Integrating RTO and Utility Processes in Planning and Cost Allocation

Final Project Report

M-43

Power Systems Engineering Research Center
Empowering Minds to Engineer
the Future Electric Energy System

Integrating RTO and Utility Processes in Planning and Cost Allocation

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Executive Summary

Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) are crucial in ensuring a secure operation, a fair, competitive market, and strategic planning for large-scale power systems. The current grid planning processes employed by ISOs/RTOs face challenges due to the complexity of integrating renewable resources, ensuring resource adequacy, and managing cost allocation. Traditional planning methods, often deterministic in nature, are insufficient for managing the long-term uncertainties and the evolving dynamics of modern power systems. Effective transmission planning requires coordinated intraregional and interregional collaboration, supported by advanced computational tools, to effectively assess future scenarios and identify the most cost-effective investments that satisfy future grid needs. This project is motivated by the need to develop forward-looking, flexible, and robust planning frameworks that anticipate diverse future scenarios, enhance grid reliability and efficiency, and ensure equitable cost allocation. It seeks to mature expansion planning and reliability-related tools while identifying ways to facilitate coordination and integration of central ISO/RTO planning functions, including cost allocation.

The project began with thoroughly examining current planning methodologies used by leading ISO/RTOs, identifying key practices, tools, and strategies in grid planning through an extensive review of public reports, studies, and tariffs, and engaging with planners within PSERC member organizations. This process helped characterize ISO/RTO planning processes, identify planning needs, and determine ways to address those needs with new planning tools. This examination culminated in the report “ISO/RTO Long-term Planning Processes.” Key findings revealed the need for better integration and coordination among primary ISO/RTO planning functions, the potential for interregional transmission projects, and the lack of established guidelines for long-term planning that align with regulatory requirements. These findings highlight the necessity for a framework that integrates essential planning functions while promoting interregional coordination. The proposed framework enhances the integration of key planning functions. It fosters the creation of flexible portfolios, considering both cost-effectiveness and reliability in the face of high uncertainty. This approach will benefit ISO/RTOs by enabling exploration across a full spectrum of investment portfolios under a broader set of performance attributes, including energy cost, reliability, and adaptability.

A prevailing trend among ISO/RTOs is employing scenario-based methods to consider diverse future conditions in their planning processes. To address the limitations of traditional deterministic approaches, this project emphasizes the adoption of stochastic methods that account for long-term uncertainties. This shift is crucial as traditional methods often fail to consider uncertain conditions adequately and require extensive time to analyze each scenario separately. Moving towards stochastic approaches allows for identifying flexible investment portfolios capable of adapting to multiple future scenarios. Advanced tools like the Adaptive Coordinated Expansion Planning (ACEP) optimizer, developed by ISU, exemplify this transition. ACEP employs stochastic programming methods to find a core investment portfolio that can flexibly adapt across various projected scenarios. This approach ensures robust planning and strategic adaptation in the face of evolving conditions within the power system landscape.

Ensuring a reliable power supply amidst the growing integration of variable renewable energy sources and the retirement of conventional thermal resources also presents significant challenges in power system planning. A key achievement of this project is the development of a software system that coordinates long-term expansion planning with reliability evaluations. The integration of ACEP with GE-MARS, a probabilistic resource adequacy tool, was developed by implementing an iterative loop that optimizes investment portfolios while meeting reliability requirements. By subjecting future portfolios to a range of realistic scenarios, we refined the ACEP formulation to improve accuracy and account for unreliability costs. Testing this application using a reduced model of the Eastern Interconnection demonstrated its effectiveness in balancing investment robustness, resource adequacy, and system adaptability. The integration of ACEP with a resource adequacy assessment is designed to streamline the decision-making process in power system management by incorporating advanced simulation and optimization techniques.

A major challenge in the development of regional and interregional transmission infrastructure is determining who will pay for projects selected in the planning process. The basic legal principle guiding cost allocation in U.S. systems is “beneficiary pays,” the idea that those who benefit from a project (or group of projects) should pay. While this principle is simple conceptually, the complexity of power systems and uncertainty inherent to long-term planning make the identification of beneficiaries a difficult task. In the final part of the project, we investigated the translation of planning model outputs into estimates of the benefits that will be seen by different market participants. Addressing the implications of uncertainty and risk in transmission expansion decisions is crucial for fair and mutually agreeable cost allocation. We analyzed the challenges posed by significant uncertainties in transmission investments, focusing on the divergence between ex ante cost allocation decisions and ex post benefits realization. This work provides valuable insights into cost allocation discussions and the equity and efficiency implications of transmission expansion.

The project “Integrating RTO and Utility Processes in Planning and Cost Allocation” represents a meaningful step towards modernizing grid planning methodologies. By integrating advanced planning tools, supporting the integration of main planning activities, and addressing cost allocation challenges, our research provides a useful contribution to power system planning effectiveness. The proposed approaches and tools will equip ISO/RTOs with the capabilities to navigate the complexities of modern power systems, ensuring a reliable, cost-effective, and sustainable energy future.

Project Publications:

[1] G. Cuello-Polo, J. McCalley, J. Mays, H. Shu. (2023). ISO/RTO Long-term Planning Processes. A Report for the Power Systems Engineering Research Center. Ames, IA. Available: *https://home.engineering.iastate.edu/~jdm/psercm43.pdf*

[2] S. Risanger and J. Mays. Congestion risk, transmission rights, and investment equilibria in electricity markets. The Energy Journal 45(1), 173–200 (2024). doi: 10.5547/01956574.45.1.sris

[3] G. Cuello-Polo, and J. McCalley, “Enhancing Grid Development through Integration of ISO/RTO Planning Functions,” IEEE PES GM, 2024.

Student Theses:

[1] G. Cuello-Polo, “Enhancing ISO/RTO Planning Strategies for Robust Transmission Infrastructure,” Ph.D. dissertation, Iowa State University, Dec 2025 (Expected).

[2] H. Shu, “Electricity Market Design: Contractual Forms, Transmission Cost Allocation, and Short-term Pricing Strategies,” Ph.D. dissertation, Cornell University, June 2025 (Expected).

Part I

Long-term Planning Processes and Strategies of ISO/RTOs

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1. The “ISO/RTO long-term planning process” report

Independent system operators (ISOs) and regional transmission organizations (RTOs) play a crucial role in adapting bulk power systems to satisfy future needs. These entities conduct regional assessments, establish local resource adequacy standards, and analyze the impacts of new interconnections through technical and economic studies for planning purposes. They also support the demand and resource balance ahead of time while minimizing costs and aligning with public policy objectives. Coordinated and effective planning is critical for maintaining reliable service and promoting competitive power markets.

Understanding the planning processes of ISO/RTOs, which are key in shaping the future grid, is beneficial for the community. Such knowledge enables developing strategies to improve these processes and foster contributions to grid development. This project produced the report “ISO/RTO Long-Term Planning Processes,” offering a detailed overview of planning activities, including technical and economic assessments, public policy integration, and cost allocation strategies. The report covers leading ISO/RTOs in North America and Europe, such as the California Independent System Operator (CAISO), the Electric Reliability Council of Texas (ERCOT), ISO New England (ISO-NE), Midcontinent Independent System Operator (MISO), the New York Independent System Operator (NYISO), PJM Interconnection (PJM), Réseau de Transport d’ Électricité (RTE), and Southwest Power Pool (SPP). It serves as a valuable resource for understanding the complexities of ISO/RTO planning and informs ongoing efforts to enhance grid development through improved planning tools and methodologies.

The report was developed through a structured process involving three main steps. First, the project team formulated questions to benefit the planning community, gathering feedback from industry advisors to build the questionnaire. Next, initial responses to these questions were collected from publicly available sources, including reports, studies, and tariffs for each ISO/RTO. Finally, these findings were compiled into a comprehensive report and reviewed by ISO/RTO planners within PSERC member organizations. This report characterizes ISO/RTO planning processes, identifying needs and challenges and helping explore ways in which planning tools can contribute to them.

Additionally, the paper “Enhancing Grid Development through Integration of ISO/RTO Planning Functions,” derived from the previously mentioned report, was accepted and presented as a proceedings paper at the 2024 IEEE PES General Meeting. This paper not only summarizes the current planning processes employed by leading ISO/RTOs but also introduces a framework for integrating key planning functions. The proposed framework offers a broader examination of the benefits associated with the identified transmission projects through traditional mid-term planning by considering a more extended planning horizon under uncertain conditions. It also guided the development of a software system integrating stochastic expansion planning optimization and resource adequacy assessments, as detailed in Part 2, “Integration of Expansion Planning Applications and Resource Adequacy Assessments,” of this report.

The “ISO/RTO long-term planning processes” report is available online at:

https://home.engineering.iastate.edu/~jdm/psercm43.pdf.

Part II

Integration of Expansion Planning Applications and Resource Adequacy Assessments

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1. Introduction

Expansion planning (EP) tools serve as a useful approach to determining the most economically viable investments required in power grids to satisfy future system needs. This optimization problem can identify investments in generation (also known as generation expansion planning or GEP), transmission (also known as transmission expansion planning or TEP), or both combined (often referred to as co-optimized EP or GTEP) [1], [2], [3]. EP tools have become an integral complement of conventional reliability and economic studies carried out by transmission planners, aiding informed decision-making. Notably, several generation and transmission planners in North America and Europe rely on EP tools such as Aurora, UPLAN NPM, EGEAS, PLEXOS, MONA, and Antares-Xpansion in their planning processes [4][5][6][7]. In 2022, the Energy Systems Integration Group, sponsored by the U.S. Department of Energy, reviewed the modeling capabilities of available EP tools, emphasizing the need for their effective incorporation into transmission planning [8]. This collaborative effort with leading power system planners in the United States concluded that while high-level generation and transmission portfolios obtained from EP tools are valuable, they require robust linkage to downstream analyses for validation as economically and operationally sufficient.

Integrating capacity expansion results with detailed studies such as resource adequacy (RA) assessment, power flow, and production cost models (PCM) is required for comprehensive power system planning, ensuring a broader capture of future investment benefits. This validation process can identify infeasibilities and weaknesses, thereby enhancing the development of more informative and practical expansion portfolios. In EP models, ensuring RA often involves imposing a planning reserve margin (PRM) constraint, requiring that the combined firm capacity of all resources meets or exceeds the peak demand plus an externally determined reserve margin [8]. While thermal generators typically contribute their full nameplate capacity, variable renewable energy resources are adjusted downwards through Effective Load Carrying Capability (ELCC) curves to reflect their availability during periods of highest loss of load probability (LOLP). This adjusted capacity contribution of renewable resources is also considered in EP models to approximate the more rigorous assessment offered by probabilistic RA modeling [8].

There is a growing need to develop expansion planning (EP) tools that accurately account for unreliability costs through a probabilistic RA approach. This allows generation and transmission planners to make more informed decisions by identifying the most economical and reliable strategies for future scenarios. To enhance the accuracy of the Adaptive Coordinated Expansion Planning (ACEP) tool used in [9], [10], [11], particularly in terms of reliability, we propose extending ACEP's capabilities to consider a broader range of realistic scenarios using the Multi Area Reliability Simulation tool (GE-MARS) developed by General Electric. This section describes the integration approach we used to develop an iterative loop that coordinates long-term expansion planning with a reliability evaluation tool. Additionally, we present the results obtained from testing our methodology using a reduced model of the Eastern Interconnection. By integrating ACEP with a resource adequacy assessment, this approach aims to streamline decision-making in power system management through advanced simulation and optimization techniques.

2. State-of-the-art approaches for integrating resource adequacy assessments in power system expansion planning

Several efforts have been documented to improve the deterministic approach, traditionally used in EP tools, emphasizing the probabilistic nature of outages and resource availability. The different approaches to integrate RA assessment and EP tools include: (1) explicitly incorporating reliability constraints into the mathematical model, (2) using decomposition methods to simultaneously address expansion planning and reliability, and (3) employing an iterative approach with independent tools. The iterative approach involves a two-stage process: first, developing a cost-effective expansion plan in terms of investment and operation, and then identifying additional investments required to meet specific reliability criteria (e.g., Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), or Expected Unserved Energy (EUE)).

One of the most widely reported techniques is Benders' decomposition, initially applied in [12] and subsequently in [13], [14], [15], [16]. his method reformulates the complex nonlinear program used for long-term planning into a series of linear programs (LP) or mixed-integer programs (MIP) that can be solved with existing probabilistic simulation algorithms. Benders' decomposition includes a master problem that determines optimal capacity investments over the planning horizon and subproblems that calculate annual operating costs and system reliability. The process begins by generating trial solutions from the master problem. Subsequently, dual multipliers are computed for each subproblem, quantifying the impact of marginal changes in plant capacities on operating costs and reliability [12]. These multipliers are then fed back into the master problem, which is adjusted and solved again to produce a new trial capacity plan. This iterative process continues, with the master problem and subproblems being solved alternately until an optimal solution is reached. Recently, [17] applied Bender's decomposition by integrating Branch-and-Bound (B&B) for solving the investment master problem (a MIP problem), Stochastic Dual Dynamic Programming (SDDP) for the operation subproblem, and Monte Carlo simulation for the reliability subproblem. This methodology was implemented using the OptGen software by PSR, which employs a scenario-based approach [17]. It was applied in a real-world context to optimize the expansion planning of the Bolivian power system [17].

Some authors have implemented an explicit incorporation of reliability constraints into the EP mathematical programming model. For example, [18] developed a chance reliability constraint based on LOLP incorporated into the EP mathematical model. The constraint was defined as a first-order approximation to the Gram-Charlier series representing the density function of available capacity minus load. Similarly, [19] applied two probabilistic reliability criteria (LOLE) as constraints: one addressing the overall reliability of the transmission system and another for individual buses or nodes. They solved the integer programming problem using a probabilistic B&B method that leverages a network flow approach and the maximum flow-minimum cut theorem. In another study, [20] also introduced a GEP model that incorporates LOLP as a reliability criterion. This model optimizes investment, operation, and maintenance costs by framing the LOLP-constrained GEP problem as a MIP problem.

Authors in [21] proposed an integrated approach that combines EP tools and reliability assessments while considering the correlation between variable renewable energy (VRE) and load. The authors developed an iterative algorithm to generate a pool of candidate expansion schemes based on the investment and operational costs of new lines with different topologies. They then calculated the reliability of each candidate scheme using criteria such as LOLP, Loss of Load Frequency (LOLF), and Expected Energy Not Supplied (EENS). This study utilized the IEEE RTS-79 system for simulation experiments using MATLAB 2017b and CPLEX 12.6, focusing on the Transmission Expansion Planning (TEP) problem without considering capacity expansion investments. In a different study, [22] propose an iterative modeling approach that integrates a customized GEP model with Probabilistic RA assessment and PCM. The GEP utilized in the study represents discrete generating units, considering grid operations such as unit commitment and economic dispatch for averaged hours of all weekdays and weekends each month (576 operating periods) without chronological linkage between periods. The study employs a nonsequential RA model called the Probabilistic Resource Adequacy Suite (PRAS) by the National Renewable Energy Laboratory (NREL) and uses PLEXOS as the PCM tool. A similar approach was implemented for distribution systems in [23].

Recently, [24][3][11] proposed a stochastic-based EP model called the Adaptive Coordinated Expansion Planning (ACEP) model that co-optimizes generation and transmission investments and operation costs across multiple future scenarios, identifying a set of core investments over time that minimize specific adaptation investments required for future scenarios. In [6], the authors applied ACEP to provide useful insights into the Transmission Expansion Plan of the Midcontinent Independent System Operator (MTEP) using a reduced model of the Eastern Interconnection. Additionally, a validation technique called the folding horizon simulation (FHS), developed in [25], [26], is executed after running ACEP. This method helps expose the ACEP core solutions to out-of-sample uncertainties, giving a better understanding of how robust the plans are [11]. Given the significant advance of RA tools considering a wider set of probabilistic factors and EP tools co-optimizing generation and transmission investments while considering multiple futures, several benefits can be obtained from integrating separate but powerful modeling tools through interface software linking them.

3. The Adaptive Coordinated Expansion Planning (ACEP) tool

Expansion planning (EP) tools offer a valuable alternative for analyzing current power grids in the context of future scenarios, helping utility companies, grid operators, and policymakers make informed decisions about how to meet future electricity demand in the most cost-effective, reliable, and sustainable way. These tools optimize the mix of generation technologies (e.g., coal, natural gas, nuclear, wind, solar, etc.) and transmission investments to meet future electricity demand at the minimum costs while also accounting for technical, societal, and environmental factors, as well as uncertain parameters. The challenge that long-term planners face is inherently uncertain, as it involves making predictions about the future. Traditionally, uncertainty has been addressed through deterministic approaches with sensitivity analysis, involving running simulations repeatedly for values that span the range of each uncertain parameter. The sensitivity-based deterministic method is time-consuming and suggests potential improvements in transitioning to stochastic methods, which aim to identify flexible investment portfolios.

Research, such as that by [27], demonstrates that stochastic programming methods can reveal investment opportunities that deterministic models might miss. Stochastic-based EP models, like the ACEP model, optimize both investment and operational costs across various future scenarios. This tool has been developed using General Algebraic Modeling Systems (GAMS) software and involves developing a set of future scenarios that capture the effects of the uncertainties in the expansion planning problem, such as load growth, investment costs, fuel prices, and renewable portfolio standards. In general, ACEP helps identify two types of investments: core investments and adaptation investments. Core investments represent a set of investments throughout the planning horizon that most effectively transitions to a feasible solution for each future. Adaptation investments are those specific investments needed in each period to transition from the core investments to a certain future scenario. This method helps identify the most flexible system by minimizing future adaptation investments to any other future scenario. By using ACEP, the planner can also define the level of robustness and flexibility by carefully choosing a parameter that balances core and adaptive investments. This way, it offers flexible investment plans showing core and necessary adaptation investments over time, enabling a tradeoff between cost, robustness, and adaptation risk.

The ACEP model, as introduced by [9], differs from traditional stochastic programs (TSP) in its investment planning approach. While both TSP and ACEP involve two decision stages, TSP establishes core investments at the start (t=1) and introduces scenario investments from period t=2 onwards, incorporating inter-temporal memory where decisions build on previous ones. In contrast, ACEP establishes core investments as a trajectory over time, with scenario investments or "adaptations" extending from this core at each time period without inter-temporal memory. TSP uses non-anticipativity constraints to maintain consistent investments across scenarios, whereas ACEP does not require these constraints, as it calculates new adaptation investments each period [28].

To illustrate the conceptual investment trajectories for these expansion planning models, Figure 3-1 and Figure 3-2 provide a high-level overview of the different planning approaches. These figures are plotted within the generation and transmission investment space, with dashed lines, partitioning the space, representing different time steps within the planning horizon. Additionally,

S futures are represented to highlight differences in addressing uncertainty. Figure 3-1 depicts the deterministic approach, with multi-colored circles ($D_{s \in S}$), representing deterministic investments made at each time step for each particular scenario. Figure 3-2 compares ACEP and TSP, with the larger red circles indicating “here and now” decisions or core investments and multi-colored circles ($A_{s \in S}$) representing “wait and see” decisions. Due to the differences in the core investments, with the TSP core established at the t=1 time period and the ACEP core evolving as a trajectory over time, TSP is often seen as suitable for identifying immediate investment needs, while ACEP is considered better for long-term planning, focusing on what investments to make over time.

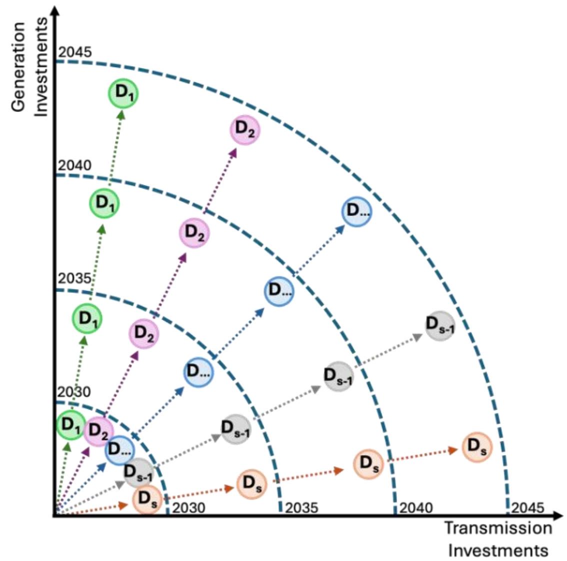

Figure 3-1 Deterministic planning investment approach.

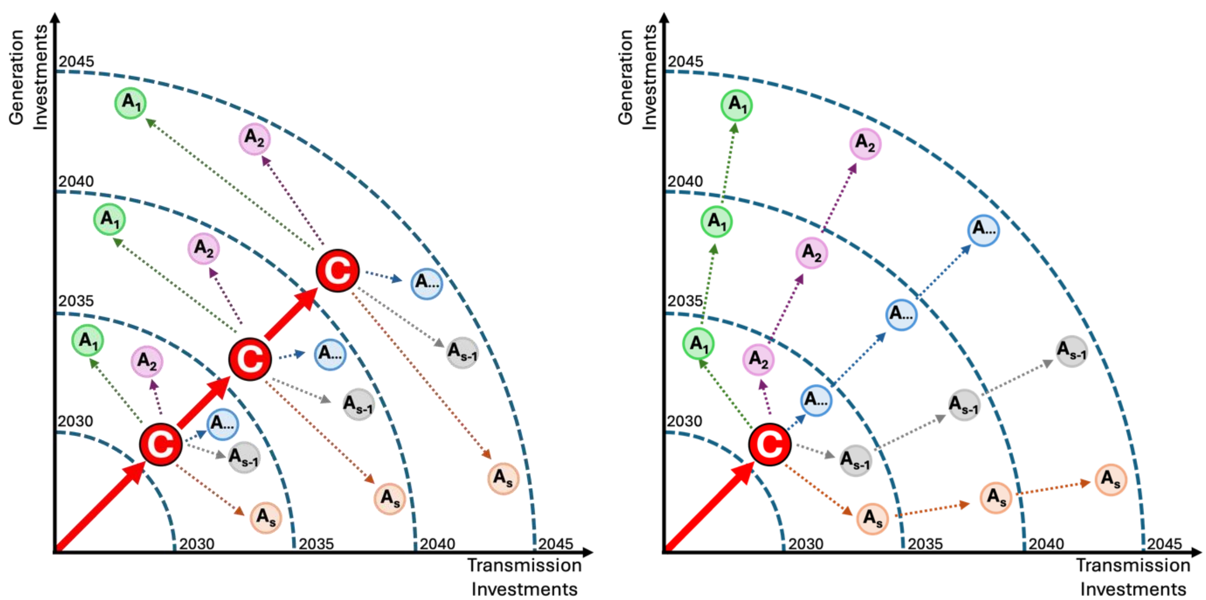

Figure 3-2 Comparison of ACEP (left) and TSP (right).

