, and Storage Expansion, given transmission plans from different TEPs, Carbon Price = $80/Metric Ton CO2e, Battery cost at 100% level = $42.45/kWh-year

4.5 Conclusions and Limitation

With renewable penetration increasing in many power systems, the need for the transmission grid to bring remote renewables to market is growing, as is the need for storage. Because of the 10 year or longer lead times for grid reinforcements, this transmission should be planned in a proactive manner, anticipating how generation and storage siting, amounts, types, and timing will be affected (Krishnan et al., 2015; Liu et al., 2013b; Sauma and Oren, 2006; Spyrou et al., 2017). Will the best plans for integrating renewables include large amounts of transmission, large amounts of storage, neither, or both? It remains to be

seen. Whatever the answer is, a transmission expansion planning tool with generation and storage co-optimization will decrease the cost of renewable integration relative to naïve planning that does not anticipate how supply and storage investors will react to changes in the grid.

This chapter presents and applies a proactive transmission expansion planning model with generation-storage co-optimization, building on our previous work on transmission-generation co-optimization (Ho et al., 2016). After applying this model to the test case, I show examples to calculate the economic value of model enhancements to consider storage expansion (VoMES) in TEP proactively.

The results show that considering storage expansion in TEP will change the transmission plan by helping to identify and correct: (1) overbuilt line capacities that can be avoided by building storage, primarily near renewable energy generation locations and (2) underbuilt line capacities that convey renewable resources that turn out to be economical only when accompanied by storage. In other words, the results show that the storage can both complement and substitute for transmission expansion.

The VoMES in my example is primarily the net of two cost changes: the incremental investment for larger amounts of generation and storage expansion in a fully proactive TEP model, and the savings that the increased investment makes possible in operating costs, such as fuel and carbon costs. Both occur because of improved transmission planning resulting from co-optimization with storage. On the other hand, a naïve transmission plan, which is the result of a planning process that disregards potential storage expansion, can discourage investment in solar generation and storage expansion.

As shown in the example application to the western U.S. and Canada, as storage costs are reduced in the year 2034, the VoMES in TEP increases. This highlights the need for a transmission planner to consider storage expansion in the planning process. However, this VoMES is sensitive to the policies that are affecting the power system: in our case, the carbon price will affect the VoMES in TEP significantly.

To conclude, improved TEP models have value if they result in system plans with lower costs. This chapter has shown how this value can be quantified for one particular improvement, the incorporation of storage. Elsewhere, my colleagues have quantified the value of enhancing transmission models to include just generation co-optimization (Spyrou et al., 2017) and I have calculated the value of recognizing long-run uncertainties in regulatory, economic, and technological conditions in Chapter 3 (also in Xu and Hobbs (2019)). In several cases these values are comparable in magnitude to the size of the transmission investments themselves.

Chapter 5 A Model-Based Assessment of Border Carbon Adjustments in the Western North American Electricity Sector, Part I: Background, Model, and Theoretical Results

5.1 Chapter Summary

This is the first of two chapters in which I provide a multi-objective impact comparison of two groups of potential border carbon adjustment (BCA) schemes that can be applied to the California AB32 carbon cap-and-trade system, in particular, the electricity sector. The California carbon pricing policy is a unilateral system embedded in an interconnected power system for western North America: the Western Electricity Coordinating Council (WECC). Chapter 5 (this chapter) focuses on the introduction, model formulation, and theoretical results, while Chapter 6 presents the numerical results and resulting conclusions about the policy as well as the needed model improvements.

In this chapter, following the general introduction (Sections 5.2 and 5.3), I modify JHSMINE to facilitate the modeling of BCA by introducing new variables and constraints (Section 5.4). More specifically, I enhance JHSMINE to incorporate bilateral trading of energy credits between generators and state-level Load-Serving Entities (LSEs), such modeling of bilateral energy credit trading is a generalization of renewable credit trading and keeps track of the imports/exports of power flowing between the states, which are the subjects of BCA.

After presenting the model formulation, I provide some model properties and theoretical results in Sections 5.5 and 5.6. My results show that if the Californian emission regulator charges imports based on a uniform technology-neutral rate that is applied to all types of import sources, such a policy will function like a technology-neutral subsidy

towards the internal generators of California, given an assumed carbon price. If, on the other hand, the Californian emission regulator charges imports in a way that discriminates based on the source technology, my results confirm what is well known from previous analyses: that such a policy will create incentives to "contract shuffle" in order to make energy credits flowing into California look cleaner than energy contracts flowing between states in the rest of WECC (Bushnell et al., 2014). Furthermore, if the California emission regulator (California Air Resources Board, CARB) also chooses to rebate emission charges for exports,[20] such a policy will push energy credits contracts from California emitting generators to the rest of WECC, creating an extra incentive to import clean energy from the rest of WECC. The contribution of this work is that: to the best of my knowledge, it is the first time that the BCA mechanism is incorporated within a power system planning model.

5.2 Introduction

All carbon pricing policies are limited in geographical and/or sector coverage (World Bank, 2017). Further, limited coverage will introduce so-called carbon leakage: increased emissions in non-regulated jurisdictions or sectors because of higher costs in the regulated jurisdictions/sectors due to carbon pricing (IPCC, 2014). This fact has spawned proposals for "border carbon adjustments" (BCA) in which imports and exports of commodities between regulated and external jurisdictions are regulated, subsidized, and/or taxed (or border tax adjustment, BTA) (Fischer and Fox, 2012; Ismer and Neuhoff, 2007). Intuitively, the regulations/subsidies/taxes can be imposed upon the most elemental form

[20] Rebate exports here means to exempt the Californian emitting generators from the allowance surrendering for the amount of power exported to the rest of WECC.

of interactions: inter-state transactions. A BCA on import transactions typically requires the buyer or the seller to pay a carbon tax or surrender carbon emission allowances at an assumed emission rate for the commodity, perhaps differentiated by source or other attributes. BCA regulation can also specify whether to rebate export carbon taxes paid on transactions or otherwise exempt them from paying for emissions (Fischer and Fox, 2012).

However, because of the homogeneity of electricity (i.e., electricity end-users cannot easily distinguish where or how their electricity is produced in interconnected power systems), two problematic but highly related facts emerge. First, estimates of the emission rate of cross-border power flow can be inconsistent and even misleading (Jiusto, 2006). Consider a simple example (see Figure 5.1) in which node A consumes 50 MW as does node B, and they are connected by a 50 MW transmission line. At node B, there are two plants: a gas plant generating 50 MW and a hydro facility generating 50 MW of electricity, and there are no plants at node A. As a result, there is 50 MW of power flow flowing from node B to node A. From the perspective of A, how much emission should be associated with this inbound power flow? Should we accept an assumption made by the regulator, known as the deemed emission rate?

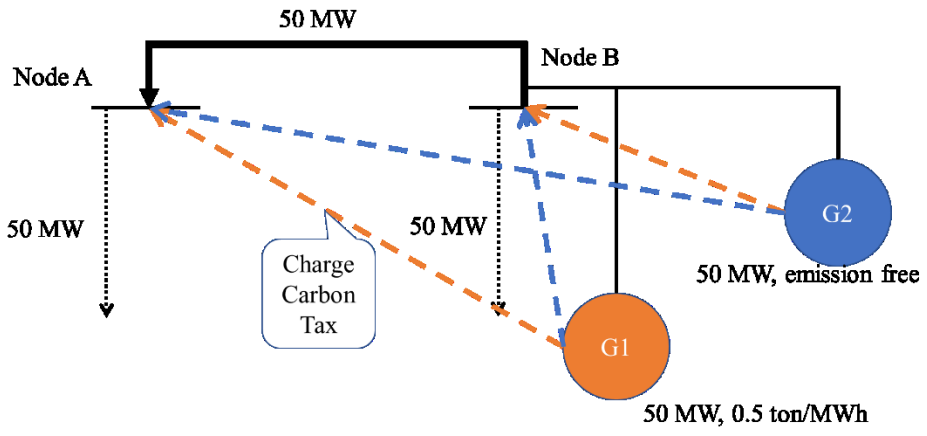

Figure 5.1. A two-node diagram: How much emission should be associated with the 50 MW power flow? Orange arrows: the assumed sources of transactions before carbon tax; Blue arrows: after carbon tax.

An intuitive answer is to look at the contract signed for this 50 MW power flow and set the emission rate as the emission rate of the supply-side of the transaction; however, this leads to the second problematic result of the homogenous electricity commodity: contract shuffling (or secondary dispatch). If the original contract (designated as orange arrows in Figure 5.1) is signed between consumers at node A and the gas plant at node B, and the emission regulator at node A chooses to put a carbon tax on this contract, the gas plant can instead sign a contract with consumers at node B and let the hydro facility serve the demand at node A (blue arrows in Figure 5.1); as a result, the imported power seems emission-free, and the generators avoid carbon taxes that A might charge imports without changing their physical dispatch at all. Such an effect has been widely recognized by academia; for example, Bushnell et al. (2014); Chen et al. (2011); Ismer and Neuhoff (2007); and policymakers, for example, CAISO (2018).

Efforts have been made to solve this dilemma of deemed emission rates for cross-border transactions. To policymakers in the regulated jurisdiction, a "solution" would be a set of deemed rates that would reduce the leakage without distorting market efficiency. There are several alternative approaches to calculate a deemed rate that would need to be assessed against these policy objectives. For instance, the California Independent System Operator (CAISO) had proposed the so-called two-stage framework, which tried to calculate the real-time composition of the California net imports (CAISO, 2017); although this proposal was not finally chosen, it highlights the possibility of using the real-time information to identify which outsider really supports the demand inside the carbon pricing

regime and then setting the deemed rate accordingly. On the other hand, the "marginal emission" for the regulated market can also be a candidate proposal. This can be argued based on a set of analyses of the price pass-through of carbon cost, such as in Kim et al. (2010), Sijm et al. (2012). Since electricity prices will be raised because of the imposed carbon cost (passing-through), the effective carbon tax can be set at the bid price of the marginal unit in the regulated market. Using marginal pricing principles, the system operator can calculate the rise in price because of carbon pricing and, based on such a rise in price, artificially lower the price faced by external generators. Such an approach has been proposed in the carbon pricing plan of the New York Independent System Operator (NYISO) (NYISO, 2018). Specifically, the marginal emission factor has been estimated for the United Kingdom (UK) in Hawkes (2010), and for Pennsylvania-New Jersey-Maryland (PJM) interconnection in (PJM, 2019).

The elements of BCA policy include not only the deemed emission rate for the cross-border transaction (how much to charge), and whether to discriminate among sources or over time (e.g., day vs night, summer vs winter), but also the direction of BCA (whom to charge/rebate): whether to charge imports or to rebate exports or both (Fischer and Fox, 2012). Thus, in this chapter and the next, I focus on providing a comprehensive impact assessment of different BCA schemes on the power system.

More specifically, I ask the following two questions: (1) for a unilateral carbon pricing jurisdiction in an interconnected electricity market, how will BCA schemes affect the local emission reduction, emission leakage, regional electricity production, transmission expansion, and consumer payments? And (2) given the current California cap-and-trade system, if I define a "better" BCA scheme as one achieving more system-wide

economic efficiency (i.e., lower overall emissions and higher societal welfare), do such schemes potentially exist and how large are their benefits?

5.3 Background

5.3.1 Emission Control by Emission Pricing

In 1970, the U.S. Congress passed the profoundly influential 1970 Clean Air Act; this act aimed to protect the public health from air pollution no matter the cost, as it forbade benefit-cost analysis for air quality standard quantification (Oates, 1994). Standards were to be set on the basis of a single objective: to protect public health. At about the same time, people started to recognize the potential for the use of economic instruments for emission, as argued in seminal papers by Baumol and Oates (1971) and Baumol (1972). There ensued a fierce debate on whether to use economic instruments or continue with command-and-control stands (Weitzman (1974), Montgomery (1972), and Baumol (1972)), but academia and governments gradually accepted the idea of internalizing the environmental externalities by charging at a fixed price (tax), or, more commonly, establishing an emission allowance market by setting the standards first and creating tonnage-based rights that could be traded among companies in order to motivate cost-efficient control. As a result, in Title IV of the 1990 Amendments to the 1970 Clean Air Act, the U.S. Congress directed the Environmental Protection Agency to establish a nationwide emission permits trading system for SO_2, a big step toward acceptance of emission pricing (EPA, 2019b).

The rest of the world then followed this precedent, broadening such market-based air pollution programs to include NOx and, especially, greenhouse gas emissions (hereafter,

I use greenhouse gas and carbon emission interchangeably.[21]) The European Union Emission Trading System (EU ETS) started to function in 2005. It was the first international emission trading system to cover the greenhouse gasses of CO_2, N_2O, and PFCs, and it aimed to cut greenhouse gas emissions by 2030 to 57% of the 2005 level (European Commission, 2019b). The Canadian government created its own carbon pricing policy in 2018, requiring all local governments to establish a carbon pricing mechanism with a price floor (Morneau, 2018). The British Columbia system, established in 2008, was seen as a model for the rest of the country. In summary, governments all over the globe, including China, the most emitting country in the world, have started to recognize that emission pricing is an important policy tool to encourage carbon emissions reductions (World Bank, 2017), although some governments have grown skeptical of carbon trading as a stand-alone mechanism and have adopted other policies either to stabilize the carbon price and/or subsidize green technology development and adoption, e.g., the carbon price floor proposed by U.K. (Hirst, 2018).

The original pioneer of emission trading, the United States, has, however, fallen behind in the trend towards carbon pricing. Currently, there are only two sub-national carbon cap-and-trade systems in the United States, the Regional Greenhouse Gas Initiative (RGGI) (RGGI, 2018), and the California cap-and-trade system (CARB, 2014; Pavley, 2016). Many other carbon pricing attempts are dead, including the national Waxman-Markey bill that came close to adoption in 2009 (Waxman and Markey, 2009), and the Clean Power Plan proposed by the Obama Administration in its closing days (EPA, 2019a),

[21] Greenhouse gases (GHGs) are not limited to carbon emissions as they also include, for instance, Methane (CH_4), Nitrous oxide (N_2O), and Perfluorocarbons (PFC). However, when people quantify the level of effluent, all these GHGs are represented in the unit of [mass]/CO_2e, which is short for Carbon Dioxide Equivalent. The calculations are based on the global-warming potential (GWP).

the carbon tax bill in Washington state (Washington Secretary of State, 2018), and the cap-and-trade bill in Oregon (Joint Committee on Carbon Reduction, 2019). At the time of writing this thesis, the only new attempt to implement carbon pricing in the U.S. is led by the New York power system operator, which is trying to incorporate the social cost of carbon emission into the electricity markets (NYISO, 2018).

5.3.2 Local Carbon Pricing and Carbon Leakage Mitigation

Although more and more governments have joined the effort of cutting carbon emission by means of carbon pricing, the coverage of such policies is far from global. For the United States, only 10 of the 50 states are covered by California and RGGI. Therefore, this limited coverage leads to concerns about emission leakage in forms of a shift of production activity from regulated regions to unregulated regions who then export to the former (IPCC, 2014). In terms of the major objectives of carbon policy outlined above (cost and global emissions reduction), the inconsistent carbon policies that lead to leakage may be inefficient in that costs are increased to the economy because of shifts in production patterns while net emissions reductions are less than desired, resulting in high costs per unit of actual emissions reduction.

With the recognition of this potential source of inefficiency and ineffectiveness, current carbon pricing regimes usually attempt to mitigate carbon leakage in some manner. For instance, EU ETS allocates some emission permits at no cost to sectors facing the carbon-pricing-introduced risk (European Commission, 2019a). This policy can lower prices in those sectors, increasing the competitiveness of regulated facilities in external

markets as well as internal markets subject to import competition.[22] By protecting vulnerable sectors through this subsidy, the emission regulator attempts to keep production activities inside the carbon pricing regimes. As a result, emissions will tend to stay within the regulated region. However, depending on the extent of competitiveness of outside supply, such measures, by lowering prices and increasing local demand, may also make local carbon goals more difficult and expensive to achieve (Zhao et al., 2010).

Another choice is the aforementioned BCA, which directly deals with cross-border transactions. For instance, the two subnational carbon pricing regimes of the U.S., RGGI and California Cap-and-Trade, adopt distinctly different BCA schemes for the electricity system in which they are nested. On the one hand, RGGI is neither charging importing power for embodied carbon nor rebating allowances to exported power (RGGI, 2018). Meanwhile, on the other hand, the California cap-and-trade system charges imports, requiring electricity importers to specify the source of electricity contracts and to surrender allowances based on the emissions rate of supply (CARB, 2014). If no particular source is specified, a generic allowance surrender rate at 0.428ton/MWh is imposed. California also does not rebate allowances for California plants that export power to other jurisdictions. Other States in the U.S. have also actively considered adopting carbon pricing. For instance, the electricity system operator of New York state, NYISO, proposed adopting a carbon cost roughly at $50/ton for generation sold in its market. Note that New York State is a member of RGGI, and the proposed carbon price is much higher than the current RGGI allowance price, which is around $5/ton up to the time of writing this thesis (RGGI, 2018).

[22] Per the rules of the EU ETS, a sector is facing such a risk if the carbon pricing introduces a direct or indirect cost of more than 5%, and if this sector's trade intensity with non-EU countries is above 10%. Trade intensity for each sector is calculated as the ratio between (Imports + Exports) and (Total Revenue + Imports) (Bolscher and Graichen, 2018).

Such a unilateral action thus necessitates the adoption of a BCA scheme, and NYISO proposes to lower the *ex-post* price faced by importers by the amount of CO_2 premium caused by the new carbon pricing.[23]

5.3.3 Review of Previous Analyses of BCA in Electricity and Other Sectors

Since the seminal work of Markusen (1975), which pointed out that border taxes can be designed to internalize international externalities, there has been a great deal of literature on the impact of unilateral carbon pricing and border carbon adjustments. Most have focused on competition among regulated and unregulated economic sectors within an economy and/or international trade (Antimiani et al., 2013; Burniaux et al., 2013; Eichner and Pethig, 2015; Elliott and Fullerton, 2014; Fouré et al., 2016; Ismer and Neuhoff, 2007; Lanz and Rausch, 2011). The policies analyzed include unilateral taxation of imports, the forgiveness of carbon prices for exports, bilateral trade agreements, etc. For example, Antimiani et al. (2013) argue that BCA can be ineffective for limiting carbon leakage and call for a cooperative solution between other economies without emission regulation. Additionally, Eichner and Pethig (2015) and Elliott and Fullerton (2014) gave examples of unilateral carbon pricing that can introduce negative carbon leakage to the rest of the system, i.e., the carbon pricing implementation lowers emissions outside of the jurisdiction as well as inside. Several works on BCA focus on the electricity sector, including Bushnell et al. (2014); Chen et al. (2011); Levin et al. (2019). For example, Chen et al. (2011) and

[23] For example, suppose one importer imports 1 MW into NYISO region and the LMP at the boundary bus is $60/MWh, which is obtained from the *ex post* process after the real-time operation. Then NYISO examine the market result and identified that this marginal price is set by a gas power plant inside NYISO with a 0.5 ton/MWh emission rate. NYISO then concludes that $40/ton x 0.5ton/MWh = $20/MWh out of $60MWh is raised by the carbon price. Instead of paying the importer at $60/MWh, NYISO will pay $60/MWh - $20/MWh = $40/MWh. (NYISO, 2018).

Bushnell et al. (2014) revealed that the high volume of contract shuffling in the electricity sector could accompany high carbon leakage in the California cap-and-trade system.

As for the methodologies used by this literature, many papers have adopted general equilibrium models, such as Antimiani et al. (2013); Burniaux et al. (2013); Elliott and Fullerton (2014); Ismer and Neuhoff (2007); Lanz and Rausch (2011). Others use engineering-economic models of individual economic sectors that allow a richly detailed representation of technological details and the impacts of policy on individual market participants. In this work, I choose a bottom-up approach in order to capture the diversity of generation technology, transmission limitations, and geographical distribution of fuels and demands that are critical to determining the impact of carbon regulation on trade patterns, costs, and prices within the power sector. I model the expansion decision of power generation, the hourly operation decision of generation and transmission, and the bilateral trading of the energy credit in a single optimization, which in turn is equivalent to a partial equilibrium that involves each relevant participant of the electricity sector. Similar modeling approaches can be seen in Bushnell et al. (2014); Lanz and Rausch (2011); Levin et al. (2019); Palmer et al. (2017). Other electricity analyses have been more aggregate, considering only supply curves in different markets (Chen, Liu, Hobbs), or just short-run operational (dispatch) effects ((Hytowitz, 2018)). Lanz and Rausch (2011) provided a comparison between the results from the top-down modeling approach and the bottom-up one, modeling a national carbon pricing policy in the United States; Levin et al. (2019), with a power system expansion planning model, showed that the adoption of carbon tax in Texas as a cost-efficient way to reduce emissions while Renewable Portfolio Standard is less effective.

For analyses that model the electricity sector as complementarity problem representation of a partial equilibrium, I refer readers to references such as Chen et al. (2011); Zhao et al. (2010). My work here is different from the existing works in the following two respects:

1) I provide detailed engineering-economic modeling of generation and transmission expansion in response to carbon pricing policies, whereas most previous works do not consider transmission investment.
2) I provide detailed modeling of energy credit trading for renewable portfolio standards and its interaction with trade, leakage, contract shuffling, and BCA issues, and how they jointly affect investment. In contrast, previous works either focus on carbon pricing, e.g., Chen et al. (2011) or disregards interstate/inter-jurisdictional interactions, e.g., Levin et al. (2019).

5.4 Model Formulation

5.4.1 General overview

The general approach I take is to first formulate a partial equilibrium problem for a competitive multi-jurisdictional electricity market with transmission constraints and different carbon and RPS rules in each jurisdiction or subset of jurisdictions. Then I show that there exists a single optimization model whose solution satisfies those equilibrium conditions. If the solution is unique, then the optimization model can be used to simulate the market and show the impact of alternative formulations of carbon border tax rules. This general approach is widely used in energy market modeling (Gabriel et al., 2013), and in environmental regulation in the power sector; an example was demonstrated by Chen et al. (2011).

Figure 5.2 summarizes the market structure in my model using a two-node example (please imagine the two nodes as two states), omitting the commodities of operating reserves, RPS credits, and carbon credits for the moment. The electricity market is in the middle, connected by solid arrows. Electricity is a differentiated commodity by location and time, so the location and timing of consumption and production must be accounted for, resulting in differentiated prices. In this chapter, I treat the electricity market as a central pool-based market.[24] Generation companies generate electricity and sell it to an Independent System Operator (ISO) at the nodal locational marginal price (LMP), and the ISO transmits the electricity to the load-serving entities (LSEs), charging LSEs at location marginal price. Dashed arrows connect the relevant participants in the energy credit market, in which the generators perform bilateral trading of energy credits with the LSEs, and the latter buys the energy credits.

[24] As seen later in the experimental design (Chapter 6), the WECC power system is comprised of not only central pool-based markets like those of California, but also bilateral-contract-based electricity markets, e.g., Northwest Power Pool, in which vertically integrated utilities trade physical power transactions among themselves. However, the central-pool modeling approach will not distort the result here. This is because under the assumption of the absence of market power, the equivalence among the (1) central pool-based market, (2) vertical integrated utility and, (3) bilateral market between generation companies and load-serving entities has been proved by Boucher and Smeers (2000). Metzler et al. (2003) find an analogous equivalence in the case of a Cournot market among oligopolistic generators who are price taking with respect to the cost of transmitting power between nodes of a network.

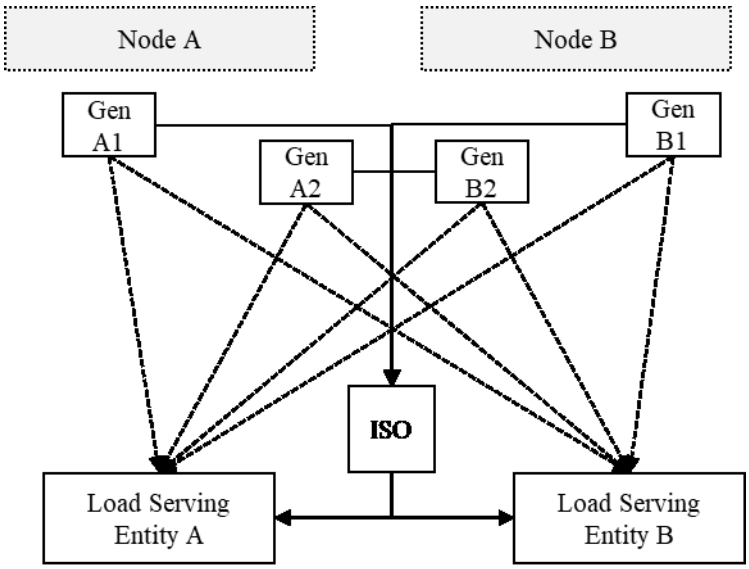

Figure 5.2. A two-node diagram of the Electricity and Energy Credit Bilateral Trading

Why do I model energy credits as separate commodities from electricity? The short answer is that I use the credits and the associated market to separate other attributes of electricity from the power attribute. When electricity is generated from a power plant, it is, in fact, tagged with different attributes, including the power, the associated emissions, the type of generation technology (especially the type of renewable energy), the point of origin or sink (if a bilateral contract is signed), and the timing of the generation. In addition to the power, a demand/supply for another attribute is created when the regulator establishes a market-based policy instrument to encourage or limit that attribute. For instance, demand for renewable credits by LSEs is created when an RPS law is passed by the regulator; each LSE must provide a certain fraction or more of its sales from qualifying renewable sources. In the case of carbon, it is essential to account for the point of sink, for example, if a carbon-priced generator claims part of its electricity production is exported to a region outside of the carbon pricing regime. Meanwhile, the point of origin must be accounted for if a local requirement is established, such as the case of unilateral carbon

pricing: the electricity generated inside the carbon pricing regime will be charged the carbon price if it emits carbon dioxide. The timing of the production can possibly be relevant, for example, in cases where the deliverability of the renewable credit is required to be accounted for at the hourly level. In a proposed (but not implemented) carbon accounting scheme for the CAISO, hourly accounting would have been required (CAISO, 2017), which would have been burdensome and of questionable effectiveness (Hogan, 2017). Indeed, a regulator might be suspicious if a factory only working at night claims that it is emission-free because it buys all its solar credits from a solar farm; there are press reports of facilities claiming solar credits for solar generation at night (Watts, 2014).

As these other attributes are simultaneously generated while the electricity is generated, I can, in fact, use a single energy credit variable to generalize all of them: this variable will be indexed with the generator k (for the point or state of origin, the generation technology, and the emission), the node or state w (for the point where the power sinks), and hour h (for the time of generation). In the following model, I call this variable $cpf_{w,h,k}$, which stands for the "contract power flow." In different constraints, this variable plays different roles. For example, in the LSE cost minimization, $cpf_{w,h,k}$ can be used to account both for imported emission (if multiplied by the deemed rate) while the generator k is located outside the carbon-pricing state w, while also accounting for imported renewable credits (if the generator k is identified as a renewable resource by the state government; in other words, $RE_{w,k} = 1$). Although rare, a generator can be both renewable and emitting carbon, e.g., a biomass steam turbine, and so have nonzero amounts of both types of attributes, which can be accounted for by this single variable.

I organize the rest of the section in the following manner. Initially, I introduce new notation (variables, constraints, and coefficients) to JHSMINE (see Chapter 2) so that JHSMINE includes variable $cpf_{w,h,k}$ in a way that models regulation of power attributes. Then I list the optimization problems of different market players, and finally, at the end of this section, I show that the modified JHSMINE is equivalent to the union of these individual problems, by showing that JHSMINE's KKT conditions are the same as the concatenation of the individual player problems' KKTs plus market clearing for each commodity. Please bear in mind that in this Chapter, JHSMINE is used in a setting of deterministic and static (single year) planning. Consequently. the indices of (s,y) are dropped, and transmission and generation expansion costs are annualized so that I calculate the annualized total cost and profits for each player. This assumes that multiyear dynamics in policy and technology are not a great influence on the outcome of the market; this may not be the case, but verifying that is left to future research.

5.4.2 Special Notation for Accounting for Power Generation Attributes

i_k Index: Bus i where the generator k is located.

w_k Index: State w that financially owns the generator k; also called the home state of the generator k in this Chapter.

$cpf_{w,h,k}$ Variable: Energy credit contract from the generator k to state-level LSE w at the hour h, unit: MW.

$cpfb_{w,h,k}$ Variable: Energy credit contract purchased by the state-level LSE w from the generator k at the hour h, unit: MW.

$cpfs_{w,h,k}$ Variable: Energy credit contract sold by the generator k to the state-level LSE w at the hour h, unit: MW.

λ Dual variables: shadow prices of the constraints; the meaning and the unit depend on the super/subscript.

AER_h Parameter: Average emission rate at hour h, additional super/subscript will apply depending on the context, unit: ton/MWh.

$DR_{w,h,k}$ Parameter: Deemed emission rate assumed for the energy credit contract between the state-level LSE w and the generator k at the hour h, unit: ton/MWh.

$GCOMI_k$ Parameter: Initial generator availability of the generator k, unitless, zero to one. For a full definition, check Chapter 2.

$GEXCA_k$ Parameter: Annualized generation expansion cost, unit: $/year.

$GVC_{h,k}$ Parameter: Variable cost of generator k, which is composed of fuel cost and variable O&M cost, unit: $/MWh.

$LCOMI_l$ Parameter: Initial transmission availability of the transmission line l, unitless, binary. For a full definition, check Chapter 2.

$LEXCA_l$ Parameter: Annualized transmission expansion cost for transmission line l, unit: $/year.

MER_h Parameter: Marginal emission rate at hour h, additional super/subscript will apply depending on the context, unit: ton/MWh.

5.4.3 ISO problem

The ISO's objective is (1) to maximize its annualized profit from arbitraging across the nodes of the network and (2) to expand the network if profitable by paying the

annualized capital cost of the transmission line.[25, 26] The objective is to maximize equation (5.1), where the variable $\lambda_{h,i}^{LMP}$ is the locational marginal price; the meanings of other variables/parameters are given in Chapter 2.

$$\text{Maximize} \quad ISO = \sum_h HW_h \cdot \sum_l \left(\sum_i LBI_{i,l} \cdot \lambda_{h,i}^{LMP} \right) \cdot pf_{h,l} \rightarrow \text{Congestion Rent}$$
$$- \sum_l LEXCA_l \cdot lincexp_l \rightarrow \text{Transmission Construction Cost} \tag{5.1}$$

Constraints (5.2) and (5.3), below, are the upper and lower limits of the power flow imposed by transmission line thermal limits.[27] Constraint (5.4) keeps track of the line availability, and constraint 5.5 below is the upper limit of the line availability and the expansion decision.

$$pf_{h,l} - LTM_l \cdot lstat_l \leq 0 \quad (\overline{\lambda}_{h,l}) \quad \forall h,l \tag{5.2}$$

$$-pf_{h,l} - LTM_l \cdot lstat_l \leq 0 \quad (\underline{\lambda}_{l,h}) \quad \forall h,l \tag{5.3}$$

$$lstat_l - \left(LCOMI_l + lincexp_l \right) = 0 \quad (\lambda_l^{Te}) \quad \forall l \tag{5.4}$$

$$\left(lstat_l, lincexp_l \right) - 1 \leq 0 \quad (\lambda_l^{Ts}, \lambda_l^{Tx}) \quad \forall l \tag{5.5}$$

The optimality conditions, i.e., the Karush–Kuhn–Tucker conditions, of the ISO problem can be derived as in (5.6) to (5.7).[28] Note that I scaled up the hourly constraint by the number of hours HW_h while deriving the optimality conditions in the remainder of

[25] Although the ISO is not maximizing the congestion rent in the real word, it is a good approximation since it is equivalent to maximizing the surplus from supply and demand bids. See Hobbs et al. (2000).

[26] Given the discount rate (i) and the lifetime (N), the annualized capital cost (A) is calculated by multiplying the overnight capital cost (P) by the capital recovery factor (CRF), where the latter is defined as CRF = $i(1+i)^N/((1+i)^N-1)$. The annualized capital cost represents a cash flow stream occurring at the end of each operating year before the end of the lifetime, and such a cash flow stream is equivalent to the overnight cost in the present value.

[27] Readers should notice that this is a pipes and bubbles representation, but a linearized DC load flow is possible.

[28] For linear programming, KKT conditions serve as both necessary and sufficient optimality conditions. See Nocedal and Wright (2006).

this section. Also note that if the thermal limit is limiting the power flow, i.e., (5.9) or (5.10) is binding, a price difference between the two ends of the line will emerge because of (5.6).

$$pf_{h,l}\ free,\quad \left(\bar{\lambda}_{h,l}-\underline{\lambda}_{h,l}\right)-\sum_{i} LBI_{i,l}\cdot\lambda_{h,i}^{LMP}=0\quad \forall h,l \tag{5.6}$$

$$0\le lstat_l \perp -\sum_{h} HW_h\cdot LTM_l\cdot\left(\bar{\lambda}_{h,j}+\underline{\lambda}_{h,l}\right)-\lambda_l^{Te}+\lambda_l^{Ts}\ge 0\quad \forall l \tag{5.7}$$

$$0\le lincexp_l \perp LEXCA_l+\lambda_l^{Tx}+\lambda_l^{Te}\ge 0\quad \forall l \tag{5.8}$$

$$0\le \bar{\lambda}_{h,l} \perp -pf_{h,l}+LTM_l\cdot lstat_l\ge 0\quad \forall h,l \tag{5.9}$$

$$0\le \underline{\lambda}_{h,l} \perp pf_{h,l}+LTM_l\, lstat_l\ge 0\quad \forall h,l \tag{5.10}$$

$$\lambda_l^{Te}\ free,\quad lstat_l-\left(LCOMI_l+lincexp_l\right)=0\quad \forall l \tag{5.11}$$

$$0\le \lambda_l^{Ts},\lambda_l^{Tx} \perp -\left(lstat_l,lincexp_l\right)+1\ge 0\quad \forall l \tag{5.12}$$

5.4.4 Generation Companies

Each generation company (GenCO) *k* attempts to maximize its annualized profit from the energy market, and thus, the objective is to maximize (5.13) subject to the Constraints (5.14) to (5.17); please notice that inasmuch as I formulate this as a GenCO specific problem, I omit "for all *k*" from the constraint domain. Furthermore, I omitted nonnegative constraints for simplicity. I omit requirements for operating reserves, but these can be readily included as discussed in Chapter 4, and as shown there, they do not make a significant difference in the market outcomes for the WECC market; this is also true for the linearized unit commitment shown in Chapter 4.

The objective function of each GenCo (5.13) is the annual net profit, which equals the revenues from both the electricity market and the energy credits market minus the variable cost, carbon allowance cost, and the fixed operation and maintenance cost. If profitable, the generation companies will expand the generation fleet by paying the annualized

expansion cost; if it is not economical to keep the plant running, the generation capacity will be retired. It is noteworthy that, for a generator inside a carbon pricing regime, if the export contract is subject to the rebate, extra revenue will be generated for every contract leaving the state.

$$\text{Maxmize } (\forall k) \quad GP_k = \left(\begin{array}{l} \underbrace{\sum_{h} HW_h \cdot \lambda_{h,i}^{LMP} \cdot gopt_{h,k}}_{\text{Electricity Revenue}} \\ + \underbrace{\sum_{h} HW_h \cdot \left(\sum_{w} \lambda_{w,h,k}^{EC} \cdot cpfs_{w,h,k} \right)}_{\text{Energy Credit Revenue}} \\ - \underbrace{\sum HW_h \cdot GVC_{h,k} \cdot gopt_{h,k}}_{\text{Variable Fuel and O\&M Cost}} \\ - \underbrace{\sum HW_h \cdot CTAX_{w_h} \cdot GER_k \cdot gopt_{h,k}}_{\text{Carbon Emissions Cost}} \\ + \boxed{\underbrace{\sum HW_h \cdot CTAX_{w_h} \cdot GER_k \cdot \left(\sum cpfs_{w,h,k} \right)}_{\text{Border Carbon Rebate}}} \\ - \underbrace{\text{[illegible]}}_{\text{Fixed O\&M Cost}} \\ - \underbrace{\text{[illegible]}}_{\text{Generation Construction Cost}} \end{array} \right) \tag{5.13}$$

The constraint (5.14) is the capacity limit of the generation output for each hour accounting for both forced outage rates and (in the case of renewables) wind or solar availability, and Constraint (5.15) requires the generator k to sell all the energy credits generated. The constraint (5.16) keeps track of the plant status, i.e., how much of the maximum capacity is available in a given hour. The constraint (5.17) is the upper limit of the generator availability, expansion decision, and retirement decision. See Chapter 2 for more explanation on the constraints.

$$gopt_{h,k} - GNPL_k \cdot GHAV_{h,k} \cdot gstat_k \le 0 \quad (\lambda_{h,k}^{cap}) \quad \forall h \tag{5.14}$$

$$gopt_{h,k} - \sum_w cpfs_{w,h,k} = 0 \quad \left(\lambda_{h,k}^{Credit}\right) \quad \forall h \tag{5.15}$$

$$gstat_k - \left(GCOMI_k + gincexp_k - gincret_k\right) = 0 \quad (\lambda_k^{Ge}) \tag{5.16}$$

$$\left(gstat_k, gincexp_k, gincret_k\right) - 1 \le 0 \quad (\lambda_k^{Gs}, \lambda_k^{Gx}, \lambda_k^{Gr}) \tag{5.17}$$

I can derive the optimality conditions of the generation profit maximization as (5.18) to (5.19). The optimality conditions illustrate how power plants will be operated. For instance, Condition (5.18) states that if the generator is operated below its capacity limit, the marginal benefit from selling electricity and energy credit must be equal to the marginal cost, which is composed of the carbon allowance payment and the variable cost. Please pay attention to the condition (5.19), where the boxed term only appears for the case in which state w_k is rebating the energy credit for any contracts involving exports from the at state.

$$0 \le gopt_{h,k} \perp -\lambda_{h,i_k}^{LMP} - \lambda_{h,k}^{Credit} + CTAX_{w_k} GER_k + GVC_{h,k} + \lambda_{h,k}^{cap} \ge 0 \quad \forall h \tag{5.18}$$

$$\left.\begin{aligned} &0 \le cpfs_{w,h,k} \perp -\lambda_{stt,h,k}^{EC} \boxed{-CTAX_{w_k} GER_k} + \lambda_{h,k}^{Credit} \ge 0 \quad \forall w \ne w_k, h \\ &0 \le cpfs_{w_k,h,k} \perp -\lambda_{w_k,h,k}^{EC} + \lambda_{h,k}^{Credit} \ge 0 \quad \forall h \end{aligned}\right\} \tag{5.19}$$

$$0 \le gstat_k \perp GFOM_k \cdot GNPL_k - \sum_h HW_h \cdot GHAV_{h,k} \cdot GNPL_k \cdot \lambda_{h,k}^{cap} - \lambda_k^{Ge} + \lambda_k^{Gs} \ge 0 \tag{5.20}$$

$$0 \le gincexp_k \perp GEXCA_k \cdot GNPL_k + \lambda_k^{Ge} + \lambda_k^{Gx} \ge 0 \tag{5.21}$$

$$0 \le gincret_k \perp -\lambda_k^{Ge} + \lambda_k^{Gr} \ge 0 \tag{5.22}$$

$$0 \le \lambda_{h,k}^{cap} \perp -gopt_{h,k} + GNPL_k \cdot GHAV_{h,k} \cdot gstat_k \ge 0 \quad \forall h \tag{5.23}$$

$$\lambda_{h,k}^{Credit} \ free, \quad gopt_{h,k} - \sum_w cpfs_{w,h,k} = 0 \quad \forall h \tag{5.24}$$

$$\lambda_k^{Ge} \ free, \quad gstat_k - \left(GCOMI_k + gincexp_k - gincret_k\right) = 0 \tag{5.25}$$

$$0 \le \lambda_k^{Gs}, \lambda_k^{Gx}, \lambda_k^{Gr} \perp -\left(gstat_k, gincexp_k, gincret_k\right) + 1 \ge 0 \tag{5.26}$$

5.4.5 Load-Serving Entities

I assume the LSE demand is purely inelastic (i.e., a fixed load), and thus the LSE is to minimize the cost of serving the load while meeting the RPS obligation.[29] I also assume LSEs are the so-called "first importers" of electricity, which is a term used in the California system to assign the obligation of paying for carbon emission. In other words, an LSE is assumed to be the owner of the electricity at the first point of delivery in California and would be the point of regulation (CARB, 2014). As a result, they are the subject of BCA (boxed term in the objective function 5.27). The deemed emissions rate applied can vary based on the policy assumptions for the particular run. The objective function of an LSE is to minimize (5.27) subject to constraints (5.28) to (5.32). Please notice that insomuch as I formulated this as a state-level LSE-specific problem, I omitted "for all *w*" from the constraint domain. Furthermore, I omitted nonnegative constraints for simplicity.

[29] This can be readily generalized to the cases where the demand is elastic, as shown in Chen et al. (2011). However, this results in a nonlinear program in general.

$$\text{Minimize } (\forall w) \quad CC_w = \sum_h HW_h \cdot \left(\begin{array}{l} \underbrace{\sum_i \lambda_{h,i}^{LMP} \cdot \left(LOAD_{h,i} - n_{h,i}^{Load} \right)}_{\text{Electricity Payment}} \\ + \underbrace{\sum_i VOLL \cdot n_{h,i}^{Load}}_{\text{Cost of Lost Load}} \\ + \underbrace{\sum_k \lambda_{w,k}^{RPS}}_{\text{RPS Noncompliance Penalty}} \\ \underbrace{+ \sum_{i,k} \lambda_{w,h,k}^{EC} \cdot cpfb_{w,h,k}}_{\text{Energy Credit Payment}} \\ + \underbrace{\boxed{\sum_k CTAX_w \cdot DR_{w,h,k} \cdot cpfb_{w,h,k}}}_{\text{Border Carbon Charge}} \end{array} \right) \tag{5.27}$$

Constraints (5.28) and (5.29) are, respectively, the general RPS requirement and the instate RPS requirement. Note that energy credits brought from other states are not eligible for meeting the instate RPS requirement in this formulation. Constraints (5.30) and (5.31) are the upper limit of the alternative compliance credits that LSE can buy from the government and the upper limit of load shedding. The constraint (5.32) is a requirement to LSEs that the served load must be equal to the sum of bought energy credits, which will specify the composition of the generation that meets the supported load at an hourly resolution.

$$\sum_h HW_h \left(n_{w,h}^{RPS} + \sum_k RE_{w,k} cpfb_{w,h,k} \right) \geq RPS_w \cdot \sum_h HW_h \cdot \left(\sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) \right) \quad (\lambda_w^{RPS}) \tag{5.28}$$

$$\sum_h HW_h \left(n_{w,h}^{RPS} + \sum_{k \in K_w} RE_{w,k} cpfb_{w,h,k} \right) \geq IRPS_w \cdot \sum_h HW_h \cdot \left(\sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) \right) \quad (\lambda_w^{IRPS}) \tag{5.29}$$

$$\sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) - n_{w,h}^{RPS} \geq 0 \quad (\lambda_{w,h}^{ACUB}) \quad \forall h \tag{5.30}$$

$$LOAD_{h,i} - n_{h,i}^{Load} \geq 0 \quad (\lambda_{h,i}^{LSUB}) \quad \forall h, i \in I_w \tag{5.31}$$

$$\sum_{k} cpfb_{w,h,k} - \sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) = 0 \quad (\lambda_{w,h}^{Dev}) \quad \forall h \tag{5.32}$$

We can derive the optimality conditions of the LSE problem as in (5.33) to (5.40). Again, the boxed item in the condition (5.35) only appears if the LSE is under the unilateral carbon pricing jurisdiction, and the latter chooses to implement a BCA that charges the importing transaction.

$$0 \leq n_{w,h}^{RPS} \perp ACP_w + \lambda_{w,h}^{ACUB} - \left(\lambda_w^{RPS} + \lambda_w^{IRPS} \right) \geq 0 \quad \forall h \tag{5.33}$$

$$\begin{aligned} 0 \leq n_{h,i}^{Load} \perp & VOLL + \lambda_{h,i}^{LSUB} - \lambda_{h,i}^{LMP} \\ & - \lambda_{w,h}^{Dev} - RPS_w \cdot \lambda_w^{RPS} - IRPS_w \cdot \lambda_w^{IRPS} - \lambda_{w,h}^{ACUB} \geq 0 \quad \forall h, i \in I_w \end{aligned} \tag{5.34}$$

$$\left. \begin{aligned} & 0 \leq cpfb_{w,h,k} \perp \lambda_{w,h,k}^{EC} \boxed{+CTAX_w DR_{w,h,k}} - RE_{w,k} \lambda_w^{RPS} - \lambda_{w,h}^{Dev} \geq 0 \quad \forall h, k \notin K_w \\ & 0 \leq cpfb_{w,h,k} \perp \lambda_{w,h,k}^{EC} - RE_{w,k} \left(\lambda_w^{RPS} + \lambda_w^{IRPS} \right) - \lambda_{w,h}^{Dev} \geq 0 \quad \forall h, k \in K_w \end{aligned} \right\} \tag{5.35}$$

$$\begin{aligned} 0 \leq \lambda_w^{RPS} \perp & \sum_h HW_h \cdot \left(n_{w,h}^{RPS} + \sum_k RE_{w,k} cpfb_{w,h,k} \right) \\ & - RPS_w \cdot \sum_h HW_h \cdot \left(\sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) \right) \geq 0 \end{aligned} \tag{5.36}$$

$$\begin{aligned} 0 \leq \lambda_w^{IRPS} \perp & \sum_h HW_h \cdot \left(n_{w,h}^{RPS} + \sum_{k \in K_w} RE_{w,k} \cdot cpfb_{w,h,k} \right) \\ & - IRPS_{stt} \cdot \sum_h HW_h \left(\sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) \right) \geq 0 \end{aligned} \tag{5.37}$$

$$0 \leq \lambda_{w,h}^{ACUB} \perp -n_{w,h}^{RPS} + \sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) \geq 0 \quad \forall h \tag{5.38}$$

$$0 \leq \lambda_{h,i}^{LSUB} \perp LOAD_{h,i} - n_{h,i}^{Load} \geq 0 \quad \forall h, i \in I_w \tag{5.39}$$

$$\lambda_{w,h}^{Dev} \ free, \quad \sum_k cpfb_{w,h,k} - \sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) = 0 \quad \forall h \tag{5.40}$$

5.4.6 Market Clearing Conditions

As aforementioned, there are two markets in this equilibrium: the electricity market with its market-clearing condition (5.41) and the energy credit market with its market-clearing condition (5.42).

$$\lambda_{i,h}^{LMP} \ free, \quad \sum_{k \in K_i} gopt_{h,k} + \sum_{l} LBI_{i,l} pf_{h,l} - \left(LOAD_{h,i} - n_{h,i}^{Load} \right) = 0 \quad \forall h, i \quad (5.41)$$

$$\lambda_{w,h,k}^{EC} \ free, \quad cpfs_{w,h,k} = cpfb_{w,h,k} = cpf_{w,h,k} \quad \forall w, h, k \quad (5.42)$$

5.4.7 An Equivalent Single Optimization

There is a single optimization that is equivalent to the equilibrium comprising the problems of GenCos, LSEs, and the ISO in the above subsections. The objective function of such a single optimization is to minimize (5.43), which is the sum of all individual objectives. Note that the boxed term only appears when the carbon pricing regime charges the import at the assumed carbon tax/price and/or rebates carbon charges to exports.

The first boxed term "LSE Border Carbon Charge" is the total payment from the LSEs to the emission regulator (who is not a market party within the model) due to the imported energy credit contracts; the domain of the summation, i.e., (w, $k \notin K_w$) indicates that the BCA only applies to imported energy credit contracts. The second boxed term "Generation Border Carbon Rebate" is the total revenue of GenCOs from the rebating action from emission regulators; the domain of the summation, i.e., $w \neq w_k$ indicates that GenCOs are gaining rebate revenue from all contract leaving its home state w_k. Readers are welcome to confirm that (5.43) is the same as the objective function listed in Chapter 2 except the boxed terms, which are the modifications that this Chapter makes to the basic JHSMINE model of Chapter 2. By leaving out the emission regulator's revenues form the

objective, this model simulates the actions of market parties in response to an emissions permit cost or tax.

$$
\begin{aligned}
\text{Minimize} \quad SC &= \sum_{w} CC_{w} - \sum_{k} GP_{k} - ISO \\
&= \underbrace{\sum_{h} HW_{h} \cdot \left(\sum_{i} VOLL \cdot n_{h,i}^{Load} \right)}_{\text{LSE Lost of Load Cost}} \\
&+ \underbrace{\sum_{h} HW_{h} \cdot \left(\sum_{w} ACP_{w} \cdot n_{w,h}^{RPS} \right)}_{\text{LSE RPS Noncompliance Penalty}} \\
&\boxed{+ \underbrace{\sum_{h} HW_{h} \cdot \left(\sum_{w} CTAX_{w} \cdot DR_{w,h,k} \cdot cpfb_{w,h,k} \right)}_{\text{LSE Border Carbon Charge}}} \\
&+ \underbrace{\sum_{h} HW_{h} \cdot \left(\sum_{k} GVC_{h,k} \cdot gopt_{h,k} \right)}_{\text{Gen. Variable Cost}} \\
&+ \underbrace{\sum_{h} HW_{h} \cdot \left(\sum_{k} CTAX_{w_k} \cdot GER_{k} \cdot gopt_{h,k} \right)}_{\text{Gen. Carbon Cost}} \\
&\boxed{- \underbrace{\sum_{h} HW_{h} \cdot \left(\sum_{k} CTAX_{w_k} \cdot GER_{k} \cdot \left(\sum_{w} cpfs_{w,h,k} \right) \right)}_{\text{Gen. Border Carbon Rebate}}} \\
&+ \underbrace{\sum_{k} GEXCA_{k} \cdot GNPL_{k} \cdot gincexp_{k}}_{\text{Gen. Expansion Cost}} \qquad (5.43) \\
&+ \underbrace{\sum_{k} GFOM_{k} \cdot GNPL_{k} \cdot gstat_{k}}_{\text{Gen. Fixed O\&M Cost}} \\
&+ \underbrace{\sum_{l} LEXCA_{l} \cdot lincexp_{l}}_{\text{Trans. Expansion Cost}}
\end{aligned}
$$

The constraints (i.e., from (5.44) to (5.57)) are the union of all individual operation and construction constraints appearing in the above subsection.

$$-gopt_{h,k} + GNPL_{k} \cdot GHAV_{h,k} \cdot gstat_{k} \geq 0 \quad \forall h,k \qquad (5.44)$$

$$gopt_{h,k} - \sum_{w} cpfs_{w,h,k} = 0 \quad \forall h,k \tag{5.45}$$

$$GCOMI_k + gincexp_k - gincret_k = gstat_k \quad \forall k \tag{5.46}$$

$$-\left(gstat_k, gincexp_k, gincret_k\right) + 1 \geq 0 \quad \forall k \tag{5.47}$$

$$\left|pf_{h,l}\right| \leq LTM_l \cdot lstat_l \quad \forall h,l \tag{5.48}$$

$$LCOMI_l + lincexp_l = lstat_l \quad \forall l \tag{5.49}$$

$$-\left(lstat_l, lincexp_l\right) + 1 \geq 0 \quad \forall l \tag{5.50}$$

$$\sum_{h} HW_h \left(n_{w,h}^{RPS} + \sum_{k} RE_{w,k} cpfb_{w,h,k} \right) \geq RPS_w \cdot \sum_{h} HW_h \cdot \left(\sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) \right) \quad \forall w \tag{5.51}$$

$$\sum_{h} HW_h \left(n_{w,h}^{RPS} + \sum_{k \in K_w} RE_{w,k} cpfb_{w,h,k} \right) \geq IRPS_w \cdot \sum_{h} HW_h \cdot \left(\sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) \right) \quad \forall w \tag{5.52}$$

$$\sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) - n_{w,h}^{RPS} \geq 0 \quad \forall w,h \tag{5.53}$$

$$LOAD_{h,i} - n_{h,i}^{Load} \geq 0 \quad \forall h,i \tag{5.54}$$

$$\sum_{k} cpfb_{w,h,k} - \sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) = 0 \quad \forall w,h \tag{5.55}$$

$$\sum_{k \in K_i} gopt_{h,k} + \sum_{l} LBI_{i,l} pf_{h,l} - LOAD_{h,i} + n_{h,i}^{Load} = 0 \quad \forall h,i \tag{5.56}$$

$$cpfs_{w,h,k} = cpfb_{w,h,k} = cpf_{w,h,k} \quad \forall w,h,k \tag{5.57}$$

It can be shown that there are one-to-one correspondences between all optimality conditions of the single optimization and the union of the optimality conditions of the individual problems and market clearing constraints shown above. See a proof in Appendix A. This implies the following fact: if there exists a solution of the equilibrium problem, i.e., the union of market party KKT conditions and market clearing conditions in Sections 5.4.3 to 5.4.6, it will also be an optimal solution from the single optimization constituted by (5.43)-(5.57), and vice versa. Furthermore, if one is unique, then the other is also. This

implies that I can obtain an equilibrium solution for the market by solving the single optimization problem. In summary, in the remainder of the analysis, I will solve a single optimization, which is equivalent to the market equilibrium problem.

5.5 Properties of the Model & Market Structure

In this subsection, I discuss some important properties and essential instruments that I will frequently refer to or use while explaining numerical results in Chapter 6. First, I will discuss the deliverability constraint, which never appears in the previous works before; and subsequently, I will discuss some properties of two important dual variables, $\lambda_{w,h}^{Dev}$ and λ_{w}^{RPS} that can be derived from the KKT conditions. These discussions will lay the groundwork for further consideration of theoretical results in Section 5.6.

5.5.1 Deliverability of the Energy Credits

If I define that *"energy credits are delivered"* as "*the net of the inbound/outbound of energy credit transactions equals the sum of cross-border power flows*," I can prove the deliverability of energy credits in the model. Consequently, all renewable energy credits traded in the model will satisfy the deliverability requirement specified in the RPS of some states; e.g., Arizona RPS requirement, which requires the renewable credits sold to Arizona LSE must be available to Arizona consumers (DSIRE, 2018). The proof goes as follows.

By summing up (5.56) (node-level energy balance) to the state-level and comparing the result with (5.55), I can reach (5.58), which shows that all credits bought by a state must satisfy the state-level energy balance.

$$\sum_{i\in I_w, k\in K_i} gopt_{h,k} + \sum_{i\in I_w, l} LBI_{i,l}\, pf_{h,l} - \sum_{k} cpfb_{w,h,k} = 0 \quad \forall w, h \tag{5.58}$$

$$\sum_{k\in K_w}\left(\sum_{w'} cpfs_{w',h,k}\right) = \sum_{k\in K_w}\left(gopt_{h,k}\right) \quad \forall w, h \tag{5.59}$$

Then, by summing (5.45) over all generators in one state (the result is Eq. (5.59)) and comparing the result with (5.58), I obtain the equality of (5.60) which states that all the energy credit contracts inbound/outbound from the state must, jointly, be equal to the sum of tie-line power flow minus the pseudo-tie power flows. The tie-lines are the lines connecting two states, and the pseudo-tie power flows occur whenever a pseudo-tie plant is operating. Pseudo-tie plants are defined here as the plants with financial ownership inside one state while the plant itself is physically in another state, i.e., ($k \in K_w$, $i_k \notin I_w$).[30]

$$
\begin{aligned}
&\sum_{k} cpfb_{w,h,k} - \sum_{k \in K_w} \left(\sum_{w'} cpfs_{w',h,k} \right) \\
&= \sum_{i \in I_w, k \in K_i} gopt_{h,k} + \sum_{i \in I_w, l} LBI_{i,l} pf_{h,l} - \sum_{k \in K_w} gopt_{h,k} \\
&= \sum_{i \in I_w, l} LBI_{i,i} pf_{h,l} - \sum_{k \in K_w} gopt_{h,k} + \sum_{i \in I_w, k \in K_i} gopt_{h,k} \\
&= \underbrace{\sum_{i} LBI_{i,i} pf_{h,l}}_{\text{Tie-line power flow}} \underbrace{- \sum_{k} gopt_{h,k} + \sum_{i} gopt_{h,k}}_{\text{Pseudo-tie Plant Generation}} \quad \forall w, h
\end{aligned}
\tag{5.60}
$$

In summary, the model formulation guarantees that every bilateral cross-border energy credit transaction can be delivered by the cross-border power flows between the origin and destination states. It is not possible for more energy credits to be delivered into a state or other jurisdiction (or less, for that matter) than the amount of net power flows.

It should be noted that the deliverability defined here is only one of many deliverability requirements; to wit, the deliverability shown here is in the hourly resolution and at the state level and might be either overly restrictive or loose. It can be overly restrictive either because (1) the regulator might not require deliverability at all, for example, allowing

[30] There are other definitions of pseudo tie plant. A pseudo tie plant might not be "owned" but instead operated as if it is within the other state. A NV renewable plant might allow itself to be controlled by a California entity (e.g., imbalance power is provided within California) in order to qualify being Californian renewable. In this case, for this particular Nevada generator, w_k = California, but $i_k \notin I_{CA}$.

the usage of the so-called unbundled renewable energy credit to fulfill the RPS requirement, or because (2) the regulator might require deliverability in a coarse time-resolution, for example, a yearly balance. These situations are readily accommodated in this modeling framework, as shown in Chapter 2. On the other hand, the deliverability requirement here, however, can also be overly loose as it only requires the state-level tie-power flow feasibility, while, in reality, the deliverability requirement of the energy credit contract might be in the form of specifying not only the points of origin and sink but also the path defined by the balancing areas through which a power transaction is deemed to flow. In bilateral power transactions in the west, paths must be defined for day-ahead energy transactions, and transmission capability "acquired" (even though the true physical flows may be much different), such as required by the Electronic Tag maintained by the North American Energy Standards Board (NAESB, 2016). These, too, can be modeled in a linear programming framework (Hobbs and Rijkers, 2004). Given that the current hourly, state-level deliverability requirement has a middle-level stringency, I conclude that it is a good approximation for the policies currently in place in the western US; in other words, my model requires that LSEs meet the RPS requirement at annual level, but also need to buy and account for the energy credits at the hourly level as part of the annual accounting.

5.5.2 The Dual Variable of the Energy Credit Deliverability Constraint

As a preparation of the forthcoming discussion in Section 5.5.3, here, I show that dual variables of the energy credit deliverability constraint (5.55), $\lambda_{w,h}^{Dev}$, will converge to a single value among the states without a BCA. In my case study, this means that this price of energy contracts is the same among all non-California states, but can differ from the California value. This result comes with certain assumptions: I assume at any hour, for

any state without a BCA, the demand is supported by at least one non-renewable energy credit contracts. Mathematically, I state this assumption as follows: (in the absence of this assumption, the shadow prices can diverge)

$$\text{for all } h, w: \{DR_{w,h,k} = 0,\ \exists k: RE_{w,k} = 0, cpfb_{w,h,k} = cpfs_{w,h,k} = cpf_{w,h,k} > 0\}.$$

To prove this, initially, I perform variable substitution on the following complementary constraints (excerpted below from Section 5.4, from each individual player problem; in particular, I excerpted the conditions from states without BCA and the conditions from non-renewable generators):

$$\lambda_{h,k}^{Credit}\ free, \quad gopt_{h,k} - \sum_{w} cpfs_{w,h,k} = 0 \quad \forall h,k,$$

$$0 \le gopt_{h,k} \perp -\lambda_{h,i_k}^{LMP} - \lambda_{h,k}^{Credit} + CTAX_{w_k} GER_k + GVC_{h,k} + \lambda_{h,k}^{cap} \ge 0 \quad \forall h,k,$$

$$0 \le cpfs_{w,h,k} \perp -\lambda_{w,h,k}^{EC} + \lambda_{h,k}^{Credit} \ge 0 \quad \forall w,h,k,$$

$$\lambda_{w,h,k}^{EC}\ free, \quad cpfs_{w,h,k} = cpfb_{w,h,k} = cpf_{w,h,k} \quad \forall w,h,k,$$

$$0 \le cpfb_{w,h,k} \perp \lambda_{w,h,k}^{EC} - \lambda_{w,h}^{Dev} \ge 0 \quad \forall w,h,k.$$

By variable substitution, I reach the following result:

$$0 \le cpf_{w,h,k} \perp \underbrace{\lambda^{LMP} + CTAX + GER + GVC + \lambda^{cap}}_{R_{h,k}} - \lambda_{h}^{Dev} \ge 0 \quad \forall w,h,k, \text{ or}$$

$$0 \le cpf_{w,h,k} \perp R_{h,k} - \lambda_{w,h}^{Dev} \ge 0 \quad \forall w,h,k. \tag{5.61}$$

Because a portion of the above condition will appear again several times later in this chapter, I use a shortcut to represent that part; to wit, I use $R_{h,k}$ to represent the net of the electricity price minus the sum of the carbon allowance payment (if any), the variable cost, and the economic rent from the capacity constraint. The right side of the condition says that this margin from the electricity market (including a deduction for the capacity shadow price) equals the price of the energy contract if the contracted amount is nonzero.