The mathematical formulation of the ACEP model is detailed in [11]. A general formulation of the model considering a set of future scenarios $s \in S$ is presented in Equation (1). The core costs for each year $y \in Y$, denoted as $CORE_y$, represent the main investments, while $A_{y,s}$ and $O_{y,s}$ represent the adaptation investment and operational costs for each year and future scenario. The model operates as a linear program but can be adjusted to a mixed integer linear program if binary variables are required. Equation (1 assigns a probability weight to each future scenario denoted as Pr_s. A key feature of the model is the β parameter, known as the robustness parameter, which is user-defined. This parameter allows the adjustment of the balance between core and adaptation costs. Figure 3-3 illustrates two ACEP trajectories using the same set of axes as in Figure 3-2. The left trajectory shows a scenario with a small β value (< 1), where adaptive investments are more prominent, indicated by longer arrows extending from the core in red. In contrast, the right trajectory represents a scenario with a large β value (> 1), where the core investments, shown in red, dominate. This indicates a more robust but costlier portfolio with fewer future adaptations, represented by thicker adaptation arrows and smaller multi-colored circles.

$$min \qquad \sum_{y}^{Y}\left[CORE_y + \beta * \sum_{s}^{S} Pr_s * (A_{y,s}) + \sum_{s}^{S} PR_s * (O_{y,s})\right] \tag{1}$$

$Subject\ to$:

$$\begin{gathered} Operational\ contraints\ \forall\ s \in S \\ Policy\ constraints\ \forall\ s \in S \\ Generation\ and\ transmission\ line\ limits \\ DC\ power\ flow \\ Power\ balance \\ Regulation\ reserve\ requirements \\ Energy\ Storage\ contraints \end{gathered}$$

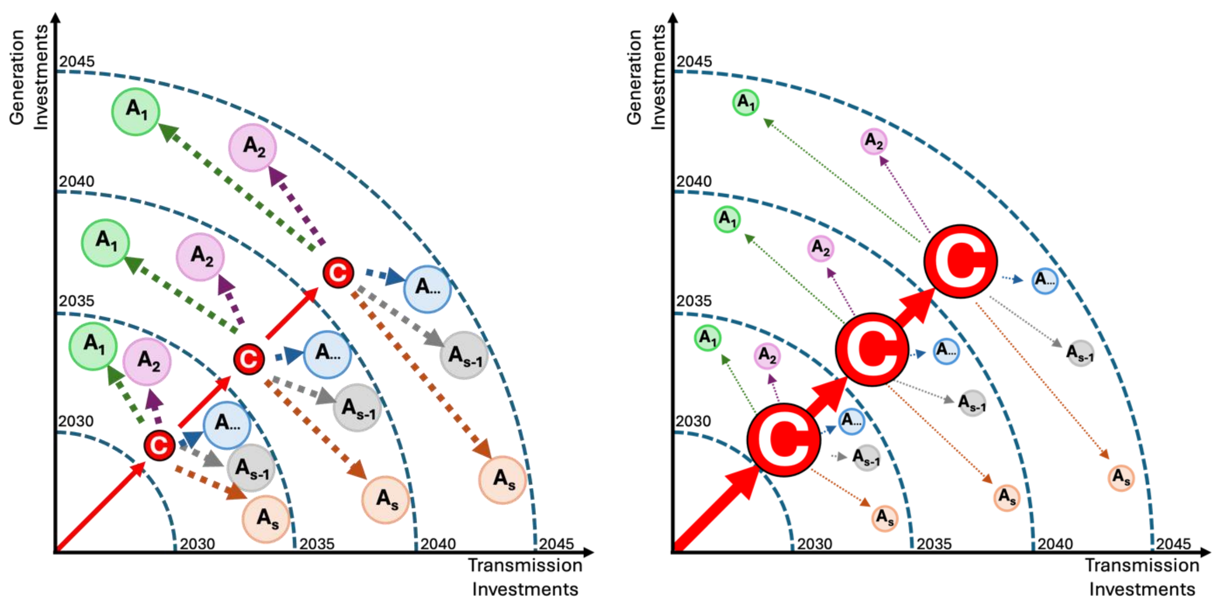

Figure 3-3 ACEP solutions illustrating the effect of varying the β parameter: low β (left) and high β (right).

3.1 Resource adequacy considerations in ACEP

Most EP tools incorporate RA constraints to ensure that solutions meet demand at all times. These constraints typically involve the use of PRM values as measures to guarantee that generation portfolios have sufficient capacity to meet the system's peak load under any circumstances. PRM is a standard metric in the power system industry, representing the amount of extra accredited capacity above the expected peak demand, usually expressed as a percentage (see Equation (2)). Accredited capacity is the portion of a power plant's total capacity considered reliable and available during peak demand periods, accounting for factors like maintenance schedules, generating unit performance, and the availability of intermittent resources such as wind and solar power. Currently, annual and local PRM values are calculated through probabilistic resource adequacy assessments using commercial tools like PRISM, SERVM, and GE-MARS. Simulations are conducted to evaluate different reserve levels until a desired RA criterion is achieved (e.g., LOLE ≤ 0.1 days/year).

$$PRM = \frac{(Total\ Accredited\ Capacity - Peak\ Demand)}{Peak\ Demand} * 100\% \tag{2}$$

In ACEP, the PRM constraint, as represented by Equation (3), s applied for each year and future scenario, using a fixed, system-wide PRM value across the entire planning horizon, all future scenarios, and local areas. However, this approach does not account for the spacial and temporal variations in capacity needs or the uncertainties associated with each particular future. On the left-side of the equation, the capacity credit of a plant $g \in G$ is denoted as CC_g, and the plant's installed capacity at a specific bus $b \in B^p$ within a pool $p \in P$ for a given year $y \in Y$ and future $s \in S$ is denoted as $G_{b,g,y,s}$. On the other side of the equation, PRM is a fixed value, while the peak demand at a given bus within the pool for a specific year and future is denoted as $D'_{b,y,s}$.

$$\sum_{B^p,G} CC_g * G_{b,g,y,s} \geq (1 + PRM) * \sum_{B^p} D'_{b,y,s} \ \forall \ p \in P, y \in Y, s \in S \tag{3}$$

The improvement implemented through this project involves refining the ACEP formulation, specifically the RA constraint, to shift from using a fixed, system-wide PRM for all futures to a set of dynamic PRM values differentiated by geographical areas, futures, and years. Accurate PRM values are derived from RA assessments (externally calculated as explained in Section 4), ensuring the system's adequacy at any time for each future scenario. This approach more accurately reflects the variations in PRM based on geographical location, time, and future conditions. Equation (4) presents the modified constraint, where the PRM value for a given area $a \in A$, year and future is denoted as $PRM_{a,y,s}$. Implementing this constraint enhances the accuracy of calculations, though it increases the ACEP computational burden, as it is now imposed more locally and must be satisfied by each area within the pool of interest. This improvement significantly impacts and enhances the precision of both core and adaptation investment calculations.

$$\sum_{B^a,G} CC_g * G_{b,g,y,s} \geq \left(1 + PRM_{a,y,s}\right) * \sum_{B^a} D'_{b,y,s} \ \forall \ a \in A, y \in Y, s \in S \tag{4}$$

It is important to note that ACEP identifies a set of core investments over time and specific adaptations for each period to transition from the core to a particular future. Equation 4 does not necessarily guarantee that implementing only core investments will ensure a reliable system. Instead, it ensures that adaptation investments account for specific capacity needs in addition to the core investments, thereby guaranteeing RA in each future scenario and period and improving the accuracy of both core and adaptation investment calculations. The robustness of the core solution is determined by adjusting the robustness parameter β, which balances costs and adaptation risks. This robustness can be evaluated using a technique called folding-horizon simulation (FHS), which iteratively tests the core solution against uncertainties not represented by the future scenarios considered in ACEP [11]. The primary goal of the ACEP improvement implemented in this project is to achieve more accurate calculations of core and adaptation investments by appropriately considering PRM values obtained from RA assessments for each future, period, and area. ACEP provides flexibility by identifying a set of core investments that minimize adaptation costs across various future scenarios, reducing dependence on the choice of scenario. Additionally, the planner can control the degree of robustness (i.e., the balance between core and adaptation investments) while ensuring resource adequacy across all considered future scenarios.

4. Integration of ACEP and resource adequacy assessments

To enhance the accuracy of the ACEP tool, the current formulation has been refined by replacing the resource adequacy constraint that assumes a fixed, system-wide PRM value with a more dynamic approach that incorporates PRM values specific to different geographical areas, scenarios, and years. These PRM values are obtained through iterative probabilistic resource adequacy assessments conducted by an external RA tool. This refinement is designed to improve ACEP's ability to account for unreliability costs by subjecting select years within each future portfolio to a broader range of realistic scenarios. If a reliability index fails to meet the established criteria, necessary adjustments will be made to the PRM constraints in the ACEP formulation, thereby ensuring that the tool yields more accurate and reliable investment decisions.

Options for incorporating PRM in the ACEP formulation in terms of area and time are illustrated in Figure 4-1, where the complexity of each method is evaluated on a scale ranging from 1 to 6. A complexity level of 1 indicates methods that offer lower accuracy but are less computationally demanding, while a level of 6 represents the highest degree of accuracy, though with significantly increased computational intensity. Our strategy focuses on adopting PRM values differentiated by area and evaluated annually, corresponding to level 4 on the complexity scale. This approach was selected to strike a balance between achieving sufficient accuracy in the model's calculations while keeping the computational burden within reasonable limits.

Area \ Time	Planning Horizon	Annually	Seasonally
System-wide/Pool	1	2	3
Area	2	4	5
Local Resource Zones	3	5	6

Computational Complexity

Figure 4-1 Computational complexity associated with the selection of PRM calculations by area and time frame.

For this study, an exhaustive review of commercial tools available for conducting probabilistic RA assessments was initially conducted. Table 4-1 provides a summary of the reviewed tools and their key features. GE-MARS was ultimately selected due to its ability to integrate with external tools. Originally developed in Fortran, GE-MARS was enhanced in 2019 with the introduction of a Python Application Programming Interface (API) called Snappy. Snappy facilitates reading and writing model inputs, launching simulations, and preparing reports within Python. GE-MARS utilizes a full sequential Monte Carlo simulation to calculate RA indices at the area level, with pool indices derived from the individual areas within each pool. The tool performs chronological system simulations by combining randomly generated operating histories of units over time with hourly load cycles, load modifiers, and transmission links [29]. Simulations are generally run until either a convergence criterion is met or a predetermined number of samples have been completed.

Table 4-1 Summary of resource adequacy tools.

Feature	**PSS-SINCAL (Siemens)** [30], [31]	**PRAS (NREL)** [32], [33], [34], [35]	**GE-MARS (GE)** [36]	**MECORE (BC Hydro)** [37], [38], [39]	**PRISM (PJM)** [40]	**PowerSIMM Planner (Ascend Analytics)** [41], [42]	**SERVM (Astrape Consulting)** [43],	**TransCARE (EPRI)** [44], [45],	**NH2 (CEPEL)** [46], [47], [48], [49]	**GridPath RA Toolkit (GridLab, Moment Energy Insights, and Blue Marble Analytics)** [50], [51].
Method	Convolution method.	Convolution method and Hybrid Method (convolution and Monte Carlo).	Monte Carlo method.	Monte Carlo and convolution method.	Convolution method.	Monte Carlo method.	Monte Carlo method.	Convolution method.	Convolution, M onte Carlo or hybrid method.	Monte Carlo or weather-synchronized simulations.
Tool's Capabilities	Reliability indices calculated for load nodes, areas, or the entire network.	Reliability indices calculated for areas.	Reliability indices calculated for areas. It performs chronological hourly simulations.	Up to 1,000 buses and 2,000 branches. Indices calculated for buses or overall system and monthly, seasonal, or annual.	Up to 700 and 4,500 units. Reliability indices are computed weekly, seasonally, and annually over a two-area model.	Studies include production costs, power flow, financial analysis, and RA.	It simulates hourly chronological simulations. Reliability indices calculated for areas. It is linked to SQL-server.	Up to one million contingencies and up to N-9 contingencies (five lines and four generating units tripped) can be evaluated. It uses SQL-server database.	Up to 3,000 buses and 5,000 circuits. Reliability indices can be disaggregated at the system, area, and bus level and classified by failure modes.	Reliability indices are calculated daily, monthly, or annually for areas. It has been tested for a one-year case study.
Indices Computed	SAIDI, SAIFI, CAIDI.	EUE, LOLE.	LOLE, LOEE, frequency and duration of outages.	LOLP, LOLE, LOEE, ENLC, EDLC, ADLC, ELC, EDNS, EDC, BPII, BPECI, BPACI, MBECI, SI.	LOLE, LOLP.	LOLP, LOLH, LOLE.	LOLH, LOLE, EUE.	SAIFI, LOLE, EUE.	SPP, LOLP, LOLE, EPNS, EENS, LOLF, LOLD.	LOLP, LOLE, LOLH, EUE, average event duration.
Other Features	- Compatible with SCADA, Distribution Management System (DMS), Meter Data Management System (MDMS), and GIS applications. - Modeling from basic balanced circuits and buses to four-wire circuits with full substation models.	- Compatible with Regional Energy Deployment System Model (ReEDS) and the Resource Planning Model (RPM). - Results include regional shortfall and surplus, power transfer on interfaces, unit availability, and state-of-charge of storage. - ELCC and EFC calculation.	- Automatic postprocessin g calculations and report generation using Python. - It can model as many interconnected areas as needed. - The modeling includes transfer limits and long-term contracts.	- Multiple unit derating states recognized. - It uses OPF to reschedule generation and avoid load curtailments if possible.	- It is composed of an analytic engine (SAS) and a database tool (Oracle). - Outage statistics of generators can be represented with more than two states. - Maintenance optimized or manually specified by the user.	- It integrates EP studies with reliability analysis. FORs, historical weather and load data, and future expectation of load growth are the main inputs. - It keeps correlation between variables (load-weather, generation-weather) and across time. - ELCC calculation.	- It integrates LOLE studies with an hourly and intra-hour chronological production cost model. - It quantifies the likelihood, magnitude, and economic cost caused by reliability events. - ELCC calculation.	- Based on TRELSS (EPRI's software for probabilistic studies). - Compatible with OFCT and cascading failure analysis tools. - Compatible with PSS/E. - Studies of the impact of variable resources on system reliability.	- It works with MODCAR for data management and visualization. - NH2 integrates OPF to implement remedial actions. - Users can select the model of the performance analysis (AC or DC power flow).	- Integrated with an open-source power system tool named GridPath which performs production-cost and capacity-expansion modeling. - Dataset, algorithm, and instructions are publicly available. - Temporal and geographical correlations over the study area.

The proposed iterative approach to integrating ACEP and RA assessments conducted by GE-MARS is described in Figure 4-2 and involves the following steps:

1. **ACEP run:** The ACEP tool is initially run in GAMS with assumed PRM values for each future and year.
2. **ACEP results post-processing:** Core investments and adaptation investments are identified and recorded for each iteration. Besides, given that the PRM constraint in ACEP is upper-limit unbounded (see Equation (4), the actual reserve values produced by ACEP for each future and year are also identified.
3. **Conversion to GE-MARS format:** The investment portfolios produced by ACEP for each future and year (including both core and adaptation investments) are converted into a format compatible with GE-MARS.
4. **GE-MARS run:** Specific years within the 20-year planning horizon are then assessed for each future using GE-MARS.
5. **Resource adequacy index check and PRM adjustment (if needed):** RA indices are evaluated for each future scenario and year. If any RA index does not meet the specified criteria, the PRM value associated with that particular future and year is adjusted in the ACEP model, and the ACEP run is repeated (returning to Step 1). Equation (5) is used to adjust PRM values for the next iteration of the ACEP run.

$$PRM_{New} = PRM_{Old} + (LOLE_{Old} - 0.1) * \alpha + 0.05 \tag{5}$$

   Where,

$$\alpha = \frac{\Delta_{PRM}}{\Delta_{LOLE}} = \frac{0.01}{2.5}$$

6. **Stopping condition:** The simulations proceed iteratively until the resource adequacy levels for each area, future, and year are deemed acceptable.

The resource adequacy criterion selected for steps 3 and 4 is LOLE < 0.1 days/year, a common industry metric. While the exploration of additional criteria (e.g., duration and frequency of outages, loss of energy expected (LOEE), etc.) could be considered in future studies, the overall approach remains unchanged. Python was chosen as the interface tool, enabling seamless integration that allows ACEP and GE-MARS to run iteratively until all futures and evaluated periods meet the resource adequacy criterion. This iterative approach ensures that ACEP and GE-MARS are effectively integrated to produce reliable and optimized investment plans while accommodating variations in PRM and resource adequacy requirements.

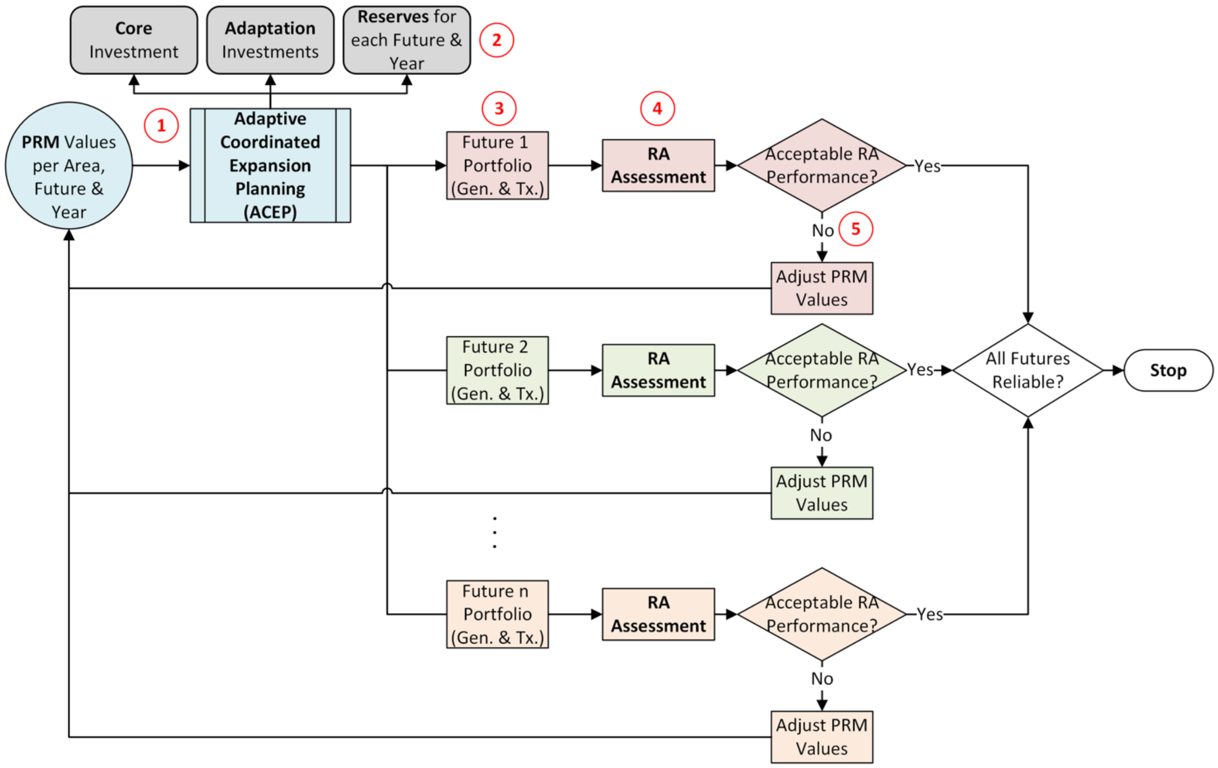

Figure 4-2 High-level diagram describing the integration of ACEP and RA assessments (GE-MARS).

5. Implementation of ACEP with integrated resource adequacy assessments

To test the ACEP/GE-MARS integration, we use a reduced model of the Eastern Interconnection, focusing on the MISO system and simplified versions of its first-tier neighbors, including SPP, PJM, the Southeast, and Canada. Even though five regions (referred to as pools in this study) were considered, the primary focus was on the MISO region, specifically its internal areas, MISO North/Central and MISO South. Consequently, expansion investments were allowed only within the MISO region, with no modifications in the external regions.

The initial step involved developing a set of representative futures to capture the effects of uncertainties in expansion planning. A future is defined as a specific combination of uncertainties considered in the model. Defining these uncertainties and determining the number of futures is challenging because increasing the number of scenarios raises the computational intensity, and the selected scenarios must effectively represent uncertainties over the planning horizon. In this study, nine uncertainties were considered, with each taking a low, medium, or high value, resulting in a total of 3^9 = 19,683 possible scenarios. To manage this complexity and ensure a comprehensive representation of uncertainties, three futures (F1-F3) from the MISO Transmission Expansion Plan (MTEP) process were used, and the GAMS ScenRed2 function was employed to expand the set by identifying four additional representative futures (F4-F7). Figure 5-1 illustrates the reduced future subset and their associated uncertainty levels.

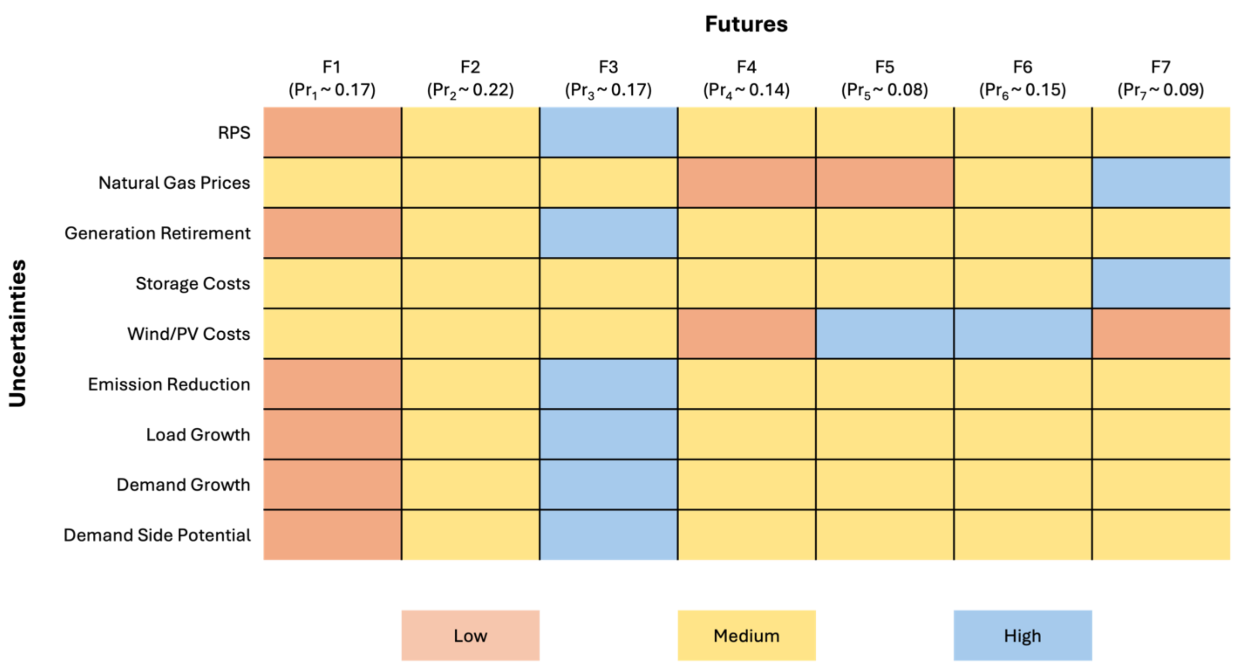

Figure 5-1 Futures considered in the ACEP/GE-MARs integration.

5.1 ACEP modeling development

The Eastern Interconnection (EI) includes a large network of about 90,000 buses and 110,000 branches, making it too complex for direct use in expansion planning models. To address this, the network model needs to be simplified and reduced in size so that planners can perform studies efficiently while still capturing key characteristics of the system. For this study, a reduced representation of the EI with a focus on the MISO region that was developed by [11] was used. Figure 5-2 illustrates the network topology of the reduced system, including 936 transmission lines and 201 buses.

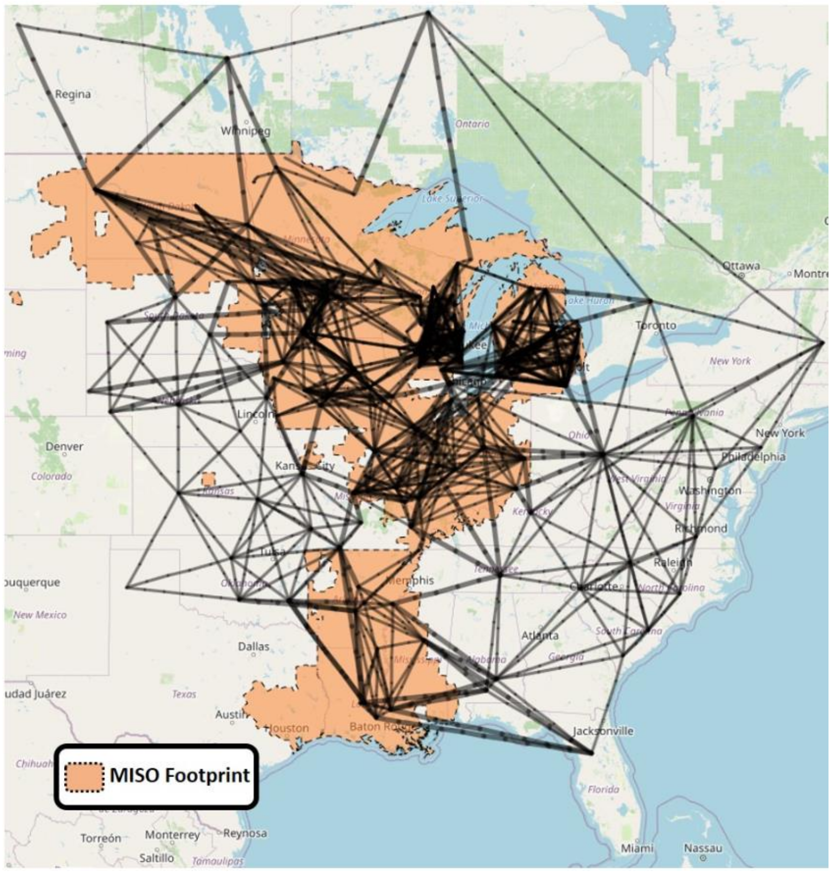

Figure 5-2 Reduced model of the EI with a focus on the MISO region [11].

The network reduction process involved several key steps, starting by identifying buses to be retained in the MISO region based on voltage level (>345 kV) and their location within each Local Resource Zone (LRZ). The reduced MISO network was then obtained using Kron reduction. Subsequently, the reduced MISO network was integrated with the Interconnection Seams network by developing tie lines between MISO and external regions, with flow limits based on historical data. To map generation from the full network to the reduced one, thermal generators were moved from eliminated buses to retained ones according to the load factor matrix, while renewables were relocated to the geographically closest reduced bus. Economic data, such as Fixed O&M (FOM), Variable O&M (VOM), and heat rates, were collected from previous studies, including the Interconnection Seams study and NREL ERGIS database. Finally, renewable profiles, fuel forecasts, and load profiles were developed by extracting renewable data from NREL, fuel prices from EIA, and load profiles from FERC, ensuring the reduced network retained essential characteristics for accurate planning studies. More details about this process can be found in [11]. Figure 5-3 shows the approximate location of the existing generation fleet in the EI.

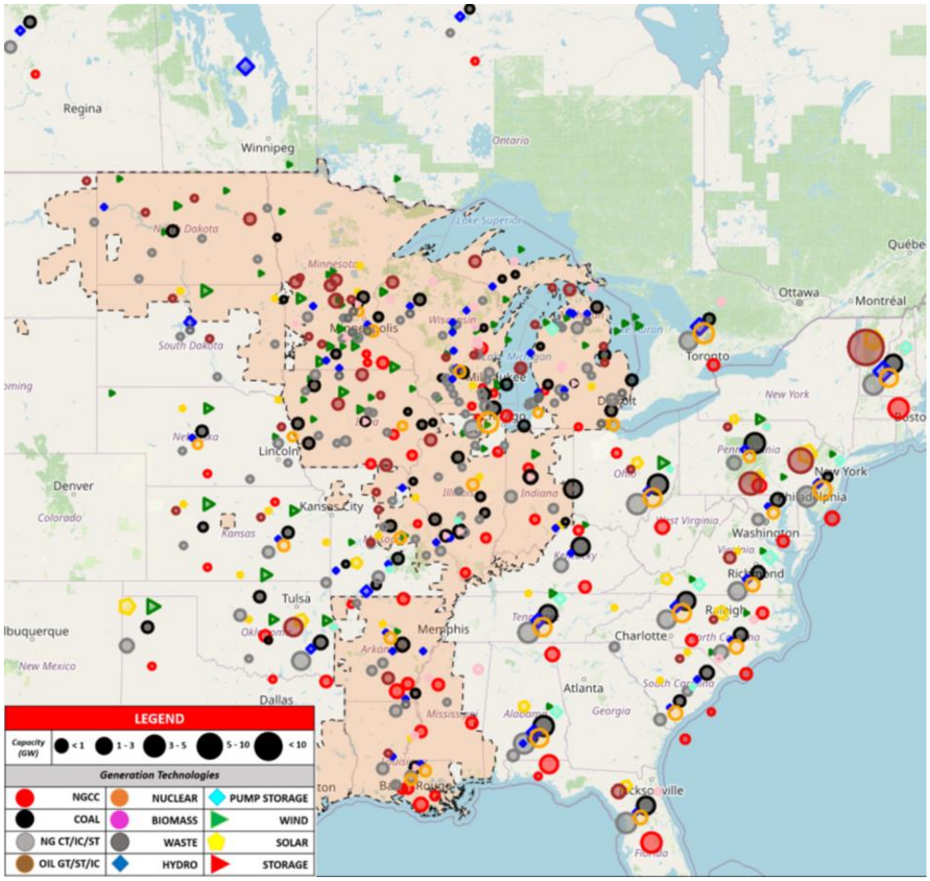

Figure 5-3 Existing generation in the EI connection [11].

To estimate transmission investment costs in the reduced MISO/EI model, costs were averaged between the sending and receiving ends based on AC transmission line costs by voltage level and states within the MISO footprint [50]. These costs were then normalized by potential capacities, converting them into units of $/MW-mile. Figure 5-4 illustrates the normalized costs of transmission lines in units of $B/GW, taking into account both cost and circuit length. For lines outside MISO, costs were sourced from previous studies [52], [53].

Regarding generation, a range of candidate technologies was evaluated, including natural gas combined cycle (CC), natural gas combustion turbine (Gas GT), natural gas CC with carbon capture and sequestration (CC CCS), utility-scale wind (Wind), utility-scale solar (Solar), distributed solar (DPV), battery storage, demand response (DR), and energy efficiency (EE) programs. Table 5-1 shows capacity credit values considered in ACEP for the candidate technologies. The generation investment costs were projected by considering their cost evolution over the planning horizon, with renewable technologies like wind and solar assigned low, medium, and high values to capture uncertainty across future scenarios. DR and EE programs were assumed to have no associated investment costs. The remaining investment costs were derived from the NREL Annual Technology Baseline (ATB) database [54]. Figure 5-5 presents the projected investment costs for each type of candidate technology.

ACEP simulations were conducted over a 20-year planning horizon, considering four investment years: 2026, 2032, 2038, and 2044. Since this study primarily focused on the MISO region, expansion investments were permitted only within the MISO footprint while aiming to minimize the operational costs of the entire EI. Additionally, 30-year end effects were considered to account for future operational costs and subsequent investments that could impact the overall solution.

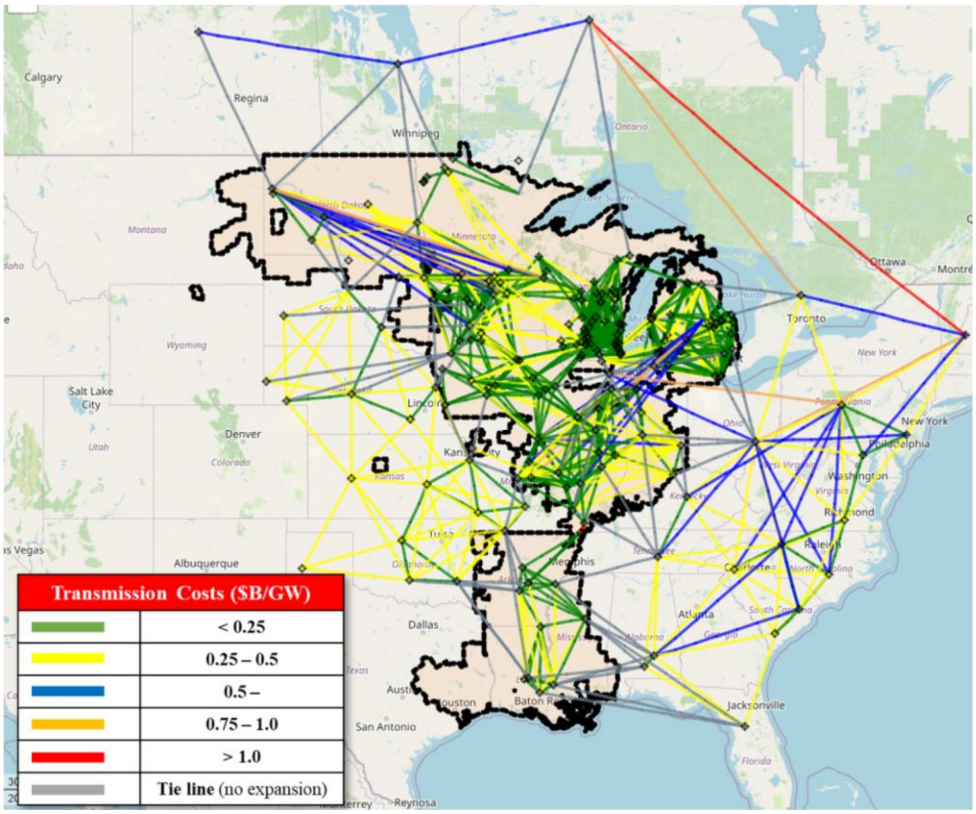

Figure 5-4 Line investment costs in the reduced network [11].

Table 5-1 Capacity credit values assumed in ACEP.

Candidate technology	Description	Capacity credit
CC_N	Natural gas combined cycle	1
CC_CCS_N	Natural gas CC with carbon capture and sequestration	1
Gas_GT_N	Natural gas combustion turbine	1
Solar_N	Utility-scale solar	0.25
STO_N	Battery storage	0.94
Wind_N	Utility-scale wind	0.4
DPV_N	Distributed solar	0.4
EE_N	Energy Efficiency	1
DR_N	Demand Response	1

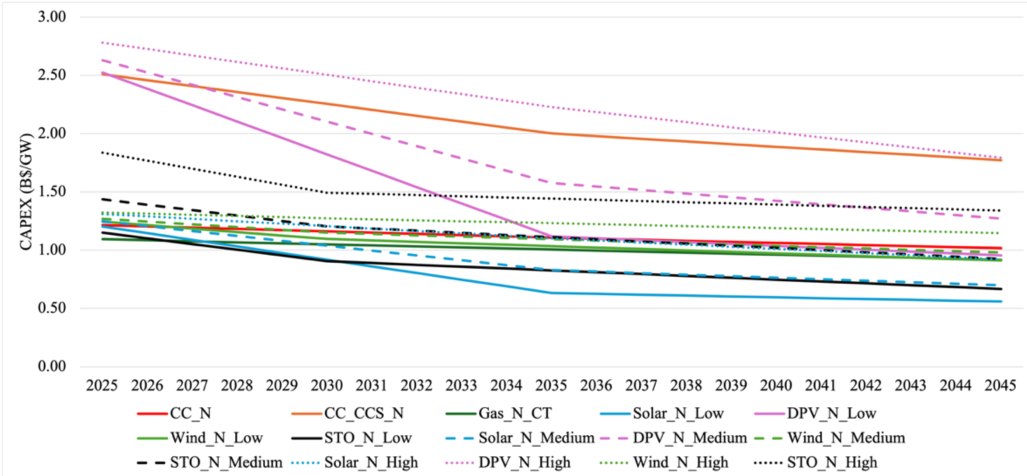

Figure 5-5 Investment costs for candidate technologies.

5.2 GE-MARS modeling development

While ACEP employs a nodal model, GE-MARS operates with a multiarea system representation. To integrate results from ACEP into GE-MARS, a format conversion is necessary. Both tools consider the same pools (MISO, SPP, Canada, Southeast, and PJM), but in GE-MARS, the MISO pool is subdivided into North/Central and South areas to more accurately identify expansion needs, as suggested by this study. Interface tie limits between areas and pools in GE-MARS were calculated by aggregating transmission line capacities used as inputs in ACEP. Given the seven future scenarios, GE-MARS requires seven simulations per iteration, each utilizing data from ACEP, particularly related to the generation fleet.

Generation data from ACEP is converted to GE-MARS format based on the generation type, with the maximum capacity of units for each year serving as a common input across all unit types. Table 5-2 details the modeling approach used in GE-MARS for each type of technology considered in this study. To ensure compatibility between the two tools, generation units from ACEP's states or regions are mapped to the corresponding areas in GE-MARS. On the demand side, ACEP requires input data by bus, year, and season, while GE-MARS operates with annual peak and energy values per area, as well as an hourly load profile for a representative year for each area. To match GE-MARS's requirements, demand data from buses within the same area in ACEP is aggregated. Both tools also incorporate low, medium, and high values for peak and energy demand, depending on the future scenario considered. Figure 5-6 shows a diagram of the main information needed to run GE-MARS, with required inputs highlighted in red.

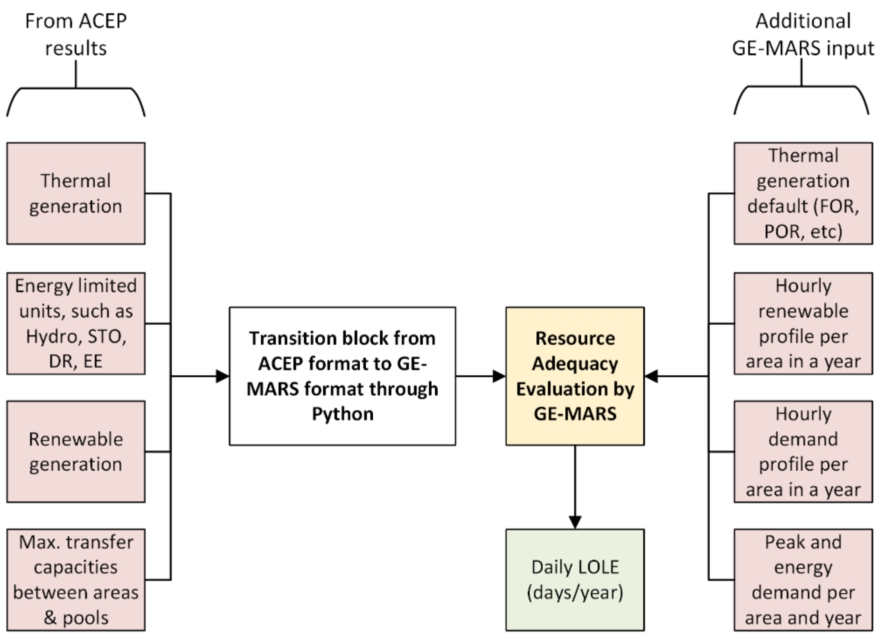

Figure 5-6 Diagram of information needed to run GE-MARS with inputs in red.

Table 5-2 Generation modeling in GE-MARS.

Generation type	GE-MARS model	Description
Biomass	TH	Thermal unit modeled through maximum rating and default parameters, including forced outage rate, number of transitions, and planned outage rate.
CC		
Coal_ST		
Gas_GT		
Gas_IC		
Gas_ST		
Nuclear		
Oil_GT		
Oil_IC		
Oil_ST		
Waste		
CC_N		
CC_CCS_N		
Gas_GT_N		
Hydro	EL2	Energy Limited Unit (Type 2): Unit with specified capacity and available monthly energy scheduled deterministically.
PS	ES	Energy Storage Unit: Unit with specified generating and charging capacity and storage capacity scheduled as needed subject to storage limitations.
STO_N		
Wind_N	DS	Demand Side Hourly Modifier: Each unit specifies a net hourly load modification.
Solar_N		
DPV_N		
EE_N	EL3	Energy Limited Unit (Type 3): Unit with specified capacity and available monthly energy scheduled as-needed.
DR_N		

Evaluating each year for each future would significantly increase the computational intensity of the loop. In order to manage this complexity, simulations were conducted for four selected years within the 20-year planning horizon: 2026, 2032, 2038, and 2044. The simulations used daily LOLE as the convergence index, with a convergence tolerance of 0.05 checked for the MISO pool. GE-MARS was configured to automatically schedule generation planned maintenance, and no forced outages in the tie interfaces or firm import and export contracts between pools and areas were modeled.

The forced outage rate (FOR) and planned outage rate (POR) values used in this study were primarily derived from the MISO 2022-2023 LOLE Study Report [55]. FOR values, as shown in Table 5-3, were applied to both existing and new units without considering variations in plant size. In contrast, MISO employs four seasonal FOR and POR values for each unit based on the MISO's Generator Availability Data System (PowerGADS) [55]. This study also utilized a single load, wind, and solar shape per area, differing from MISO's approach of using multiple shapes, which enhances model accuracy by better capturing geographical variations in these factors.

Generally, more precise modeling of generation units and load leads to more reliable results. Nonetheless, despite limited available data for a more accurate model, this study aims to highlight the benefits of a holistic planning approach that integrates two essential planning tools. By considering multiple future scenarios and incorporating critical information from Resource Adequacy (RA) assessments, this methodology provides a broader perspective on expansion strategies. It simultaneously evaluates the potential impacts of various futures on investment decisions, demonstrating how strategic planning can effectively address uncertainties and guide robust investment decisions. This approach underscores the importance of a comprehensive and integrated assessment in expansion planning.

Table 5-3 Default parameters used to model thermal units in GE-MARS.