Put differently, the energy and contract revenues on the margin equal the variable and carbon costs plus the capacity economic rent.

Returning to the subject of the convergence of $\lambda_{w,h}^{Dev}$ among the states without BCA, readers should quickly notice that as the model maintains the energy balance at the node-level as well as the state-level, one deliverability constraint is redundant; i.e., I can drop the deliverability constraint for one state without affecting the solution, which I call the reference state (w^*.) If the reference state is a state without BCA; i.e., if $DR_{w*,h,k} = 0$, I will then have the following condition:

$$\begin{aligned}&\exists k : RE_{w*,k} = 0, cpf_{w*,h,k} > 0\\&\Rightarrow R_{h,k} = 0\end{aligned}$$

This generator, however, can sell its credit to other states without BCA, so it must satisfy the following condition as well (from condition (5.61)):

$$R_{h,k} - \lambda_{w,h}^{Dev} \geq 0 .$$

Combining these two intermediate results, I conclude: for other states without BCA, $\lambda_{w,h}^{Dev}$ must satisfy the following:

$$\lambda_{w,h}^{Dev} \leq 0 \quad \forall h, w \text{ s.t. } DR_{w,h,k} = 0 . \tag{5.62}$$

Similarly, for the same reason, a generator that supports any state without BCA other than $w*$ must satisfy the following condition:

$$\begin{aligned}&\text{for all } w \neq w^*, h : \{DR_{w,h,k} = 0, \exists k : RE_{w,k} = 0, cpf_{w,h,k} > 0\}\\&\Rightarrow R_{h,k} - \lambda_{w,h}^{Dev} = 0\\&\Rightarrow \lambda_{w,h}^{Dev} = R_{h,k} \geq 0.\end{aligned} \tag{5.63}$$

Combining the results of Condition (5.62) and Condition (5.63), I can conclude this subsection with the following result:

$$
\begin{aligned}
\text{if} \quad & \forall h, w \, s.t. \, DR_{w,h,k} = 0, \quad \exists k, RE_{w,k} = 0, cpf_{w,h,k} > 0 \\
\text{and if} \quad & \text{the deliverability constraint is dropped for one state } s.t. \, DR_{w,h,k} = 0 \\
\text{then} \quad & \forall h, w \, s.t. \, DR_{w,h,k} = 0, \quad \lambda_{w,h}^{Dev} = 0
\end{aligned}
\tag{5.64}
$$

5.5.3 The Dual Variable of the Renewable Portfolio Standard Constraint

In this subsection, I will show that the dual variable of the renewable portfolio standard constraint, also known as the renewable energy credit (REC) price, will converge to a single value among the states with neither BCA nor in-state RPS. I assume that REC credits generated in one state can be used in any other state in the west. In the more general case where only subsets of states can trade RECs with each other, this result will not apply (e.g., Perez et al. (2016))

Similarly to result (5.61), for renewable generators, if they are able to sell the energy credit to a state with neither BCA nor in-state RPS, the energy contract must satisfy the following condition:

$$0 \le cpf_{w,h,k} \perp R_{h,k} - \lambda_w^{RPS} \ge 0 \quad \forall h, w, DR_{w,h,k} = 0, RE_{w,k} = 1, IRPS_w = 0 \tag{5.65}$$

Suppose one state that has neither a BCA nor an in-state RPS (no Constraint (5.52)) (call it A) has a REC price of λ_A^{RPS} and there is another state also with neither BCA nor in-state RPS (call it B) with a different REC price λ_B^{RPS}. Inasmuch as there must exist a generator selling its credit to state A at a specific hour $h*$, I then have (from (5.65)):

$$
\begin{aligned}
0 < cpf_{A,h*,k} \perp R_{h*,k} - \lambda_A^{RPS} = 0 \\
0 \le cpf_{B,h*,k} \perp R_{h*,k} - \lambda_B^{RPS} \ge 0.
\end{aligned}
$$

By taking the difference between these two conditions, I have:

$$\lambda_A^{RPS} \ge \lambda_B^{RPS}. \tag{5.66}$$

Since the notation of A and B are exchangeable, I conclude that all REC prices converge to a single value among all states that are with neither BCA nor in-state RPS.

5.6 Theoretical Results

In this section, I provide theoretical results that readily follow from the properties established in Section 5.5, plus some data assumptions. Theoretical results shown here will explain most of the numerical results will appear later in Chapter 6.

5.6.1 A-B-C-D-L Relation

In this section, I introduce an essential instrument to which I will frequently refer in the following discussion: the *A-B-C-D-L* relation. Before delving into the mathematical formulation, here are some special simplifications I make for the purposes of this section: as all the following formulas are respected in each hour, the index of hour can thus be omitted. Besides, for any generator k, if its home state w_k is without an RPS, it is considered as a non-renewable generator by any other state. To put these assumptions in mathematical language, I implement the assumptions as follows in the database for the case study in Chapter 6:

$$\begin{aligned} &\text{for } k: IRPS_{w_k} = RPS_{w_k} = 0, \\ &\Rightarrow RE_{k,w} = 0 \quad \forall w. \end{aligned}$$

Furthermore, as all states but California in my WECC test system are without both a BCA and an in-state RPS requirement[31] (DSIRE, 2018), results derived from the Section 5.5 apply; that is, their REC prices λ_w^{RPS} converge to a single value and the dual variables

[31] Please notice that, there are at least two types of restrictions of energy credit trading, which are conceptually related. One is identified as in Perez et al. (2016), specifying the origin of the the energy credit; the other, is to require the deliverability to the consumer, as I am using here. These two are related in the way that the former is more specific while the latter is more general.

of the energy credit deliverability constraint $\lambda_{w,h}^{Dev}$ converge to zero (0). I can thus call the union of all WECC states but California as "the Rest of WECC", or "ROW" for short.

As a result, for the purposes of analyzing REC and energy credit prices, I can simply represent the WECC system using two areas, California and the Rest of WECC (ROW). Furthermore, at each hour, I can group all generators in WECC into eight ($8 = 2^3$) groups (see Table 5.1), depending on (a) whether or not a generator is renewable, (b) whether or not the ownership of this generator is in California, and (c) whether the generator is selling its energy credit to California or the ROW. A generator group can be empty, and they are not mutually exclusive; the groups can also differ by each hour.

Table 5.1. Eight Groups of Generators

Group	Home	Renewable	Sell Energy Credits to
K_1	California	Yes	California
K_2	California	Yes	ROW
K_3	California	No	California
K_4	California	No	ROW
K_5	ROW	Yes	California
K_6	ROW	Yes	ROW
K_7	ROW	No	California
K_8	ROW	No	ROW

Due to the impact of California's BCA, the energy credit contract flowing into California or out of California will have an impact on the KKT conditions of each individual player; for example, for a generator belonging to K_1 (i.e., renewable generators that belong to California and sell energy credits to the California LSE), the energy credit contract variable must satisfy the following condition:

$$\forall k \in K_1 \quad \begin{cases} 0 < cpf_{CA,h,k} \perp R_{h,k} - \lambda_{CA}^{IRPS} - \lambda_{CA}^{RPS} - \lambda_{CA,h}^{Dev} = 0 \\ 0 \le cpf_{ROW,h,k} \perp R_{h,k} - CTAX_{CA} DR_{h,k} - \lambda_{ROW}^{RPS} \ge 0 \end{cases}$$

$$\rightarrow \underset{A}{\lambda_{CA}^{RPS}} + \underset{B}{\lambda_{CA}^{IRPS}} - \underbrace{CTAX_{CA} DR_{h,k}}_{D_{h,k}} - \underset{L_h}{\lambda_{CA,h}^{Dev}} \ge \underset{C}{\lambda_{ROW}^{RPS}}$$

$$\rightarrow L_h \ge C - A - B + \max\left(D_{h,k} \mid k \in K_1\right).$$

The maximum condition in the last inequality arises because this condition applies to all k, but the $CTAX_{CA}\ DR_{h,k}$ term is the only one that is specific to a given k.

In words, the extra payment to deliver energy contracts in California (L_h) is at least equal to (1) the difference between California's RPS price (from the general RPS constraint, A, and the in-state RPS constraint, B) and the ROW RPS price (C), plus (2) the maximum carbon cost per MWh among all renewable generators in California ($D_{h,k}$). I call such a condition the "*A-B-C-D-L*" relation. Note that for generators in group K_1-K_4, $D_{h,k}$ only appears if the California emission regulator chooses to rebate emissions costs associated with exports from California. Similarly, I can derive the *A-B-C-D-L* relation for each group from K_1 to K_4:

$$K_1 : L_h \ge C - A - B + \max\left(D_{h,k} \mid k \in K_1\right),$$

$$K_2 : L_h \le C - A - B + \min\left(D_{h,k} \mid k \in K_2\right),$$

$$K_3 : L_h \ge \max\left(D_{h,k} \mid k \in K_3\right),$$

$$K_4 : L_h \le \min\left(D_{h,k} \mid k \in K_4\right).$$

For generators in group K_5-K_8, I can have a similar derivation. For example, for generators in K_5 (renewable generators that belong to ROW but sells its energy credits to California), I have:

$$\forall k \in K_5 \quad \begin{cases} 0 < cpf_{CA,h,k} \perp R_{h,k} + CTAX_{CA} DR_{h,k} - \lambda_{CA}^{RPS} - \lambda_{CA,h}^{Dev} = 0 \\ 0 \le cpf_{ROW,h,k} \perp R_{h,k} - \lambda_{ROW}^{RPS} \ge 0 \end{cases}$$

$$\rightarrow \underset{A}{\lambda_{CA}^{RPS}} - \underbrace{CTAX_{CA} DR_{h,k}}_{D_k} - \lambda_{CA,h}^{Dev} \ge \underset{C}{\lambda_{ROW}^{RPS}}$$

$$\rightarrow L_h \ge C - A - B + \max\left(D_{h,k} \mid k \in K_5\right).$$

As a result, for generators in group K_5-K_8, I summarize the results as follows:

$$K_5 : L_h \ge C - A + \max\left(D_{h,k} \mid k \in K_5\right),$$

$$K_6 : L_h \le C - A + \min\left(D_{h,k} \mid k \in K_6\right),$$

$$K_7 : L_h \ge \max\left(D_{h,k} \mid k \in K_7\right),$$

$$K_8 : L_h \le \min\left(D_{h,k} \mid k \in K_8\right).$$

To conclude this section, I summarize the A-B-C-D-L relation for all eight groups of generators in terms of conditions on L_h:

$$\left.\begin{array}{l} \text{if } K_1 \ne \varnothing : C - A - B + \max\left(D_{h,k} \mid k \in K_1\right) \\ \text{if } K_3 \ne \varnothing : \max\left(D_{h,k} \mid k \in K_3\right) \\ \text{if } K_5 \ne \varnothing : C - A + \max\left(D_{h,k} \mid k \in K_5\right) \\ \text{if } K_7 \ne \varnothing : \max\left(D_{h,k} \mid k \in K_7\right) \end{array}\right\} \le L_h \le \begin{cases} \text{if } K_2 \ne \varnothing : C - A - B + \min\left(D_{h,k} \mid k \in K_2\right) \\ \text{if } K_4 \ne \varnothing : \min\left(D_{h,k} \mid k \in K_4\right) \\ \text{if } K_6 \ne \varnothing : C - A + \min\left(D_{h,k} \mid k \in K_6\right) \\ \text{if } K_8 \ne \varnothing : \min\left(D_{h,k} \mid k \in K_8\right) \end{cases}$$

(5.67).

5.6.2 Scope Limit

While providing theoretical results, I limit my scope to commonly appeared cases that satisfy the conditions listed below; in other words, although there exist $2^8 = 256$ situations depending on which of the eight categories of generators are empty, I limited my scope to a subset of 15 situations.

1) The portion of the REC price of California that corresponds to the non-instate price and the REC price of ROW are equal; that is A = C.

2) The REC price of California in-state RPS is nonzero; that is ($B > 0$).
3) At least one Californian renewable generator sells its generated energy credit locally; that is, $K_1 \neq \emptyset$,
4) No California renewable generator sells its generated energy credit to ROW; that is $K_2 = \emptyset$, and
5) At least one ROW conventional generator sells its generated energy credit to any state of ROW; that is $K_8 \neq \emptyset$,
6) At least one Californian conventional generator is generating electricity; that is $K_3 \cup K_4 \neq \emptyset$,
7) At least one ROW renewable generator is generating electricity; that is $K_5 \cup K_6 \neq \emptyset$, and
8) At least one ROW generator is selling its energy credit to California; that is $K_5 \cup K_7 \neq \emptyset$.

5.6.3 Technology-Neutral Deemed Rate

In this section, I show that if the emission regulator implements the technology-neutral deemed emission rate for power imports to California, including both the time-varying and static deemed rates cases, such an implementation will function as a technology-neutral subsidy to all Californian generators. To wit, while $D_{h,k}$ is the same for all generators in K_5-K_8, L_h will rise with higher D_h. This will increase the profitability of generation in California and, therefore, in many cases, the amount of such generation that is built and operated. The argument goes as follows.

Initially, under the technology-neutral deemed rate, the A-B-C-D-L relations of all eight generator groups in inequality (5.67) are recast as follows (given $A = C$):

$$\left.\begin{array}{r}\text{if } K_1 \neq \varnothing : -B \\ \text{if } K_3 \neq \varnothing : 0 \\ \text{if } K_5 \cup K_7 \neq \varnothing : D_h\end{array}\right\} \leq L_h \leq \left\{\begin{array}{r}\text{if } K_2 = \varnothing \\ \text{if } K_4 \neq \varnothing : 0 \\ \text{if } K_6 \cup K_8 \neq \varnothing : D_h\end{array}\right. .$$

This is derived as follows. When $A = C$, the conditions involving K_5 and K_7 are the same, and consequently, $L_h = D_h$ due to $K_8 \neq \varnothing$, furthermore, $K_4 = \varnothing$ and $K_3 \neq \varnothing$, implying a situation that California is a pure importer of energy credits and all Californian non-renewable energy credits stay local.

Overall, within the limited scope specified in Section 5.6.2, I can conclude that if the REC price of California and that for the ROW coincide, I will have $L_h = D_h$, and California is a pure importer of energy credits; consequently, a higher deemed rate will introduce higher revenue to the local generators in a technology-neutral way. Furthermore, imported contracts will not receive any extra revenue for their contracts: L_h and D_h will cancel each other. In other words, for conventional generators in the ROW, the price at which they trade their energy credits with Californian LSEs is zero, and they only receive the energy price; for ROW renewable generators trading with Californian LSEs, the energy credit trading price is just the REC price.

More interestingly, given the deemed emission rate, as a higher carbon price will introduce a higher D_h, it will also act as a higher subsidy to local generators. This will result in both more local (gas-based) generation in California, as well as higher profits for that generation sector. Consequently, if the regulator sets a high value for the technology-neutral deemed emission rate, the carbon price itself will behave as a subsidy to the emitting generators within California rather than a cost.

5.6.4 Technology-Based Deemed Rate

Under the same assumptions mentioned at the beginning of Section 5.6.2, I show below the theoretical result while the Californian emission regulator chooses to base the deemed emission rate on the generation technology associated with each energy credit contract; that is, $DR_{h,k} = GER_k$. Such a policy will cause low emission energy credits from ROW to be imported to California as much as possible: all imported energy credits will appear to be emitting less than any energy credit flowing among the states of ROW.

Initially, under the technology-based deemed rate, A-B-C-D-L relations of all eight generator groups (given A = C) are as follows:

$$\left.\begin{array}{l} \text{if } K_1 \neq \varnothing : -B \\ \text{if } K_3 \neq \varnothing : 0 \\ \max\left(D_{h,k} \mid k \in K_5 \cup K_7\right) \end{array}\right\} \leq L_h \leq \left\{\begin{array}{l} K_2 = \varnothing \\ \text{if } K_4 \neq \varnothing : 0 \\ \min\left(D_{h,k} \mid k \in K_6 \cup K_8\right) \end{array}\right.$$

Assuming that $A = C$, consider the following situations: (a) if $K_4 \neq \varnothing$, then K_5 or K_7 must be emission-free, and $L_h = 0$, implying that if California is importing any energy credit while exporting simultaneously, imports must look emission-free. Now consider (b) if $K_4 = \varnothing$; i.e., California is purely importing credits, inasmuch as $K_5 \cup K_7 \neq \varnothing$ and $K_6 \cup K_8 \neq \varnothing$, I can further conclude that any energy credit contract transaction inbound to California (i.e., K_5 or K_7 or both) must emit no more than the energy credit contract transaction flowing among ROW states (i.e., K_6 or K_8 or both). In other words, if a ROW-ROW contract is emission-free (in the eyes of the Californian emission regulator), all imports will be emission-free.

In conclusion, if the Californian regulator implements a BCA with technology-based deemed emission rates, imported energy credits are either emission-free (if

California is exporting any credits) or as clean or cleaner than the energy credits flowing between ROW states (if California is not exporting any credits).

5.6.5 Rebating Exports with Technology-Based Deemed Rate

In this section, I will show that: while the Californian emission regulator chooses to rebate exports in addition to charging imports, such a policy results in export to the ROW of emitting energy credits generated inside California; this contrasts with what I might call the "vacuum" effect (drawing in zero-emission credits from the ROW) caused by charging imports. By looking at the A-B-C-D-L relationships, which I reproduce below given A = C, I can conclude that energy credits flowing from California to ROW (K_4) or among ROW states (K_6 or K_8) must emit more than what flows to California.

$$\left.\begin{array}{l} K_1 \neq \varnothing : -B + \max\left(D_{h,k} \mid k \in K_1\right) \\ \max\left(D_{h,k} \mid k \in K_3 \cup K_5 \cup K_7\right) \end{array}\right\} \leq L_h \leq \left\{\begin{array}{l} K_2 = \varnothing \\ \min\left(D_{h,k} \mid k \in K_4 \cup K_6 \cup K_8\right) \end{array}\right.$$

The California emission regulator's policy of rebating carbon costs associated with exports will encourage the emitting energy credits to be exported (generators in K_4 need to be the heavily emitting ones to satisfy the conditions above). However, the LSEs still have to acquire energy credits to match the demand they serve; because of the charges on imports, the only choice left for Californian LSE is to buy clean energy credit from the ROW. As a result, just like the fact that charging imports creates an incentive to importing low-emitting energy credits, rebating exports creates an extra economic incentive to generate emission-free energy credits inside California or ROW.

In summary, this section has shown the following results, several of which are counter-intuitive, which have not appeared in the literature before:

1) A technology-neutral deemed emission rate will work as a technology-neutral subsidy towards Californian generators; in particular, given a deemed rate, this subsidy is higher when the carbon price is higher.
2) Charging imports based on emission rates of the source-side of the ROW-to-CA power contract will create an incentive to import emission-free power contracts as much as possible up to the point that the most emitting ROW-to-CA power contract looks as clean as or cleaner than any ROW-to-ROW power contract.
3) Rebating exports based on emission rates of the source-side of CA-ROW will create incentives for emitting generators in California to export their power contract; as a consequence, a California LSE is left with a stronger incentive to buy emission-free power as much as possible, from both the ROW and California.

5.7 Conclusions and Limitations

In this chapter, I provide the model structure and some theoretical results for analyses of BCA policies power markets subject to local carbon regulation in some jurisdictions as well as RPS policies. The model structure presented here showed necessary is a modification to the basic JHSMINE formulation of Chapter 2, which paves the way for the numerical results of the next chapter. It is, however, noteworthy that this enhanced JHSMINE can perform more analyses other than just the single state (California) carbon pricing that readers will see in the next chapter; for example, multi-state carbon pricing can be easily modeled by changing some parameters. On the other hand, limiting the scope can provide very useful theoretical results: what I show in Section 5.6 shed light on the

numerical observation, e.g., why rebating the carbon costs of California exports can encourage the system to build more clean energy in the ROW.

However, as noted above, all of the theoretical results that I derived are subject to strong assumptions, e.g., free-trading of renewable energy credits throughout the WECC except California, the in-state renewable policy of California is always binding with positive shadow prices, etc. Such complication arises from the fact that I use a single variable to represent both the interstate power contract (used to account for carbon emissions) and renewable credit trading; in other words, carbon emission accounting and renewable credit accounting are bundled. The theoretical results would be much more generalizable if these two products were modeled as unbundled.

Chapter 6 A Model-Based Assessment of Border Carbon Adjustments in the Western North American Electricity Sector, Part II: Experimental Design and Case Study

6.1 Chapter Summary

In this chapter, I demonstrate the experimental design and the results for the research questions raised at the end of Section 5.2. To reiterate, the questions I address are as follows:

1) For a unilateral carbon pricing jurisdiction in an interconnected electricity market, how will BCA schemes affect local emissions reduction, emissions leakage, regional electricity production, transmission expansion, and consumer payments?
2) Given the current California carbon pricing scheme, if I define a "better" border-cost adjustment scheme as one achieving more system-wide economic efficiency (i.e., lower overall emissions and higher societal welfare for the WECC as total), would such as scheme require changing the definition of which emissions are subject to BCA (to charge power imports or to rebate power exports)? Or would it require a change in the deemed emissions rate (how much to charge)?

To address these questions, I consider several possible modifications of the current implementation of AB32 in California (CARB, 2014) and separate the alternative schemes under investigation into two groups. *Group One* represents alternative approaches for calculating the deemed emission rate set for energy credit contracts that Californian LSEs import. *Group Two* is composed of four alternatives in which the emission regulator allows either none, either, or both charging of emissions associated with imports and rebating of emissions associated with exports; the deemed rate scheme is assumed to be the

technology-based deemed rate scheme. These alternatives are summarized in Table 6.1. Comparisons of these alternatives allow me to address the above research questions.

Table 6.1. Alternative Carbon Border Tax Adjustment Schemes

Comparison Group	Case ID	Charge Imports	Rebate Exports	Deemed Rate Scheme
Base Case	0	No	No	N.A.
1 (Alternative levels of deemed rates for imports)	1	Yes	No	Technology-based
	2	Yes	No	Constant*
	3	Yes	No	Time-varying Marginal-Internal
	4	Yes	No	Time-varying Marginal-External
	5	Yes	No	Time-varying Average-Internal
	6	Yes	No	Time-varying Average-External
2 (Alternative treatment of exports)	7	No	No	N.A.
	8 (Same as 1)	Yes	No	Technology-based
	9	No	Yes	Technology-based
	10	Yes	Yes	Technology-based

*A range of levels of the constant deemed rate are evaluated

The impact metrics include overall regional (WECC) carbon emissions, indicators of emissions leakage based on distributions of carbon emissions between California and the ROW, distribution of electricity production among states and generation types, total market (social) costs, and California consumer payments. Although my emphasis is on overall efficiency (the minimum social cost of achieving alternative targets for emissions reduction), the other metrics will shed light on the trade-offs between the local and regional objectives, and help California policymakers to infer the effectiveness of the policy on improving local welfare.

As for total carbon emissions and local emissions distributions, my results lead to several policy-relevant conclusions. (1) The current practice of charging California imports based on emission rate of the source facility of the energy contract can lead to large amounts of carbon leakage, while basing the charge on marginal emission rate of non-

California generators can lead to the highest reduction in carbon leakage but with an increase of California consumer payments. (2) Refining the deemed emission rate to vary by time of day or season of the year only leads to shifting of emission from generators external to the carbon pricing regime to internal generators (reducing carbon leakage), while the total emissions only decrease by a limited amount. (3) Among all the assessed BCA schemes, a scheme that bases the deemed rate on the marginal external emission rate leads to the best overall economic efficiency, in terms of being on the efficient frontier of west-wide emissions versus total social cost. I note that these conclusions may be system-specific and may not apply in general to all local carbon regulation schemes that are considering BCA schemes.

With regard to the relationship between carbon emissions and California consumer payments, my results show the following. (1) A higher constant deemed rate will raise California consumer costs, but that they are at least in part offset by increases in California government revenues from carbon permits. (2) Among the time-varying schemes in Group One, the cheapest cost to California consumers can be achieved by basing the deemed rate on the average emissions caused by internal generators, followed by marginal emissions caused by internal generators. (3) Among the schemes in Group Two, when rebating exports and charging imports are happening simultaneously, the system can achieve the west-wide carbon emission reduction with a slight increase in consumer cost.

In the following sections, I start by defining alternative deemed emission rates in Group One and alternative BCA structures in Group Two (Section 6.2). To calculate some of those equilibria, an iterative Gauss-Seidel approach is required to find marginal or average emission rates in a power system planning model; that method is summarized in

Section 6.3. I then move on to explain the data I use in this set of analyses (Section 6.4). Finally, after showing and discussing the results of the comparisons (Section 6.5), , I present a set of concluding remarks and a summary of key results (Section 6.6).

6.2 Deemed Rate Schemes

As mentioned in the previous section, I investigate two groups of BCA schemes. In this section, I provide a roadmap of how I model different deemed rate schemes (Group One), while Group Two's schemes are self-explanatory. Group One is composed of six alternative deemed emission rate schemes (Cases 1-6, Table 6.1), i.e., cases that differ in how the parameter sets $DR_{w,h,k}$ is calculated. The deemed emission rate (hereafter, deemed rate) is defined as how much CO_2e emissions the regulator assigns to each energy credit transaction. For simplicity, the dimension of CO_2e (metric tons) is hereafter is referred to as tons.

The first deemed rate setting (Case 1, Table 6.1) is based on the supply-side of a contract as currently implemented in the California carbon pricing system, where the first deliverer (importer) must specify the source of emission associated with the contract and surrender the associated emission allowances in proportion to the source's emissions. If the first deliverer can (or chooses) not to specify the source, an "unspecified-source" emission will apply at 0.428 ton/MWh (Bushnell et al., 2014; Pavley, 2016).[32] Intuitively, this provides an approach for coal plants to mask their emissions by not reporting the source, but it may also be viewed as penalizing renewable sources whose emissions are less than that rate. However, in this analysis, the "unspecified-source" is not modeled for the

[32] For example, in 2017, among all imported electricity (around 94 TWh), 20% of imports are unspecified. For comparison, around 21 TWh is specified coal and gas while 51 TWh is non-emitting resources. See the precise numbers reported in CARB (2019b).

following two reasons: (1) all interstate contracts are tagged with a source-generator, so the emissions are already source-specified (see the previous chapter), and (2) as we see in the results, the contract shuffling volume is so large that even though imported generation is assumed to be required to be source-specified, shuffling conceals the true source. As a result, imports can appear almost emission-free, at least from the point of view of the BCA. This obviates the need to model the masking of imported emissions using "unspecified-source." [33]

The second deemed rate setting (Case 2, Table 6.1) is to apply a uniform deem rate for all contracts at all times, i.e., a constant, non-dynamic technology-neutral deemed rate. I test a range of deemed rates from zero (0) to 0.45 ton/MMBTU, the latter corresponding to the emission rate of a typical natural gas combustion turbine. At one extreme, a zero deemed rate is the same as the pure supply-side/source-based carbon pricing case in which only California sources are regulated (Chen et al., 2011), because LSEs have no responsibility to report the imported emission and surrender the associated allowances. Under any of the uniform deemed rates tested, there will be no incentive to shuffle contracts.

The third and fourth types of deemed rate settings apply a time-varying deemed rate, and they are respectively based on the marginal emissions *internal* or *external* to the carbon pricing jurisdiction (Cases 3 and 4, Table 6.1); in other words, the deemed rate of each hour is defined as *how much emissions changes internally (or externally) to the carbon pricing jurisdiction if the state-level load served by internal (external) sources varies by 1 unit.* As mentioned in the previous chapter, setting the deemed rate based on marginal

[33] This analysis, the cost of efforts to identify a source of import is assumed to be negligible; however, the model can be extended to include difficulty of source-specification using an assumed transaction cost; and such an assumption may affect the results.

emissions of internal generators follows the logic of "the carbon pricing policy rais(ing) the cost of marginal units which in turn set the electricity prices" (NYISO, 2018). It is then argued that by basing the deemed rate on internal marginal emissions, the regulator can roll back the extra payment to the outside generators caused by internal carbon pricing (ibid.). In this sense, the alternative (Case 3) I test here is closest to the NYISO proposal (ibid.).

The fifth and sixth types of deemed rate settings also apply time-varying deemed rates, but they are respectively based on the average, rather than marginal, emissions internal or external to the carbon pricing jurisdiction (Case 5 and 6, Table 6.1).

To calculate marginal emissions in Cases 3 and 4, I raise the load of the carbon pricing jurisdiction (in this case, California) by a small incremental amount in each hour. I do this by moving up the energy demand on every bus inside the state in proportion to the original demand (Eq. 6.1 below uses California as an example). And then, I re-dispatch the entire multistate system; the incremental system-wide emissions are the marginal emissions respect to the demand increase. This total is then apportioned to internal and external emissions rates as follows. External marginal emissions are calculated by dividing incremental external emissions by incremental external generation. Internal marginal emissions are instead obtained by dividing incremental internal emissions by incremental internal generation.

To take California as an example: the external marginal emissions are the sum of incremental emissions from the generators located in the rest of WECC. The marginal internal (external) emission *rate*, however, is the incremental emissions inside (outside) the carbon regime divided by the incremental generation inside (outside) of the jurisdiction (Eq. 6.2 uses California as an example). It is noteworthy that when I am calculating the

external marginal emission rate, it is possible that the all the incremental generation of interest is from inside the state, making the denominator equal to zero (or vice versa); in this case, I set the marginal emission rate to zero.[34]

$$LOAD_{h,i}^{\text{Newdispatch}} = LOAD_{h,i} + \Delta \cdot \frac{LOAD_{h,i}}{\sum_{i' \in I_{CA}} LOAD_{h,i'}} \quad \forall i \in I_{CA} \tag{6.1}$$

$$\left.\begin{aligned} MER_h^{\text{Internal}} &= \frac{\sum_{k \in K_{CA}} GER_k \cdot gopt_{h,k}^{\text{Newdispatch}} - \sum_{k \in K_{CA}} GER_k \cdot gopt_{h,k}}{\sum_{k \in K_{CA}} gopt_{h,k}^{\text{Newdispatch}} - \sum_{k \in K_{CA}} gopt_{h,k}} \\ MER_h^{\text{External}} &= \frac{\sum_{k \notin K_{CA}} GER_k \cdot gopt_{h,k}^{\text{Newdispatch}} - \sum_{k \notin K_{CA}} GER_k \cdot gopt_{h,k}}{\sum_{k \notin K_{CA}} gopt_{h,k}^{\text{Newdispatch}} - \sum_{k \notin K_{CA}} gopt_{h,k}} \end{aligned}\right\} \tag{6.2}$$

Meanwhile, the average emission rate calculation does not involve re-dispatch and is calculated as in Eq. 6.3:

$$\left.\begin{aligned} AER_h^{\text{Internal}} &= \frac{\sum_{k \in K_{CA}} GER_k \cdot gopt_{h,k}}{\sum_{k \in K_{CA}} gopt_{h,k}} \\ AER_h^{\text{External}} &= \frac{\sum_{k \notin K_{CA}} GER_k \cdot gopt_{h,k}}{\sum_{k \notin K_{CA}} gopt_{h,k}} \end{aligned}\right\} \tag{6.3}$$

In summary, I shall test all six alternative deemed rates systems in Group One, defined above, some of which may involve extra calculation. In the next section, I will demonstrate the Gauss-Seidel iteration approach I use to calculate time-varying deemed rates.