Summary type	Description	Forced Outage Rate	Planned Outage Rate
Biomass	Biomass	0.0904	0.1142
CC	Combined Cycle	0.0585	0.0863
Coal_ST	Conventional Steam Coal	0.0904	0.1285
Gas_GT	Natural Gas Combustion Turbine	0.0593	0.0602
Gas_IC	Natural Gas Internal Combustion	0.0593	0.0602
Gas_ST	Natural Gas Steam Turbine	0.1184	0.1413
Nuclear	Nuclear	0.0295	0.0637
Oil_GT	Oil-fueled Combustion Turbine	0.0511	0.0602
Oil_IC	Oil-fueled Internal Combustion	0.0511	0.0400
Oil_ST	Oil-fueled Steam Turbine	0.0511	0.1393
Waste	Waste-to-energy plants	0.0904	0.1142
CC_N	New Combined Cycle	0.0585	0.0863
CC_CCS_N	New Natural Gas Combined Cycle with Sequestration	0.0511	0.0863
Gas_GT_N	New Natural Gas Combustion Turbine	0.0593	0.0602

6. Results

To test the integration of ACEP with GE-MARS, two studies were conducted using different robustness parameters in ACEP. These studies represent distinct planning strategies, reflecting different levels of planners' budgets and their willingness to take on risk. In the first study, a robustness parameter of β=1 was used, representing a planning strategy that prioritizes core investments over adaptation investments. In contrast, the second study used a robustness parameter of β=0.1, which explores a solution inclined to invest less in the core and more in adaptations compared to the β=1 scenario. For both cases (β=1 and β=0.1), the ACEP/GE-MARS simulation converged after eight iterations. This section presents the results of the first three iterations and the final iteration for each case. Detail analysis of key findings and their implications can be found in Subsection 6.3.

6.1 Solution for a planning strategy using a robustness parameter β=1

Figures Figure 6-1 to Figure 6-4 illustrate the main outcomes of the iterative process using β=1. With an initial assumed PRM of 17% across all areas and futures, ACEP produced the core investment portfolio, as shown in the first bar of Figure 6-1, and the adaptation investments, as displayed in the top-left graph of Figure 6-2. The investment portfolios from the first iteration resulted in the reserve values depicted in the top graph of Figure 6-3. Subsequently, RA assessments were performed, yielding the LOLE values shown in the top graph of Figure 6-4. Since the LOLE values in the first iteration exceeded 0.1 days/year, the PRM values in ACEP were adjusted, necessitating further iterations. This process continued until the eighth iteration, which achieved the required LOLE.

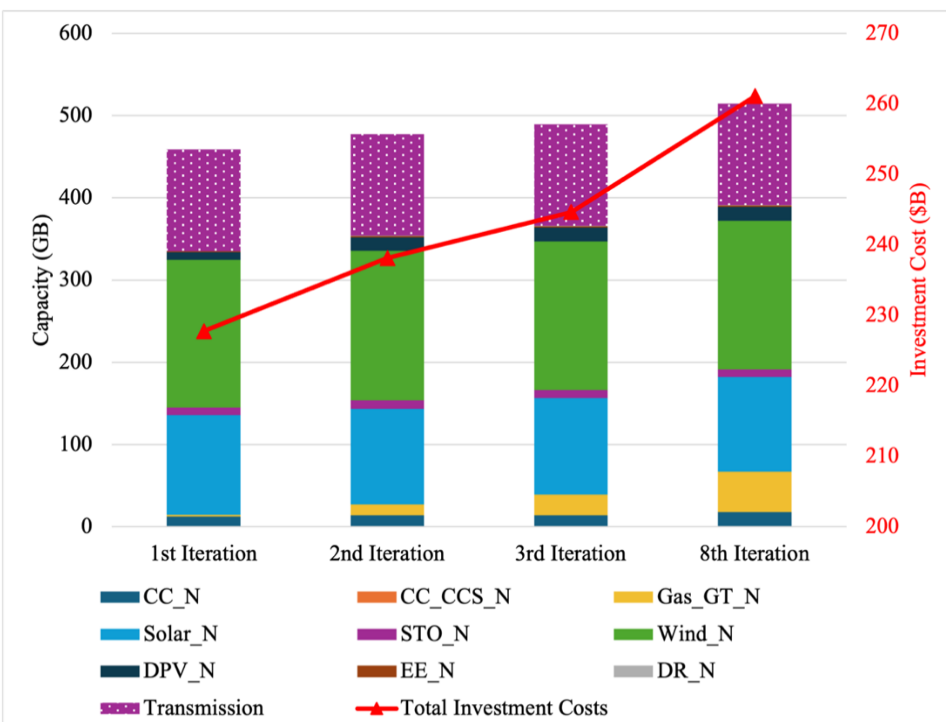

Figure 6-1 Total generation and transmission core investments (GB and $B) for each iteration using β=1.

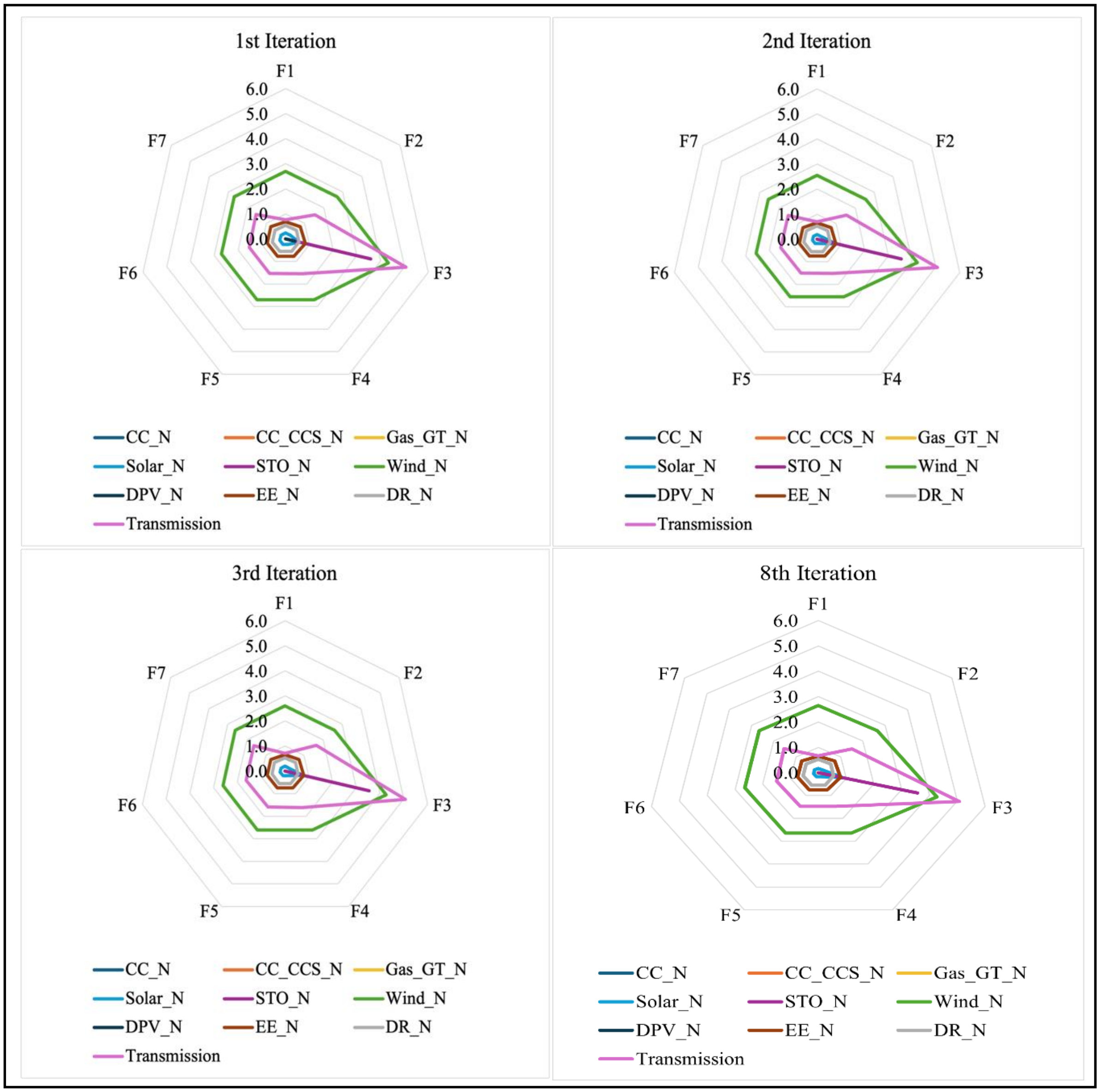

Figure 6-2 Time-averaged adaptation investments (GW) for each iteration using β=1.

Figure 6-3 Accredited capacity reserve for each iteration using β=1.

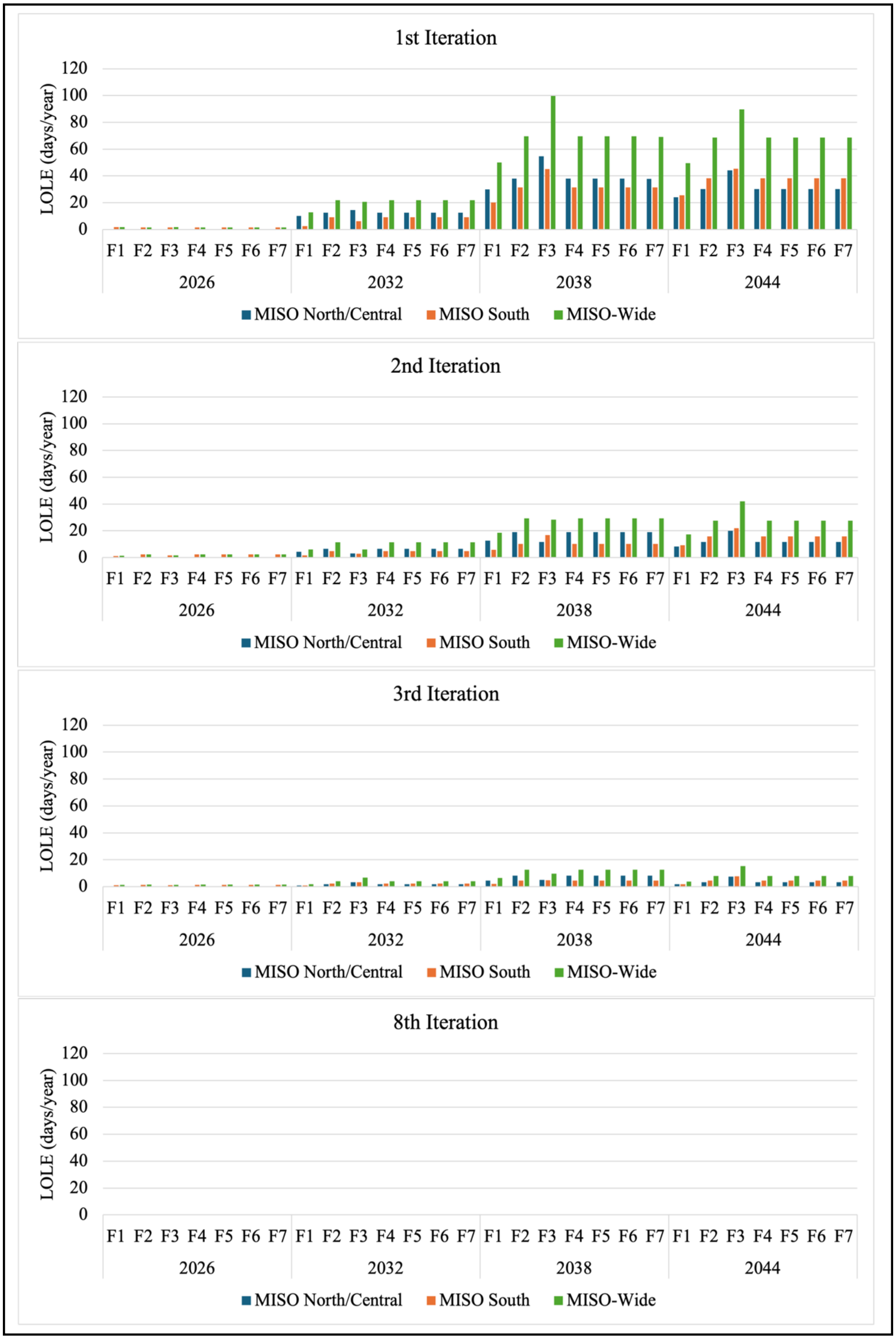

Figure 6-4 LOLE values for each iteration using β=1.

6.2 Solution for a planning strategy using a robustness parameter β=0.1

Figures Figure 6-5 to Figure 6-8 present the key results from the iterative process when using a robustness parameter of β=0.1. Starting with an initial PRM assumption of 17% for all areas and future scenarios, ACEP generated an initial set of core and adaptation investments, as depicted in the initial bars of Figure 6-5 and Figure 6-6, respectively. These initial investment strategies produced reserve values, which are illustrated in the top graph of Figure 6-7. Following this, RA assessments were conducted, resulting in LOLE values shown in the top graph of Figure 6-8. In this case, similar to the previous scenario, the initial LOLE values exceeded the target threshold of 0.1 days/year, prompting adjustments to the PRM values and necessitating additional iterations.

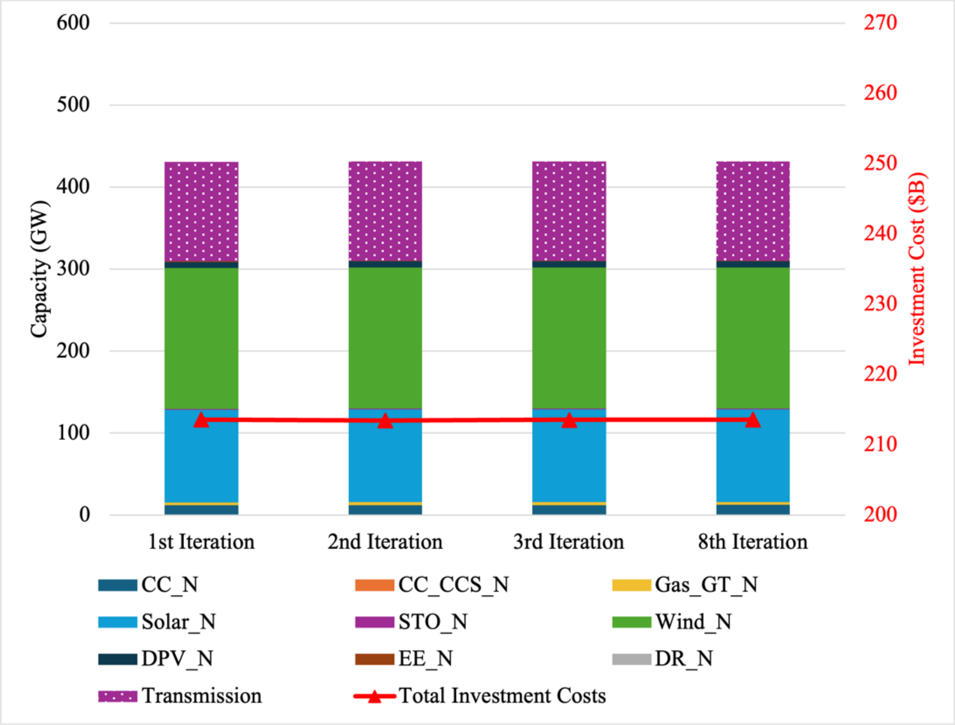

Figure 6-5 Total generation and transmission core investments (GB and $B) for each iteration using β=0.1.

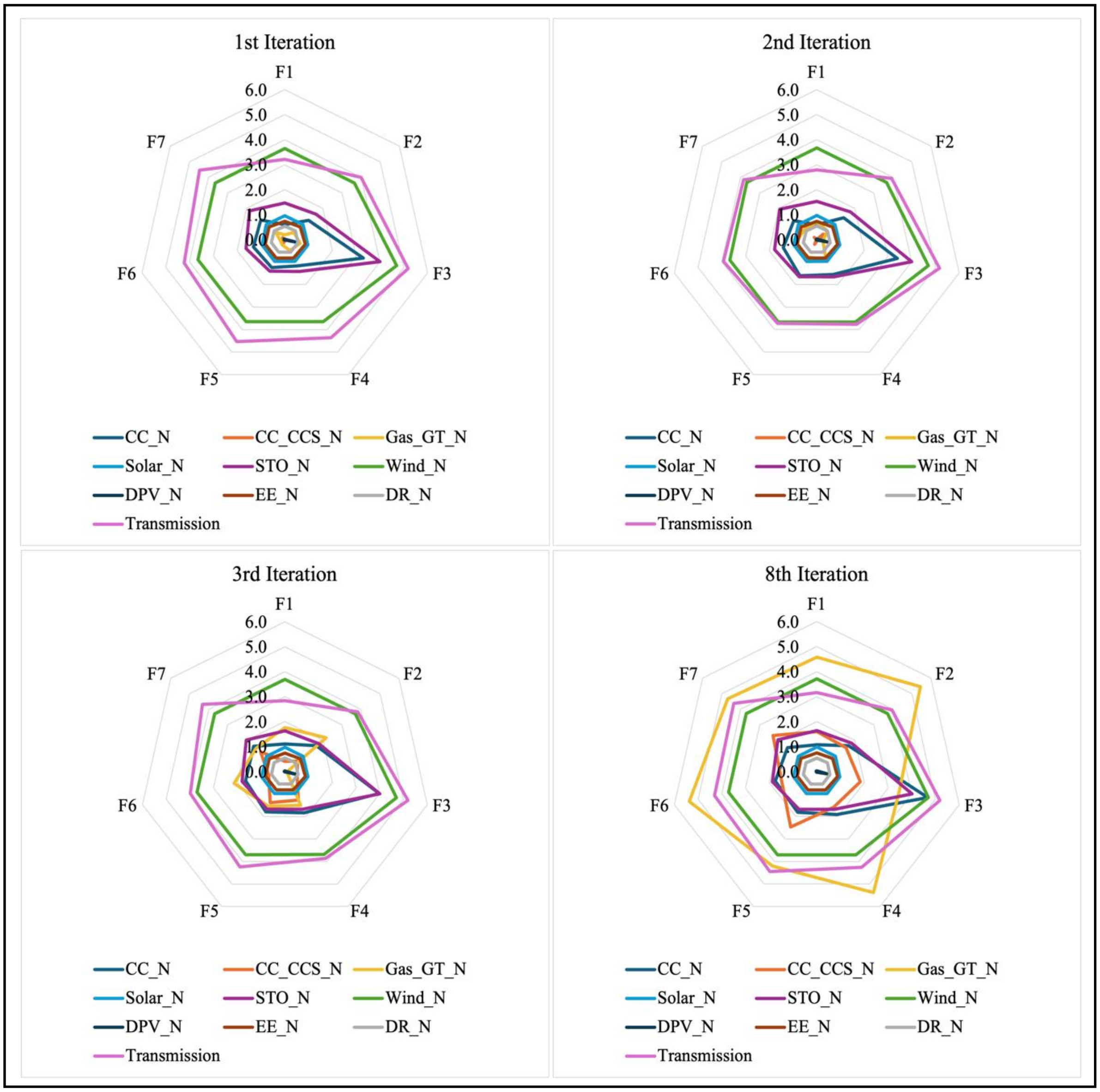

Figure 6-6 Time-averaged adaptation investments (GW) for each iteration using β=0.1.

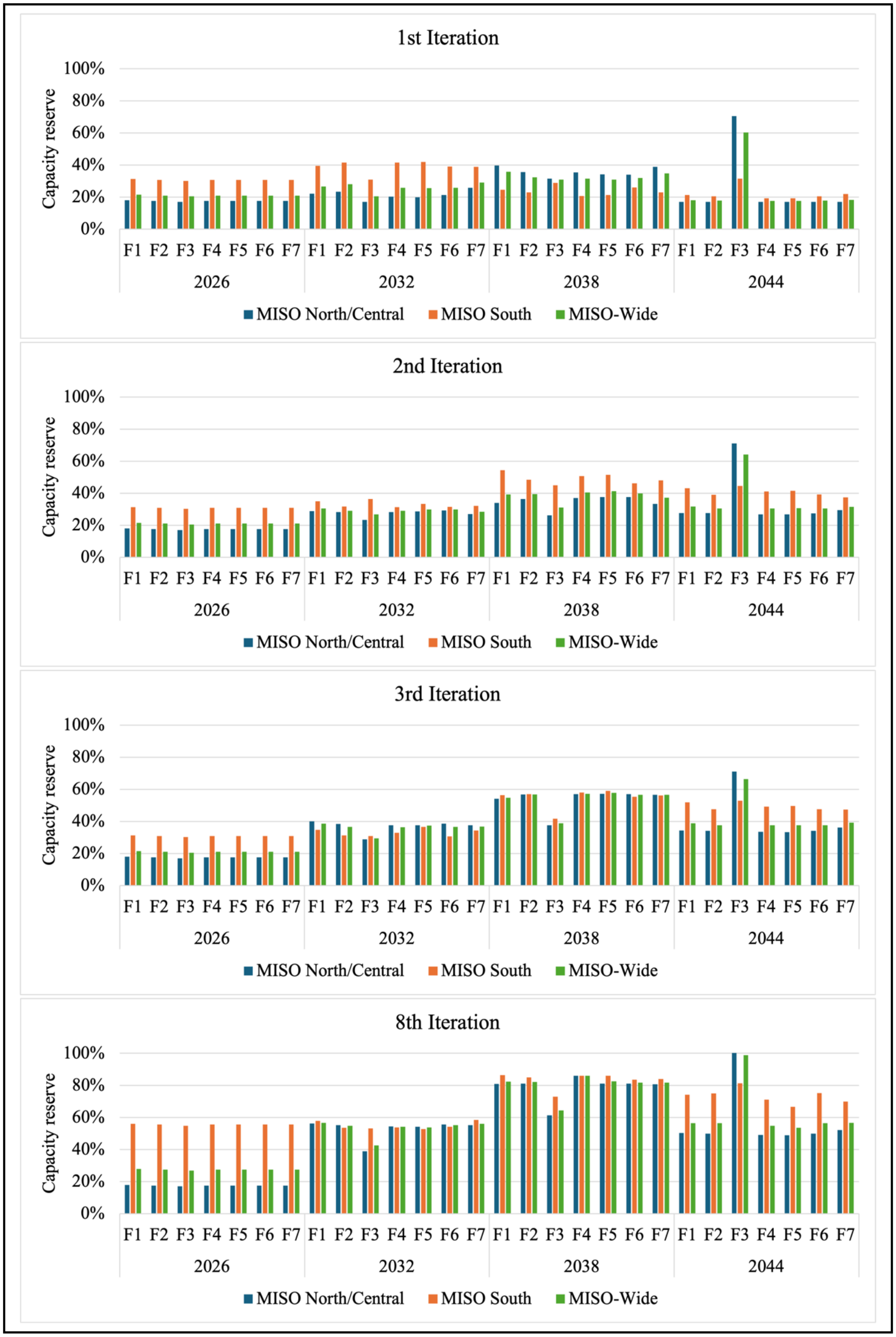

Figure 6-7 Accredited capacity reserve for each iteration using β=0.1.