[34] This is the short run marginal emissions with fixed capitals, rather than long-run marginal emissions.

6.3 Find Time-Varying Deemed Emission Rates – a Fixed Point Problem

Finding the time-varying deemed rates in Cases 3-6 is essentially finding the solution to a fixed-point problem. To wit, let the procedure of calculating the marginal/average emission rate (i.e., Equations 6.1 to 6.3) be represented as a fixed point problem in which we are attempting to find the solutions **x***, **y***, **DR** to the following vector-valued function

$$\mathbf{DR} = f_{ER}\left(\mathbf{x}^*, \mathbf{y}^* \mid \mathbf{DR}\right),$$

where (**x***, **y***) represents the vector comprising the optimal solution of the investment decision **x** and the operation simulation **y** minimizing the societal cost, given a vector of deemed rates **DR** and other parameters (not shown). In other words, (**x***, **y***) satisfies the following:

$$\left(\mathbf{x}^*, \mathbf{y}^*\right) = \underbrace{\qquad}_{(\mathbf{x},\mathbf{y})\in\mathbf{F}} \mathbf{x}, \mathbf{y} \mid \mathbf{DR})$$

where **F** stands for the feasible region, and *SC*() is the societal cost defined in the previous chapter. Thus, finding a deemed rate equal to the marginal/average emission rate is basically calculating the following fixed-point problem:

$$\mathbf{DR} = f_{ER}(\mathbf{x}^*, \mathbf{y}^*) = f_{ER}(\arg\min_{\mathbf{x},\mathbf{y}\in\mathbf{F}} SC(\mathbf{x}, \mathbf{y} \mid \mathbf{DR}))$$

Such a fixed-point problem corresponds to a cat-and-mouse game formed by the regulator and the power sector participants. Initially, suppose the regulator sets the deemed rate at some nominal marginal (or average) emission rate $\mathbf{DR}^0$ (which might be estimated from previous periods, for instance), and gives another chance to the system to re-dispatch. As a result, the new marginal generators (and emissions $\mathbf{DR}^1$) might differ from those in the previous periods, or total emissions may change (Figure 6.1, inner feedback loop). Generation and transmission expansion decisions will affect dispatch results,

marginal/average emissions, and deemed rates; the dispatch resulting in each hour will, in turn, change the value of generation and transmission addition and affect the expansion decision (Figure 6.1, outer feedback loop).

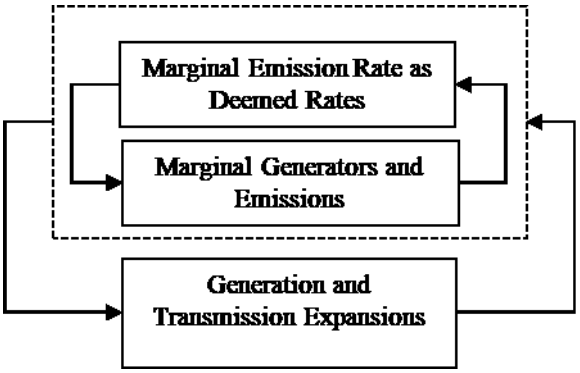

Figure 6.1. Deemed rate (if set based on marginal emission rate) will influence the marginal generator and vice versa

In this analysis, I use a double-loop fixed-point iteration algorithm in Figure 6.2 to attempt to find the solution to such a fixed-point problem. Note that a fixed point may not exist, or if it does exist, the algorithm may be unsuccessful in finding it. Outer Loop A (Yellow box, Figure 6.2) explicitly models the interaction between the investment **x** and the market operation and deemed rate setting (**y**, **DR**). I define the convergence of Loop A as being achieved when the change in the objective function value (SC, societal cost, see Chapter 5) between Loop A iterations is small enough (i.e., $< \varepsilon_A$).

The inner Loop B (Grey box, Figure 6.2), on the other hand, is a fixed point iteration to find the deemed rate with a fixed generation and transmission expansion plan; in other words, modeling the interaction between the market operation **y** and deemed rate setting (**DR**). I define the convergence of Loop B as a small enough mean deviation of deemed rates between Loop B iterations (i.e., $< \varepsilon_B$). In case Loop B is not converging but exceeds

the iteration limit (here, 20), then I take the average values from the last 10 iterations. Note that within the Loop B, the investment decisions are treated as fixed numbers.

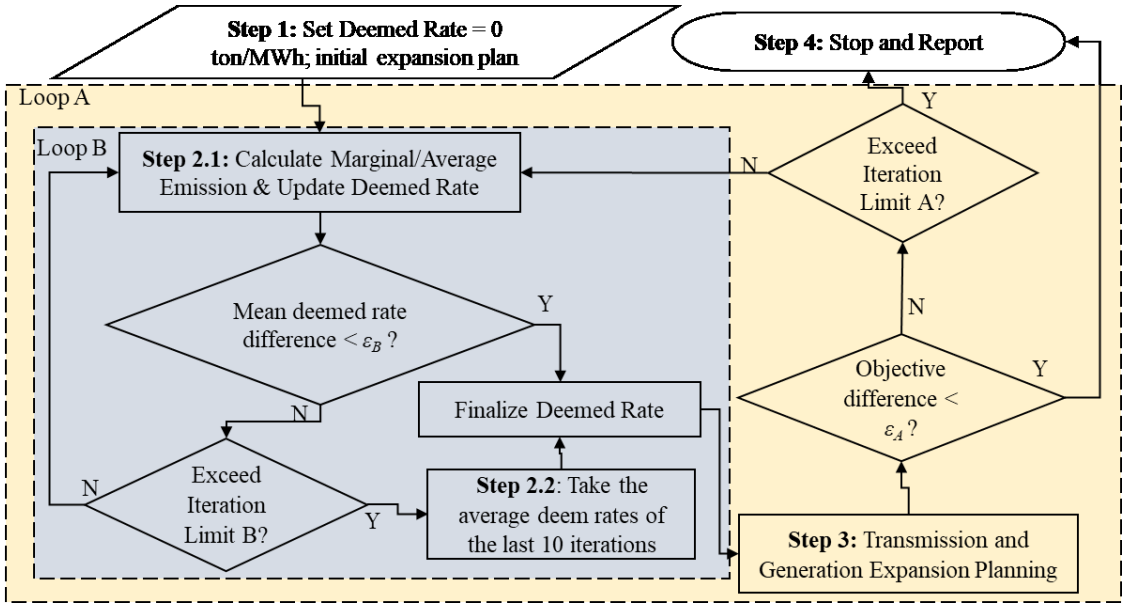

Figure 6.2. Diagram of the algorithm of modeling time-varying deemed rate based on marginal and average emission rate

It is easy to observe that Loop B is one fixed-point iteration. Loop B iterates between the market operation **y** and deemed rate setting (**DR**) given the generation fleet and the transmission topology until the convergence criterium ε_B is achieved or the literation limit B is exceeded. Notably, this is a Gauss-Seidel iteration that iterates between the following two steps:

$$\tilde{\ } \quad \text{in } SC\left(\mathbf{x} = \mathbf{x}^A, \mathbf{y} \mid \mathbf{DR}\right),$$

$$\mathbf{DR} \leftarrow f_{ER}\left(\mathbf{x}^A, \tilde{\ } \right. ,$$

where $\mathbf{x}^A$ is the fixed expansion plan from outer Loop A. I do not attempt to prove either the existence or the convergence of such Gauss-Seidel iteration in this thesis. However, the method is a widely utilized approach in the energy model literature, and some analysis

of its convergence properties is given in the context of other applications (Greenberg and Murphy, 1985).

6.4 Experimental Setting

To define a baseline, I run a model without the Californian carbon price as the first step. Then I test each BCA scheme, i.e., both Groups One and Two, with two assumed Californian carbon price realizations ($20/ton and $40/ton.)[35]

In this set of analyses, I run the modified JHSMINE model (Section 5.4) for the WECC in the year 2034. The system is a reduced network based on the 2026 Common Case of the WECC (WECC, 2017) with 361 buses and 712 transmission lines using the network reduction method developed in Zhu and Tylavsky (2018). Readers can find more details of the network reduction procedure in Appendix B. A map of the network is shown in Figure 6.3.

[35] Up to the time of writing this thesis, the most recent five rounds of the California-Quebec joint auction of carbon allowance yielded allowance prices in a range $15.05/ton – $17.16/ton, following an increasing trend over time (CARB, 2019c). $20/ton here is selected as a reasonable price close to price levels today, while $40/ton is selected as a high carbon price case. This $40/ton is roughly the same as the current carbon tax in British Columbia, Canadian $50/ton given an interest rate of 1.25 between US$ to CA$. (Morneau, 2018).

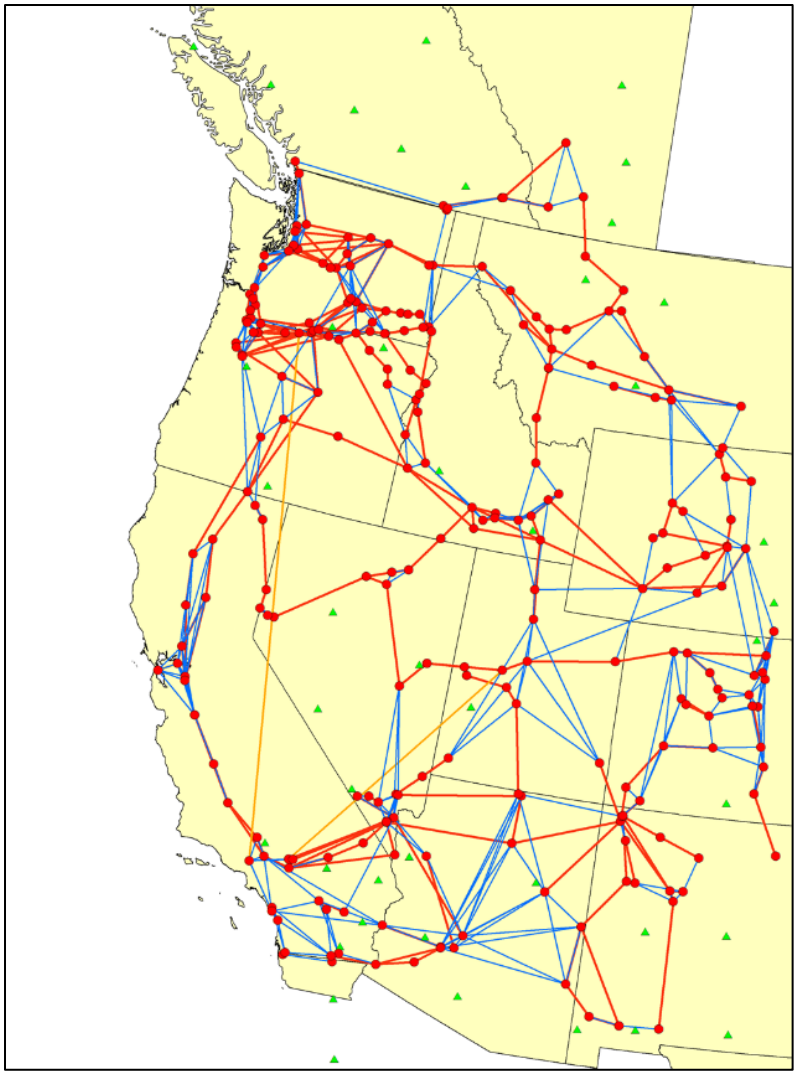

Figure 6.3. Map of the test system. Red dots are buses, and green triangles are renewable generation candidates. Red lines are existing AC lines, and orange lines are existing High-voltage DC lines. Blue lines are the equivalent lines resulting from network reduction.

For generators, there are 1504 aggregated existing ones and 810 candidates, spanning 32 technologies, including Coal, Gas (Combined Cycle and Combustion Turbine), Nuclear, Wind, Solar, Geothermal, and Biofuel. Only gas generation can be built as conventional thermal generators with a 5-GW limit on each bus, while renewables, i.e., Wind, Solar, Biofuel, and Geothermal, can only be expanded at 53 candidate sites and will need new transmission lines to be connected to the grid. These 53 candidate sites (on top of the

existing 361 buses) and their maximum installed capacity are identified in Western Governors' Association and U.S. Dept. of Energy (2009). Specifically, I double the renewable potentials of California, 5 out of 53 sites (compared to Chapters 3 and 4), to avoid situations where California could possibly deplete its renewable potential. All the assumed capital costs of generation expansion are based on WECC and Energy and Environmental Economics (2017) and are differentiated by location.

Transmission lines candidates are categorized into two types: backbone reinforcements and renewable connections. There are 54 reinforcement candidates for the backbone network arcs in Figure 6.3. In addition, there are 104 renewable connection candidates that can be developed to connect the 53 candidate sites. Transmission expansion candidate costs are calculated based on the length of the transmission line, the width, and the type of land-use, and the voltage level, using the base cost of the conductors and substations as found at WECC (2014c). There are four (4) days (96 hours) simulated to represent the year 2034, based on the method shown in Appendix D of this thesis.

Renewable Portfolio Standards (RPS) data for the year 2034 are from DSIRE (DSIRE, 2018), and demand data are from WECC-LTPT (WECC, 2016b). Because state-level RPS policies do not cover every type of utility in the state, I adjust the requirement according to the share of the total electricity sales that is covered by RPS. For example, although Washington State requires that 15% of the electricity demand be met by renewables in 2030, that requirement only covers utilities that serve more than 25,000 customers. As these utilities were serving 87.1% of the total load of Washington in 2017, , the effective RPS of Washington requirement is therefore about 13.1% of total Washington demand. In cases where the RPS data for the year 2034 are not available, I assume the RPS will stay

the same as the latest specified number. For example, in 2030, California requires 60% of its demand to be supplied by renewables, and 75% of the requirement should be met by generation directly connected to California or delivered without substituting electricity from another source; I assume this number will not change in 2034. The alternative compliance penalty is $100/MWh for all states with RPS, i.e., in case there is a renewable energy capacity shortage, the LSE needs to pay such a penalty (or buy renewable credits from the state government) to fulfill the RPS requirement. The RPS requirement used in this Chapter is shown in Table 6.2. For British Columbia, there is a $40/ton Carbon Tax, but no BCA is implemented.

Table 6.2. Assumed RPS Requirements in 2034

State	RPS	State	RPS
Alberta	30.0%	Mexico	0.0%
Arizona	14.6%	New Mexico	16.1%
British Columbia**	93.0%	Nevada	22.8%
California*	59.3%	Oregon	35.2%
Colorado	21.0%	Utah	0.0%
Idaho	0.0%	Washington	13.1%
Montana	13.4%	Wyoming	0.0%

* CA also requires 75% of the RPS requirement to be met by in-state renewable generation
** All WECC regions, except British Columbia, are assumed to account generation from large (>20MW) hydroelectric facilities as non-renewable

I put some restrictions on interstate energy credit trading.[36] First, in the case of existing generating units, only those with a nameplate capacity higher than 200 MW can

[36] As mentioned in Chapter 5, in my experimental setting, the electricity and energy credit are bundled. (I.e., energy credit contracts are specified by source-sink at an hourly level, and these contracts are supported by interstate powerflows.) Furthermore, the definition of energy credit setting is not limited to renewable resources. For instance, if 60% of California electricity demand is supported by contracts from renewable resources, the remaining 40% must be from non-renewable ones, and, consequently, California LSEs have to buy non-renewable credits to support such a composition (possibly at zero price). As another example, if a generator is deemed unable to sell its credits to California, it is effectively unable to sign a bilateral electricity contract with California LSEs because the electricity and energy credits are bundled.

sell energy credits out of the state. Consequently, it can be assumed that the difficulty is great for selling power to a state other than the home state. Second, for any plant, energy credits can only be sold to the home state, the neighboring state, or the state adjacent to its neighboring state. For example, a plant located in Arizona can sell its credit to anywhere in the WECC except Alberta, British Columbia, Washington, and Montana.

I also made several simplifications of the model setup to speed up the solution process. For example, power flow is modeled as a transshipment power flow model (as shown in Section 5.4), not as a DC load flow, and generating unit commitment is not included as well as storage expansion and investment. At the expense of larger models and slower computation times, these complications could be included.

6.5 Numerical Results

In this results section, I first look at the time-varying property of marginal/average emission rates resulting from the calculation of the deemed rates (Section 6.5.1). Then I examine to look at the impacts of adopting different BCA schemes within Groups One and Two; the impact metrics include (a) WECC, California, and ROW emissions (Section 6.5.2), (b) California and ROW electricity production (Section 6.5.3), (c) transmission expansion in WECC (Section 0), and (d) Cost to California Consumers (Section 6.5.5.). And finally, I identify the carbon border tax schemes that achieve the best overall economic efficiency (Section 6.5.6.)

6.5.1 Time-Varying Property of Marginal/Average Emission Rate

Does the Gauss-Seidel approach proposed in Section 6.3 succeed in finding time-varying deemed rates? The answer is a qualified yes. Figures 6.4 and 6.5 show the state-level marginal emission rates of internal and external generators in different hours of one

of the four days as an example (Sept 30th, 2034), calculated in the inner loops of the algorithm (Figure 6.2, Grey box) and the expected (average over the final iterations) value used in the final expansion model. I make three remarks here. First, short-run marginal emission rates indeed vary in different hours, ranging from zero to around 0.7 ton/MWh. Second, the internal and external marginal emission rates are significantly different in several hours. Finally, the cat-and-mouse game happens in which the iterative process does not converge and instead alternates between two or more values. As a result, the expected value has to be taken over several iterations; this would be an implementation issue in real life.

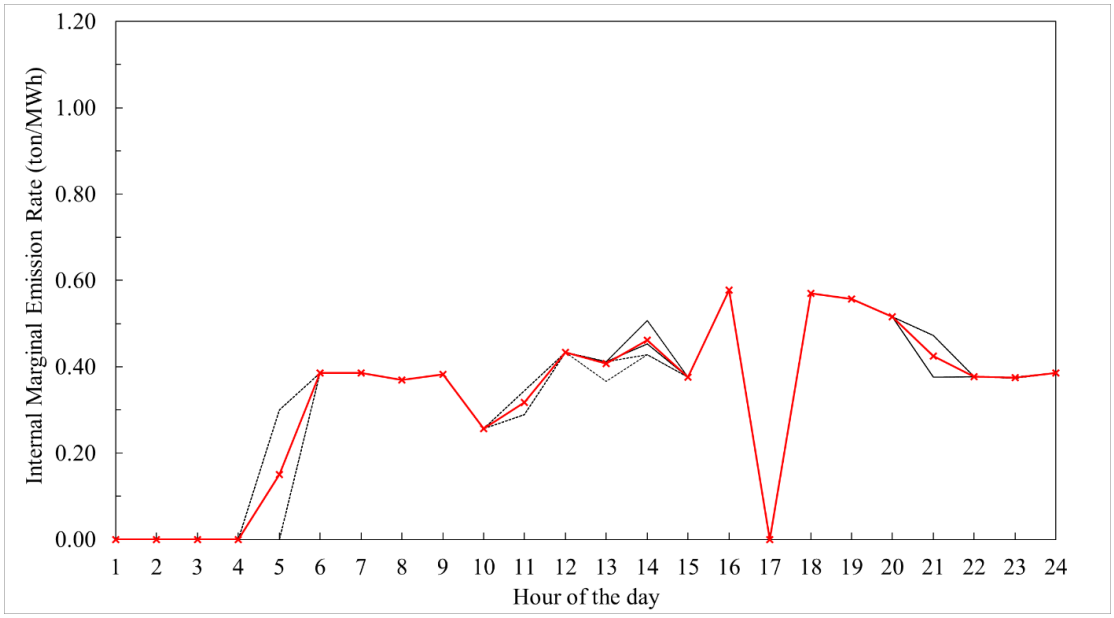

Figure 6.4. Marginal emission rate (internal California) over the last 10 iterations (dotted lines) and their average (red line with cross marks) (Carbon Price = $40/Ton, Sept 30th, the year 2034)

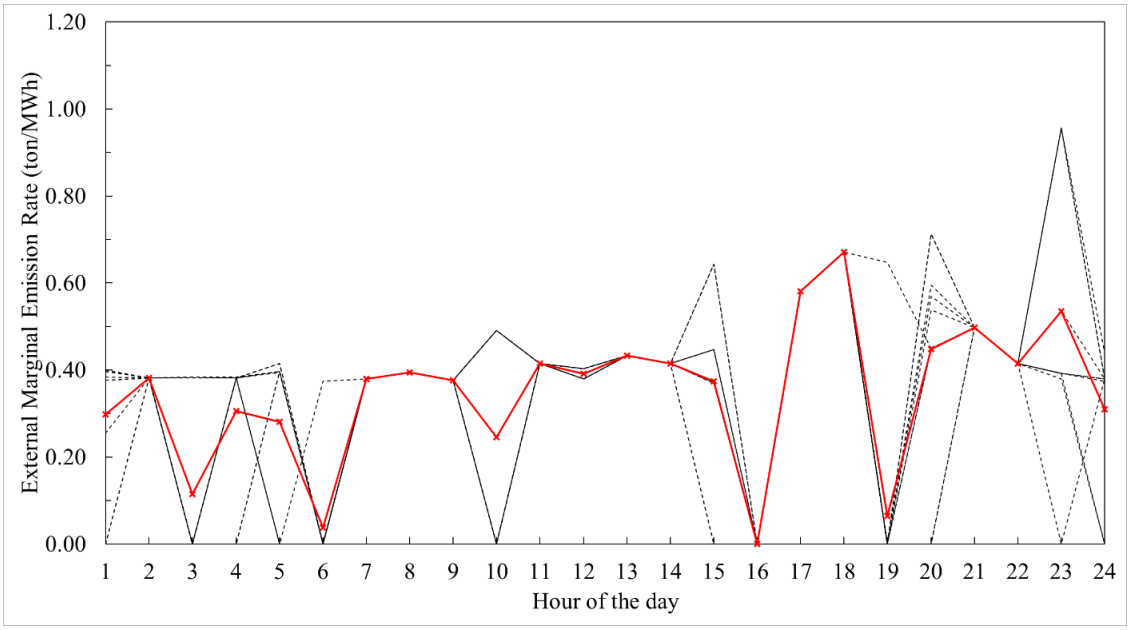

Figure 6.5. Marginal emission rate (external to California) of the last 10 iterations (dotted lines) and their average (red line with cross marks) (Carbon Price = $40/Ton, Sept 30th, the year 2034)

The average emission rates (Equation 6.3) for one day are shown in Figure 6.6. Similar results are observed for the other three days simulated in 2034. Overall, the average emission rates show more stability than the marginal emission rates. The average emission rates of external generators are universally higher than their internal counterparts and are less variable in that California is a relatively cleaner state with almost no coal capacity (except the must-run combined heat and power plants) and more renewables, including solar, wind, and geothermal capacity. Internal average emission rates are relatively higher in the late afternoon because of the lack of clean-energy during those intervals, while they are close to zero during the late night as most internal generators that are operating are emission-free during that time (e.g., from Bio, Geothermal, Hydro, and Wind). For the average emission rate calculation, the expected value from multiple iterations is not necessary as it quickly converges within the limit in every case.

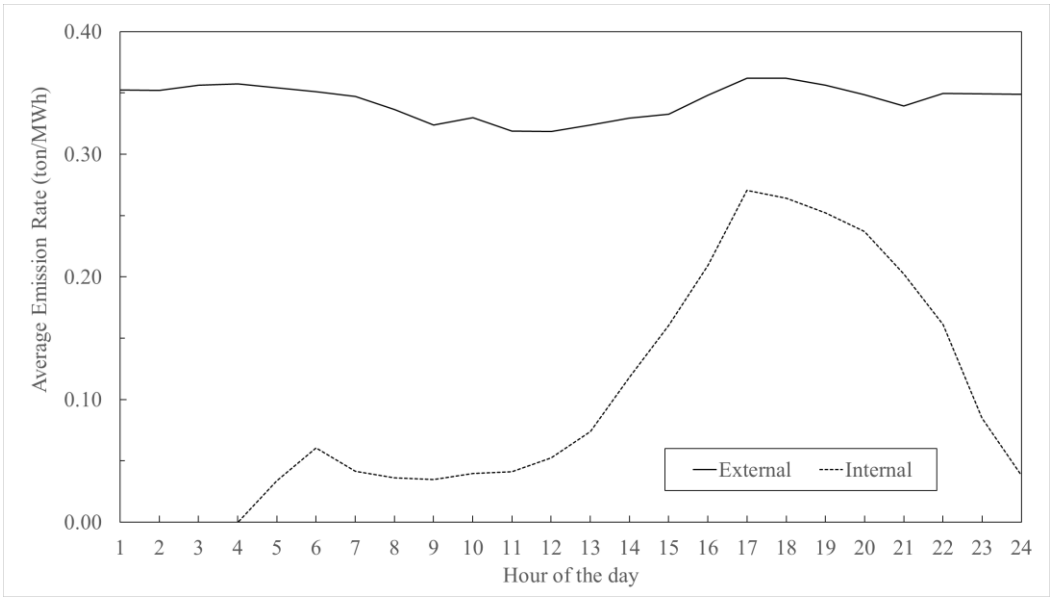

Figure 6.6. Average emission rate (internal and external to California, Carbon Price = $40/Ton, Sept 30th, the year 2034)

6.5.2 BCA Impact on California, ROW, and Total Carbon Emissions

How will each BCA scheme impact carbon emissions and leakage? In this section, I will answer this question by showing how different BCA schemes will affect the emissions of California, the ROW, and both together (all WECC) as a system under the base case assumptions of Section 6.4.

The primary emission leakage metric I select in this Chapter is the WECC-wide, ROW, and California mass differences, which are calculated by "Emissions in Mton/year under a Case (from Table 6.1)" minus "Emissions in Mton/year without California Carbon Price". If such a number is positive, then emissions increase because of a policy implementation specified by a case in Table 6.1; if furthermore this increase is in the ROW, then there is emissions leakage. For example, without California carbon price (i.e., Case 0 in Table 6.1), the ROW emissions are at 251.18 Mtons/year; however, ROW emissions increase to 270.12 Mtons/year when carbon price = $40/ton and California adopts the technology-based deemed rate scheme (i.e., Case 1 in Table 6.1). In this case, the leakage to

ROW is (270.12 – 251.18 =) 18.94 Mtons/year. A special case can thus arise: if such a number is negative in ROW, then this is a negative leakage. For example, as shown later, if when the carbon price is at $40/ton and California adopts a constant deemed rate at 0.41 ton/MWh, the ROW emissions fall to 245.18 Mtons/year; the leakage is (245.17 – 251.18 =) -6.01 Mtons/year.

6.5.2.1 Local Carbon Price Can Increase System Emissions

Before delving into the comparison of BCAs, I make the following related observation concerning the numbers I show later in this section. It is a seemingly counterintuitive result that carbon pricing within California can *increase* WECC-wide emissions, showing a significant amount of carbon leakage. Further, this effect is *worse* when carbon prices are higher. In particular, among all investigated deemed rate schemes (in fact, in both Group One & Two), the highest WECC-wide emission increase results from no BCA case (or constant deemed rate = 0 ton/MWh) while the carbon price is $40/ton; in that case, California emissions are reduced by 17.88 Mtons/year, but ROW emissions are *increased* by 19.26 Mtons/year, resulting in *a system-wide emission increase of 1.37 Mtons/year*. The second worst case is the result of the technology-based deemed rate scheme, the current implementation. For example, when the carbon price is at $40/ton, California emissions decrease by 17.67 Mtons/year, but ROW emissions increase by 18.94 Mtons/year, resulting in a 1.26 Mtons/year overall increase.

In fact, a simple example can explain such a result: suppose there are two gas generators that consume the same natural gas source at $5/MMBTU with an emission factor at 0.06 ton/MMBTU. Assume further that one is in California and has a marginal cost at $35/MWh, while the other one is in ROW and has a marginal cost at $40/MWh. If the

non-fuel variable O&M cost is zero in both generators and their per MMBTU fuel cost is the same, the ROW gas generator must be emitting more as its heat rate is higher (8 MMBTU/MWh > 7 MMBTU/MWh). Intuitively, without a carbon price, the system will first dispatch the cleaner unit, as it uses less fuel. Further assume that California imposes a carbon price of $20/ton, and then the clean generator has an effective marginal cost of:

$$\$20/\text{ton} \times 0.06\ \text{ton/MMBTU} \times 7\ \text{MMBTU/MWh} + \$35/\text{MWh} = \$43.4/\text{MWh},$$

which is higher than the dirtier generator in ROW. As a result, California's carbon price only makes the cleaner generator more expensive to dispatch, and consequently WECC-wide emissions will increase when generation is shifted to the out-of-state source. BCA with technology-based deemed rates cannot eliminate such an effect due to the contract shuffling issue discussed in Chapter 5. With this being discussed, the comparisons between BCAs are shown as follows.

6.5.2.2 Group One: Different Deemed Rate Schemes

Alternative Constant Annual Rates. Figures 6.7 to 6.9 show emissions from California, ROW, and WECC as a total, respectively, as a function of different uniform deemed rates (Case 2). As a reference, without California's carbon price, JHSMINE generates a result showing that California emits 30.09 Mtons/year, while ROW emits 251.18 Mtons/year (shown as the horizontal lines in Figures 6.7 and 6.8, respectively). As a comparison, in 2017, California actually reported a carbon emission of 38.58 Mtons from in-state generators (CARB, 2019b).

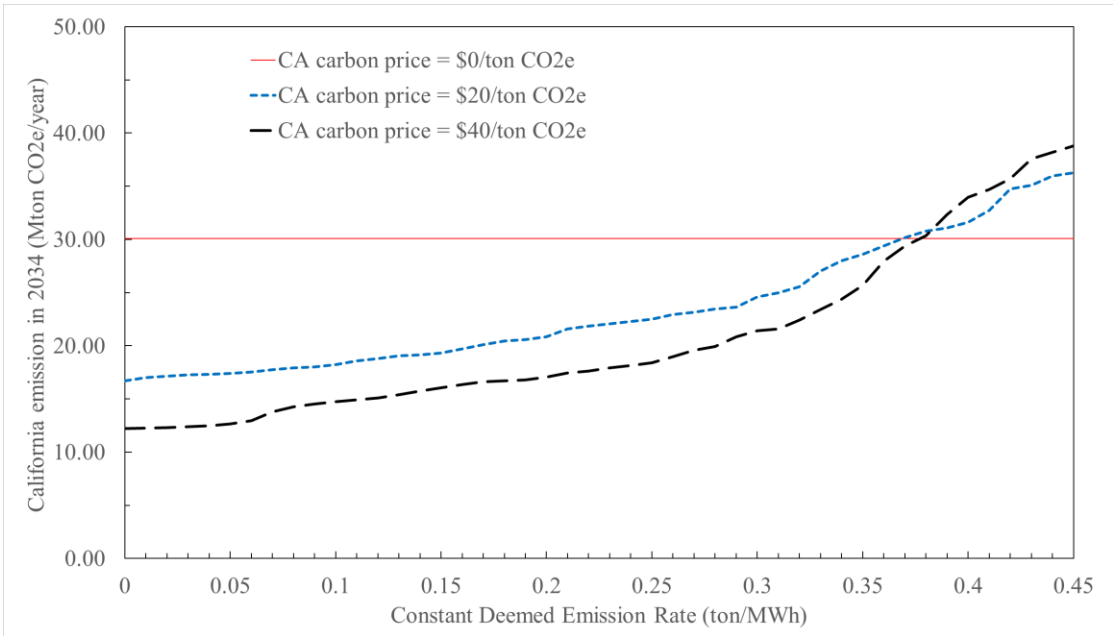

Figure 6.7. California carbon emissions with different constant deemed rates, Case 2

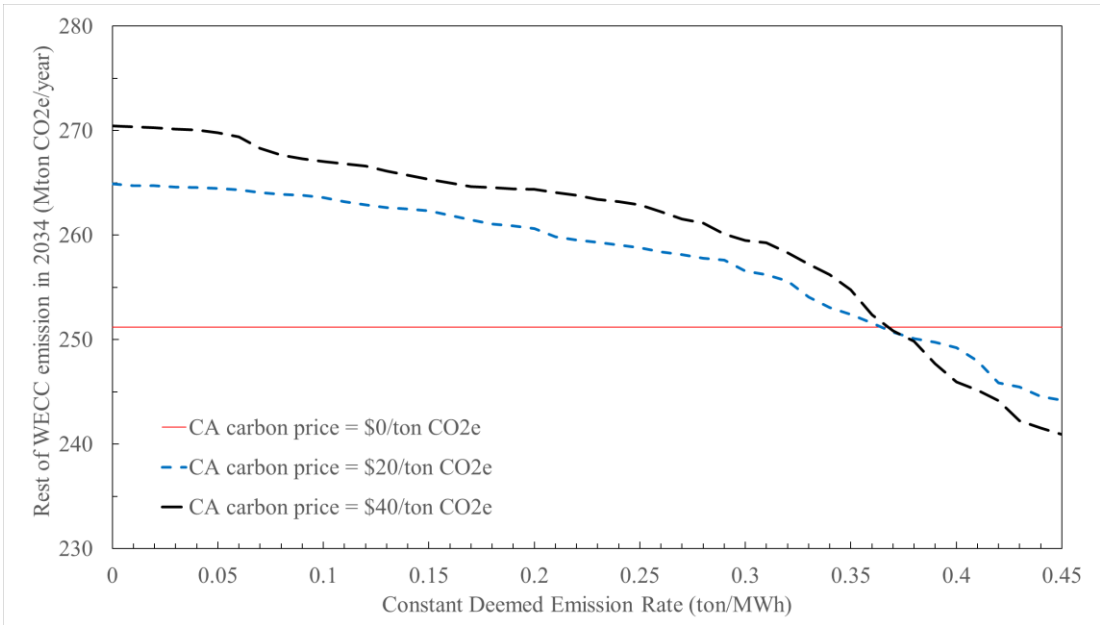

Figure 6.8. Rest of WECC carbon emissions with different constant deemed rates, i.e., Case 2

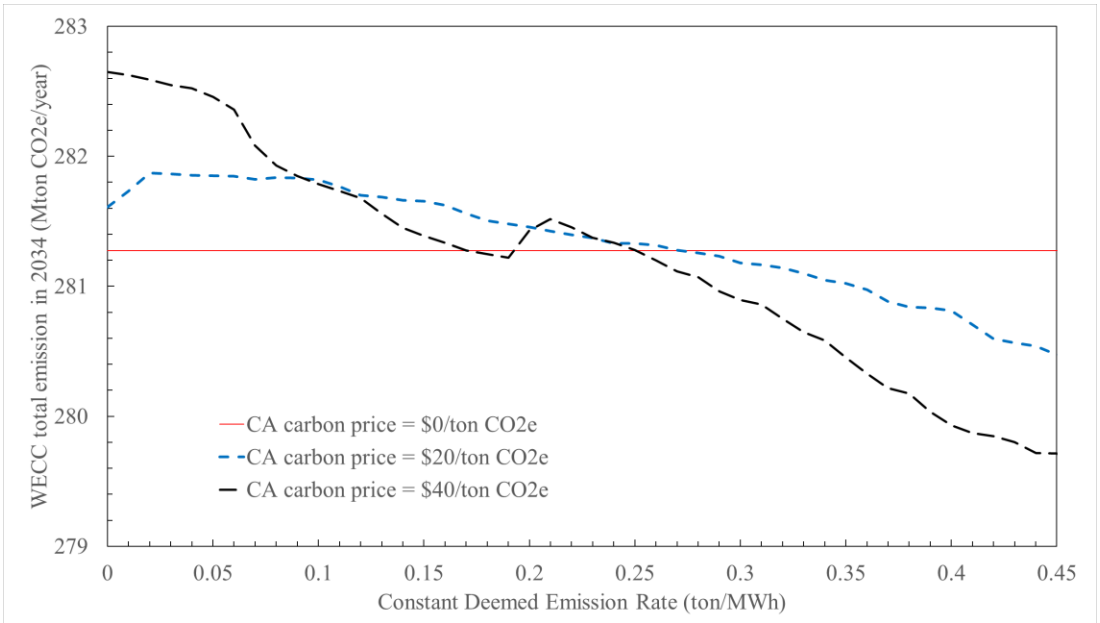

Figure 6.9. WECC total carbon emissions with different constant deemed rates (Case 2)

The second observation is that the higher the constant deemed rate is, the more the carbon emissions California generators emit, and the fewer carbon emissions are from the ROW. The reason is that the higher deemed rate makes import more expensive, and consequently, California will choose to rely on more gas power from inside. Meanwhile, WECC total emissions are very stable over that range (e.g.., ranging from 280.47 to 281.87 Mtons/year with different constant deemed rates while carbon price = $20/ton). In other words, a higher constant emission rate will bring the emissions back to California (raising emissions from about 16.71 Mtons/year to 36.29 Mtons/year under a $20/ton carbon price, and 12.21 Mtons/year to 38.79 Mtons/year under a $40/ton carbon price, , Figure 6.7), while reducing carbon leakage (lowering ROW emission from about 264.90 Mtons/year to 244.18 Mtons/year, under a $20/ton carbon price, and 270.44 Mtons/year to 240.92 Mtons/year under a $40/ton carbon price, Figure 6.8) while making the total system cleaner, but not greatly so (Figure *6.9*). The change in total WECC emissions is one to two orders

of magnitude lower than the shift in emissions between California and ROW as the deemed rate changes. The largest difference between WECC-wide emissions is about 1% of the total. These differences are roughly doubled when California's carbon price is doubled.

Intriguingly, the local emission trends from all three carbon price scenarios ($0, $20, and $40) cross each other while the constant deemed rate is about 0.36-0.37 ton/MWh: beyond this point, the higher the carbon price is, the more CO_2e California generators will emit relative to the $0 price case. This is because an increase of carbon price within California, an importer in the electricity system, under a fixed deemed emission rate will simply increase the cost of importing; thus, California will rely more on its own generation fleet to support the load, and thus more emissions happen inside California.

This phenomenon is consistent with the theoretical results of Section 5.6, in which I showed technology-neutral deemed rates would function as a subsidy to all Californian generators, which increases California generation profits and production as the deemed rate increases.

Time-Varying versus Constant Deemed Rates. I now turn my attention towards to the time-varying deemed rates and ask: *Can a time-varying deemed rate do a better job of cutting emissions?* In this section, I provide comparisons in Tables 6.3 and 6.4, which show the emissions if the deemed rate scheme for power imports to California is set at (1) technology-based deemed rates, (2) time-varying deemed rates of all four combinations of average versus marginal rates and internal versus external sources, or (3) a constant deemed rate equal to the corresponding yearly average. The yearly average is calculated using Eq. (6.4) For example, in the scenario where the Californian carbon price is $40/MWh, if the emission regulator selects time-varying internal marginal emission rates as deemed rates,

the yearly average of such time-varying rates is 0.26 ton/MWh. A comparison between (2) and (3) will reveal the net effect caused by the deemed rate time-variation.

$$DR^{avg} = \sum_{h} HW_h DR_h \tag{6.4}$$

Table 6.3. Comparison of Emissions of BCA with Different Deemed Rate Schemes Applied to Only California Imports (Carbon price = $20/ton), Group1, Cases 1-6

Case	California Carbon Price = $20/ton		Change in Emissions (Mton/year)					
			California		Rest of WECC		WECC Total	
	Deemed Rate Setting	Yearly Avg. Value (ton/MWh)	Time-vary	Constant over year	Time-vary	Constant over year	Time-vary	Constant over year
3	Marginal-Internal	0.28	-4.18	-6.62	3.92	6.61	-0.26	-0.02
4	Marginal-External	0.40	-0.80	1.52	-0.29	-1.98	-1.10	-0.46
5	Average-Internal	0.07	-12.02	-12.34	12.40	12.88	0.38	0.55
6	Average-External	0.30	-4.85	-5.49	4.73	5.39	-0.12	-0.09
1	Technology-based		-13.34		13.64		0.31	
Base Case	Emission with no Carbon price (Mton/year)		30.09		251.18		281.27	

Table 6.4. Comparison of BCA with Different Deemed Rate Schemes (Carbon price = $40/ton), Group1, Cases 1-6

Case	California Carbon Price = $40/ton		Change of Emission (Mton/year)					
			California		Rest of WECC		WECC Total	
	Deemed Rate Setting	Yearly Avg. Value (ton/MWh)	Time-vary	Constant over year	Time-vary	Constant over year	Time-vary	Constant over year
3	Marginal-Internal	0.26	-6.36	-11.12	6.19	11.04	-0.17	-0.07
4	Marginal-External	0.41	0.46	4.60	-3.10	-6.01	-2.64	-1.40
5	Average-Internal	0.05	-16.92	-17.45	18.03	18.63	1.11	1.18
6	Average-External	0.30	-7.99	-8.70	7.55	8.32	-0.44	-0.38
1	Technology-based		-17.67		18.94		1.26	
Base Case	Emission with no Carbon price (Mton/year)		30.09		251.18		281.27	

By comparing the columns of "time-varying" and "constant" in Tables 6.3 and 6.4, I can conclude that introducing time-variation with the internal marginal emission rate can introduce more emissions inside California and correspondingly reduce emissions in the ROW; in other words, such time-variation lowers the carbon leakage by sacrificing the local emission reductions. For instance, when the carbon price is $20/ton, imposing time-varying ratesbased on the internal marginal emission rate lowers the emission reduction (or equivalently, increase the emissions) in California by (6.62 – 4.18 =) 2.44 Mtons/year. In the same example, ROW emissions are reduced by (6.61 – 3.92 =) 2.69 Mtons/year. The higher the carbon price is, the more such impact I observe. For instance, the pair of numbers above increases to 4.76 Mtons/year and 4.85 Mtons/year when the carbon price is at $40/ton.

On the other hand, time-variation based on the external marginal emission rate can behave in the reverse direction from using the internal rates: it reduces California emissions and increases the rest of WECC values. The net effect, however, is an overall decrease of WECC-wide emissions, and such an emission reduction is the largest among different deemed rate alternatives within each carbon price scenario. Overall, the largest WECC-wide decreases shown in the two tables result from using time-varying rates are seen in the marginal-external case; there is no obvious intuition for why time variation would result in less leakage in that situation.

In contrast, time-varying deemed rate schemes based on average emission rates show almost no difference compared to their yearly-stationary counterparts. This is at least in part because the average emission rate has much less time-variability or is very low compared to the marginal emission rate and thus is more similar to the constant deemed rate (Tables 6.3 and 6.4).

Overall, different schemes based on imposing deemed rates on imports to California have varying impacts on the local emission and carbon leakage (on the order of 0-20 Mton/yr), and can lower system-level emissions by 0-2.64 Mton/yr.

6.5.2.3 Group Two: Charge Imports and Rebate Exports

The previous subsection considered only policies that penalize power imports to California, without rebating emission expenses for California Exports. Tables 6.5 and 6.6 show the changes in emissions if I allow power exports to receive emission cost rebates in JHSMINE. In all shown cases, the selected deemed rate scheme is the technology-based deemed rate, where energy credits flowing across the California border pay according to the source emissions (in the case of charging imports to California) or are rebated according

to source emissions (in the case of rebating exports). Simultaneously charging imports and rebating exports (Case 10) will decrease local emissions, with an overall decrease in WECC-wide emissions. This holds for both carbon price scenarios, but the amount of WECC-wide reduction is small (0.11MT for Case 10 in Table 6.5, and 0.34 MT in Table 6.6).

Table 6.5. Emission Comparisons of Different BCA with/without Charging Imports and Rebating Exports (Carbon Price = $20/ton), Cases 7-10 (Technology-based deemed rate)

Case (Table 6.1)	Californian Carbon Price = $20/ton		Change in Emissions (million ton/year) relative to no Carbon Pricing		
	Charge Import	Rebate Import	California	Rest of WECC	WECC Total
7	No	No	-13.38	13.69	0.31
8 (same as 1)	Yes	No	-13.34	13.64	0.31
9	No	Yes	-2.57	2.43	-0.14
10	Yes	Yes	-2.15	2.04	-0.11
Base Case	Total emissions with no Carbon price (Mton/year)		30.09	251.18	281.27

Table 6.6. Emission Comparisons of Different BCA with/without Charging Imports and Rebating Exports (Carbon Price = $40/ton), Cases 7-10 (Technology-based deemed rate)

Case (Table 6.1)	Californian Carbon Price = $40/ton		Change in Emissions (million ton/year) relative to no Carbon Pricing		
	Charge Import	Rebate Import	California	Rest of WECC	WECC Total
7	No	No	-17.88	19.26	1.37
8 (same as 1)	Yes	No	-17.67	18.94	1.26
9	No	Yes	-3.36	3.54	0.18
10	Yes	Yes	-2.95	2.61	-0.34
Base Case	Total emissions with no Carbon price (Mton/year)		30.09	251.18	281.27

These comparisons indicate that, instead of only charging imports which increase the WECC-wide emissions, rebating exports at the same time can be a pathway to lowering carbon leakage and overall system-wide emissions. These results are consistent with the theoretical results that I provided in Section 5.6.5: the action of rebating exports creates an extra incentive for ROW or California to dispatch low-emitting generation to support the demand in California. , ,

6.5.3 BCA Impact on Electricity Production Type and Location

The previous sections' emission results show that technology-neutral deemed rate schemes (i.e., constant or time-varying deemed rates) when applied to imports alone can indeed mitigate carbon leakage more effectively than a technology-based scheme, and basing deemed rates on marginal external emission information can reduce system-wide emissions. Further, rebating exports in addition to charging imports using a technology-based scheme can lead to both a leakage reduction and a limited amount of system-wide emission reduction. A question thus arises: *what are the reasons for the observed incremental carbon leakage mitigation and the observed incremental system-wide emission reduction?* My results in this section show that:

1) Different deemed rates schemes mitigate the leakage by shifting gas generation back to California (resulting in spatial distributions closer to the base case, Case 0, with carbon price = $0/ton) while barely changing the overall generation mix,
2) Rebating exports in addition to charging imports can indeed encourage emission-free generation built out in ROW; however, this effect is limited to the states from which California can directly buy power. Most of this "promised" emission cut is, however, offset by the decrease of renewable energy in other ROW states. The

emission cuts I show in Section 6.5.2 are due to the replacement of coal-fired power in ROW.

All figures in this subsection show the net energy generation changes in comparison to Case 0 where California carbon price = $0/ton. To begin with, the generation mixes of California and ROW of Case 0 are shown in Table 6.7.

Table 6.7. Generation Mixes of California and the Rest of the WECC under Case 0; i.e., California Carbon Price = $0/ton, the year 2034

Units: TWh/yr	California	ROW states where California can directly trade power*	ROW states where California cannot directly trade power**
Bio	11.61	5.09	8.08
Coal	1.17	113.96	60.14
Geo	23.58	13.07	0.00
Hydro	25.84	124.09	81.73
NatGas	75.48	117.65	57.25
Nuclear	0.00	44.75	0.00
Solar	13.65	9.07	0.00
Wind	23.69	38.93	14.03
New-Bio	1.76	0.00	0.00
New-Geo	23.81	20.59	0.53
New-NatGas	3.86	2.70	50.49
New-Solar	41.13	10.70	0.00
New-Wind	11.13	34.53	27.89
Total	256.71	535.14	300.15

* Including states of Washington, Oregon, Arizona, Nevada, Idaho, Utah, Colorado, New Mexico, and Baja California of Mexico.
** Including states of Montana, Wyoming, Texas, and Canadian provinces of British Columbia, and Alberta.

6.5.3.1 Group One: Comparison of Different Deemed Rate Schemes

Alternative Constant Annual Rates. Figures 6.10 to 6.12, respectively, show the generation mixes of California, , ROW, and WECC system under the constant deemed

emission rate scheme where the California carbon price = $40/ton.[37] All plots show the annual energy changes compared to the Base Case where California carbon price = $0/ton. (Changes under the carbon price of $20/ton are less dramatic and are mentioned briefly below.) Higher deemed rates barely affect any generation type except for gas-fired power. For instance, the scale of Figures 6.10 and 6.11 is much larger than Figure 6.12. With a higher deemed rate for California power imports, the system dispatches California gas-fired power plants more heavily, which substitutes for gas-fired power generation in ROW. This is consistent with the theoretical result developed in the previous Chapter: a constant deemed rate acts as a subsidy for California generators. This implies that changes in WECC-wide emissions are mainly due to small differences in gas generator efficiencies between California and the ROW.

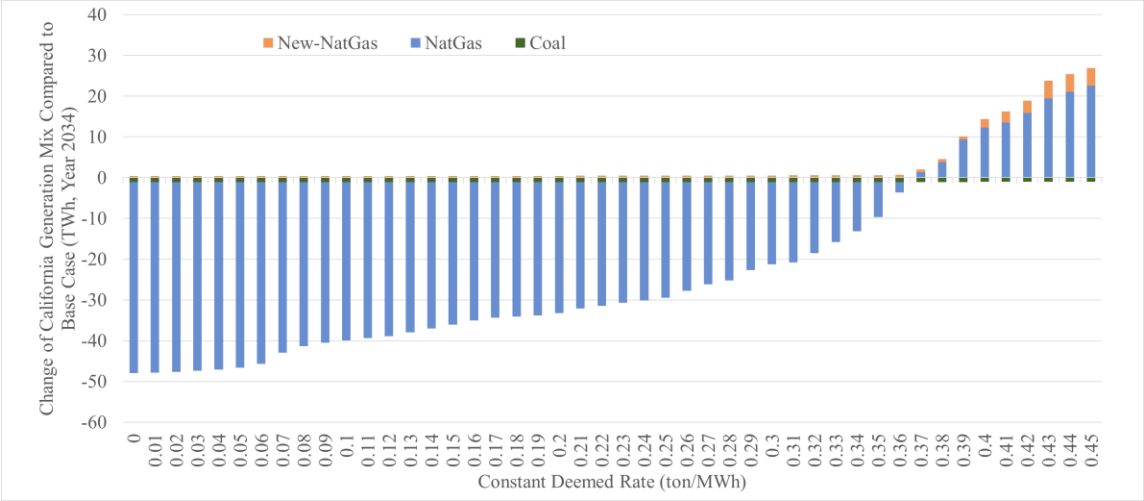

Figure 6.10. Change of Generation mix of California, under constant deemed rate Scheme (0 – 0.45 ton/MWh), Carbon Price = $40/ton; i.e., Case 2 minus Case 0

[37] In Figure 6.12, for sake of simplicity, I combine changes from all renewable generations together. As seen in Figures 6.10 and 6.12, these changes are only from the ROW generations.

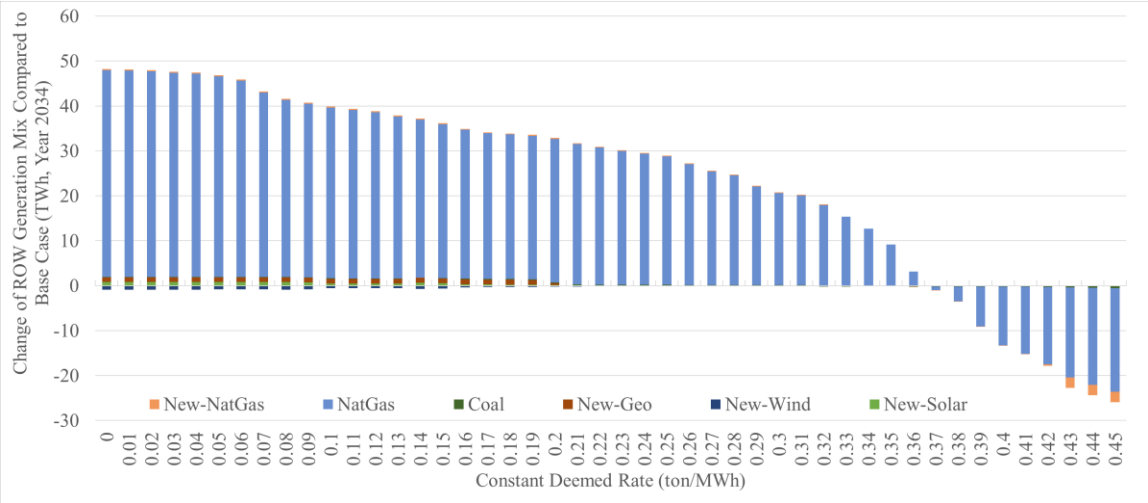

Figure 6.11. Change of Generation mix of the Rest of WECC, under constant deemed rate scheme (0 – 0.45 ton/MWh), Carbon Price = $40/ton; i.e., Case 2 minus Case 0

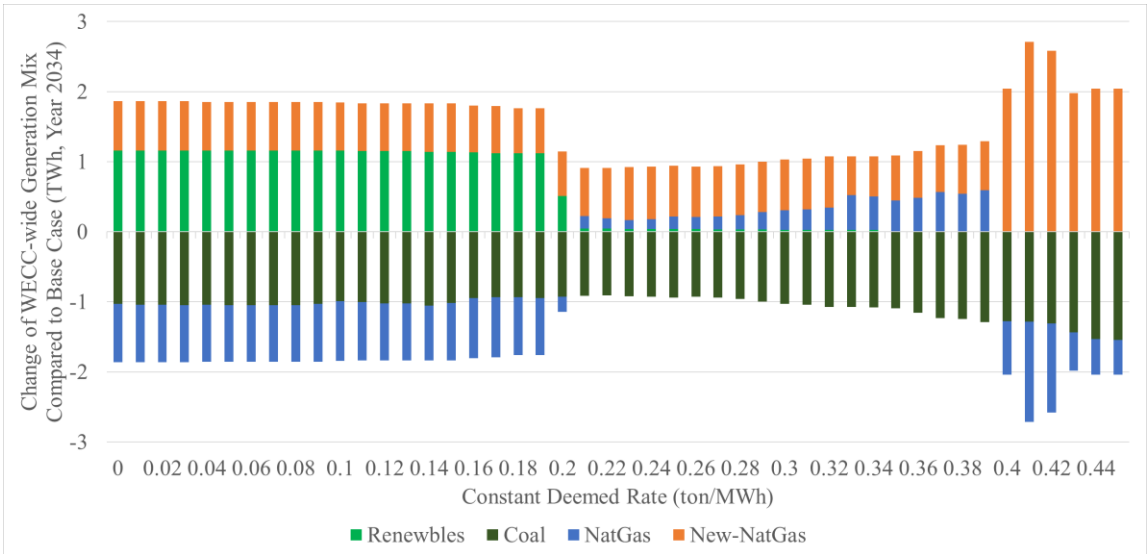

Figure 6.12. Change of Generation mix of the WECC as total, under constant deemed rate scheme (0 – 0.45 ton/MWh), Carbon Price = $40/ton; i.e., Case 2 minus Case 0

It is noteworthy that renewable generation is higher than Case 0 when the constant deemed rate is less than 0.2 ton/MWh (Figure 6.12); however, for those same deemed rates, total emissions are also higher than Case 0. As explained in Section 6.5.2.1, this is because

the increased gas-power in ROW is in fact dirtier than the decreased gas-power in California.

Figures 6.13 to 6.15, respectively, show the generation mixes of California, ROW, and WECC system under other deemed rate scheme alternatives with carbon price = $40/ton. All plots show the changes upon the no California carbon price case. Like the observations above under the constant deemed rate scheme, the only significant effect of other alternatives is on gas-fired power. One exception is the deemed rate based on marginal external emissions: under this scheme, besides the gas-fired power, ROW builds slightly more solar energy (at 1.65 TWh), cuts some wind energy (-1.66 TWh), and most importantly, cut coal-fired power production (-2.86 TWh), and consequently provides some emission reduction (as seen in Section 6.5.2.2). As shown in Figure 6.15, at the system-level, the emission reduction is achieved by substituting ROW coal power with California gas power. When carbon price equals $20/ton, the "homecoming gas-fired power" basically follows the same pattern shown in Figures 6.13 to 6.15, although the effects are somewhat smaller in magnitude.

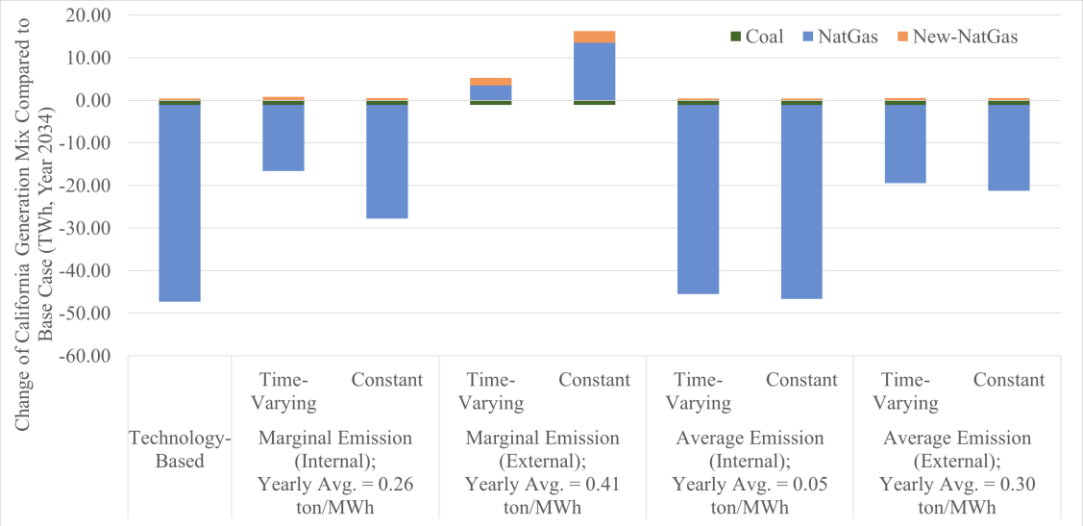

Figure 6.13. Comparison of the change of generation mixes within California under different deemed rate schemes, Carbon Price = $40/ton; i.e., Cases 1-6 minus Case 0

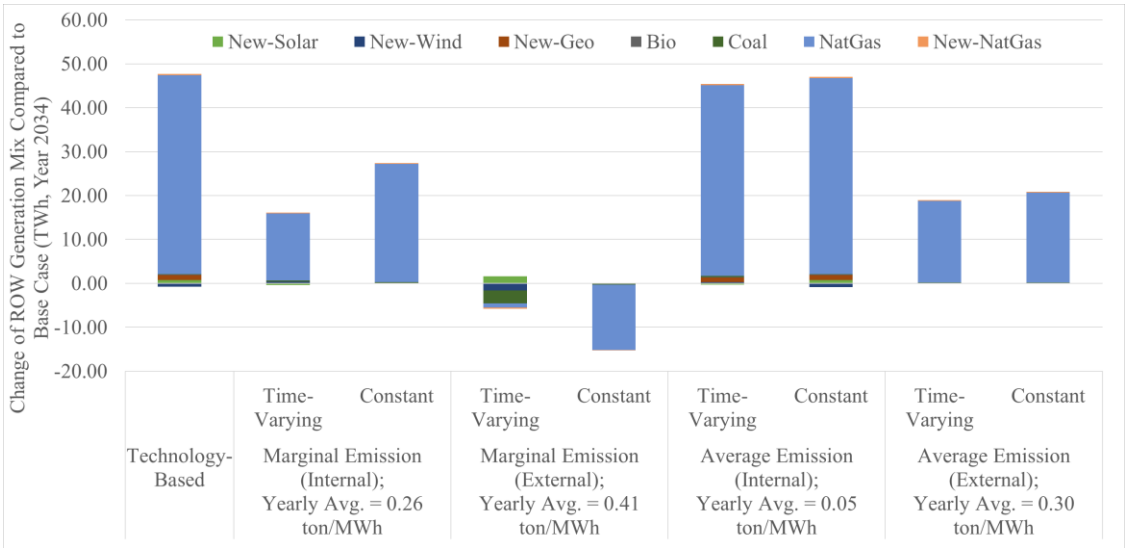

Figure 6.14. Comparison of the change of generation mixes of the Rest of WECC under different deemed rate schemes, Carbon Price = $40/ton; i.e., Cases 1-6 minus Case 0

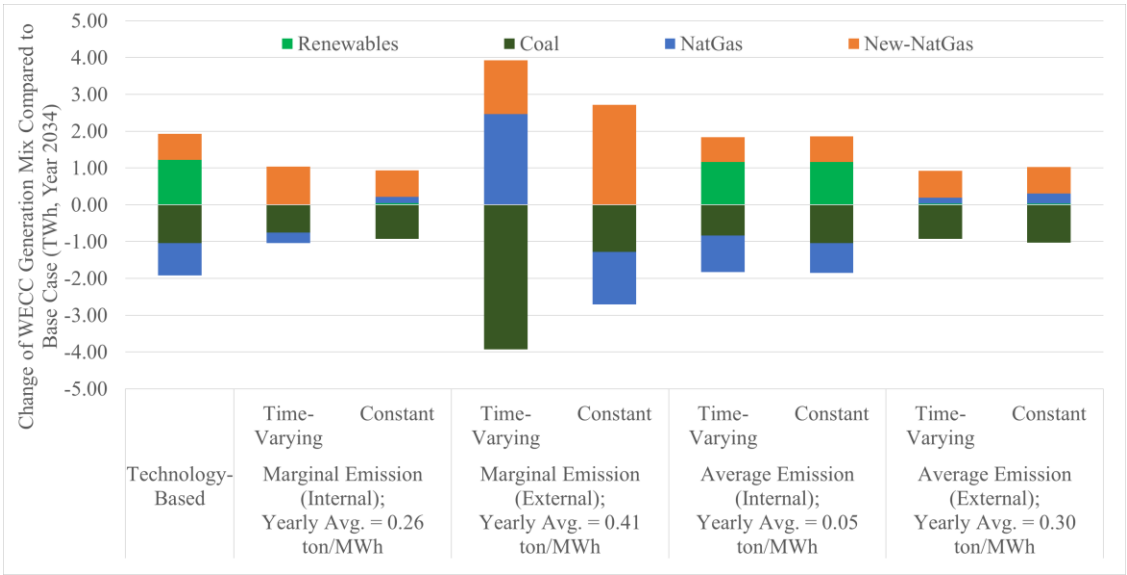

Figure 6.15. Comparison of the change of WECC-wide generation mixes under different deemed rate schemes, Carbon Price = $40/ton; i.e., Cases 1-6 minus Case 0

6.5.3.2 Group Two: Charge Imports and Rebate Exports

Tables 6.8 and 6.9 compare generation mixes within just California with different BCA schemes with and without rebating of emission costs of exports under scenarios of Carbon price = $40/ton. When carbon price equals $20/ton, the changes basically follow the same pattern, although the effects are somewhat smaller in magnitude.