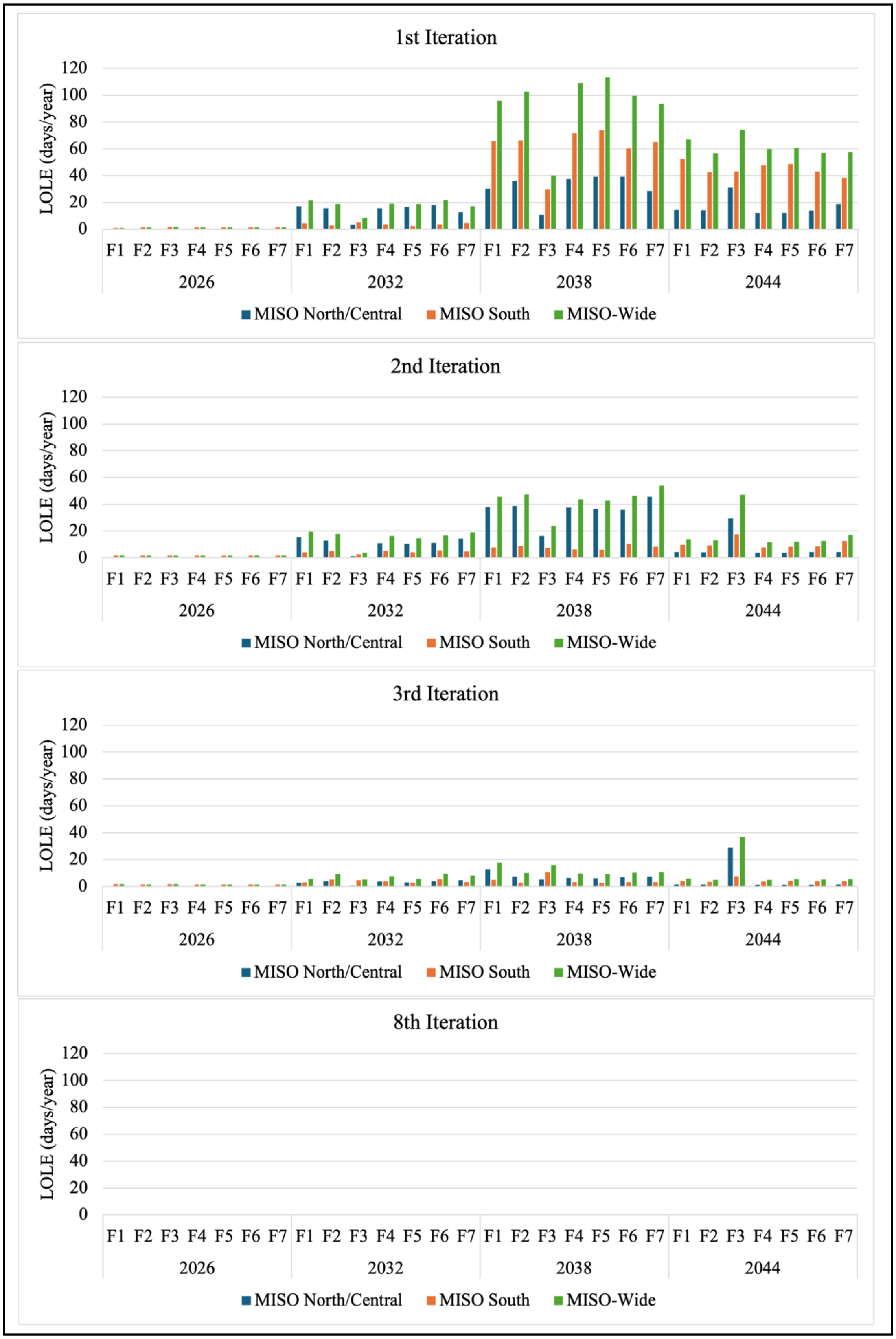

Figure 6-8 LOLE values for each iteration using β=0.1.

6.3 Key findings and implications

The results of this study reveal several important insights and key findings. The following subsections discuss the primary outcomes and their implications.

6.3.1 PRM-constrained expansion planning

Constraining generation investments to a fixed, system-wide PRM over the entire planning horizon can lead to a power system that is not consistently reliable across its footprint. The initial iteration showed that a 17% PRM for both MISO North/Central and South was insufficient to meet the desired LOLE. Through iterative ACEP/GE-MARS simulations, we identified the PRM values necessary to ensure system reliability, as shown in Figure 6-3 and Figure 6-7.

An interesting observation is the close similarity between the PRM values identified using different robustness parameters, $\beta=1$ and $\beta=0.1$. The average difference between the PRM values obtained with these two strategies is less than 5%. This indicates that regardless of the planning strategy (whether prioritizing core investments over adaptations or vice versa), the reserves required to ensure capacity adequacy for each area, future scenario, and year remain largely unchanged.

For the year 2026, both $\beta=1$ and $\beta=0.1$ scenarios resulted in a MISO-wide PRM value of approximately 28%. This value is close to the highest seasonal MISO-Wide PRM value (25%) reported in the LOLE study conducted by MISO [56]. The differences in results may be attributed to variations in modeling approaches used for resource adequacy assessments.

PRM values are inherently dynamic; they evolve over time and differ across regions due to factors such as demand behavior, infrastructure topology, the composition of the operating generation fleet, and weather variations. Given the uncertainties associated with these factors, it is essential to conduct RA assessments that account for these uncertainties and help identify capacity needs under a wide range of future scenarios over a long-term planning horizon.

6.3.2 Analysis of investment strategies through robustness parameter adjustment

The results demonstrate the capability of the ACEP tool to simultaneously identify least-cost core and adaptive generation and transmission investments across multiple future scenarios. Figure 6-1 and Figure 6-5 provide a breakdown of the cumulative core generation and transmission capacity investments, along with the associated core investment costs for robustness parameters $\beta=1$ and $\beta=0.1$, respectively. In general, as the value of β increases, both the cumulative core generation and transmission capacity and their costs rise, due to a reduced reliance on adaptive investments, which are typically more expensive. Consequently, the robustness of the core portfolio also increases with higher β values, as fewer adaptive investments are needed to meet the requirements across different future scenarios over the planning horizon.

Figure 6-2 and Figure 6-6 present spider plots that depict the time-averaged adaptive generation and transmission investments for $\beta=1$ and $\beta=0.1$, respectively. These adaptive investments are those required by the core investments to adjust to specific scenarios. As the value of β decreases, the preference shifts towards adaptive investments, making the core investments less resilient to uncertainties. From a planner's perspective, the β parameter serves as a strategic tool to balance the trade-off between core and adaptive investments. A lower β value results in a less costly core but one that is less robust to the uncertainties assessed by the ACEP model. Conversely, a higher β value yields a more resilient but more expensive core investment. Thus, planners can adjust the β parameter experimentally to develop a range of robust core investment portfolios tailored to different levels of uncertainty and risk tolerance.

6.3.3 Generation investments by type of technology

The core investments from the final iteration reveal distinct preferences for generation technologies under different robustness parameters. For both β=1 and β=0.1, wind energy emerges as the most favored technology, accounting for 35% and 40% of total investments, respectively. Solar energy follows as the second most attractive option, comprising 22% and 26% of the total investments for β=1 and β=0.1, respectively.

However, a notable difference appears in the third most invested technology. In the β=1 scenario, natural gas combustion turbines (CTs), referred to as Gas_GT_N in the study, occupy the third spot, accounting for 10% of the total investments (a significant increase from just 0.5% in the first iteration). In contrast, for β=0.1, natural gas CTs contribute only 1% to the total core investments. Despite this, natural gas CTs emerge as the most frequently chosen technology across all futures for β=0.1.

This trend suggests that as the grid integrates more renewable energy sources and retires existing thermal units, there is a growing need for technologies that can provide flexible and reliable capacity to meet RA requirements. Results obtained by the ACEP/GE-MARS tool highlight a preference for natural gas combustion turbines as a least-cost conventional option to complement the integration of renewable energy resources, supporting system reliability while satisfying operational and policy requirements. These turbines are particularly valuable in providing quick-start capabilities and dispatchable power, which are essential for compensating for the variability and intermittency associated with renewable energy sources, thereby ensuring the grid's adaptability to future uncertainties.

6.3.4 Risk-averse investments

ACEP helps identify risk-averse investments by analyzing their performance across various future scenarios over the planning horizon. Figure 6-2 and Figure 6-6 show that, except for Future 3, the additional investments needed to transition to different futures are fairly consistent. However, adaptation investments for Future 3 are significantly higher, indicating a higher level of risk. If substantial resources are allocated to address the uncertainties associated with Future 3 and these uncertainties do not materialize, it could result in over-investment. Unlike deterministic expansion studies, which analyze futures individually without considering their interactions, ACEP offers a flexible approach by identifying a least-cost core investment trajectory that can transition smoothly across multiple futures. This simultaneous analysis allows planners to develop more robust and cost-effective investment strategies that account for various uncertainties and avoid unnecessary expenditures, ultimately enhancing the efficiency and adaptability of power system planning.

6.3.5 Changes associated with the incorporation of RA assessments into ACEP

Incorporating RA assessments into ACEP through iterative recalculation of PRM values by GE-MARS leads to different investment strategies to meet the additional firm capacity required for the RA criterion, depending on the chosen robustness parameter β. For a higher robustness parameter (β=1), the adaptation investments remain relatively constant across iterations while core investments increase. Conversely, when a lower robustness parameter (β=0.1) is used, adaptation investments increase with each iteration, while core investments remain constant. This highlights that regardless of the RA requirements for expansion planning, the additional investments needed to meet the adjusted PRM will be allocated either core or adaptive investments, depending on the β value selected by the planner. Notably, there is a significant difference in the results between the first iteration and the final iteration when the LOLE requirements are met. This demonstrates the importance of incorporating RA assessments into ACEP, as it allows for more precise planning outcomes. By providing planners and stakeholders with detailed information about future capacity needs, the integrated approach supports the development of flexible investment strategies that are both adaptive and capable of meeting RA requirements across all potential futures and throughout the planning horizon.

7. Conclusions

This study highlights the role of advanced expansion planning tools in identifying the most economically viable investments required to meet future power system constraints. Traditional power system planning often involves studying multiple future scenarios individually, which can be both time-consuming and limited in scope. ACEP offers a sophisticated framework that evaluates the integrated influence of various scenarios more effectively. By cooptimizing generation and transmission investments, ACEP helps identify the least-cost core plan that requires the minimum adaptive investment to satisfy the particular needs of multiple futures considered. ACEP enhances the ability to balance investment costs with system robustness, providing a more comprehensive understanding of how different planning strategies perform across multiple futures.

Integrating the ACEP model with RA assessment through the GE-MARS tool represents a significant advancement in power system planning. This integration enhances the accuracy of investment calculations by ensuring that they are reliable across a range of future scenarios. By incorporating RA assessments into ACEP, we can more precisely determine the investments needed to maintain system reliability under multiple futures, thus providing planners with a clearer understanding of how to balance core and adaptation investments. This software system streamlines long-term planning efforts, empowering transmission system planners to make informed decisions and create flexible portfolios that prioritize both cost-effectiveness and reliability, considering uncertainties in the energy landscape.

One of the primary benefits of ACEP is its application of the robustness parameter, β. This parameter provides that ACEP is a flexible tool for exploring a spectrum of investment strategies, enabling the optimization of core and adaptive investments based on varying robustness and risk tolerance levels. A lower β value results in a more economical core investment but with reduced robustness against uncertainties, making it less resilient to unforeseen future conditions. Conversely, a higher β value leads to a more robust but expensive core investment, enhancing the system's ability to handle a broader range of potential future scenarios. Adjusting β allows planners to tailor their investment portfolios to different risk profiles and budget constraints, ultimately supporting a more balanced and adaptable approach to power system expansion. This strategic flexibility is essential for developing investment plans that not only meet current needs but also accommodate future uncertainties, ensuring long-term cost-effectiveness and reliability in power system planning.

Future research should focus on refining the ACEP model by integrating additional factors to enhance its accuracy. For instance, incorporating seasonal capacity credits for wind and solar resources would provide a more precise assessment of their contributions. On the GE-MARS side, improving the modeling of renewable generation by integrating more wind and solar profiles to reflect the geographical variations could further enhance the calculation’s accuracy. In terms of thermal generation, more precise FOR and POR values that account for a more historical database could also improve the modeling. Although these additions would increase computational complexity, it is likely to yield more reliable results by better modeling existing assets. Furthermore, evaluating the impact of interregional transmission investments through the ACEP/GE-MARS could offer valuable insights. Such an exploration would assess how interregional transmission affects RA indices and could reveal benefits in terms of overall system reliability.

As the power grid undergoes significant transformations driven by the integration of variable renewable energy sources, the retirement of conventional resources, and evolving regulatory demands, effective transmission planning becomes increasingly complex and crucial. Advanced computational tools are now essential for enhancing decision-making capabilities in this dynamic environment. This project addresses these challenges by developing a sophisticated software system integrating long-term expansion planning with probabilistic resource adequacy assessments. By combining the ACEP tool with GE-MARS, the system provides a robust framework for optimizing investment portfolios and ensuring reliability while addressing uncertainties and unreliability costs. The iterative approach employed demonstrates the tool's capability to balance investment robustness, resource adequacy, and system adaptability. By offering advanced simulation and optimization techniques, this integrated solution empowers transmission planners to make more informed decisions, ultimately contributing to a more adaptable and efficient power grid.

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Part III

Using Transmission Planning Model Outputs in Cost Allocation

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1. Introduction

1.1 Background

A wealth of recent research finds that large-scale expansion of regional and interregional transmission infrastructure in the U.S. would bring economic, reliability, and environmental benefits [1]–[3]. Planned additions to transmission, however, currently fall well short of the level deemed beneficial in models, with studies of deeply decarbonized U.S. systems projecting a need to double or even triple transfer capacity in the coming decades [4], [5]. One of the major challenges holding up investment is cost allocation: since many stakeholders are likely to benefit from expanded transmission infrastructure, it is difficult to come to a consensus on how to divide project costs among them. While this issue is common to many types of shared infrastructure projects (see, e.g., [6]), it may be particularly acute in the case of meshed electricity networks due to the potential for a change in one element to affect power flows across the entire system.

An underlying principle for cost allocation, codified by the Federal Energy Regulatory Commission (FERC) in Order 1000 [7] is that transmission costs should be allocated "in a manner that is at least roughly commensurate with estimated benefits." In principle, sufficiently detailed planning models could be used both to establish the net social benefits of a project and to estimate a distribution of those benefits among users, and [8] argues that these models would be the best available basis for determining a reasonable cost allocation. At the same time, both our information and our models fall well short of what would be needed for a precise computation, leading others to question the approach [9]. Judge Richard Cudahy of the U.S. Court of Appeals, dissenting in a case connected to Order 1000, articulates the opposing view as follows: "The majority has expressed a need for more precise numbers about benefits, burdens and a variety of other aspects. Now it has enhanced that need by suggesting the use of cost-benefit analysis (a method, some think, of dressing up dubious numbers to reach more impressive solutions). I will say preliminarily that I think the majority is under the impression that somehow there is a mathematical solution to this problem, and I think that this is a complete illusion. Despite the frequency with which cost-benefit analysis is used, it does not resolve the difficulty of accurately or meaningfully measuring the costs and benefits involved with these grid strengthening projects. Cost allocation, particularly at these extraordinarily high voltages, is far from a precise science, and there are no mathematical solutions to determining benefits region by region or subregion by subregion" [10]. This skepticism has perhaps been validated by the emergence since Order 1000 of a wide range of cost allocation methods that have all been determined to meet the "roughly commensurate" threshold, leading to inconsistent treatment of similar projects based on the process by which they were approved. Ongoing disputes led FERC to reopen the issue of cost allocation in a 2022 Notice of Proposed Rulemaking [11].

1.2 Overview of the Problem

This chapter addresses several questions connected to the use of models in identifying beneficiaries of transmission expansion, calculating their benefits, and allocating cost in a manner consistent with the "beneficiaries pay" standard. Despite the challenges, [12] reflects that "In the absence of an economically and politically acceptable formula, a direct benefits modeling approach as advocated by Hogan may prove the only workable solution." The Organization of MISO States

(OMS), which includes regulators from a politically diverse set of states in the Midcontinent Independent System Operator (MISO) region, largely endorses the approach in its Statement of Principles for cost allocation [13]. In this context, the chapter considers both how existing methods can create conflict by ignoring modeled benefits as well as the factors that may prevent a "direct benefits modeling" approach from being workable.

At least three categories of issues affect the computation of benefits and the translation of modeled benefits to a mutually agreeable cost allocation. The first category relates to the models themselves. Transmission planners use a variety of software tools to inform planning, which can be broadly split into 1) security analysis tools, involving detailed power flow models but no economic criteria, 2) production cost tools, which simulate market outcomes with a fixed resource mix, 3) expansion planning tools, which optimize the addition of new generation and transmission resources, and 4) resource adequacy tools, which evaluate the reliability provided by a given resource mix given simulated weather and outage scenarios. In principle, socially optimal transmission decisions could be given by an expansion planning model (number 3 above) that incorporated production cost simulations (2) on a number of scenarios comparable to that used in resource adequacy analysis (4) and including fully specified power flow constraints (1), while also considering the strategic behavior of market participants. The intractability of such a model means that benefit calculations must be performed on separate tools that are simplified along different dimensions, leading to the potential for benefits to be either omitted or duplicated. The second category relates to explicit disagreements on the value of particular benefits. While economic outcomes have a shared measure, benefits related to reliability and public policy are more difficult to quantify. In particular, different jurisdictions in the same regional market often assign different values to carbon reduction and air pollution mitigation. Additionally, some jurisdictions within a market may give more weight to producers of electricity (e.g., to support job creation), while others prioritize consumers. The third category relates to uncertainty in the input parameters required for planning models (e.g., future demand growth and technology improvements). Even if the benefits could be quantified in a straightforward way, the significant uncertainty inherent to the system means that the ex ante estimates of expected benefits could be very different from the actual benefits seen ex post. Since participants are unlikely to agree on the probability of potential future scenarios, and may even benefit from strategically misrepresenting their views on those probabilities, they are unlikely to agree on estimated benefits.

We primarily address the first and third of these issues, leaving a more comprehensive discussion of the second to future work. Existing model-based approaches for cost allocation can be divided between those assessing benefits based on changes in power flows [14]–[17] or in prices[8], [18]–[22]. While physical approaches are sometimes used in practice, and it is possible that physical usage correlates with economic benefits, the connection is not clear and we take the more direct economic approach. The economics-based models can be further divided between those computing benefits directly [8], [18], [22] and those employing concepts from cooperative game theory to address the bargaining power of different participants [19]–[21]. Conceding the salience of bargaining power, we pursue the former approach due to its clearer connection to the "beneficiaries pay" principle. Among the models analyzed, none explicitly include uncertainty and only [21] includes recourse decisions in the form of generation investment. Along these lines, we extend the approach sketched on simple examples in [22] to a stochastic program co-optimizing the expansion of transmission and generation over a long time horizon. While such models have been considered by many researchers [23]–[26], the primary focus in the literature has been identifying high-quality planning solutions rather than investigating the implications for cost allocation. Using our model, we establish beneficiaries and calculate benefits under many possible realizations of uncertainty, providing a more comprehensive understanding of the implications of network expansion for all involved parties. While we do not explicitly model the effect that cost allocation decisions may have on the network expansion decisions themselves, as in [27], these potential consequences are a theme throughout the discussion.

1.3 Report Organization

Through theoretical analysis and a numerical study on a stylized version of the Electric Reliability Council of Texas (ERCOT) system, we discuss five issues:

1. How to construct a valid counterfactual against which to measure benefits of a transmission investment. Here, our primary argument is that at a minimum models must include the different generation and storage investments likely to arise in response to different transmission expansion decisions.
2. When cost should be allocated to generators. While current practice in U.S. systems typically allocates cost to new interconnecting generators but then excludes them from subsequent cost allocation, we conclude that a direct benefits modeling approach would instead allow new generators to connect without cost but then allocate cost to them throughout their life.
3. Whether to allocate costs on a project-by-project basis or as a portfolio. In the numerical study, allocation at the project level implies that positive cost is allocated to participants with negative net benefits overall; on this basis, we find that portfolio-based allocation is more consistent with the "beneficiaries pay" principle.
4. The potential to compensate market participants who see negative expected benefits from expansion decisions. Here we suggest that the surplus gained from transmission expansion could in principle be used to compensate participants who see negative net benefits, potentially reducing conflicts.
5. The potential that participant-level benefits realized ex post will be significantly out of alignment with ex ante estimates. Again with the intent of reducing conflicts, we suggest the possibility of defining financial contracts that would effectively reallocate cost ex post to market participants based on realized benefits.

While the first three are topics of active debate among regulators and thus have near-term policy implications, the last two raise issues for longer-term consideration.

2. Stochastic Expansion Planning

As a basis for analyzing the cost allocation problem, we construct a two-stage stochastic program optimizing expansion of generation and transmission over an extended horizon given an agreed-upon set of scenarios. Capacity expansion can be posed either as a social planning problem [26], [28] or as a multi-agent game in a competitive market setting [23], [29]. Given the complexity of modeling strategic behavior, system operators at present rely on more straightforward optimization formulations [30]. We adopt the same approach, noting that because expansion of transmission tends to weaken the ability of generators to exercise local market power [31] inclusion of strategic considerations in our model would likely shift our estimates of the distribution of benefits away from generators toward consumers. The first stage of the stochastic program includes decisions for the present year, while the second stage includes decisions to be made in several subsequent years. While the analysis could also be extended to a multistage setting with each year corresponding to a stage, we use a two-stage approximation to ensure scalability in the numerical study.