Like the observations in the previous section, these alternatives strongly affect gas production from existing gas-fired plants in California. Interestingly, in all cases, the incremental effect of adding a charge to imports (i.e., from the second column to the third in the table, or from the fourth to the fifth) introduces almost no changes to generation mixes.

This is due to the significant amount of contract shuffling. As a reminder, the total California energy demand in this chapter is 343.70 TWh/year. When the carbon price is $40/ton and the BCA is absent, the total amount of California generation is 209.17 TWh/year = 256.71 TWh/year (see Table 6.7, Case 0) – 47.54 TWh/year. Meanwhile, if

the BCA is implemented with a technology-based deemed rate, total California generation rises slightly to 209.80 TWh/year. Both imply roughly 134 TWh/year net energy imports. In the case of no BCA, these 134 TWh/year net energy imports are the net of 32.37 TWh/year "California to ROW" exports and 166.90 TWh/year gross imports from ROW, of which 93.75 TWh/year is emission-free. However, with the technology-based deemed rate implemented, the 134 TWh/year net imports are, instead, composed of 8.26 TWh/year "California to ROW" exports and 142.16 TWh/year gross imports from ROW, which is 100% emission-free. In short, due to the technology-based deemed rate, all imports become emission-free without significantly changing the net imports.

Meanwhile, adding a policy of rebating exports has an impact: by comparing the second column to the fourth, or the third to the fifth, I conclude that rebating exports will encourage more gas-fired power production inside California. For instance, when the carbon price is $40/ton, the gas-fired power generation more than doubles from the first to the third column (75.48 (Base) – 46.87 = 28.61 TWh to 75.48 (Base) – 8.44 = 67.04 TWh) and from the second to the fourth column (75.48 – 46.25 = 29.23 TWh to 75.48 – 7.15 = 68.33 TWh).[38]

[38] For perspective, this can be compared to actual historical generation; in 2017, Californian natural gas power plants generated 85 TWh Electricity; California non-emitting resources generated about 110 TWh (CARB, 2019b).

Table 6.8. Change of California Generation Mix (TWh) compared to the Base Case, Carbon Price = $40/ton, the year 2034, Cases 7-10 minus Case 0

Change of Production (TWh)	No BCA (Case 7)	Import Charge Only (Case 1/8)	Export Rebate Only (Case 9)	Charge Import & Rebate Export (Case 10)
Geo	-0.16	0.04	-0.17	0.00
New-Solar	0.15	-0.05	0.17	-0.01
New-Wind	0.01	0.01	0.00	0.01
Coal	-1.10	-1.10	-1.13	-1.08
NatGas	-46.87	-46.25	-8.44	-7.15
New-NatGas	0.44	0.44	0.70	0.51
Total	-47.54	-46.91	-8.87	-7.71

ROW generation mixes under carbon price = $40/ton (Table 6.9) reveals the other side of the story: rebating exports in addition to charging imports can encourage some more emission-free generation in some part of ROW (in states where California LSE can trade energy credits), but can also discourage emission-free generation in other places. More importantly, simultaneously rebating exports and charging imports can cut emissions in its neighboring states by replacing coal-fired power. For instance, when the carbon price is at $40/ton, compared to Case 7 that only charges imports, emission-free electricity increases by 3.42 TWh in the ROW states where California LSE can buy power (see the upper part of Table 6.9). In the same comparison, however, emission-free electricity decreases by 3.79 TWh in the ROW states where California cannot directly buy power. The WECC-wide emission reduction shown in Section 6.5.2 is achieved by cutting coal power production in California's neighbor states. These results are explainable by one of the conclusions from Section 5.6.5: rebating exports can provide additional encouragement (on top of charging imports) towards the generation of ROW emission-free energy. By the results of this section, we can further see that this conclusion only applies to ROW states from which California can directly buy power.

Table 6.9. Change of ROW Generation Mix (TWh) compared to the Base Case, Carbon Price = $40/ton, the year 2034, Cases 7-10 minus Case 0

Change in Production (TWh/yr)		No BCA (Case 7)	Import Charge Only (Case 8)	Export Rebate Only (Case 9)	Charge Import & Rebate Export (Case 10)
ROW (California's Neighbor State or its Neighbor's Neighbor)*	New-Solar	0.79	0.78	0.00	0.76
	New-Wind	-4.44	-4.35	-3.58	0.26
	New-Geo	1.06	1.06	0.00	0.00
	Bio	0.15	0.14	0.03	-0.03
	Coal	0.07	0.06	0.07	-0.20
	NatGas	43.54	42.93	7.98	6.68
	New-NatGas	0.24	0.24	0.22	0.22
	Subtotal	41.42	40.86	4.71	7.70
ROW – Other**	Wind	0.00	0.01	0.00	0.00
	New-Wind	3.59	3.58	3.57	-0.20
	NatGas	2.50	2.43	0.58	0.20
	New-NatGas	0.03	0.03	0.00	0.00
	Subtotal	6.12	6.06	4.16	0.01
Total		47.54	46.91	8.87	7.71

* Including states of Washington, Oregon, Arizona, Nevada, Idaho, Utah, Colorado, New Mexico, and Baja California of Mexico.
** Including states of Montana, Wyoming, Texas, and Canadian provinces of British Columbia, and Alberta.

Table 6.10 shows the WECC-wide generation mixes under a carbon price of $40/ton. As explained in Section 6.5.2.1, even with more emission-free generation (Table 6.10, Case 7 vs. Case 0), emissions of WECC can still be higher because (relatively) clean California gas-fired power is replaced by dirtier/less-efficient gas-fired power in ROW. Following the same vein, but in the opposite direction, emissions can be cut even with less emission-free generation. For instance, in Table 6.10, if CARB charges imports and rebates exports simultaneously, renewable generation decreases compared to the no BCA case (Case 7), however, the system-wide emissions are still lower (see Section 6.5.2.3). As explained before, this happens by cutting coal power in the ROW.

Table 6.10. Change of WECC Generation Mix (TWh) compared to the Base Case, Carbon Price = $40/ton, the year 2034, Cases 7-10 minus Case

Change of Production (TWh)	No BCA (Case 7)	Import Charge Only (Case 8)	Export Rebate Only (Case 9)	Charge Both Import & Rebate Export (Case 10)
Wind	0.00	0.01	0.00	0.00
Geo	-0.16	0.04	-0.17	0.00
New-Solar	0.94	0.74	0.17	0.75
New-Wind	-0.84	-0.76	-0.01	0.07
New-Geo	1.06	1.06	0.00	0.00
Bio	0.15	0.14	0.03	-0.03
Emission-Free Subtotal	1.16	1.22	0.02	0.80
Coal	-1.03	-1.04	-1.06	-1.27
NatGas	-0.84	-0.88	0.12	-0.26
New-NatGas	0.70	0.70	0.92	0.74

6.5.4 BCA Impact on Transmission Expansion

How would different BCA schemes affect transmission expansion? Since the economic value of transmission between California and the ROW is largely derived from delivering power into California, more California local production due to whatever reason will likely lead to less transmission built-out between California and the ROW.

Before providing quantitative answers, another reminder to the readers is that, as mentioned in Section 6.4, two different sets of transmission expansion candidates are available: (1) renewable interconnectors that connect renewable generation expansions to the grid and (2) backbone reinforcements that reinforce the backbone transmission lines. Each can be expanded in continuous amounts (zero up to the upper bound), which, as Chapter 2 explains, is assumed in order to improve execution times. Since all renewable generation candidates need connections to the grid to generate electricity, the impact of different BCA

schemes on renewable interconnectors has been implicitly discussed in the previous section: BCA schemes that penalize imports only with different deemed rates have negligible impact on the expansion of renewable interconnectors since there is little impact on renewable capacity itself. In contrast, rebating California exports can incentivize more renewable interconnector expansions to wind resources in states where California LSE can buy power directly.

Consequently, in this section, I focus on the impact of BCA on backbone transmission expansions. Among all the cases being studied (i.e., Cases 0-10 in Table 6.1), new backbone reinforcements only appeared in six interstate corridors (see Figure 6.16): (1) the border between California, U.S. and Baja California, Mexico, (2) the corridor between the Intermountain station (Utah) to Mona station (Utah), (3) the border between British Columbia, Canada and Washington, U.S., (4) the border between California and Oregon, (5) the border between Arizona and New Mexico, and (6) the border between Idaho and Nevada. I consider (2) to be equivalent to a California to Utah interstate transmission line, as the Intermountain Power Project station in Utah is at the endpoint of a high-voltage DC line between California and Utah (see Figure 6.3, the orange line between Utah and California). Thus, corridors (1), (2), and (4) are essentially California border crossings that are likely to be affected by changes in net imports to California, while (3) allows more flow between Canada and the US in the Pacific Northwest. Specifically, although within-state reinforcement candidates exist in the test system, none are selected. In the following subsections, I will describe how BCA impacts these interstate transmission expansions in the two groups of analyses.

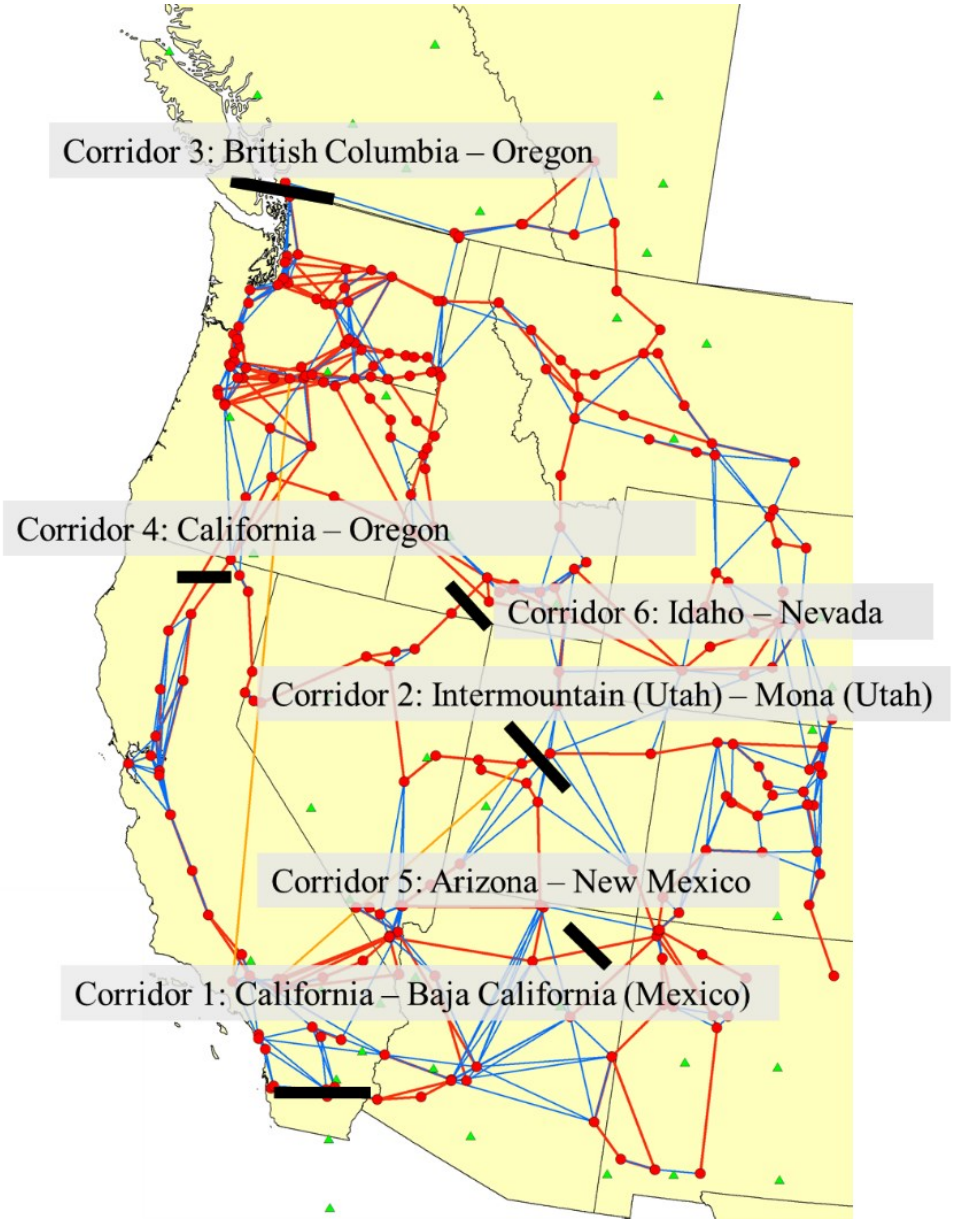

Figure 6.16. Four corridors with expanded reinforcement candidates in the test cases

6.5.4.1 Group One: Comparison of Different Deemed Rate Schemes for Import-Only Policies

Figure 6.17 shows the interstate transmission expansions when the emission regulator implements different levels of constant deemed emission rate for charging imports (Case 2). Except for the transmission expansion across the U.S.-Mexico boundary (upper

left in Figure 6.17), the other five transmission expansions decrease as the (constant) deemed rate is increased. For instance, the expanded capacity between California and Utah starts at 750 MW while the deemed rate is zero and drops to 0 MW while the deemed rate as high as 0.45 ton/MWh. The reason is that higher deemed rates decrease the amount and value of power imports to California.

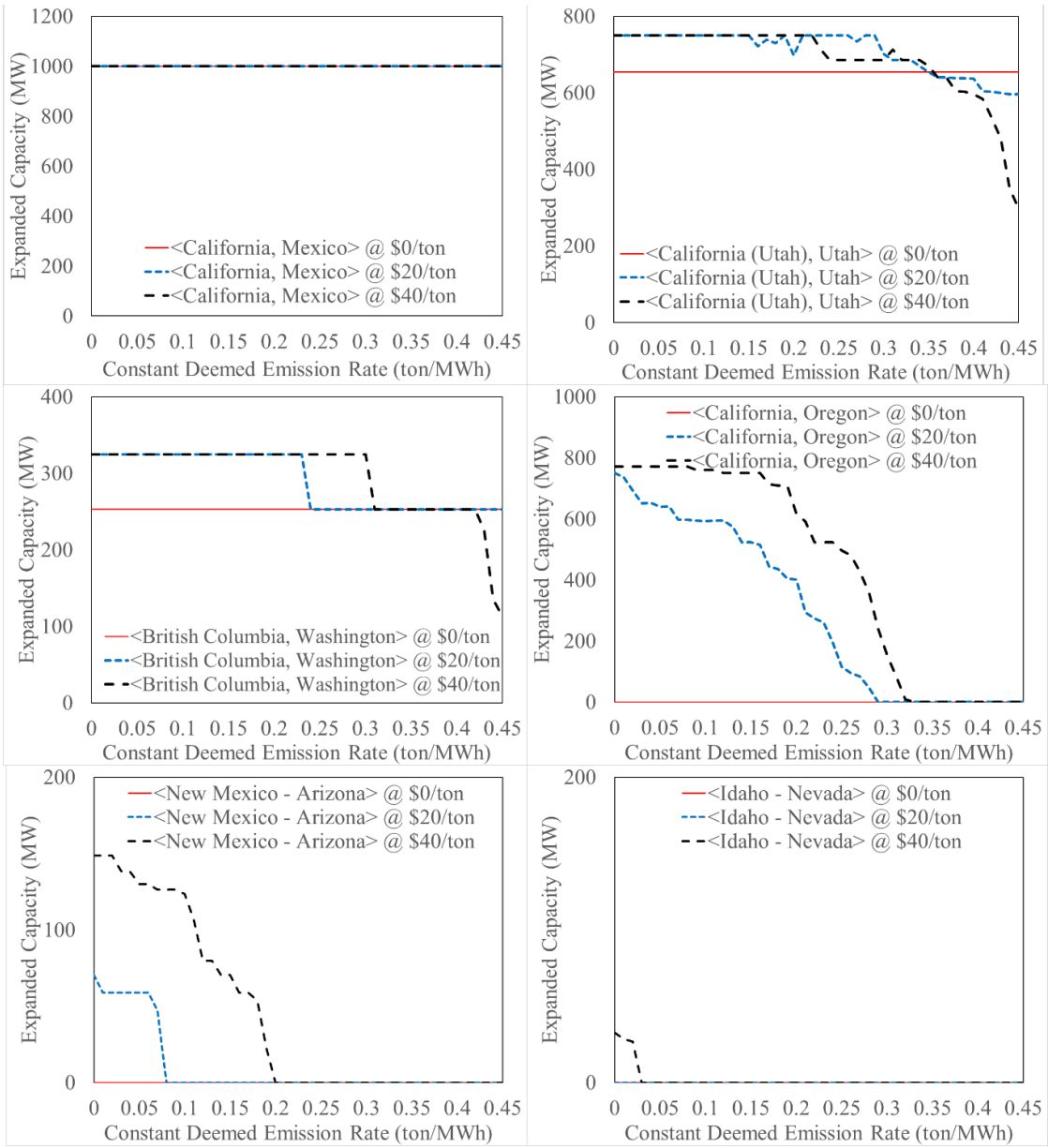

Figure 6.17. Expansions of Interstate Transmission Capacity (MW) under constant deemed rate scheme (0 – 0.45 ton/MWh); i.e., Case 2

Although only the imports flowing to California are subject to BCA, BCA's discouragement of transmission expansion can also happen at non-California boundaries. For example, as shown in the middle left and bottom of Figure 6.17, the transmission expansion between British Columbia and Washington drops from around 350 MW to 100 MW. Examination of the flows indicates that this is because the economic value of Canadian exports is decreasing as the deemed rate increases. Figure 6.17 also shows that given the constant deemed rate, the high carbon price will generally encourage more transmission expansions in these corridors, especially at the California-Oregon border. This is again because of the increase in California imports spurred by the increased cost of California power production from carbon regulation.

Figure 6.18 compares interstate transmission expansions under other deemed rate schemes (i.e., Cases 0-6 in Table 6.1). I note here that (1) these deemed rate schemes do not affect the transmission expansion between the U.S.-Mexico boundary (held at 1000 MW, the maximum expandable amount), and (2) the interstate transmission line between Idaho and Nevada is only expanded by an insignificant amount. Thus, the results of these two lines are not shown. Like the results of the constant deemed rate cases, other four interstate transmission expansions are discouraged by high deemed rates (Figure 6.18), e.g., transmission expansions under internal marginal emission rate (with annual average = 0.26 ton/MWh) are greater than the expansions under external marginal emission rate (with annual average = 0.41 ton/MWh). Furthermore, a technology-based deemed rate results in higher transmission expansions compared to other deemed rate schemes; e.g., the expanded capacity between California and Oregon is 771.41 MW when the technology-based deemed rate is implemented, ranking the first among all the test cases.

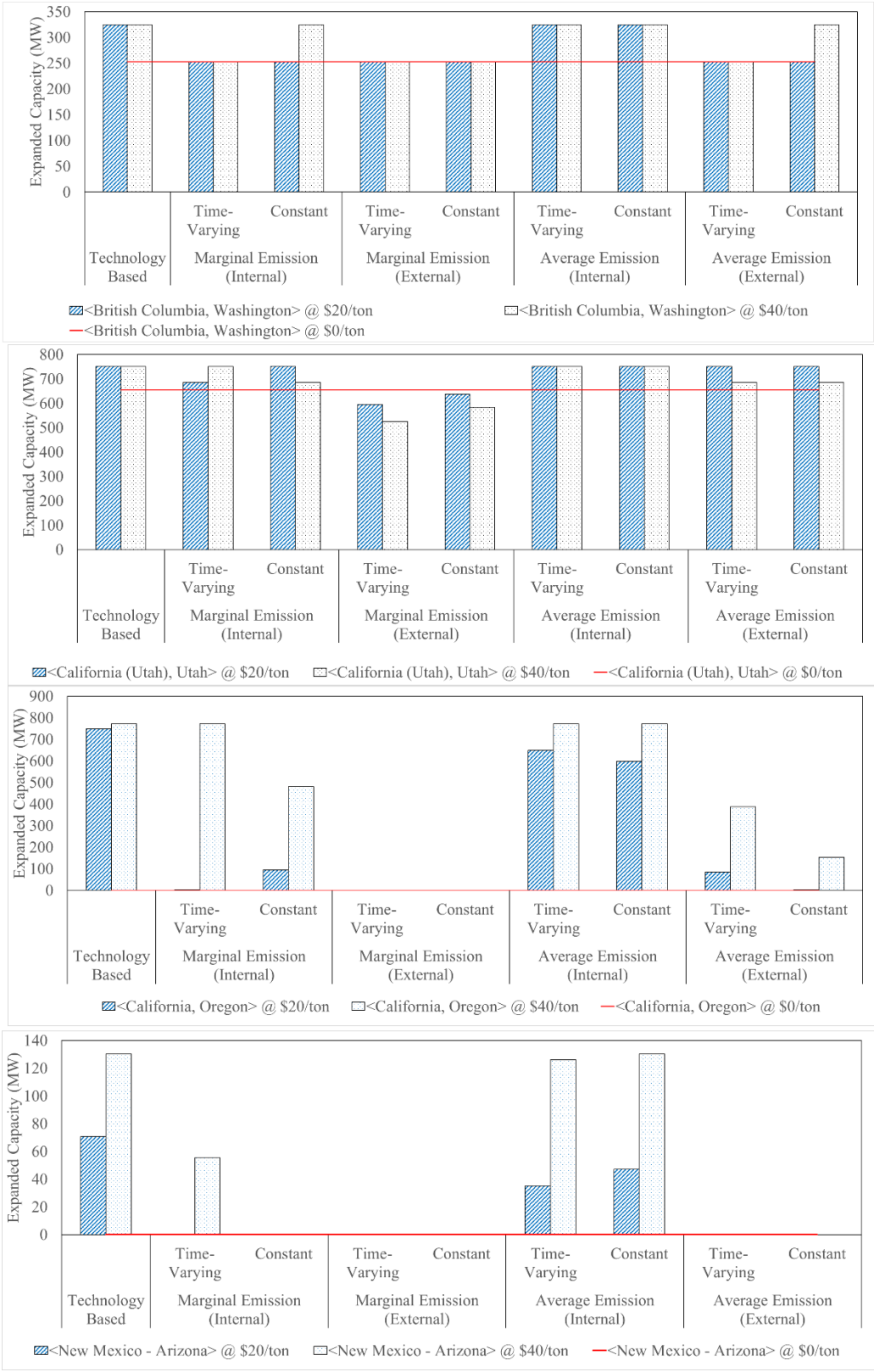

Figure 6.18. Expansions of Interstate Transmission Capacity (MW) under different deemed rate schemes, Cases 0-6

6.5.4.2 Group Two: Charge Imports and Rebate Exports

Figure 6.19 shows the interstate transmission expansions if the emission regulator chooses to rebate emissions expenditures by exports on top of the import charges. Similar to the previous section, the results of the California-Mexico transmission line and the Idaho-Nevada line are not shown here. The policy choice of rebating exports tends to lower transmission expansions in the four corridors (in Figure 6.19, compare the 1st pair of columns vs. the 3rd pair, and the 2nd pair vs. 4th pair). For instance, the expansion between the California-Oregon border is greatly suppressed because of the export rebate; in contrast, the expansion is about 749.49 MW (when California carbon price = $20/ton, and is 771.41 MW when carbon price = $40/ton) if no BCA is implemented or the technology-based deemed rate is used for charging imports. On the other hand, the action of charging imports (with a technology-based deemed rate) has almost no impact on transmission expansion (the 1st pair of columns vs. the 2nd pair, and the 3rd pair vs. the 4th pair). The exception is the transmission expansion between New Mexico and Arizona, which increases from 0 to 130.15 MW because of the import charge of California, when the carbon price is at $40/ton.

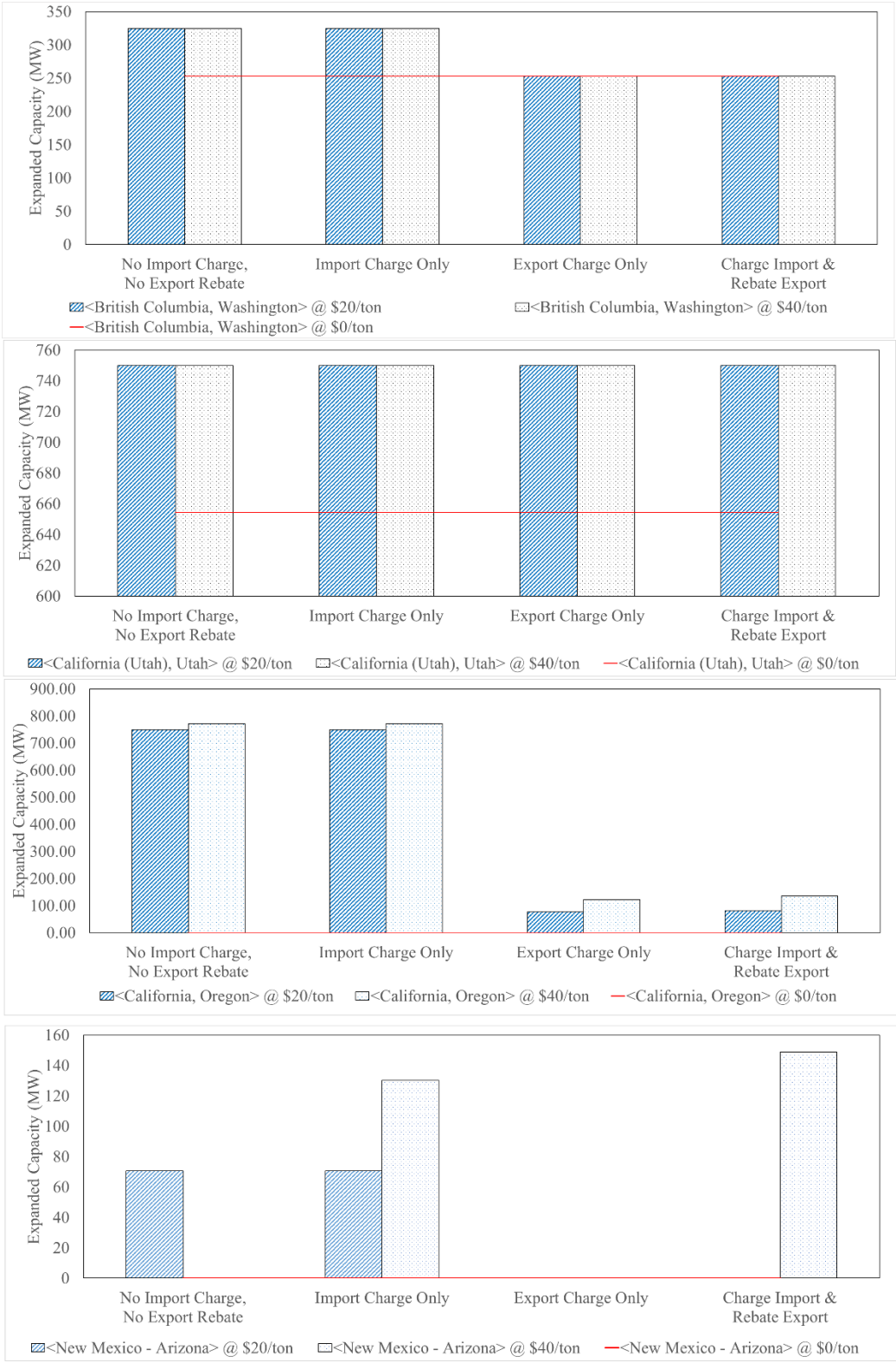

Figure 6.19. Expansions of Interstate Transmission Capacity (MW) with BCA with/without rebating exports, i.e., Cases 0 and 7-10

The negligible impact on transmission investment from the technology-based import charge is consistent with the generation results in Section 6.5.3: only insubstantial changes occur in California/ROW generation mixes because of the actions of a technology-based import charge. In this case, the importer-exporter balance between California and ROW does not shift much because of import-only BCA. Thus, the value of transmission, and therefore its expansion does not change. On the other hand, implementing a policy of rebating exports lowers the cost of (gas-fired) power exports from California, incentivizing more California gas exports and less power flows towards California. Thus, less transmission expansion is justified.[39]

6.5.5 BCA Impact on Costs to California Consumers

In this section, I will examine how different BCA alternatives affect the costs to California consumers. In this section, the cost to California consumers is quantified in two ways. One is by the wholesale energy price, which is calculated by dividing the total annual LSE payment (in $) by the total energy load (in MWh), i.e., Eq. 6.5. (See the definition of CC_w in Section 5.4.5 of Chapter 5.[40])

$$\text{Wholesale Price}_w = CC_w \Big/ \sum_h HW_h \left(\sum_{i \in I_w} \left(LOAD_{h,i} - n_{h,i}^{Load} \right) \right) \tag{6.5}$$

The second way is to net out from those consumer power payments two quantities received by the California government or California ISO on behalf of consumers: economic rents due to carbon payments (to the California Air Resources Board) and congestion rents on

[39] As explained in Chapter 5, net interstate power flow equals the net of import and export contracts. Thus, more export contracts can introduce a lower power flow, and less transmission build-out.