The problem is formulated as a mixed-integer programming (MIP) model with transmission line investment decisions as binary variables and generation investment decisions as continuous. Binary variables are needed to represent a key feature of transmission investments, namely, significant economies of scale. Further, it is typically impossible to build a transmission facility with a rating that exactly matches the need, as equipment is available only in a limited number of standardized voltage and power ratings. Transmission investments in the model can be selected from defined levels of expansion with costs reflecting economies of scale. For generation investments, we assume perfect competition and linear costs. These assumptions ensure that, conditional on the transmission network decisions, nodal electricity prices support a resource mix that maximizes long-term social welfare.

Rather than the development of the planning model itself, the primary focus of this study is the translation of the planning model results to cost allocation determinations. Many debates in transmission planning concern the selection of scenarios and benefit–cost thresholds used to justify the investment, as well as the subjective valuation of non-quantified benefits [8]. We set aside these issues, as it is sufficient for the discussion to have a planning tool that recommends transmission investments with positive expected net benefits in sample. We assume that a stakeholder process is able to construct scenarios and associated probabilities for use in the model, but do not assume that these scenarios are exhaustive, that the selected probabilities are accurate, or that the chosen scenarios and probabilities match the beliefs of individual market participants.

2.1 Notation

Sets:

y/Y: time index (years)
n/N: nodes in a scenario tree
b/B (B'): buses (without reference bus)
t/T : time blocks
l/L: lines
g/G: all generators
$g/G_R \subseteq G$: renewable generators

$g/\mathrm{G}_T \subseteq \mathrm{G}$: thermal generators
q/Q: transmission capacity increment options
i/I: power balance penalty curve segments

Parameters:

$\zeta_{\delta(n)}$ (ζ_y): discount factor of node n (in time index y)
$C_{n,g}^{\mathrm{INV}}$: annualized generation investment cost of generation technology g in node n per unit capacity ($/MW)
$C_{l,q}^{\mathrm{INV}}$: annualized transmission investment cost of line l for expansion type q ($)
C_g^{FIX}: per unit fixed operation and maintenance cost of generation technology g ($/MW-yr)
C_g^{VOM}: per unit variable operation and maintenance cost of generation technology g ($/MWh)
$C_{n,g}^{\mathrm{EN}}$: per unit production fuel cost of generation technology g in node n ($/MWh)
γ_i^{PB}: penalty value of power balance violation in segment i ($/MWh)
γ^{LINE}: penalty value of transmission line violation ($/MWh)
γ^{VOLL}: per unit benefit for serving load ($/MWh)
T_t: duration of time block t (h)
$CA_{b,g,t}$: capacity availability of generation technology g located at bus b at time t
RPS_n: renewable portfolio standard in node n (%)
$D_{n,b,t}$: demand at bus b in time block t in node n
ΔL_q: transmission capacity increment q
$SF_{l,b}$: shift factor matrix indexed by $l \in \mathrm{L}, b \in \mathrm{B}$
φ_n: the probability of node n
Z_i: Maximum MW violation of power balance constraint for segment i

Variables:

$c^{\mathrm{cap}}{}_n$: the capital cost in node n ($)
$c^{\mathrm{op}}{}_n$: the operation cost in node n ($)
$G_{n,b,g}$: total cumulative generation capacity of generation g at bus b in node n (MW)
$\Delta G_{n,b,g}$: generation investment in generation technology g at bus b in node n (MW)
$\Delta \bar{G}_{n,b,g}$: generation retirement of existing generation g at bus b in node n (MW)
$L_{n,l}$: total cumulative transmission capacity of line l in node n (MW)
$w_{n,l,q}$: binary variable to decide transmission increment q in line l in node n (MW)
$p_{n,b,g,t}$: generation dispatch of generation technology g at bus b at time t in node n (MW)
$z_{n,b,t,i}$: load curtailment segment i at bus b at time t in node n (MW)
$NI_{n,b,t}$: power net injection at bus b in node n at time t (MW)
$sl_{n,l,t}$: slack variable for power flow on line l in node n at time t (MW)

Dual Variables:

$\pi_{n,b,t}$: locational marginal price (LMP) at time block t at bus b in node n ($/MWh)
$\theta_{n,b,g,t}$: marginal value of a unit of generation technology $g \in \mathrm{G}$ at time t ($/MWh)
ν_n: unit price for contributing to the renewable portfolio standard in node n ($/MWh)

Outputs:

U_b^{load}: the aggregated load surplus at bus b
$\mathrm{U}_{b,g}^{gen}$: the per unit generation surplus of generation technology g at bus b
r_b^{load}: cost allocation ratio of the transmission expansion to bus b (%)

$r_{b,g}^{gen}$: cost allocation ratio of the transmission expansion to existing generation g at bus b (%)

2.2 Formulation

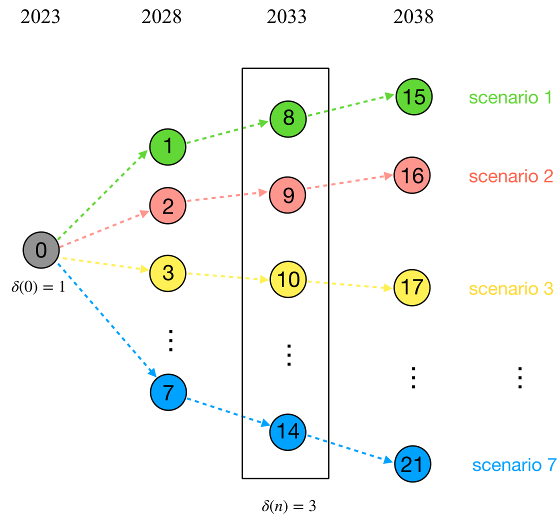

Figure 2-1 An illustration of a scenario tree with 7 scenarios and Y={1,2,3,4}.

We employ a scenario tree with nodes $n \in N$ to represent the investment trajectory for the two-stage stochastic program. Each node represents a possible state of the world, associated with a set of data. The root node $n = 0$ in the first stage represents the current state of the world. The unique predecessor of any node $n \neq 0$ is denoted as n_- and the set of predecessors of node n on the path from n to the root node is denoted as $P(n)$. The depth $\delta(n)$ of node n is the number of nodes on the path to node 0, with $\delta(0) = 1$. The depth $\delta(n)$ of node n also corresponds to a time index $y \in Y$. We use φ_n to represent the probability that the path taken through the scenario tree includes node n, with $\Sigma_{n \in N:\delta(n)=y}\, \varphi_n = 1\ \forall y \in Y$. A visual representation of such a scenario tree with $Y = \{1,2,3,4\}$ and 7 scenarios is drawn in Figure 2-1. As indicated by the dashed lines, nodes at depth 2 and 3 have a unique successor, reflecting the two-stage simplification previously mentioned. This tree structure mimics the scenario-based planning performed by many system operators, but forces convergence to a single decision in the present year. The focus of the cost allocation discussion will be on transmission investments made in the present year.

In each node n, the capital cost includes the transmission and generation investment costs incurred due to the cumulative investment decisions made on the path from node n to the root node, given by

$$c_n^{\text{cap}} = \sum_{n' \in \mathcal{P}(n)} \sum_{l \in \mathcal{L}} \sum_{q \in \mathcal{Q}} C_{l,q}^{\text{INV}} w_{n',l,q} + \sum_{n' \in \mathcal{P}(n)} \sum_{b \in \mathcal{B}} \sum_{g \in \mathcal{G}} C_{n',g}^{\text{INV}} \Delta G_{n',b,g} \tag{1}$$

In other words, investments result in ongoing capital costs throughout the years are covered by the model. This formulation reflects the fact that resources built in the earlier nodes of the model will have completed a larger fraction of their useful lives by the end of the scenario tree.
At node n, the operating cost is (2)

$$c_n^{\text{op}} = \sum_{b \in \mathcal{B}} \sum_{g \in \mathcal{G}} C_g^{\text{FIX}} G_{n,b,g} + \sum_{b \in \mathcal{B}} \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} C_g^{\text{VOM}} T_t p_{n,b,g,t} + \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{g \in \mathcal{G}} C_{n,g}^{\text{EN}} T_t p_{n,b,g,t}$$

where the first two terms are the ongoing fixed and variable operation and maintenance costs of generation, the third term is the fuel cost, and the last two terms are penalties for curtailed load and transmission constraint violations.

The system planner seeks to maximize the net present value of expected benefits over the assumed scenario tree. With the penalty curve for curtailed load serving as a proxy for price-responsive demand, the model can be formulated as a minimization problem as follows:

$$\max \sum_{n \in \mathcal{N}} \phi_n \zeta_{\delta(n)} \left(\sum_{t \in \mathcal{T}} \sum_{b \in \mathcal{B}} T_t \gamma^{\text{LOAD}} D_{n,b,t} - c_n^{\text{op}} - c_n^{\text{cap}} \right) \tag{3a}$$

$$\text{s.t. } L_{n,l} = L_{0,l} + \sum_{n' \in \mathcal{P}(n_-)} \sum_{q \in \mathcal{Q}} w_{n',l,q} \Delta L_q \ \forall n \in \mathcal{N} \setminus 0, l \in \mathcal{L} \tag{3b}$$

$$G_{n,b,g} = G_{0,b,g} + \sum_{n' \in \mathcal{P}(n)} \Delta G_{n',b,g} - \sum_{n' \in \mathcal{P}(n)} \Delta \bar{G}_{n',b,g} \ \forall n \in \mathcal{N}, b \in \mathcal{B}, g \in \mathcal{G} \tag{3c}$$

$$\left(\phi_n \zeta_{\delta(n)} T_t \theta_{n,b,g,t}\right): \ p_{n,b,g,t} \leq CA_{b,g,t} G_{n,b,g} \ \forall n \in \mathcal{N}, b \in \mathcal{B}, g \in \mathcal{G}, t \in \mathcal{T} \tag{3d}$$

$$\left(\phi_n \zeta_{\delta(n)} \nu_n\right): \ \sum_{t \in \mathcal{T}} \sum_{b \in \mathcal{B}} \sum_{g \in \mathcal{G}_R} T_t p_{n,b,g,t} \geq RPS_n \sum_{t \in \mathcal{T}} \sum_{b \in \mathcal{B}} T_t D_{n,b,t} \ \forall n \in \mathcal{N} \tag{3e}$$

$$\left(\phi_n \zeta_{\delta(n)} T_t \pi_{n,b,t}\right): \ NI_{n,b,t} = \sum_{g \in \mathcal{G}} p_{n,b,g,t} + \sum_{i \in \mathcal{I}} z_{n,b,t,i} - D_{n,b,t} \ \forall n \in \mathcal{N}, b \in \mathcal{B}, t \in \mathcal{T} \tag{3f}$$

$$-\left(L_{n,l} + sl_{n,l,t}\right) \leq \sum_{b \in \mathcal{B}'} SF_{l,b} NI_{n,b,t} \leq \left(L_{n,l} + sl_{n,l,t}\right) \ \forall n \in \mathcal{N}, l \in \mathcal{L}, t \in \mathcal{T} \tag{3g}$$

$$\sum_{b \in \mathcal{B}} NI_{n,b,t} = 0 \ \forall n \in \mathcal{N}, t \in \mathcal{T} \tag{3h}$$

$$\Delta G_{n,b,g}, \Delta \bar{G}_{n,b,g}, p_{n,b,g,t} \geq 0 \ \forall n \in \mathcal{N}, b \in \mathcal{B}, g \in \mathcal{G}, t \in \mathcal{T} \tag{3i}$$

$$z_{n,b,t,i} \geq 0 \ \forall n \in \mathcal{N}, b \in \mathcal{B}, t \in \mathcal{T}, i \in \mathcal{I} \tag{3j}$$

$$\sum_{b \in \mathcal{B}} z_{n,b,t,i} \leq \bar{Z}_i \ \forall n \in \mathcal{N}, t \in \mathcal{T}, i \in \mathcal{I} \tag{3k}$$

$$sl_{n,l,t} \geq 0 \ \forall n \in \mathcal{N}, l \in \mathcal{L}, t \in \mathcal{T} \tag{3l}$$

$$w_{n,l,q} \in \{0,1\} \ \forall n \in \mathcal{N}, l \in \mathcal{L}, q \in \mathcal{Q}. \tag{3m}$$

Constraint (3b) states that the total cumulative transmission capacity is equal to the initial existing transmission capacity plus the sum of the transmission capacity expansion along the path from node 0 to node n_{-}, while constraint (3c) states that the total cumulative generation capacity is equal to the initial existing generation plus the sum of generation capacity expansion minus generation retirement along the path from node 0 to node n. The delayed in-service date for new transmission relative to new generation is intended to capture the longer development timelines typical for transmission projects. Constraint (3d) states that power production is limited by the total installed capacity of a given technology multiplied by its availability in each time block. Constraint (3e) enforces a system-wide renewable portfolio standard (RPS), mandating a percentage of the total amount of power generation coming from renewable energy sources. Constraint (3f) calculates the net power injection at bus b, while constraint (3g) is a soft constraint limiting power flow on a transmission line. Constraint (3h) states the sum of the net power injection in the network should be zero. Constraints (3j) and (3k) state that each load curtailment segment is non-negative and the sum of load curtailment segment cannot exceed the maximum MW violation of that segment. After fixing binary variables w, we can query the dual variables of the constraints in the resulting linear program. Dual variables are scaled in order to produced unscaled prices and inframarginal rents. The dual variable $\theta_{n,b,g,t}$ of constraint (3d) can be interpreted as the marginal value of capacity of generation technology g at bus b in time block t. The dual variable $\pi_{n,b,t}$ of constraint (3f) is the locational marginal price (LMP). For completeness we define the linear program using the optimal values $w_{n,l,q}{}^{*}$ found when solving model (3) as follows:

$$\begin{aligned} \max\ & (3a) \\ \text{s.t.}\ & (3\text{b}) - (3\text{l}) \\ & w_{n,l,q} = w^{*}_{n,l,q} \qquad \forall n \in \mathcal{N}, l \in \mathcal{L}, q \in \mathcal{Q}. \end{aligned} \tag{4a}$$

3. Establishing Beneficiaries

Supposing that system planners use model (3) to identify transmission expansion decisions, this section addresses the question of how to define beneficiaries, as well as the challenges that arise even when all parties agree on the formulation and scenarios used in the model.

3.1 Establishing a Counterfactual

To measure the benefits brought by a certain transmission project, we first need to define a counterfactual against which benefits will be measured. Establishing a counterfactual to the construction of a particular transmission investment is complicated by the fact that subsequent transmission and generation investment, as well as operations, will change as a result of the investment under study. Some cost allocation schemes currently used in U.S. systems, especially those for investments motivated by reliability violations rather than economic efficiency, fail to establish a valid counterfactual because the models omit the possibility of operational changes or compensatory investments. As discussed in [32], the absence of a valid counterfactual is particularly clear in the case of interconnecting new generators.

After solving model (3) and determining expansion decisions for the present year, there are at least three ways that a counterfactual might be established. In each case, re-solving model (3) with additional constraints leads to an alternate solution with a higher objective function value. We define three options as follows:

1. Exclude the specific transmission investment and fix all other transmission and generation investments; benefits reflect the difference in operating cost between the solutions.

2. Exclude the specific transmission investment, fix all other transmission investments, and allow generation investments to optimally readjust to the counterfactual network; benefits reflect the difference in investment and operating cost between the solutions.

3. Exclude the specific transmission investment (at all levels $q \in Q$ and for either all years $y \in Y$ or just the present), but allow freedom in both generation and other transmission investments; benefits reflect the difference in investment and operating cost between the solutions.

The primary issue with the first option is that it is unrealistic and unnecessarily restrictive. Excluding the transmission investment without allowing any compensatory investments could lead to a situation with unsolvable reliability violations, leading either to an infeasible model or large costs driven by penalty parameters. The primary issue with the third option is that in order to determine participant-level benefits for the projects of interest, cost allocation determinations also need to be made for the counterfactual transmission projects. Since these allocations would in turn be determined against a similarly defined counterfactual, allowing these alternatives introduces a recursive aspect to the problem. Since allocations based on the first are guaranteed to be inaccurate and those based on the third would be impractical, we suggest that analysis should pursue the second option. Since investment in generation (as well as storage and distributed resources) is often exogenous or excluded from current models, we note the contrast between our recommendation and the claim in [8] that the information needed for cost allocation is already available in current planning models.

Putting this suggestion into practice could be challenging, especially in the case of upgrades prompted by reliability violations not observable in the linear approximations to the power flow equations typically used in capacity expansion models. At the expense of additional complexity, more complicated constraints could in principle be brought into model (3), making the construction of a valid counterfactual more straightforward. In practice, it is more common in such cases to skip the step of establishing a counterfactual altogether, instead socializing the cost of related upgrades or relying on power flow analyses with unclear connection to economic benefits. Even if an optimization model is not used, however, a better approach to assess benefits would be specifying a plausible alternative to resolve the identified reliability violations and measuring cost against this alternative. Noting the challenge, for the remainder of this chapter we assume that benefits associated with the level of reliability are captured through penalties on power balance violations in model (3).

We can formalize the construction of a counterfactual as follows. Suppose we are interested in allocating the cost of one or more transmission investments represented by a subset $W^{INV} \subset W = N \times L \times Q$ of the binary variables $w_{n,l,q}$, where we assume that the investments of interest occur at node n = 0. Then counterfactual generation investments, along with counterfactual prices and production quantities, can be found by solving

$$\begin{aligned} &\max\ (3a) \\ &\text{s.t.}\ \ (3\text{b}) - (3\text{l}) \\ &\quad w_{n,l,q} = 0 \qquad \forall (n,l,q) \in \mathcal{W}^{INV} \qquad (5\text{a}) \\ &\quad w_{n,l,q} = w^{*}_{n,l,q} \qquad \forall (n,l,q) \in \mathcal{W} \backslash \mathcal{W}^{INV}. \qquad (5\text{b}) \end{aligned}$$

3.2 Generation

We first consider the potential for generators to benefit from transmission expansion. An important distinction is between new and existing generators. At present, most U.S. systems allocate some cost to new interconnecting generators, but do not subsequently allocate cost to generators once they are built. The primary point of this subsection is to show that, in general, the current practice is the opposite of what is implied by the direct benefits modeling approach pursued in this chapter.

Evaluated at node 0, the discounted operating profit expected by a unit of generation of type g at bus b can be calculated as

$$\mathbb{E}\left(\mathcal{U}^{gen}_{b,g}\right) = \sum_{n \in \mathcal{N}} \zeta_{\delta(n)} \phi_n \left(\sum_{t \in \mathcal{T}} T_t \left(\pi_{n,b,t} - C^{\text{EN}}_{n,g} - C^{\text{VOM}}_{g} + \nu_n \mathbb{1}_{\{g \in \mathcal{G}_R\}} \right) \frac{p_{n,b,g,t}}{G_{n,b,g}} - C^{\text{FIX}}_{g} \right) \quad (6)$$

where $\mathbb{1}_{\{g \in \mathcal{G}_R\}} = 1$ if the generator can sell renewable energy credits and 0 otherwise. With $\mathbb{E}\left(\mathcal{U}^{*gen}_{b,g}\right)$ indicating expected benefits assuming the socially optimal transmission configuration and $\mathbb{E}\left(\mathcal{U}'^{gen}_{b,g}\right)$ indicating expected benefits with the counterfactual transmission configuration, the per unit expected benefit for generation of type g located at bus b from transmission expansion can then be calculated as the difference in expected operating profits:

$$\mathbb{E}\left(\Delta \mathcal{U}_{b,g}^{gen}\right) = \mathbb{E}\left(\mathcal{U}_{b,g}^{*gen}\right) - \mathbb{E}\left(\mathcal{U}_{b,g}^{\prime gen}\right) \tag{7}$$

3.2.1 Existing generators

We first consider the case of existing generators, which can more clearly benefit or be harmed by transmission expansion. The presence of new generation in either the socially optimal or the counterfactual case can indicate how existing generators of the same type and located at the same bus are affected by the expansion. We state three cases formally as Theorem (1) and Corollaries (1) and (2).

Theorem 1. *Suppose new generation of type g is constructed at bus b in both the expansion scenario, i.e.,* $\Delta G_{0,b,g}^{*} > 0$*, and the counterfactual scenario, i.e.,* $\Delta G_{0,b,g}^{\prime} > 0$*. Then existing generation of that type at that bus neither benefits nor suffers losses from the expansion, i.e.,* $\mathbb{E}\left(\Delta \mathcal{U}_{b,g}^{gen}\right) = 0$.

Proof. For model (4), the KKT conditions on $p_{n,b,g,t}$ are

$$0 \leq p_{n,b,g,t} \perp C_{n,g}^{\text{EN}} + C_{g}^{\text{VOM}} + \theta_{n,b,g,t} - \pi_{n,b,t} - \nu_n \mathbb{1}_{\{g \in \mathcal{G}_R\}} \geq 0 \ \forall n \in \mathcal{N}, b \in \mathcal{B}, g \in \mathcal{G}, t \in \mathcal{T} \tag{8}$$

By the complementarity condition, if $p_{n,b,g,t} > 0$, we have $\theta_{n,b,g,t} = \pi_{n,b,t} - C_{n,g}^{\text{EN}} - C_{g}^{\text{VOM}} + \nu_n \mathbb{1}_{\{g \in \mathcal{G}_R\}}$.