[40] To put it in words, CC_w (or the calculated wholesale price) is composed of electric energy expenditures, cost of lost load (if any), RPS non-compliance penalty (if any), energy credit payment through bilateral trading, and finally, the extra charge because of BCA.

the California grid (equal to within-California transmission congestion payments plus one-half of transmission congestion payments for interties between California and its neighbors). This second approach assumes that these rents are ultimately returned to California consumers, either through lower taxes or greater government expenditures on programs benefiting California consumers (in the case of carbon payments) or lower payments to the CAISO for operating the California grid. Presently, CARB devotes its carbon pricing revenue for a downstream program called "California Climate Investments." This program is intended to combat GHG emissions, improving public welfare and the environment through investing the cap-and-trade revenue in promoting clean transportation and other types of projects (CARB, 2019a). In the RGGI system, by comparison, payments for carbon are primarily devoted to energy conservation programs that are intended to benefit consumers ((RGGI, 2018)). Also, the CAISO's benefit-cost analyses of transmission explicitly assume that electric costs to California ratepayers are reduced if transmission congestion (the difference between consumer payments for bulk power and generation revenues) increases (Awad et al., 2010).

Figure 6.20 shows California wholesale prices under the constant deemed rate scheme (Case 2). As expected, the introduction of carbon pricing in California will raise the wholesale price; when the constant deemed rate is higher, the wholesale price will be higher. The prices with the reimbursement from the ISO and the state government vary by a much smaller amount (within $1/MWh). This highlights that the increase of the prices without reimbursement is major driven by the extra BCA payments to the government, and after accounting for redistribution of those payments back to consumers, such an increase disappears.

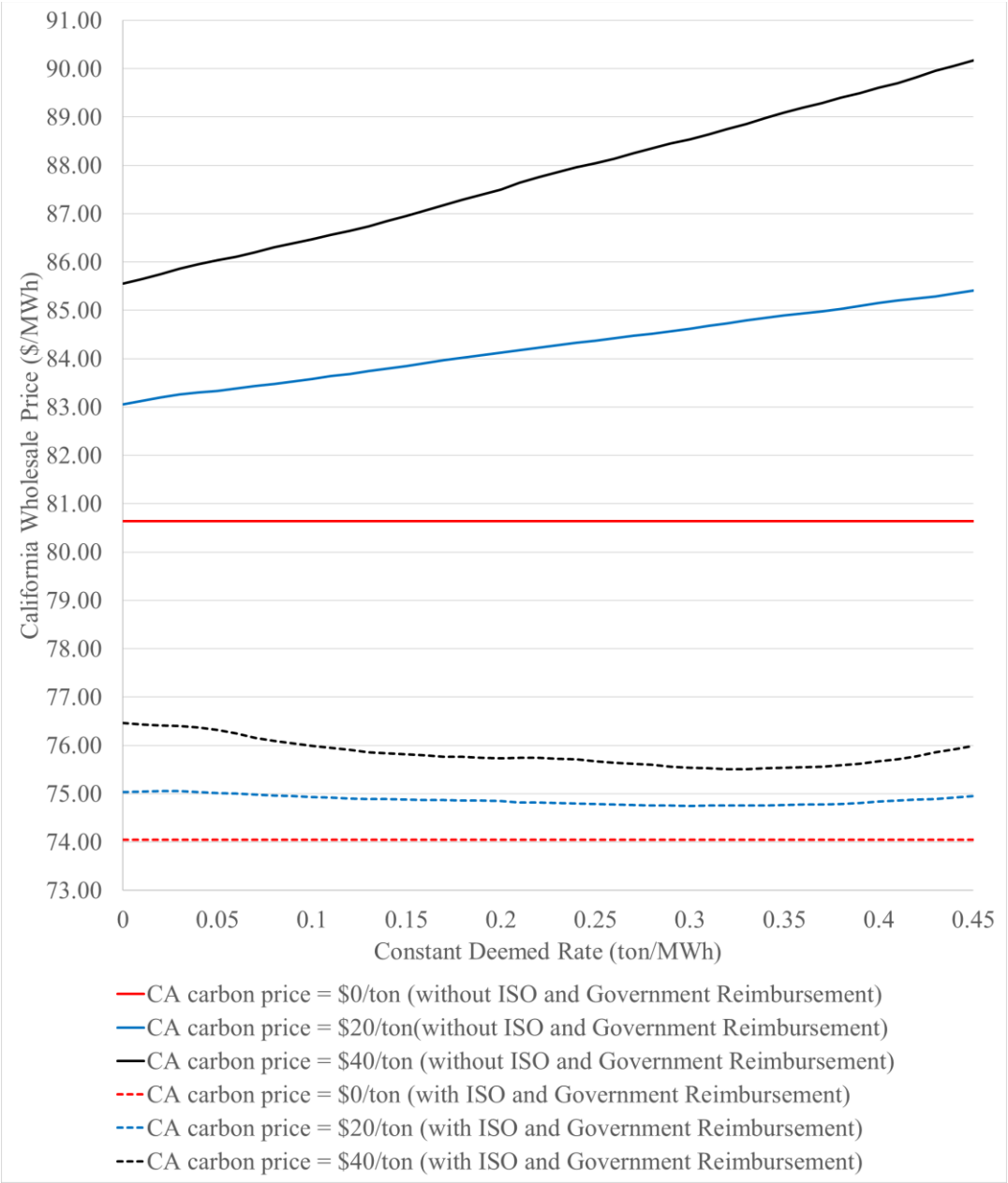

Figure 6.20. Average California wholesale prices under the constant deemed rate scheme (Case 2)

Tables 6.11 and 6.12 summarize the wholesale prices for all other BCA schemes without and with reimbursement from ISO and government within Groups One and Two. Intuitively, the introduction of carbon pricing will raise the wholesale prices paid by consumers; taking the $40/ton carbon price as an example, the wholesale price for California

rises from $80.64/MWh (Case 0) to $83.05/MWh (Case 7, the price from no BCA case without reimbursement). It is not surprising to see that nearly all BCA schemes raise the wholesale price, as Californian consumers need to pay more to import power from the ROW. But introducing time-variations in the deemed rate, however, does not induce a significant rise in electricity price compared to its yearly-average constant counterpart; in fact, the wholesale prices are sometimes lower because of the time-variation (e.g., in case of BCA based on marginal internal emission when the carbon price = $40/ton, wholesale prices decreases from $88.14/MWh to $87.89/MWh). This is a promising result if the emission regulator is trying to mitigate carbon leakage.

Nevertheless, California consumers have to pay for carbon leakage mitigation. First, without transferring state carbon permit revenues and ISO congestion revenues to consumers, when the California regulator adopts time-varying deemed rate schemes, which are most effective at mitigating leakage, the wholesale prices are universally higher than the current practice in California, , which charges imports at the technology-based deemed rate. Second, with such rent transfers to consumers, allowing deemed rates to vary over time according to hour-by-hour marginal external emissions can raise the costs to California consumers by 76.04 – 75.71 = $0.33/MWh.

Table 6.11. Comparison of California Wholesale Prices under Different BCA Schemes (Cases 0 -10), without reimbursement of carbon and transmission rents from the ISO and the state government

Group	Case ID	Carbon Price =		$20/ton		$40/ton	
		Deemed Rate Scheme	Yearly Avg. Value (ton/MWh)	Time-varying	Constant over year	Time-varying	Constant over year
1	3	Marginal-Internal	0.28/0.26	84.44	84.52	87.89	88.14
	4	Marginal-External	0.40/0.41	85.22	85.15	89.59	89.70
	5	Average-Internal	0.07/0.05	83.46	83.44	85.91	86.04
	6	Average-External	0.30/0.30	84.66	84.62	88.62	88.54
2	7	No BCA		83.05		85.56	
	1/8	Charge Imports (at Technology-based deemed rate)		83.06		85.67	
	9	Rebate Exports		83.68		86.49	
	10	Charge Imports and Rebate Exports		82.15		83.54	
Base Case	0	Carbon Price = $0/ton		80.64			

Table 6.12. Comparison of California Wholesale Prices under Different BCA Schemes (Cases 0 -10), with reimbursement from the ISO and the state government

Group	Case ID	Carbon Price =		$20/ton		$40/ton	
		Deemed Rate Scheme	Yearly Avg. Value (ton/MWh)	Time-varying	Constant over year	Time-varying	Constant over year
1	3	Marginal-Internal	0.28/0.26	74.81	74.76	75.82	75.64
	4	Marginal-External	0.40/0.41	75.00	74.84	76.04	75.71
	5	Average-Internal	0.07/0.05	74.95	74.98	76.13	76.32
	6	Average-External	0.30/0.30	74.75	74.75	75.53	75.54
2	7	No BCA		75.04		76.46	
	1/8	Charge Imports (at Technology-based deemed rate)		75.07		76.59	
	9	Rebate Exports		74.23		74.35	
	10	Charge Imports and Rebate Exports		75.17		76.37	
Base Case	0	Carbon Price = $0/ton		74.05			

6.5.6 Societal Welfare (Market Efficiency) and Total Carbon Emissions

This last set of results addresses the Pareto efficiency of alternative policies in terms of overall economic costs to the West versus total West emissions. Figure 6.21 shows the trade-off between the WECC-wide resource cost (i.e., the sum of generation, transmission expansion cost and operation cost, deducing RPS penalties[41] as well as carbon payments, which are transfer payments) and carbon emissions. The Pareto frontier (red dashed line) among alternative California-only policies is largely defined by three solutions:[42] the no

[41] In fact, RPS penalties never happen in due to the experimental design of this Chapter, see Section 6.4. The California renewable potentials are doubled from Chapters 3 and 4.

[42] Some constant deemed rate schemes also lie on the frontiers: constant deemed rate ≥ 0.38 ton/MWh when the carbon Price = $40/ton; constant deemed rate ≥ 0.37 ton/MWh when the carbon Price = $20/ton.

carbon price case (Case 0, 281.27 Mton CO_2e versus 32.94 Billion US$/year), and the two cases where the emission regulator of California bases import deemed rates on marginal external emissions (280.18 Mton CO_2e versus 32.96 Billion US$/year when carbon price = $20/ton; and 278.64 Mton/yr versus 33.01 Billion US$/yr). In other words, deemed rates based on external marginal emissions can achieve better economic efficiency than other deemed rate policies.

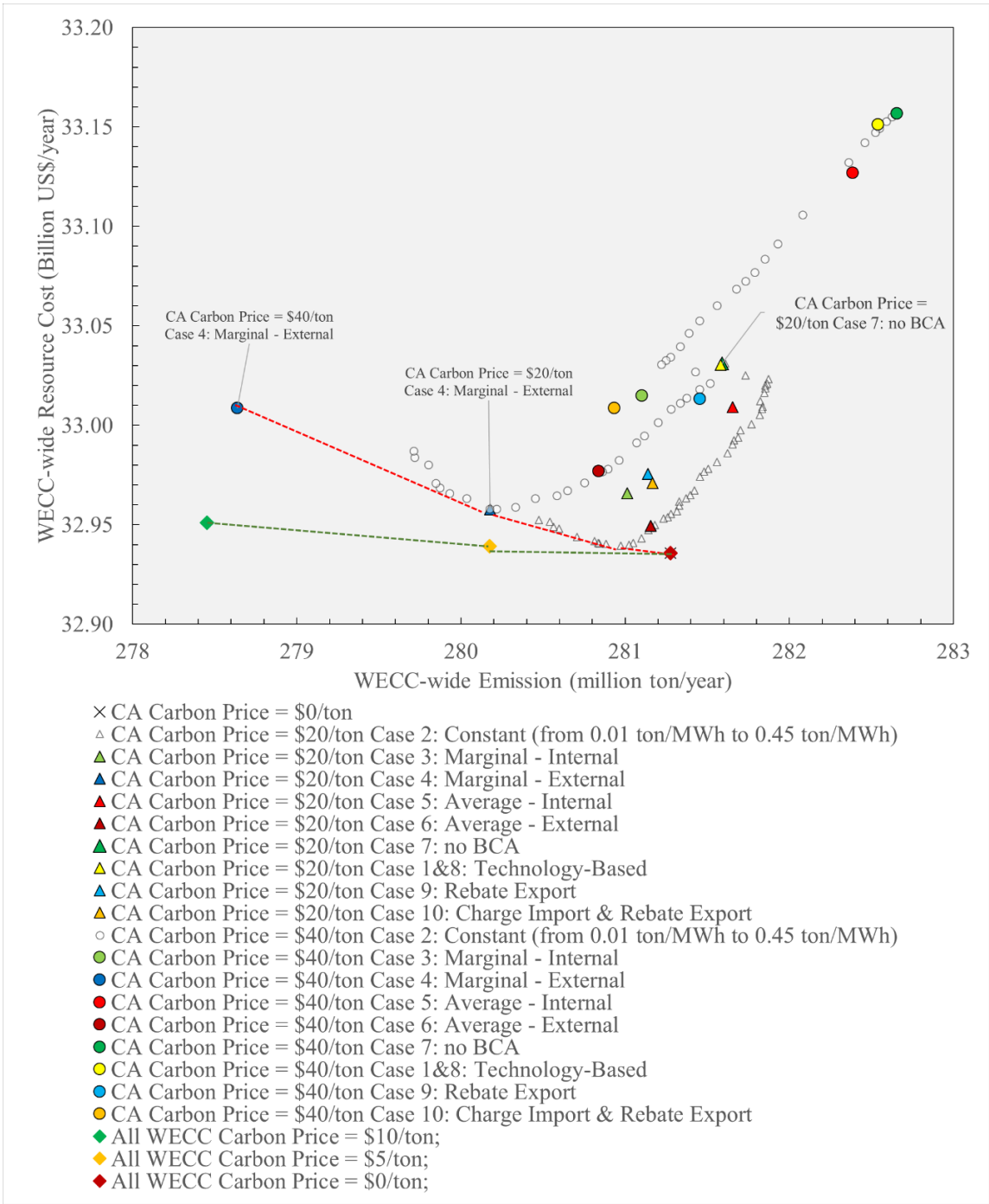

Figure 6.21. Trade-offs between WECC resource costs and emissions (different colors stand for different BCA schemes; triangles stand for cases with carbon price = $20/ton under various deemed rates; circles stand for cases with carbon price = $40/ton under various deemed rates; red dashed line shows efficiency frontier (from Cases 0-10); green dashed line and diamonds show the efficiency frontier formed by assuming carbon prices of $0, $5, and $10/ton WECC-wide)

Turning to a comparison of particular deemed rate policies within Group One (import charges only), although the deemed rate schemes based on marginal external emissions lie on the frontier, none of the time-varying deemed rates clearly dominates the deemed emission rate without time-variation. Meanwhile, with only several exceptions, higher deemed rates generally lead to higher economic efficiency by simultaneously lowering system cost and emissions (i.e., moving in the southwest direction in Figure 6.21); but the amount of emissions improvement is, however, almost negligible.

For perspective, I also provide three additional points in Figure 6.21, which represent efficient benchmark policies for the entire WECC region. These are a WECC-wide carbon price/tax applied at (1) $0/ton (for British Columbia, this WECC-wide carbon price is on top of its existing carbon tax), (2) $5/ton, and (3) $10/ton. It is noteworthy that the first case is the same as Case 0. In the case of $5/ton, overall emissions are 280.17 Mtons/year, and the WECC-wide resource cost is 32.94 billion US$/year; for the case of $10/ton, the numbers are 278.45 Mtons/year and 32.94 Billion US$/year. The corresponding incremental carbon emission abatement costs for cases (2) and (3), as compared to (1), are $3.20/ton of emission reduction and $5.44/ton of emission reduction, respectively. These rates are, as would be expected, roughly halfway between $0 and the tax.

Note that the frontier formed by cases with WECC-wide carbon price (green dotted line in Figure 6.21) clearly dominates the frontier formed by the study cases 0-10 (red dotted line), highlighting the efficiency loss from the sub-regional emission regulation, as opposed to an efficient region-wide policy. The results show that California can unilaterally motivate changes in west-wide emissions, as the red frontier shows; however, the cost of doing so per ton of emissions reduction is much more than the cost of an efficient west-

wide policy. To illustrate this, note that the slopes from the x mark to either point of the red frontier (dark blue triangles) are, respectively, $19.95/ton of reduction and $27.70/ton. These costs are approximately five times as high as the incremental costs of $3.20/ton and $5.54/ton found for the cases of WECC-wide carbon price.

6.6 Conclusions and Limitations

This chapter explores the potential cost and emissions impacts of different border-cost adjustment schemes that could possibly be implemented in the California AB32 carbon pricing system. The major conclusions are summarized in Tables 6.13 and 6.14, and are further discussed below.

Table 6.13. Major conclusions of Chapter 6 (Part 1)

Comparison	Major conclusions for Year 2034	Example
No Carbon Pricing vs. Carbon Pricing without BCA (Case 0 vs. Case 7)	Due to the imposed California carbon price: a. California emissions decrease, but WECC-wide emissions increase. The emission leakage is majorly due to the shift of gas-fired power from existing gas power plants of California to the ones in the Rest of WECC. b. More transmission expansion happens as carbon pricing without BCA essentially promotes more imports. c. Costs to consumers increase, no matter whether the CAISO or the state government transfer carbon and congestion rents to consumers. d. WECC suffers economic efficiency losses as both WECC-wide emissions and WECC-wide resource cost increase, and therefore Case 7 does not lie on the efficiency frontier for California policy cases.	Carbon Price = $40/ton, Case 7 has 0.22 Billion US$/year higher WECC cost, $4.92/MWh higher California wholesale price ($2.41/MWh if with reimbursement), 1.26 Mtons/year higher WECC-wide emissions, 972 MW more backbone transmission construction. Case 7: Leakage (increases in Rest-of-WECC emissions) is 19.26 Mtons/year and larger than the within California emission reduction 17.88 Mtons/year. The leakage ratio is at 107.7%.
Constant Technology-Neutral Deemed Rates vs. Carbon pricing without BCA (Case 2 vs. Case 7)	Compared to carbon pricing without BCA, the BCA that adopts a constant deemed rate will: a. Mitigate carbon leakage by bringing gas-fired power production from ROW back to California. b. Discourage transmission expansion. And the higher the deemed rate is, the fewer transmission expansions are. c. Without reimbursement from CAISO or the state government, the costs to consumers increase with a higher constant deemed rate. With reimbursement, however, the cost to consumers is nearly constant and can be lower than the no BCA case. d. With only several exceptions, a higher deemed rate leads to system economic efficiency gain, i.e., lower WECC-wide emission and lower WECC-wide resource cost. Some policies are on the economic efficiency frontier of California policy cases.	Carbon Price = $40/ton, and a deemed rate of 0.41 T/MWh, Compared to Case 7, Case 2 has 0.19 Billion US$/year lower WECC cost, $4.15/MWh higher California wholesale price ($0.75/MWh lower if with reimbursement), 2.78 Mtons/year less emissions, 1042 MW less backbone transmission construction. In Case 2: Leakage is negative at -6.01 Mtons/year, California emissions increase by 4.60/Mtons/year.

Table 6.14. Major conclusions of Chapter 6 (Part 2)

Time-varying Technology-Neutral Deemed Rates vs. Constant Deemed Rate (Case 3-6 vs. Case 2)	Allowing deemed rates to vary over the year generally: a. Leads to more emission leakage mitigation, but the system-wide emissions barely change, with one exception: b. Time-variation based on external marginal emission rates can relatively increase emission leakage but can also lead to emission cut by demoting coal-fired power in ROW. c. Introduces a small increase in cost to consumers if the ISO or the state government provides reimbursement. d. Time-varying deemed rates do not dominate its constant counterpart in terms of system cost and emissions, except cases based on the external marginal emission rate. Such a BCA scheme also lies on the economic efficiency frontier among all the California policy cases.	Carbon Price = $40/ton, and using non-California marginal emission rates, Compared to Case2, Case 4 has 0.04 Billion $/year higher WECC cost, $0.11/MWh lower California cost ($0.33/MWh higher with reimbursement), 1.24 Mtons/year lower WECC-wide emissions. In Case 4: Leakage in that case is negative at -3.10 Mtons/year, California emissions increase at 0.46 Mtons/year.
Rebate vs. No Rebate Exports (Case 10 vs. Case 1 or 8)	Rebating exports in addition to charging imports can a. Mitigate carbon leakage by incentivizing gas power exports. It promotes emission-free generation expansion in ROW states from which California LSEs are permitted to directly buy renewable power; however, most of this "promised" emission cut is offset by the decrease of renewable energy production in other ROW states. b. Discourage transmission expansion as less imports are needed. c. Reduce costs to consumers without reimbursement; in case reimbursement exists, costs to consumers can increase. d. Provide economic efficiency gain, i.e., lower WECC-wide emission and lower WECC-wide resource cost, thereby lying on the efficiency frontier of California policy cases...	Carbon Price = $40/ton, and using technology-specific emission rates, Compared to Case 1 or 8, Case 10 has 0.14 Billion $/year lower WECC cost, $2.13/MWh lower California cost ($0.23/MWh lower with reimbursement), 1.61 Mtons/year lower WECC-wide emissions, 719 MW less backbone transmission construction. In Case 10: Leakage in that case is 2.61 Mtons/year; California emission reduction is 2.95 Mtons/year. Leakage percentage is 88.5%.

I have compared two broad groups of BCA alternatives. Group One focuses on the deemed rate schemes assumed for power imports to California, while Group Two focuses on exploring the potential benefit of different combinations of export rebates and import charges. For the emission regulator of Californian, which would aim to cut overall emissions without being overly compromised by potential carbon leakage and the sudden

rise of the consumer payments, adopting a deemed rate scheme that is based on external marginal emissions or rebating exports in addition to charging imports can be promising alternatives.

To justify this recommendation, I first consider the impacts within California, which is the subject of the first question asked at the beginning of this chapter: *For a unilateral carbon pricing jurisdiction in an interconnected electricity market, how will BCA schemes affect emission reductions, emission leakage, regional electricity production, transmission expansion, and consumer payments?* It turns out that changing from a technology-based deemed emission rate (the present policy of the California Air Resources Board under AB32) to technology-independent deemed rates for imports indeed mitigates carbon leakage. For instance, comparing Case 1 (Technology-based) and Case 3 (time-varying internal marginal emission rate), the leakage is reduced from 13.64 Mtons/year to 3.92 Mtons/year when carbon price = $20/ton. (For the $40/ton scenario, this reduction is from 18.94 Mtons/year to 6.19 Mtons/year.) Also, that change in policy would result in emissions reductions WECC-wide rather than the emission increases that occur in Case 1.

Furthermore, among the investigated time-varying deemed rates, the one based on external marginal emissions delivers the most leakage mitigation. In the same case, WECC-wide emission reduction also occurs due to incremental solar capacity expansion and decreased coal power production. However, in all other cases, system-wide emissions barely decrease (and can increase, at least in several considered cases) if only imports are charged. This highlights that reducing leakage by assigning a technology-independent deemed rate to imports simply shifts gas-fired generation from outside California to within California. Results also show that a technology-neutral deemed rate can discourage

interstate transmission expansions, especially ones connecting California to the Rest of the WECC: the higher the deemed rate (in case of time-varying deemed rate, the annual average), the less interstate transmission lines will likely be built.

On the other hand, rebating emission expenses for California generation that is exported can partially mitigate leakage and reduce WECC-wide emissions relative to import-only BCA, but only to a very limited extent. The results also show that the action of charging imports with technology-based deemed rates barely affects transmission expansion relative to no BCA, while on the other hand, the action of rebating exports lowers the value of incremental transmission addition, and hence, less transmission capacity is expanded.

The above discussion also answers the second question: *Among all California-only policies, which BCA provides the most system-wide economic efficiency improvement?* As shown in Figure 6.21, it is the BCA scheme that bases the deemed rate on the marginal external emissions. Some solutions with higher fixed deemed rates also are cost-effective compared to other California-only policies, but do not provide as many emissions reductions. However, the incremental cost of all of these policies is about five times as high per ton of carbon removed as a WECC-wide carbon price policy that applies to all the region's emissions. Thus, the cost of the limited emissions reductions from even a large state going it alone is very high compared to coordinated regional or national policies. A single state policy would have to be justified by a lack of regional or federal alternatives, or by a desire to exercise leadership by showing the political and technical feasibility of reductions, thereby possibly increasing the probability of later regional or federal action.

However, my conclusions here are limited by, and likely sensitive to, the assumptions I made and the data I used. I highlight two limitations that should be addressed in future work:

1) In order to make the Gauss-Seidel iterative procedure for calculating marginal emissions practical, I dropped some constraints that were included in the JHSMINE versions in Chapters 3, such as DC load flow (rather than the pipes-and-bubbles considered here), convexified unit commitment (rather than merit-order commitment without intertemporal constraints), binary limitation of transmission expansion (rather than continuous expansion), and storage operations and investment, which will surely affect the results.
2) My BCA alternative list is not exhaustive: one can easily imagine that the emission regulator could choose to charge imports by, for example, discriminating between renewable generation and existing generation, or new versus existing generation investments. This would potentially provide incentives for the ROW to install more renewable capacity.

Chapter 7 Conclusions and Future Research

In this chapter, I will first review the conclusions that I have drawn in the main text, as well as some limitations to those conclusions (Section 7.1). These limitations also indicate potential avenues for future research, as discussed in Section 7.2.

7.1 Research Conclusions

Researchers and practitioners have both contributed to expanding the capability of power system planning models. Many ideas have been proposed for elaborating the models to improve their fidelity or enable those models to address new questions. However, due to limited computational capabilities, we cannot implement them all. We need to make a choice.

This situation motivates Chapter 3, the first part of this work, which is about evaluating the choices. More specifically, I addressed the following questions: *What, precisely, is a "better" planning model? How can we value, in economic terms, the extent to which one planning model performs better than another?* In Chapter 3, I proposed a systematic framework to quantify the economic benefits brought by possible enhancements to transmission expansion planning (TEP) models. I call the estimated benefits the *value of model enhancement*, VOME. It is closely related to the decision analysis concept of the *value of information*, and to my knowledge, is new to the literature.

To show the practicality of this framework, I tested it by evaluating four optional enhancements to transmission planning models: the consideration of long-run uncertainties by stochastic programming, the refinement of short-run temporal resolution by adding more load slices, the refinement of power flow representation by adding DC OPF, and the refinement of generation modeling by adding unit commitment. The test involved the use

of a TEP for the Western Electricity Coordinating Council (WECC), and concluded that the most beneficial choice is the consideration of long-term uncertainty; the VOMEs of the other choices are much less. It can be concluded, , therefore, that (1) it is beneficial to devote more effort and to allocate more resources to carefully identify relevant long-run uncertainties; and (2) a simple stochastic programming model with a small set of hours and a pipes-and-bubbles power flow simulation, which solves much faster than the most sophisticated model, can potentially yield a plan that achieves most of the potential economic benefits.

As mentioned above, power systems are continually changing, and one of the many examples is the emergence of affordable battery energy storage. *Are transmission and storage complements or substitutes?* Both transmission and storage promise to lower the cost of accommodating the increasing amount of variable renewable energy, and for that reason they appear to substitute for each other. Put simply, we either save the excess energy for later when it is needed or transmit it to another location where it is needed. However, as identified in the literature, e.g., Neetzow et al. (2018), under some circumstances transmission and storage can instead be complementary. Thus, an unambiguous answer to the complement or substitute question is thus not available.

Motivated by this, in Chapter 4, I asked and answered a set of different questions that have not appeared in the literature before: *How much benefit can we get in transmission expansion planning by anticipating storage expansion, accounting for both potential substitution and complementary relationships? How much potential benefit is lost because the transmission naively ignores the possibility of storage expansion?*

With the help of the VOME framework, in Chapter 4, I answered these questions using the WECC test case. The results reveal that: (1) the economic value brought by anticipating storage installation in TEP, which I called Value of Model Enhancement to consider Storage (VoMES), increases when the cost of storage decreases, implying a higher impact of storage installation upon the transmission expansion; (2) this VoMES is a net result of two factors: capital cost increase introduced by more renewable energy and storage installation and the consequent operation costs saving; (3) the naïve plan obtained by TEP without storage installation anticipation will cause a loss of potential net benefit (with an average loss of 14%) of storage investment; and (4) this VoMES of TEP can be sensitive to the carbon pricing policy. These results are, of course, limited to my test system.

In Chapters 5 and 6, I used the TEP model as a policy impact assessment tool and answered the following questions: *Can a state regulator significantly affect system emissions, costs, and emissions leakage by taxing or otherwise pricing of the carbon flowing into the state?*

To answer these questions, I modified my TEP model in Chapter 5, and in Chapter 6, I tested my model in the WECC system, where California, a unilateral carbon pricing jurisdiction, is located. I looked at different border carbon adjustment (BCA) alternatives and examined their impact on emission and leakage, power system investment and dispatch, transmission expansion, consumer costs, and WECC-wide economic efficiency.

The results of Chapter 6 showed that the current Californian border carbon adjustment (BCA), which charges imported power based on the emission rate of the producer's side of a power import contract, suffers a substantial amount of carbon leakage.

For instance, when California's carbon price is at $40/ton, compared to the no carbon price scenario, the rest of WECC emissions *increase* by 18.94 Mtons/year while California's emissions only decrease by 17.67 Mtons/year. In this case, the leakage percentage is 107% (= 100% × 18.94 ÷ 17.67), and carbon pricing in California *increases* the net WECC-wide emissions in the power sector. On the other hand, BCA alternatives that charge imports at technology-neutral deemed rates, including the BCA schemes that base deemed rates on marginal or average emission rates, indeed help to mitigate emission leakage. For example, when the California carbon price is at $40/ton, and the California emission regulator charges imports at the external marginal emission rates, the emission leaked to the ROW is only -3.10 Mtons/year (in fact, this is a negative leakage). Nevertheless, this leakage mitigation is accompanied by an increase in California emissions of 0.46 Mtons/year. Charing imports with at the external marginal emission rates bring the most system-wide emission reduction (3.10 – 0.46 = 2.64 Mtons/year when carbon price = $40/ton, 1.10 Mtons/year when carbon price = $20/ton), but reduction amount is <1% compared to the emission level without a carbon price. Rebating emissions costs associated with California exports in addition to charging imports can also increase WECC-wide emission reductions, but only to a limited extent.

However, all cases that I investigated are significantly more expensive than an efficient west-wide carbon tax. As shown in the results of Chapter 6, comparing to the WECC-wide carbon tax, the resource cost increase per emission reduction (or abatement cost in short) resulting from the most efficient California BCA is about five times as expensive as a WECC-wide carbon price that accomplishes the same reduction.