Then the discounted operating profit (6) can be written as

$$\mathbb{E}\left(\mathcal{U}_{b,g}^{gen}\right) = \sum_{n \in \mathcal{N}} \zeta_{\delta(n)} \phi_n \left(\sum_{t \in \mathcal{T}} T_t \theta_{n,b,t} \frac{p_{n,b,g,t}}{G_{n,b,g}} - C_{g}^{\text{FIX}} \right) \tag{9}$$

By complementary slackness, when $\theta_{n,b,t} > 0$, $\frac{p_{n,b,g,t}}{G_{n,b,g}} = CA_{b,g,t}$ holds. When $\theta_{n,b,t} = 0$, replacing $\frac{p_{n,b,g,t}}{G_{n,b,g}}$ with $CA_{b,g,t}$ would not affect the result. After replacement, the discounted operating profit (6) becomes

$$\mathbb{E}\left(\mathcal{U}_{b,g}^{gen}\right) = \sum_{n \in \mathcal{N}} \zeta_{\delta(n)} \phi_n \left(\sum_{t \in \mathcal{T}} T_t \theta_{n,b,t} CA_{b,g,t} - C_{g}^{\text{FIX}} \right) \tag{10}$$

For both models (4) and (5), the objective function and variable $G_{n,b,g}$ are defined to include summation over the path P(n). Given that node 0 is on the path of every node to the root node in the scenario tree, it follows that the KKT condition on $\Delta G_{0,b,g}$ would aggregate over all nodes within the tree, given by

$$0 \leq \Delta G_{0,b,g} \perp \sum_{n \in \mathcal{N}} \zeta_{\delta(n)} \phi_n \left(C_{0,g}^{\text{INV}} + C_{g}^{\text{FIX}} - \sum_{t \in \mathcal{T}} T_t CA_{b,g,t} \theta_{n,b,g,t} \right) \geq 0 \ \forall g \in \mathcal{G}, b \in \mathcal{B} \tag{11}$$

By complementary slackness, $\Delta G_{0,b,g} > 0$ implies

$$\sum_{n\in\mathcal{N}} \zeta_{\delta(n)}\phi_n\left(C_{0,g}^{\mathrm{INV}} + C_g^{\mathrm{FIX}} - \sum_{t\in\mathcal{T}} T_t CA_{b,g,t}\theta_{n,b,g,t}\right) = 0$$

When new generation of type g is constructed at bus b in the both expansion scenario and counterfactual scenario, i.e., $\Delta G^*_{0,b,g} > 0$ and $\Delta G'_{0,b,g} > 0$, we have $\mathbb{E}\left(\mathcal{U}^*{}^{*gen}_{b,g}\right) = \mathbb{E}\left(\mathcal{U}'^{gen}_{b,g}\right) = \sum_{n\in\mathcal{N}} \zeta_{\delta(n)}\phi_n C_{0,g}^{\mathrm{INV}}$. By the definition of benefits in (7), this leads to $\mathbb{E}\left(\Delta\mathcal{U}^{gen}_{b,g}\right) = 0$. □

Corollary 1. *Suppose new generation of type g is constructed at bus b in the expansion scenario, i.e., $\Delta G^*_{0,b,g} > 0$, but not in the counterfactual scenario, i.e., $\Delta G'_{0,b,g} = 0$. Then existing generation of that type at that bus benefits from the expansion, i.e., $\mathbb{E}\left(\Delta\mathcal{U}^{gen}_{b,g}\right) > 0$.*

Proof. As shown in Theorem 1, $\Delta G^*_{0,b,g} > 0$ implies $\mathbb{E}\left(\mathcal{U}^{\mathrm{gen}}_{b,g}\right) = \sum_{n\in\mathcal{N}} \zeta_{\delta(n)}\phi_n C_{0,g}^{\mathrm{INV}}$. $\Delta G'_{0,b,g} = 0$ implies $\mathbb{E}\left(\mathcal{U}'^{gen}_{b,g}\right) < \sum_{n\in\mathcal{N}} \zeta_{\delta(n)}\phi_n C_{0,g}^{\mathrm{INV}}$. Therefore, by (7), the difference in expected operating profits is positive, i.e., $\mathbb{E}\left(\Delta\mathcal{U}^{gen}_{b,g}\right) > 0$. □

Corollary 2. *Suppose new generation of type g is constructed at bus b in the counterfactual scenario, i.e., $\Delta G'_{0,b,g} > 0$, but not in the expansion scenario, i.e., $\Delta G^*_{0,b,g} = 0$. Then existing generation of that type at that bus suffers losses from the expansion, i.e., $\mathbb{E}\left(\Delta\mathcal{U}^{gen}_{b,g}\right) < 0$.*

Proof. As shown in Theorem 1, $\Delta G^*_{0,b,g} = 0$ implies $\mathbb{E}\left(\mathcal{U}^{gen}_{b,g}\right) < \sum_{n\in\mathcal{N}} \zeta_{\delta(n)}\phi_n C_{0,g}^{\mathrm{INV}}$. $\Delta G'_{0,b,g} > 0$ implies $\mathbb{E}(\mathcal{U}'^{g}, \mathrm{g}, \mathrm{n}) = \sum_{n\in\mathcal{N}} \zeta_{\delta(n)}\phi_n C_{0,g}^{\mathrm{INV}}$. Therefore, by (7), the difference in expected operating profits is negative, i.e., $\mathbb{E}\left(\Delta\mathcal{U}^{gen}_{b,g}\right) < 0$. □

At a high level, it can be expected that generators in exporting regions will see benefits from transmission expansion while generators in importing regions will suffer losses. Clear examples of this effect are shown in [8] and [22]````````````````````````, which analyze two-zone systems without subsequent generation investment. The more complex numerical study in this chapter largely matches this intuition.

3.2.2 New generators

We now turn attention to newly built generation. If these resources would have been built even without the transmission expansion occurring in node 0, then benefits can be defined similarly to existing generators. In this case, Theorem 1 applies and we conclude that the new generation does not benefit from the transmission. If the generation would not otherwise be built, the zero-profit condition on investment in the socially optimal expansion nevertheless holds. Given perfect competition, condition (11) implies that investment in generation technology g will continue until operating profits fall to the level of annualized investment costs.

Under an optimization modeling approach, the implication of the zero-profit condition is that new generation cannot be identified as a beneficiary. We note that the assumptions of perfect competition and linear generation investment costs that underpin the zero-profit condition are standard in tools used for expansion planning. Exceptions to this rule may apply, e.g., if there is a constraint on building generation, such that new capacity cannot be built to take full advantage of the new line. In this case, new generators would earn a rent associated with this constraint. Such exceptions are likely to be less important for large lines that would facilitate production across a wider region. Alternatively, it may be argued that the computation of excess profit in Eq. (7) reflects too narrow a conception of benefits, and the existence of a new generator could itself be considered a benefit regardless of its profitability. In this case, additional assumptions outside the planning tool would be needed to define benefit estimates.

Given the recommendation not to allocate cost for network upgrades to new generators at the time of interconnection but then subsequently allocate cost to them throughout their life, the direct benefits modeling approach supports a significant change to current practice. The overall impact that such a change would have on the cash flows seen by generators over the course of their life is not clear. Suppose a new generator signs an interconnection agreement without any accompanying network upgrades, and then welfare-enhancing network upgrades are identified by a planning model. Since the model recommending these projects would assume the presence of the new generator, it would be more likely to recommend upgrades allowing the system to make use of the new generator's energy output. Projects identified to make use of the new generator could very well be the same as those that would be identified under current, narrowly-focused interconnection procedures. Whereas current practice typically assigns the cost entirely to the new generator without accounting for externalized benefits, however, the proposed approach would allocate cost to other beneficiaries as well. As such, the overall effect would be to bring cost allocation in line with the beneficiaries pay principle.

3.3 Load

Benefits to different load zones can be defined much in the same way as benefits to generators. The major difference is that the planning model takes load as exogenous rather than as resulting from an expansion decision that may depend on transmission investment. We use an assumed value of lost load (VOLL) to compute the benefit consumers experience from a reduction in unserved energy. Since we are primarily interested in allocating cost between different zones, each of which comprises a diverse range of customers, it is reasonable to assume a single constant VOLL. However, we note that a more granular representation of price-responsive load from individual customers would enable a more targeted calculation of benefits. To simply notation, we represent load curtailment at bus b at time t by $z_{n,b,t} = \sum_{i \in \mathcal{I}} z_{n,b,t,i}$. Consumer surplus at bus b in node n is calculated as the difference between the value of energy consumed and payments made for energy and renewable energy credits. Evaluated at node 0, the expected value of consumer surplus can be written as

$$\mathbb{E}\left(\mathcal{U}_b^{\text{load}}\right) = \sum_{n \in \mathcal{N}} \zeta_{\delta(n)} \phi_n \left(\sum_{t \in \mathcal{T}} T_t \left(\gamma^{\text{LOAD}} - \pi_{n,b,t} - \nu_n RPS_n\right)\left(D_{n,b,t} - z_{n,b,t}\right) \right) \tag{12}$$

As with generation, we compute the benefits from transmission expansion to loads at bus b as the difference in surplus between the socially optimal case and the counterfactual case:

$$\mathbb{E}\left(\Delta\mathcal{U}_b^{\text{load}}\right) = \mathbb{E}\left(\mathcal{U}_b^{*\,\text{load}}\right) - \mathbb{E}\left(\mathcal{U}_b^{\text{load}}\right) \tag{13}$$

As with existing generators, the surplus difference $\mathbb{E}(\Delta\mathcal{U}_b^{\text{load}})$ can be positive, zero, or negative for loads.

3.4 Congestion Rents

In addition to generator and consumer benefits, a third component of market surplus is transmission congestion rents, computed as the difference between the payments made by load and the revenue received by generators. Under idealized assumptions, the availability of congestion rents could make the problem of cost allocation easier to solve, since congestion revenues would be sufficient to support a socially efficient level of transmission expansion [8], [33]. In this case a "top-down" cost allocation would not be required as such, since risk-neutral investors would be willing to build transmission in exchange for the resulting valuable transmission rights. In practice, economies of scale and unpriced reliability constraints mean that congestion rents are well below what would be needed to support an efficient level of investment. For example, [34] estimates that U.S.-wide congestion rents averaged approximately \$8.2B for 2016–2021, while U.S. Energy Information Agency estimates the average cost of transmission in 2022 at \$15/MWh [35], implying a total annualized cost of roughly \$63B for the current system. While imprecise, these estimates suggest that congestion rents are an order of magnitude lower than what would be required for investments in transmission to be sustained on a merchant basis.

In principle, rights to congestion rents can be allocated as part of the cost allocation process, either proportional to market participant contributions or by auction. In general, empirical evidence in U.S. markets shows that current markets for financial transmission rights result in large transfers from consumers to financial traders [36], [37] suggesting opportunities for improvements in allocation [38]. In the numerical results for this paper, we compute generator and consumer benefits without adjusting for any assigned transmission rights, noting that future studies assessing the effects of financial transmission rights would likely require downscaling the results of our zonal network model to a more detailed nodal representation.

3.5 Multi-value Planning

Inconsistent and non-intuitive cost allocation outcomes in the U.S. context can stem from projects being designated as having a single primary purpose and being evaluated according to the benefits it provides only along that dimension. U.S. systems distinguish between projects undertaken for economics, reliability, public policy, and generator interconnection, while any transmission enhancement necessarily affects outcomes across all four areas [39]. As previously noted, we leave a more complete discussion of public policy interactions for future work. We note here, however, that an advantage of the direct benefits modeling approach is that all categories of benefits can be incorporated in a consistent manner as long as a valid counterfactual can be established. From a modeling perspective, the only requirement for establishing a valid counterfactual is that model (5) must have a feasible solution after transmission expansion decisions have been fixed. Because the model penalizes power shortfalls rather than implementing a hard constraint, and because entry of new generation is not restricted, reliability constraints cannot cause infeasibility. Our implementation of an RPS in Eq. (3e) could in principle lead to infeasibility. In practice, however, most states have implemented Alternative Compliance Payments to limit the potential cost of RPS policies, meaning that a soft constraint would more accurately reflect the public policy. Once a counterfactual has been established, costs associated with reliability and public policy naturally flow into prices for energy and clean attributes, allowing straightforward inclusion in benefit calculations.

3.6 Cost Allocation

The analysis thus far leads to the conclusion that existing generation and load can be beneficiaries of transmission expansion over the long term, implying that both existing generation and load should share cost under the "beneficiaries pay" principle. In the numerical study we examine two different policies for allocating the cost of transmission investments made at node 0: allocating cost only to load, as in current practice, and allocating across both existing generation and load. When allocating cost only to load, the allocation ratio to load at bus b is determined using the following equation:

$$r_b^{\text{load}} = \frac{\left[\mathbb{E}\left(\Delta \mathcal{U}_b^{\text{load}}\right)\right]_+}{\sum_{b' \in \mathcal{B}} \left[\mathbb{E}\left(\Delta \mathcal{U}_{b'}^{\text{load}}\right)\right]_+} \tag{14}$$

where $[*]_+$ denotes $\max\{0,*\}$.

When allocating cost to both load and existing generation, with $G_{b,g}^0$ representing the quantity of existing capacity of generation g at bus b, allocation ratios are determined using the following equations:

$$r_b^{\text{load}} = \frac{\left[\mathbb{E}\left(\Delta \mathcal{U}_b^{\text{load}}\right)\right]_+}{\sum_{b' \in \mathcal{B}} \left(\left[\mathbb{E}\left(\Delta \mathcal{U}_{b'}^{\text{load}}\right)\right]_+ + \sum_{g \in \mathcal{G}} \left[G_{b,g}^0 \mathbb{E}\left(\Delta \mathcal{U}_{b',g}^{\text{gen}}\right)\right]_+\right)} \tag{15a}$$

$$r_{b,g}^{\text{gen}} = \frac{\left[G_{b,g}^0 \mathbb{E}\left(\Delta \mathcal{U}_{b,g}^{\text{gen}}\right)\right]_+}{\sum_{b' \in \mathcal{B}} \left(\left[\mathbb{E}\left(\Delta \mathcal{U}_{b'}^{\text{load}}\right)\right]_+ + \sum_{g \in \mathcal{G}} \left[G_{b,g}^0 \mathbb{E}\left(\Delta \mathcal{U}_{b',g}^{\text{gen}}\right)\right]_+\right)} \tag{15b}$$

The presence of the max operator ensures that market participants who do not benefit from a transmission investment are not allocated costs. However, it also implies that market participants that are harmed by an expansion project are not compensated as part of cost allocation. It would be straightforward mathematically to define negative allocations, i.e., compensatory payments to these participants. Since the planning model by assumption identifies a surplus-maximizing expansion plan, there would be sufficient surplus in the market to make these compensatory payments. Several recent cases in the U.S. show the potential for states or incumbents hurt by transmission expansion to intervene and prevent it from occurring (see, e.g., [40]), suggesting that compensatory payments or long-term financial rights that protected incumbents against the effect of transmission expansion could lead to fewer disputes in planning.

4. Numerical Study

This section presents results of a numerical example on a simplified model of the ERCOT system. Building on the discussion of Section 3, we document the different benefits and losses seen by generation and loads in different parts of the system. One major conclusion of the numerical study is that allocating cost on a portfolio basis is likely to be more consistent with the beneficiaries pay principle than allocating on a project-by-project basis. Further, we contrast ex post benefits derived from out-of-sample tests against in-sample estimation, computing the range of possible distributional outcomes from transmission expansion to provide insight into the challenge posed by ambiguity in future scenarios and probabilities.

4.1 Data and Study Assumptions

The study employs an 8-Bus ERCOT DC Test Case introduced by [41], with the network shown in Figure 4-1. The generation technologies considered are natural gas combined cycle (CC), natural gas combustion turbine (CT), coal, nuclear, utility-scale solar, and land-based wind. Costs for these technologies are sourced from the NREL Annual Technology Baseline database [42]. The existing generation capacity mix is obtained from the ERCOT Capacity, Demand and Reserves (CDR) Report [43]. Existing generation capacity, reported in Table 4-1, is assigned to different buses in the test system in a manner consistent with the ERCOT resource siting methodology report [44][45] but should not be expected to match locations precisely.

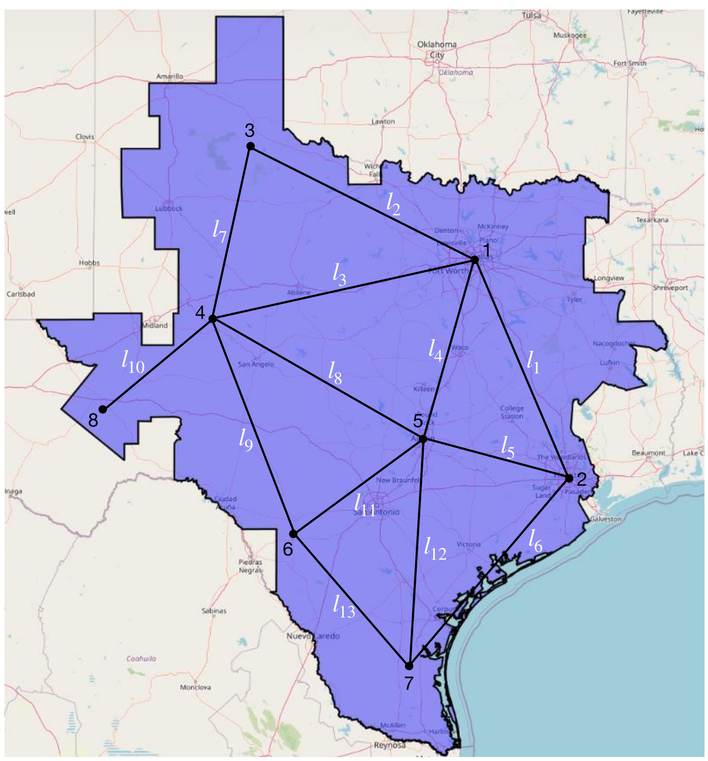

Figure 4-1 8-Bus ERCOT network.

Hourly load data for the year 2020 from [46] is used to represent the load profiles in the system. For each node n, load $D_{n,b,t}$ is obtained by multiplying this profile by a demand growth factor β_n. Hourly solar and wind availability profiles for the year 2020 are extracted from [47]) using methods described in [48], [49]. To ensure computational tractability and account for operation costs, a K-means method is employed to cluster the year of data based on the net load, from which 20 representative days (480 hours) with varying weight, i.e., T_t, are selected to represent a simulation year.

Table 4-1   Existing capacity of each generation type by bus.

Generation type	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8
GasCC	0	6,062	12,644	1,839	0	0	8,282	0
GasGT	0	10,404	6,011	2,570	0	0	9,343	0
Coal	0	2,514	7,023	0	4,031	0	0	0
Nuclear	2,400	2,573	0	0	0	1,030	0	0
Solar	0	468	1,073	0	0	0	850	6,611
Wind	0	4,865	1,330	17,291	0	0	2,969	0

In the long-term planning model, the uncertainties included are the presence of an RPS, load growth, technology investment costs for wind and solar, and fuel cost. For each uncertainty except the RPS, low, medium, and high values are estimated based on [42]; [45]. We note that given the high-quality solar and wind resources in Texas, the RPS constraint does not have a significant impact on the numerical results. A future scenario is defined as a subset of the uncertainty space that represents a specific combination of the five uncertainties. Considering a low, medium, and high value for each uncertainty, there will be a total of $3^5 = 243$ possible future scenarios. To ensure computational tractability for the MIP model, the number of scenarios must be reduced. In this study, seven scenarios with varying probabilities were selected based on the methodology described in [26]. Since we wish to avoid making assumptions on underlying scenario probabilities, we do not claim that the transmission plan identified by the model is “optimal” as such. Out-of-sample tests show positive net benefits in all scenarios, however, suggesting that the chosen clustering and scenario selection procedures lead to a high-quality solution.

A 20-year planning horizon is simulated with investment decisions made every 5 years, resulting in a tree with depth four and seven scenarios. A discount rate of 7.78% is applied to compute the net present value of the total investment cost and operational cost in the objective function. It is assumed that the operational costs for each successive 5-year interval remain constant. In light of this assumption, the discount factor, denoted as ζ_y for time index $y \in \{1,2,3,4\}$, is determined through the following formula:

$$\zeta_y = \frac{1}{(1+7.78\%)^{5(y-1)}}\left(1 + \frac{1}{(1+7.78\%)^1} + \frac{1}{(1+7.78\%)^2} + \frac{1}{(1+7.78\%)^3} + \frac{1}{(1+7.78\%)^4}\right)$$

We use the power balance penalty curve shown in Table 4-2 and transmission line violation penalty γ^{LINE} = 9251 \$/MW for all lines, congruent with the practices in [50].

Table 4-2 ERCOT power balance penalty curve.

MW violation	≤ 5	5 ~ 10	10 ~ 20	20 ~ 30	30 ~ 40	40 ~ 50	50 ~ 100	≥ 100
Penalty γ_i^{PB} (\$/MWh)	250	300	400	500	1000	2250	4500	5001

This case study assumes that there are seven types of transmission line expansion increments, with the same costs across all scenarios in each stage and for each corridor, as defined in Table 4-3. The per unit investment cost in Table 4-3 exhibits a significant decrease with increasing expansion capacity, reflecting economies of scale.

Table 4-3 Transmission line capacity increment type and investment cost

Type	Expansion (MW)	Amortized investment cost (\$M/yr)	Per unit cost (\$M/MW)
1	1400	68.93	0.61
2	1800	72.64	0.50
3	2300	78.34	0.42
4	3000	89.59	0.37
5	3600	98.79	0.34
6	4200	101.70	0.30
7	8000	154.96	0.24

The models are implemented in Julia [51] using JuMP.jl [52] and solved with Gurobi version 10.0.1 [53] using a MIP gap (where applicable) of 0.5%. The computations are performed on a Mac computer with an Apple M1 Max chip and 10 cores.

4.2 Expansion Plan

The transmission line expansions resulting from model (3) for the developed test system are summarized in Table 4-4. In the first stage (year 2023), corresponding to node 0 of the tree in Figure 2-1, six transmission expansion projects are selected. The largest of these is on path l_2, connecting the generation-rich zone b_3 with the population center b_1. Table 4-5 shows a weighted average of the total generation capacity additions made over the 20-year horizon in the seven modeled scenarios, as well as the same quantities in a counterfactual without any transmission expansion. In either case, the model builds new gas combustion turbines, solar, and wind, with no additions of coal, nuclear, or combined cycle gas in any scenario. While we expected new transmission to support the deployment of additional wind, the primary effect of expansion in our model was instead to reduce the requirement for gas turbines: the model builds roughly the same amount of wind in the counterfactual case, but substantially more gas turbines. At node 0 of the model, new gas turbines are built at b_1 in the expansion scenario, while new gas turbines are built at b_1 and b_8 in the counterfactual. No wind or solar is built in node 0, potentially due to our assumption that transmission expansions will enter service only in the second year index.

Table 4-4 Invested line capacity (MW) by scenario and by stage. Some scenarios with no line investment are omitted.

Year	Scenario	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	l_9	l_{10}	l_{11}	l_{12}	l_{13}
2023	–	0	8000	2300	0	0	1800	3600	0	0	2300	0	2300	0
2028	7	0	0	0	0	0	0	0	3000	0	0	0	0	0
2033	1,2,6	0	0	0	0	0	0	0	3000	0	0	0	0	0
2033	3,4	0	0	0	0	0	0	0	2300	0	0	0	0	0
2033	5	0	0	0	0	0	0	0	3600	0	0	0	0	0
2038	3	0	0	1800	1800	0	0	0	4200	4200	0	0	0	0

Table 4-5 Average 20-year generation capacity investment across seven modeled scenarios (MW)

Generation Type	Expansion	No Expansion
Gas CC	0	0
Gas CT	21,425	35,428
Coal	0	0
Nuclear	0	0
Solar	9,859	14,938
Wind	38,382	38,433

4.3 Portfolio vs. Project-by-Project Allocation

The first policy question we address is whether to assess the benefit of the six projects selected at node 0 on a portfolio or project-by-project basis. In our notation, the question is whether to compute a single instance of the counterfactual model (5) with W^{INV} including all six projects as a portfolio, or six separate instances of model (5) with a single element each in W^{INV}. For purposes of this subsection, we allocate costs according to Eq. (14), i.e., only to loads and only to those with positive benefits, without compensating those harmed by the expansion. We conclude that assessment at the portfolio level results in a cost allocation more consistent with the beneficiaries pay principle.

Table 4-6 shows the benefits calculated for each project evaluated separately as well as the portfolio, along with an allocation percentage across the 8 buses. The first observation is that, for each individual project except the expansion on l_6, the total expected benefit across all buses is negative. As a consequence, individual projects would not pass a benefit–cost test when assessed as such, and it may be difficult to convince loads to accept any resulting cost allocation. While not guaranteed, each project has at least one bus with positive benefits, allowing a cost allocation to be defined under our formula.

Table 4-6 Expected nodal benefits and cost allocation ratios when allocating solely to loads. For "Projects Sum," the allocation ratio for each bus is calculated based on the sum of allocated cost across all projects calculated individually. For "Portfolio," the allocation ratio for each bus is calculated from portfolio benefits.

Project		b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	Sum
	load ratio(%)	33.95	28.67	1.83	1.85	15.89	0.93	8.21	8.67	100.0
l_2 8000 MW	ΔU_b ($M)	4,904	-1,488	-1,509	-171	-831	-15	-2,015	411	-715
	r_b (%)	92.27	0.0	0.0	0.0	0.0	0.0	0.0	7.73	100.0
l_3 2300 MW	ΔU_b ($M)	3,668	-2,279	-61	-625	-2,233	-104	-908	-2,170	-4,710
	r_b (%)	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0
l_6 1800 MW	ΔU_b ($M)	-67	2,600	-2	1	53	-9	-1,887	132	822
	r_b (%)	0.0	93.32	0.0	0.04	0.0	0.0	0.0	1.90	100.0
l_7 3600 MW	ΔU_b ($M)	-456	-1,714	-912	304	85	-159	-1,525	795	-3,583
	r_b (%)	0.0	0.0	0.0	25.68	7.18	0.0	0.0	67.15	100.0
l_{10} 2300 MW	ΔU_b ($M)	181	-2,333	-10	-149	-1,439	-146	-910	2,288	-2519
	r_b (%)	7.33	0.0	0.0	0.0	0.0	0.0	0.0	92.67	100.0
l_{12} 2300 MW	ΔU_b ($M)	12	196	-5	77	1,195	12	-1848	336	-25
	r_b (%)	0.66	10.72	0.0	4.21	65.37	0.65	0.0	18.38	100.0
Projects Sum	ΔU_b ($M)	8,242	-5,018	-2,499	-563	-3,170	-421	-9,093	1,792	-10,730
	r_b (%)	40.54	13.57	0.0	5.11	10.39	0.09	0.0	29.69	100.0
Portfolio	ΔU_b ($M)	6,215	2,281	-1,379	-453	-120	15	-3,250	2,360	5,669
	r_b (%)	57.17	20.98	0.0	0.0	0.0	0.14	0.0	21.71	100.0

Figure 4-2 shows the benefit–cost ratio for the portfolio for each bus under each allocation method. The result of the project-by-project allocation is that some loads, namely, those at b_4 and b_5, can be assigned positive cost despite having negative benefits from the overall portfolio. These positive allocations result from the positive benefits found for expansion on l_6, l_7, and l_{12} when assessed individually. The benefits used for both subplots are from the “Portfolio” row in Table 4-6. As should be expected, the benefit–cost ratio is consistent across all load zones in the case of the portfolio-level allocation, but drops below zero for b_4 and b_5 in the project-byproject allocation. To avoid this issue, we suggest that it is preferable to allocate costs for a portfolio rather than individual projects.

4.4 Generator Impacts

While the previous subsection considered the impacts on load only, we now turn to impacts on generation. A summary of the aggregate allocation across all generators and loads, calculated with Eqs. (15a) and (15b), is shown in Table 4-7. We note that the aggregate benefits are substantially larger for generators than for loads in our case study, but we cannot make a general claim regarding how benefits are likely to be split in other instances. Consistent with intuition, we observe that the largest line expansion selected by the model, l_2, connects the zone in which the largest benefits accrue to generators, b_3, with the zone in which the largest benefits accrue to loads, b_1.

As discussed in Section 3.2, generators can also experience significant losses from expansion. The total expected benefits that accrue to existing generation of different types across buses is shown in Figure 4-3.

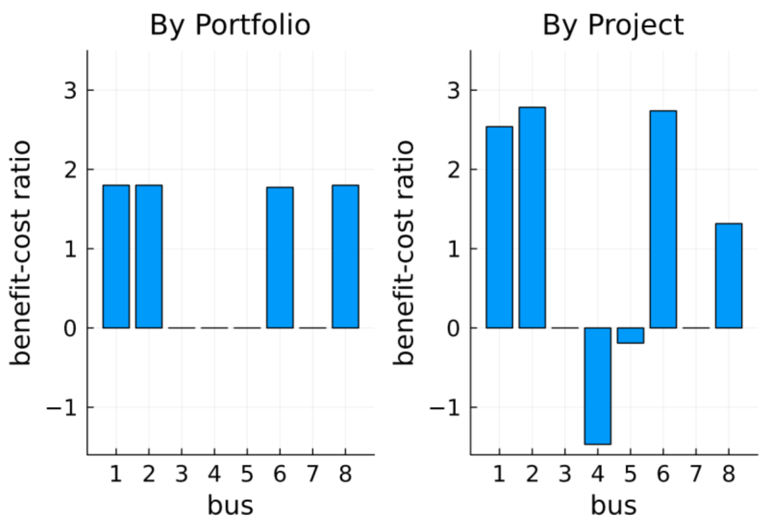

Figure 4-2 Benefit–cost ratio for different loads. While the benefit–cost ratio is consistent across all buses when cost allocation is determined on a portfolio basis, the project-by-project allocation can lead to cost being allocated to loads that do not benefit from the overall portfolio.

Table 4-7 Expected load and generation nodal benefits and cost allocation ratios for transmission expansion portfolio when allocating expansion cost to both load and existing generation. Generation benefit ΔU_b^{gen} is the aggregation of positive benefits of all generation at bus b. Sum is the sum of positive benefits across buses.

Participants	(%)	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	Sum
load	r_b^{load}	12.99	4.77	0.0	0.0	0.0	0.03	0.0	4.93	22.72
gen	r_b^{gen}	0.0	0.01	46.48	11.2	0.03	0.07	17.3	2.19	77.28

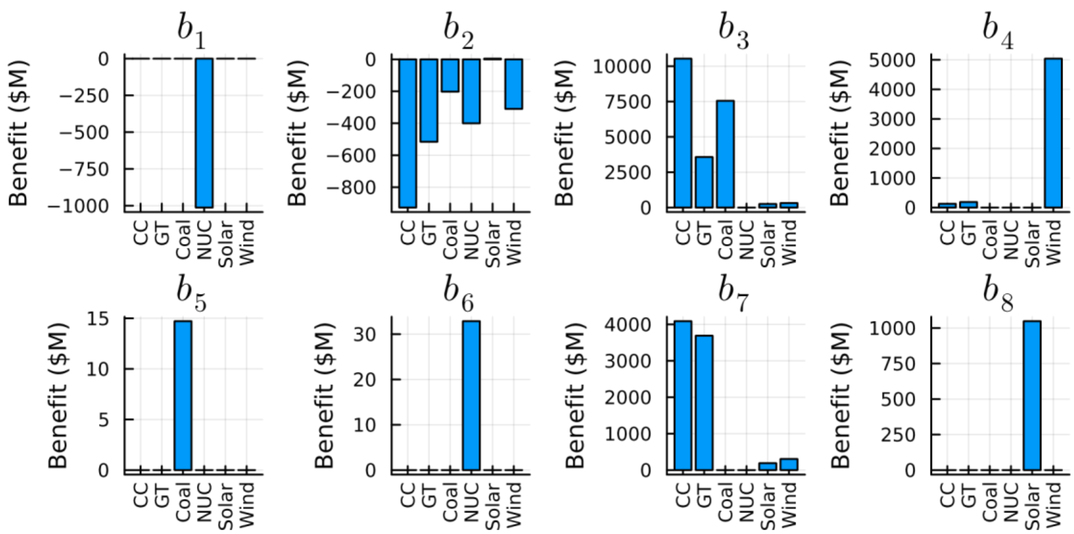

Figure 4-3 Expected benefits of existing generation of different generation technologies across buses derived from portfolio.

Whereas the allocation in Table 4-7 aggregates only the positive benefits, Figure 4-3 includes the negative impacts. Just as loads at b_1 and b_2 see the largest benefits from expansion, generators in those zones see the largest losses. The largest generator benefits occur at b_3, concentrated in existing thermal generators at that location.

4.5 In-Sample vs. Out-of-Sample Tests

The cost allocations defined above are calculated based on in-sample results, i.e., the expected zonal benefits determined as the weighted average across various scenarios where scenarios and scenario probabilities are taken from the planning model covering the whole planning horizon of 20 years. Table 4-6 and Table 4-7 show the in-sample cost allocation ratios under two policies. As discussed above, however, the scenarios and probabilities determined for the planning model do not reflect the full range of possible outcomes or participant beliefs. Accordingly, a key question is the validity of these estimates and the extent to which out-of-sample results might diverge from the in-sample expected value.

Estimating the benefits out of sample for the whole 20-year horizon is complicated computationally, because it would require definition of a complete policy describing how transmission and generation investments after the first stage will be made based on realizations of uncertainty that are not contained in our original planning model. In our context, such a policy cannot be defined: we rely on a stakeholder process to determine the scenarios and probabilities to be used in our planning model, and cannot fully specify the outcomes of future stakeholder processes. To avoid this issue, we instead perform out-of-sample tests for both cost allocation ratios on a single operating year. Specifically, we perform an out-of-sample analysis for $y = 2$, i.e., year 2028, to assess benefits of transmission expansion projects determined in $y = 1$, computing the distribution of realized benefits against the ex ante allocation. In out-of-sample tests, we used load and renewable availability data from 2022, sourced and processed in a manner consistent with the procedures outlined in Section 4.1. Since our out-of-sample tests do not have transmission investment, we employ a linear program covering the entire year of data instead of selecting representative days as in the MIP planning model. Benefits are computed for all $3^5 = 243$ possible realizations of uncertainty described above. The aggregated generation and load benefits on each bus across different scenarios in year 2028 are shown in Figure 4-4. The scenarios are ordered by the gross social benefits from the transmission expansion. It is noteworthy that while not generalizable, in our case study the expansion is beneficial under all realizations of uncertainty. It can also be observed that, while the rank ordering of zones is relatively stable overall, there are wide swings in the absolute benefits realized in each zone.

The overall distribution of benefits evaluated ex post for generators and loads is shown in Figure 4-5, with generation of all types aggregated at each bus. The blue bars indicate the number of times (out of the 243 scenarios) ex post benefits are calculated to be in each range, while the red dashed line indicates the cost allocation determined ex ante (as in Table 4-7). Here, the consequences of uncertainty are apparent, as the ex post distribution of benefits in some cases does not contain the red dashed line. In absolute terms, the deviation can be quite significant: for example, generators at b_3 may see almost 70% of total benefits from the portfolio after being allocated 46% of costs. One possible reason for biased estimates is that ex ante benefits are estimated over a longer horizon than those calculated ex post. Even if a less biased ex ante estimate could have been produced with a more targeted computation, however, the significant variance observed in realized benefits would remain.

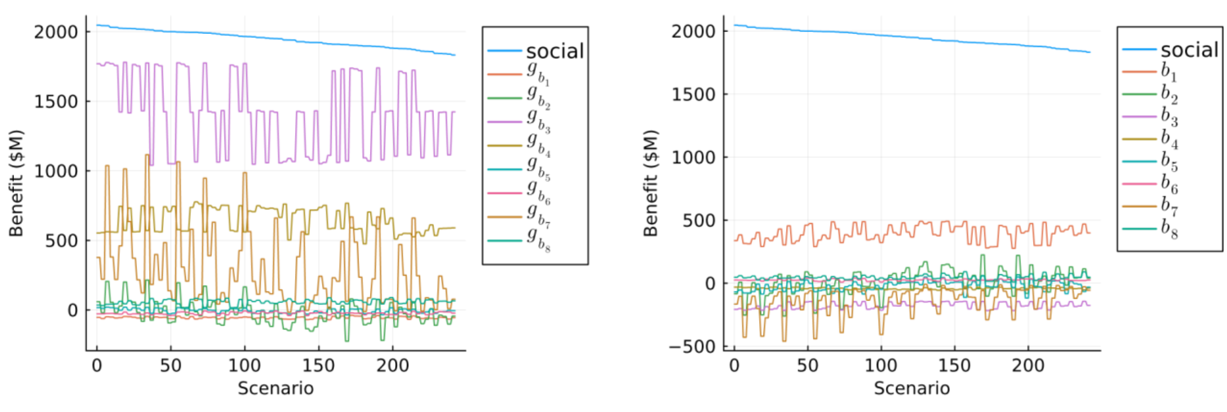

Figure 4-4 Benefits of the portfolio on out-of-sample tests in year 2028 ranked by social benefits. Left: Nodal existing generation benefits. Right: Nodal load benefits.

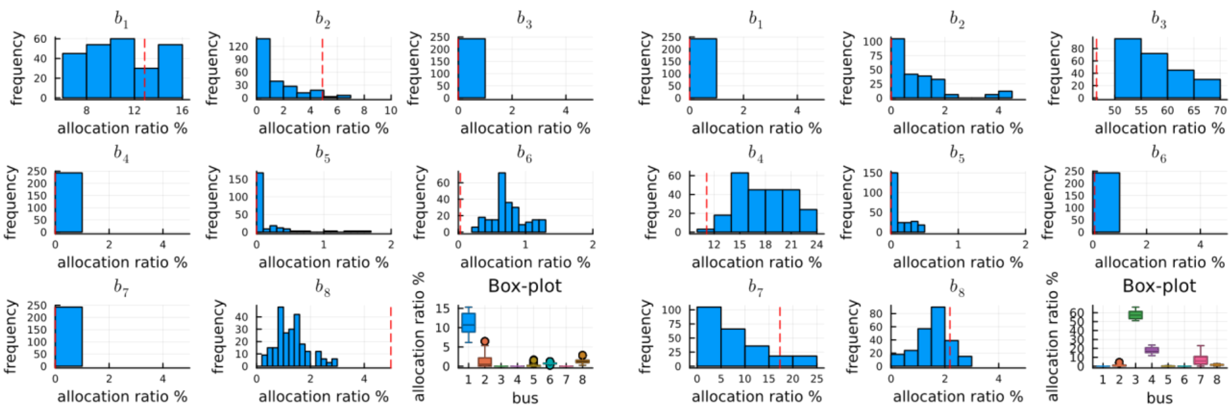

Figure 4-5 Distributional allocation ratio of the transmission expansion portfolio for all buses on out-of-sample scenarios in year 2028. Red dashed line is the portfolio allocation ratio in Table 4-7. Left: Distributional allocation ratio on load. Right: Distributional allocation ratio on generators.

To test how the benefits of the portfolio may evolve over the life of the new lines, we construct an additional test using realizations of uncertainty for the year 2038 and assuming that a 3000 MW capacity expansion on l_8 has subsequently been added to the system. Referring back to Table 4-4, an expansion on l_8 is chosen in each of the seven scenarios in the planning model, with the timing and size varying by scenario. With this 3000 MW expansion added to the system, we re-compute the benefits of the original portfolio of six transmission lines. Figure 4-6 shows the distribution of benefits when allocated only to load for the years 2028 and 2038. In year 2038, benefits shift away from loads at b_1 to those at b_2, b_5, and b_8. The shift exhibited in Figure 4-6 suggests an extension of the argument in Section 4.3 that a portfolio-level allocation should be preferred to a project-level allocation. Suppose two projects with 50-year expected lives are selected and built in consecutive years. Given that they will coexist in the network for 49 out of their 50 years, their benefits will necessarily be interdependent and could be better assessed jointly. Extending the argument further, estimates of the aggregate benefits of the network may be more accurate than estimates of the benefits provided by any subset of network elements.

Overall, the results confirm the potential for uncertainty to cause challenges in cost allocation given the disagreements that market participants will inevitably have on the probability of future scenarios. In the context of the "beneficiaries pay" standard, the distribution of possible outcomes makes it clear that an allocation of costs determined ex ante will not be commensurate with the benefits realized ex post. Economic theory offers a potential resolution to the resulting conflicts in the form of financial contracts issued ex ante that would effectively reallocate cost to the ultimate beneficiaries [54]. Given the complications involved in defining such contracts, we defer the effort to future work.

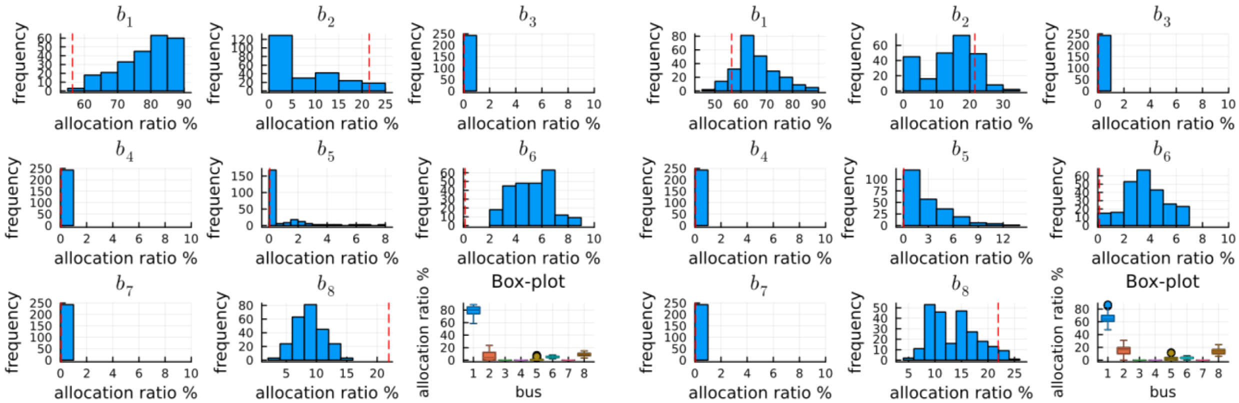

Figure 4-6 Distributional allocation ratio of the transmission expansion portfolio for all buses and generation on out-of-sample scenarios. Red dashed line is the portfolio allocation ratio in Table 4-6. Left: Distributional allocationratio in year 2028. Right: Distributional allocation ratio in year 2028 with additional 3000 MW expansion on l_8.

5. Conclusions

Given the numerous ways in which motivated parties can intervene to prevent transmission expansion, disputes over cost allocation can hold up investment in regional and interregional projects. Out of fairness and to forestall such interventions, U.S. system planners have sought methods to allocate costs according to the estimated benefits that projects will bring. In a direct benefits modeling approach, planners could in principle solve an optimization model that both established the social benefits of a project and enabled an estimate of benefits at the participant level. However, inadequacies in both the models available and the information used in them can lead to significant disagreements about the fairness of the resulting allocations.

This chapter identifies several challenges in the use of models to establish cost allocations. Given the complexity of the modeling task, planners typically use a combination of software tools to evaluate proposed projects. One consequence is that it may be difficult to establish a valid counterfactual against which benefits can be measured and to calculate all categories of benefits that could result from an expansion project. The challenge is even greater when assessing benefits out of sample, since a full calculation would require not only determining the range of scenarios to be tested but also specifying a policy for future expansion decisions given the realization of uncertainty.

Without fully resolving these challenges, the theoretical analysis and numerical study lead to five observations connected to the "beneficiaries pay" principle. First, benefit estimates should include some attempt to account for the change in the resource mix that is likely to occur with any change in the network. Second, cost should in general not be allocated to new entrants, but should be allocated to incumbents that benefit from transmission expansion. Third, allocations made on the basis of portfolios of projects are likely to be more defensible than those made on individual projects. Fourth, conflicts might be lessened with greater effort to compensate the losers from socially beneficial transmission expansion. Fifth, conflicts might be lessened with greater effort to address the risk that participant-level benefits will diverge significantly from ex ante allocation decisions.

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