7.2 Future Research

As I have previously discussed, the results and conclusions of Chapters 3 and 4 concerning the value of improved transmission models are, of course, limited to the test system and data I considered. Testing the same four modeling choices in Chapter 3 or the proactive consideration of storage modeled in Chapter 4 for another test system may give appreciably different answers as to which model improvements matter most for planning. As an example, planning for a power system with a large coal/nuclear fleet will clearly benefit from unit commitment modeling, and so even though that improvement didn't matter much in the gas- and renewable-dominated WECC system we assumed for 2034, it might be important for other situations. On the other hand, as technology and policy continually evolve, so will power systems. Ten years from now, the answers I get for the WECC system may also be dramatically different from what I obtained in this thesis.

Future research that could improve and build upon Chapter 3 includes (1) expanding the scope of the evaluation, and (2) using the obtained information to develop a possible new planning paradigm. The first point is obvious: I only test four out of eight general categories of possible enhancements identified in Table 3.1 of Chapter 3; in fact, Chapter 4 represents one of these other extensions. The second area for future work is also attractive: one of the results in Chapter 3 implies that a simple model (a stochastic program that has multiple long-run scenarios but includes only a pipes-and-bubbles power flow and a small set of hours) can capture most benefits of transmission expansion planning. This result implies that we can possibly use a simple but easy to solve model as a filter to preselect transmission candidates for more detailed analysis, such as possible transmission line corridors. With a smaller list of candidate corridors, a much more enhanced model

can be executed, especially if transmission expansion is modeled by binary variables, and possibly provide a much more beneficial plan. For instance, with fewer corridors, more high voltage lines, and other line configuration alternatives for those corridors can be modeled, together with more sophisticated load flow methods.

Desirable future research related to Chapter 4 includes the introduction of two missing elements to the analysis to provide a fairer comparison between transmission and storage. These are (1) the lifetime loss of storage capability due to deep cycling, and (2) transmission losses. In the results shown in Chapter 4, the assumed lifetime of battery storage is already much shorter than for transmission lines, and this fact is reflected in the calculation of annualized capital cost. However, as pointed out by the literature, e.g., Xu et al. (2018a), the lifetime of the battery can be much shorter if it is operated in a deep cycling mode; as a result, the current JHSMINE formulation which disregards this cost of deep cycling may, therefore, introduce bias. Similarly, disregarding transmission losses in Chapter 4 may give too much advantage to transmission candidates. Both storage and transmission involve losses in reality: to save electricity for later with storage, we must suffer an efficiency loss;[43] in the same vein, transmitting power far away results in I^2R resistance losses. Thus, proper transmission loss modeling may provide a more balanced comparison. Adding transmission loss in the TEP model has been explored in literature, for example, by Ozdemir et al. (2016).

For Chapters 5 and 6, the limitations of this analysis of BCA present opportunities for future work to investigate the interaction between carbon and renewable policies. In my current implementation, the ineffectiveness of technology-neutral deemed rates is

[43] Which is modeled in JHSMINE and Chapter 4.

partially due to the fact of high prices for in-state renewable energy credits in California. As a result, the economic incentives provided by technology-neutral deemed rates can only boost Californian gas-powered generation and consequently increase California emissions. Questions that remained unanswered include: *How would the carbon policy and renewable policy interact under alternative assumptions concerning the amount of California resources, or the existence and stringency of renewable policies in the West? What if other states, such as Oregon and Washington, implement carbon pricing?* Beside, in order to make the Gauss-Seidel iterative procedure for calculating marginal emissions practical, I dropped some constraints that were included in the JHSMINE versions in Chapters 3, such as DC load flow (rather than the pipes-and-bubbles considered here) and convexified unit commitment (rather than merit-order commitment without intertemporal constraints). Investigating how these simplifications affected my result would be also an interesting extension of this research.

To conclude, coming up with new model formulations and capabilities is usually assumed to improve planning, but this is not necessarily the case. Indeed, it is well recognized in other fields, such as ecology, that more complex models are not necessarily better in prediction system outcomes (Radosavljevic et al., 2014). The benefits of planning enhancements should be assessed, and compared to their costs. These benefits include not only potentially more economic grid expansion plans, but also better policy designs; the value of improved models for better policy decision making has not been systematically addressed, and should be a topic of future research.

Appendix A – Central Planning and Perfect Competition

In this appendix, I provide abstract proofs for two key arguments that I asserted to be true in the main text of this thesis:

1) If solved to optimal, the linearized transmission-generation-storage expansion planning (L-TGSEP in short) is equivalent to the equilibria formed by the perfect competition among transmission, generation, and storage with the capability of expansion of each; in short, central planning and perfect competition (Samuelson, 1952).
2) The transmission-generation-storage expansion planning with binary transmission expansion (B-TGSEP in short) is equivalent to a situation where transmission expansion planner is a societal-welfare maximizing leader, and all players react perfectly competitively to the transmission expansion decisions and the short-run locational marginal prices. See Spyrou (2019) for related proof.

Before delving into the proofs, here is some notation that only applies in this appendix.

I	Players, $i = 1 \dots n$; where the player 1 is reserved for transmission planner.
J	Markets, $j = 1 \dots m$; note that the market here can be any market, e.g., electricity markets, energy credit markets, ancillary service markets, or capacity markets; more specifically, these markets can differ within themselves by time and location; e.g., electricity market at node A and Hour h.
A_i^b, A_i^s, A_i^o	Matrices associated with constraints of the player i and its "buy/sell/other" decision variables.
b_i	Vectors of the right-hand sides of the constraints of the player i;
c_i^b, c_i^s, c_i^o	Vectors of coefficients in objective functions; the length of the first two vectors is m, while the length of the third varies by players.

p Vector of the market-clearing prices; the length of this vector is m in that there exist m markets.

R Vector of the right-hand sides of the market-clearing conditions; the length of this vector is m in that there exist m markets.

x_i^b Vectors of "buy" decision variables of the player i; as there are m markets, the length of this vector is m.

x_i^s Vectors of "sell" decision variables of the player i; as there are m markets, the length of this vector is m.

x_i^o Vectors of all "other" decision variables of the player i; a decision variable is an "other" decision variable if it does not participate in any market activity. The length of this vector varies by players. Examples are capacity variables if there exists no capacity market, or slack/surplus/artificial variables to be added for the Standard from of Simplex.

β_i Vectors of the shadow prices of the constraints of the players i in the central planning.

γ Vector of the shadow prices of the market constraints in the central optimization.

λ_i Vectors of the shadow prices of the constraints of the player i;

I prove the first result by showing the one-to-one correspondence between the union of the Karush–Kuhn–Tucker conditions (KKTs) of individual planers & market-clearing conditions and the KKTs of the central planning. To start, let us see, for each individual player i, its optimization is as following (notice that the equal sign "=", the less or equal sign "≤", and the greater or equal sign "≥" are all element-wise)

$$
\begin{aligned}
\text{Minimize } (\forall i) \quad & -(c_i^b)^T x_i^b + (c_i^s)^T x_i^s + (c_i^o)^T x_i^o + p^T (x_i^b - x_i^s) \\
\text{s.t.} \quad & A_i^b x_i^b + A_i^s x_i^s + A_i^o x_i^o = b_i \quad (\lambda_i) \\
& x_i^b, x_i^s, x_i^o \geq 0
\end{aligned} \quad .
$$

Please note that the notation of this problem is the standard form of the linear programming (Nocedal and Wright, 2006) and is general enough to represent any player that participates in markets so long as his optimization is linear; this includes generation expansion with relaxed unit commitment, storage expansion, transmission expansion with relaxed expansion decision, etc. Specifically, the last term of the objective function is the revenue or payment generated in all markets. The corresponding KKTs are as follows (here I call these conditions O_i):

$$
\left.
\begin{aligned}
& 0 \leq x_i^b \perp -c_i^b + p - (A_i^b)^T \lambda_i \geq 0 \\
& 0 \leq x_i^s \perp c_i^s - p - (A_i^s)^T \lambda_i \geq 0 \\
& 0 \leq x_i^o \perp c_i^o - (A_i^o)^T \lambda_i \geq 0 \\
& \lambda_i \text{ free}, A_i^b x_i^b + A_i^s x_i^s + A_i^o x_i^o = b_i
\end{aligned}
\right\} O_i \quad \forall i
$$

Then, I cast the market clearing conditions as follows (here I call it M):

$$
\sum_i (x_i^s - x_i^b) = R \, .
$$

On the other hand, I cast the central planning problem; i.e., a societal welfare maximization, as follows (please note that I cast it in a minimization form):

$$
\begin{aligned}
\text{Minimize} \quad & -\sum_i (c_i^b)^T x_i^b + \sum_i (c_i^s)^T x_i^s + \sum_i (c_i^o)^T x_i^o \\
\text{s.t.} \quad & A_i^b x_i^b + A_i^s x_i^s + A_i^o x_i^o = b_i \quad (\beta_i) \quad \forall i \\
& \sum_i (x_i^s - x_i^b) = R \quad (\gamma) \\
& x_i^b, x_i^s, x_i^o \geq 0 \quad \forall i
\end{aligned} \quad .
$$

I give the KKT conditions associated with the central planning as follows, (here I called them CP):

$$
\begin{aligned}
&0 \le x_i^b \perp -c_i^b + \gamma - (A_i^b)^T \beta_i \ge 0 \quad \forall i \\
&0 \le x_i^s \perp c_i^s - \gamma - (A_i^s)^T \beta_i \ge 0 \quad \forall i \\
&0 \le x_i^o \perp c_i^o - (A_i^o)^T \beta_i \ge 0 \quad \forall i \\
&\beta_i \text{ free}, A_i^b x_i^b + A_i^s x_i^s + A_i^o x_i^o = b_i \\
&\gamma \text{ free}, \sum_i (x_i^s - x_i^b) = R.
\end{aligned}
$$

It thus readily follows that there is a one-to-one correspondence between the "*CP*" and the union of "O_i for all i" and "M". Specifically, there is a correspondence between shadow prices: $\beta_i \leftrightarrow \lambda_i$ and $\gamma \leftrightarrow p$. Since the central planning model is a linear program, its KKT conditions sufficiently and necessarily define its optimal solution; on the other hand, as its KKTs are the same as the union of individual KKTs of each player and market clearing constraints, the optimal solution of central planning supports the equilibria formed by each player.

The proof from the other direction follows the same logic: if a solution (x, λ, p) supports equilibria; i.e., it satisfies all individual KKTs and market clearing conditions, it must be an optimal solution of the central planning model. This completes the proof of the equivalence between the central planning and the perfect competition, the famous Samuelson Principle mentioned in Samuelson (1952).

The second result awaiting proof is as follows: the TGSEP with binary transmission expansion decision variables; i.e., B-TGSEP is equivalent to a situation where transmission expansion planner is maximizing societal welfare while anticipating everyone will react in perfect competition to the transmission expansion decision. To prove this result, initially, I recast the central planning model with one modification; that is, I restrict the "other" variable of the transmission expansion planner, x_1^o, to be binary:

$$
\begin{aligned}
\text{Minimize} \quad & -\sum_i (c_i^b)^T x_i^b + \sum_i (c_i^s)^T x_i^s + \sum_i (c_i^o)^T x_i^o \\
\text{s.t.} \quad & A_i^b x_i^b + A_i^s x_i^s + A_i^o x_i^o = b_i \quad \forall i \neq 1 \\
& A_1^b x_1^b + A_1^s x_1^s = b_1 - A_1^o x_1^o \\
& \sum_i (x_i^s - x_i^b) = R \\
& x_i^b, x_i^s \ \forall i; \quad x_i^o \geq 0 \ \forall i \neq 1; \quad x_1^o \in \{0,1\}.
\end{aligned}
$$

As a result, this B-TGSEP is a mixed-integer program (MIP), which is lacking KKT-based optimality conditions; therefore, an equivalency towards perfect competition is not readily available.

To help me move forward, here is an essential intermediate result: given the existence of an optimal solution of a math program *MP*, one can separate the optimal solution into any two partial results, say x^* and y^*. Then by fixing x^* in *MP*, he can get a second math program, say MP_x; it readily follows that y^* is an optimal solution of MP_x. To put it formally, I have:

$$
\begin{aligned}
\text{if} \quad & (x^*, y^*) = \arg\min_{(x,y)\in F} f(x, y) \\
\text{then} \quad & y^* = \arg\min_{(x,y)\in F, x=x^*} f(x, y).
\end{aligned}
$$

This intermediate result can be proved by contradiction: if y^* is not an optimal solution of MP_x and the feasible region (given x^*) is not empty because y^* is one of feasible solution of MP_x, there must exist another $y' \neq y^*$ such that $f(x^*, y') < f(x^*, y^*)$ and (x^*, y') is also feasible. This violates the statement of (x^*, y^*) being one optimal solution of the problem *MP*.

Now, turn back to the B-TGSEP, and suppose that I solved it to the optimal and have an optimal solution:

$$
\left[x_1^{b*}, x_1^{s*}, x_1^{o*}, \left(x_i^{b*}, x_i^{s*}, x_i^{o*} \right)_{i\neq 1} \right].
$$

By fixing the transmission expansion solution, x_1^{o*}, in the central planning problem, it should be clear to readers that the following is true (note the terms in red):

$$\left[x_1^{b*}, x_1^{s*}, \left(x_i^{b*}, x_i^{s*}, x_i^{o*}\right)_{i\neq 1}\right] \quad \text{is the optimal solution of}$$

$$\begin{aligned}
\text{Minimize} \quad & -\sum_i (c_i^b)^T x_i^b + \sum_i (c_i^s)^T x_i^s + \sum_{i\neq 1} (c_i^o)^T x_i^o \\
\text{s.t.} \quad & A_i^b x_i^b + A_i^s x_i^s + A_i^o x_i^o = b_i \quad (\lambda_i) \quad \forall i \neq 1 \\
& A_1^b x_1^b + A_1^s x_1^s = b_1 - A_1^o x_1^{o*} \quad \lambda_1 \\
& \sum_i (x_i^s - x_i^b) = R \quad (p) \\
& x_i^b, x_i^s \ \forall i; \quad x_i^o \geq 0 \ \forall i \neq 1.
\end{aligned}$$

In other words, the B-TGSEP problem, an MIP, can be recast as follows, a Stackelberg-Game (or leader-follower game):

$$\begin{aligned}
\text{Minimize} \quad & -\sum_i (c_i^b)^T x_i^b + \sum_i (c_i^s)^T x_i^s + \sum_i (c_i^o)^T x_i^o \\
\text{s.t.} & \left\{ \begin{array}{ll}
\text{Minimize} & -\sum_i (c_i^b)^T x_i^b + \sum_i (c_i^s)^T x_i^s + \sum_{i\neq 1} (c_i^o)^T x_i^o \\
\text{s.t.} & A_i^b x_i^b + A_i^s x_i^s + A_i^o x_i^o = b_i \quad (\lambda_i) \quad \forall i \neq 1 \\
& A_1^b x_1^b + A_1^s x_1^s = b_1 - A_1^o x_1^o \quad \lambda_1 \\
& \sum_i (x_i^s - x_i^b) = R \quad (p) \\
& x_i^b, x_i^s \ \forall i; \quad x_i^o \geq 0 \ \forall i \neq 1.
\end{array} \right\} \\
& x_1^o \in \{0,1\}
\end{aligned}$$

Now, readers may have noticed that the math program in the parenthesis is a linear program: a linear generation-storage expansion planning problem; and thus, there exists an equivalent perfect competition equilibrium among each player (the first result I proved in this appendix). Thus, by substituting the math program inside the parenthesis by the equilibrium condition, B-TGSEP problem can be equivalently recast as:

$$
\begin{aligned}
&\text{Minimize} \quad -\sum_i (c_i^b)^T x_i^b + \sum_i (c_i^s)^T x_i^s + \sum_i (c_i^o)^T x_i^o \\
&\text{s.t.} \left\{ \begin{array}{l}
0 \le x_i^b \perp -c_i^b + p - (A_i^b)^T \lambda_i \ge 0 \quad \forall i \\
0 \le x_i^s \perp c_i^s - p - (A_i^s)^T \lambda_i \ge 0 \quad \forall i \\
0 \le x_i^o \perp c_i^o - (A_i^o)^T \lambda_i \ge 0 \quad \forall i \ne 1 \\
\lambda_i \text{ free}, A_i^b x_i^b + A_i^s x_i^s + A_i^o x_i^o = b_i \quad \forall i \ne 1 \\
\lambda_1 \text{ free}, A_1^b x_1^b + A_1^s x_1^s = b_1 - A_1^o x_1^o \\
p \text{ free}, \sum_i (x_i^s - x_i^b) = R.
\end{array} \right\} \\
&x_1^o \in \{0,1\}
\end{aligned}
$$

Then I can conclude the following is true: the TGSEP with binary transmission expansion decisions (B-TGSEP) is equivalent to a situation where transmission expansion planner is maximizing the societal welfare anticipating that all players react perfectly competitively to the transmission expansion decisions; in other words, transmission expansion planner is a societal planning leader. The meaning of the assumption that all players are in perfect competition is two-fold: it requires not only perfect competitive short-run markets, but also no strategic behavior in the expansion planning of generation and storage.

Appendix B – Network Reduction Procedure

This appendix demonstrates the network reduction procedure that I performed to produce the 300-bus network used in Chapter 3 and the 361-bus network used in Chapter 6. This network reduction procedure adopts the algorithm developed in Zhu and Tylavsky (2018). For a general review of network reduction methods, also see Zhu and Tylavsky (2018). The general steps involved in executing this method are as follows:

1) *Read Inputs:* The inputs include a power flow case, the original network, and a set of buses the user wants to preserve; hereafter, preserved buses. The power flow case records the withdraws/injections and power flows on transmission lines. The original network records the rating, the impedance, the from-bus, and the to-bus of each transmission line; furthermore, it records if any bus is a generator bus, a load bus, or the slack bus.
2) *Network Reduction One:* The algorithm preserves all transmission lines that directly connect the preserved buses. For other lines, the algorithm creates "equivalent" lines and associated impedances based on Ward's equivalent circuit calculation (Ward, 1949); no rating is provided. For details of how equivalent lines are created, please see Zhu and Tylavsky (2018). Importantly, there is no membership of which lines are aggregated into which equivalent line.
3) *Network Reduction Two:* The algorithm preserves existing lines and generates the new equivalent ones again; however, in this step of the network reduction, transmission lines between a larger set of buses are preserved, which is the union of preserved buses and generator buses.

4) *Shortest-Path Finder:* For a given generator bus, the algorithm executes the shortest pathfinder to find which preserved bus is the closest in the second reduced network. The closeness of two buses is defined as the electrical distance, where the definition can be found in Allen et al. (2008) and Shi et al. (2012). This step creates a membership between the generator buses and the preserved buses.

5) *Generators Replacement:* Return to the first reduced network: the generators and associated injections are moved to the closest preserved bus identified in step 5.

6) *Load Redistribution:* The algorithm recalculates the load on every bus, such that power flows on the preserved lines are the same as the original power flow case. Again, there exists no membership between the original load buses (and withdrawal) and the preserved bus.

7) *Output Report:* The outputs include: the reduced network (obtained in step 2), generator bus – preserved bus membership, and finally, recalculated load on each bus.

Now, the network reduction procedure followed in this thesis is slightly different due to the critical role of the membership between the original load buses and the preserved buses. This membership is essential for the calculation of *how the load is distributed from the balancing authority area (BAA) level to the reduced network*. Suppose load distribution factor of the original network is called $OD_{a,i'}$, where a is the index of BAA and i' is the index of the original bus. Further assume I have a membership between the original bus to the preserved bus is available and call it $MB_{i,i'}$, where i is the index of the reduced network bus. The load distribution factor of the preserved network $PD_{a,i}$ can be calculated as:

$$PD_{a,i} = \sum_{i'} MB_{i,i'} OD_{a,j}$$

To construct the membership $MB_{i,i'}$, instead of completely following the algorithm above, I modified step 3 and 4 of the algorithm: by providing the union of generator buses and load buses to the algorithm while it produces the second reduced network in step 3, the membership between the generator buses plus the load buses and the preserved buses will be created in step 4. Step 6 is, thus, ignored.

Importantly, load replacement using $PD_{a,i}$ cannot guarantee the power flows on the preserved lines are identical between the reduced network and the original network; this necessitates the quality assurance procedure for network validation. For example, in this thesis, I constructed and checked a map of reduced network with generators, load pockets, which is provided in (Xu and Hobbs, 2018). Furthermore, I also performed the product cost modeling to make sure the power flows pass the sanity check; e.g., California is importing on path 66, also known as California Oregon Intertie (COI), etc.

The details of 300-bus network reduction can be seen in Ho et al. (2016), and the details of the 361-bus network can be seen in Xu and Hobbs (2018). In principle, I preserved most WECC paths (WECC, 2013b) by preserving high voltage lines (≥ 230 kV) in the paths.

Appendix C – Generation Aggregation

This appendix documents the generation aggregation procedure I followed in this thesis. The generator aggregation is a two-step process: (1) identifying which generators can be aggregated as one; (2) calculating the operation parameters of the aggregated generators from individual ones.

In the database of this thesis, for generators to be aggregated as one (step 1), generators must have the following parameters in common; I also call them the aggregation criteria:

1) State ownership: they must be owned/contracted by companies in the same state.
2) Balancing Authority Area membership: they must be in the same balancing authority area.
3) Generating Technology
4) Bus: they must be located on the same bus on the reduced network. Such membership is obtained from the network reduction procedure (See the previous appendix).
5) Fuel: for two generators to be aggregated into one, they must use the same fuel; e.g., two coal plants that are both using Wyoming coal are eligible to be aggregated into one if they also satisfy other aggregation criteria.
6) Time-series: for two units to be aggregated into one, they must share the same availability time series. It is usually the case that they are generators of the same dam, wind farm, or solar farm.
7) Must-run status: A must-run unit can only be aggregated into another must-run unit. In my aggregation process, an original generator is a must-run unit if it is a co-generation or its minimum run is above 90% of its maximum capacity.

The second step is to calculate the aggregated parameters from the individual ones. I follow the principle of capacity-proportional output; i.e., if two generators are aggregated, they are always dispatched in proportion to their maximum capacity. With this general principle applied, I set the detailed rules as follows:

1) Maximum run (in MW): the sum of all capacities of generators being aggregated into the same one.
2) Average Heat Rate (in MMBTU/MWh): the average heat rates of different generators are aggregated using the capacity weighting method. For example, if a 1 MW generator with heat rate at 7 MMBTU/MWh is combined with a 2 MW generator with heat rate at 7.5 MMBTU/MWh, the resulting heat rate is

$$\frac{1\ \text{MW} \cdot 7\ \text{MMBTU/MWh} + 2\ \text{MW} \cdot 7.5\ \text{MMBTU/MWh}}{1\ \text{MW} + 2\ \text{MW}} = 7.3\ \text{MMBTU/MWh}.$$

The average heat rate used in aggregation is measured when the generator is at the maximum output.

3) Minimum Run (as a fraction of the maximum capacity): I used the maximum of all minimum runs of the generators being aggregated into one. For example, if a 1 MW generator with 0.5 MW (50%) minimum run is aggregated with a 2 MW generator with 0.5 MW (25%) minimum run, the result minimum run (as a fraction of maximum run) is 50%. Otherwise, if the minimum run is set at 25% and the aggregated generator is operated at 0.75 MW, according to the capacity-proportional output principle, the first generator will be operated at 0.25MW, violating its minimum run.

4) One-minute Ramp Rate (as a fraction of the maximum capacity): I used the smallest of all generators being aggregated. The reason is similar to the calculation of the minimum run.
5) Start-up cost ($/MW of maximum capacity): I used the capacity-weighted value.
6) Variable Operation and Maintenance (VOM) cost ($/MWh): I used the capacity weighted.
7) Planned Outage Rate (%): I uniformly set it to 2% for all generators.
8) Forced Outage Rate (%): I used the capacity-weighted value.
9) Minimum Downtime (hour): I used the longest minimum downtime of all the generators being aggregated into the same one; the rationale follows the example of the calculation of the minimum run.
10) Minimum Uptime (hour): I used the longest minimum uptime of all the generators being aggregated into the same one; the rationale follows the example of the calculation of the minimum run.

Appendix D – Simulation Period Selection

In this appendix, I demonstrate the procedure of the operation period selection (in this appendix, the Procedure). The Procedure aims to select the representative hours/days/weeks for the operation simulation in JHSMINE (see Chapter 2) and is an extension of the method developed in Xu and Hobbs (2018). In this appendix, the word "period" can be "hour," "day," or "week," depending on whether the reader or I am selecting "hour," "day," or "week." Also, note that all notations only apply within this appendix. For general references on period selection, I refer readers to Nahmmacher et al. (2016) and Poncelet et al. (2017).

Three processes form the base of this Procedure: (1) the clustering, (2) the random sampling, and (3) the result filtering. The clustering method is to cluster all periods (index p) into N groups, based on a specified distance metric ($D_{p1,p2}$), which the Procedure adopts to characterize the dissimilarity between different periods. Each group n will have a different size, noted as $Size_n$. For instance, the Procedure can cluster 365 days in one year into 2 groups, with $Size_1 = 200$, $Size_2 = 165$.

With all period groups established, the random sampling picks one period from each group to form a sample (index m) and then repeats this procedure M times. The third step is to filter the M samples to select the best one: by assuming the sampled period in each group will repeat $Size_n$ times, the Procedure re-constructs the whole year for each sample m. Then for each sample, a criterium C_m is calculated. Out of the M samples, the Procedure picks the one with the minimum C_m. The details of the Procedure are as follows.

Initially, the Procedure reads inputs of the following:

1) Time-series: $V_{p,t,s}$, 0 – 1 values standing for the profile of the time-series s at the time t of the period p. The time t is the hour index of the day/week p; i.e., $t \in [1, 24]$ if p is a day, while $t \in [1, 168]$ if p is a week. For instance, when I select days, $V_{1,2,3} = 0.5$ means: at the 2nd hour of day 3, the 1st time series has a value at 0.5.
2) Weight of the time-series W_s. For instance, $W_1 = 1$ and $W_2 = 0.5$ means the first time series is as twice important as the second one.
3) Period Type: choices include (a) hour, (b) day, or (c) week.
4) Time-series Distance metric: choices include (see details at the end): (a) Euclidean distance, (b) Manhattan distance (also known as City-Block distance), (c) Histogram-based distance, and (d) Cumulative-histogram-based distance. For choices (c) and (d), a total number of bins is needed for the histogram construction. Note that the inverse of the cumulative histogram is the classic duration curve.
5) A number of the representative period, i.e., a number of clusters, N. Each period is indexed with $n = 1 \ldots N$.
6) Clustering method. choices include (a) K-medoid clustering and (b) Hierarchical Clustering (James et al., 2013). For choice (b), the Procedure needs a specified tree cut method.
7) Number of random samples, M.
8) Criterium of the "best" sample. Choices include (a) total weighted deviation of means; (b) total weighted deviation of means and standard deviations, (c) total weighted deviation of histograms, and (d) total weighted deviation of cumulative histograms.

After reading the inputs above, the Procedure performs the following steps.

1) For each time series s, each period p, the Procedure constructs a histogram $H_{p,s,b,}$ and a cumulative histogram $CH_{p,s,b}$. Note b is the index of blocks of the histogram.

2) For each time series s, between each period pair $p1$ and $p2$, a distance $TSD_{s,p1,p2}$ is calculated. E.g., suppose there exist two (2) time series, and we are selecting days from 365 days; there will be 2 · 365 · 365 = 266450 elements in this $TSD_{s,p1,p2}$ matrix, as $TSD_{s,p1,p2}$ is a distance matrix, it is symmetric.

   a. Euclidean distance:

$$TSD_{s,p1,p2} = \sqrt{\sum_t \left(V_{p1,t,s} - V_{p2,t,s}\right)^2} \ ;$$

   b. Manhattan distance:

$$TSD_{s,p1,p2} = \sum_t \left|V_{p1,t,s} - V_{p2,t,s}\right| ;$$

   c. Histogram-based distance:

$$TSD_{s,p1,p2} = \sum_b \left|H_{p1,s,b} - H_{p2,s,b}\right| ;$$

   d. Cumulative-histogram-based distance:

$$TSD_{s,p1,p2} = \sum_b \left|CH_{p1,s,b} - CH_{p2,s,b}\right| .$$

3) The distance between the days are calculated as

$$D_{p1,p2} = \sum_s W_s TSD_{s,p1,p2} \ .$$

4) Use the selected clustering method to cluster the periods based on $D_{p1,p2}$, the general outputs of this step include:

   - N clusters, with each size being $Size_n$;
   - A membership between periods and clusters, $MB_{n,p}$;
   - If the K-medoid is selected, N medoids.

5) Randomly select one period from each cluster and repeat this procedure M times.

6) For each sample m, the Procedure constructs a sampled year as if the sampled period from cluster n repeats $Size_n$ times. For instance, suppose there are two groups with $Size_1 = 200$, and $Size_2 = 165$; one day from each group is sampled, and thus a sample has two days, A and B. Then a sample year is constructed, with 200 days being identical to day A and 165 identical to day B.

7) For each sample year m, each time series s, calculate the mean ($mean_{s,m}$), standard deviation ($std_{s,m}$), yearly histogram ($YH_{b,s,m}$), and yearly cumulative histogram ($YCH_{b,s,m}$).

8) The criterium is calculated as follows, where the superscript *pop* stands for the population.

   a. Total deviation of means:

$$C_m = \sum_s W_s \left| mean_{s,m} - mean_s^{pop} \right| ;$$

   e. Total deviation of means and standard deviations:

$$C_m = \sum_s W_s \left(\left| mean_{s,m} - mean_s^{pop} \right| + \left| std_{s,m} - std_s^{pop} \right| \right) ;$$

   f. Total deviation of histograms:

$$C_m = \sum_{s,b} W_s \left| YH_{b,s,m} - YH_{b,s}^{pop} \right| ;$$

   g. Total deviation of cumulative histograms:

$$C_m = \sum_{s,b} W_s \left| YCH_{b,s,m} - YCH_{b,s}^{pop} \right|$$

9) Pick up the sample with the minimum criterium. The Procedure ends here.

To pick the 4 days used in Chapter 6, I specified the inputs as follows.

1) Time-series: renewable and hydro time series data are from the WECC common case 2026 (WECC, 2016a); Load data are from the WECC storage report (Xu and Hobbs, 2018); all of the time series are normalized to 0-1.
2) Time series weight: Weights of load time series are an average load of each balancing area; the weight of each of the other time series is the total nameplates of the existing generators using time series. For example, there are two (2) generators, 1 MW and 2 MW, using time series s_1, the weight is 1 MW + 2MW = 3 MW.
3) Period Type: Day.
4) Time-series distance metric: Histogram-based distance with the total bin number B = 50.
5) Cluster number: $N = 4$.
6) Cluster method: K-medoid.
7) The number of random samples, M = 100,000.
8) Criterium: Total weighted deviation of means and standard deviations.

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