ELECTRIC POWER RESEARCH INSTITUTE

Program on Technology Innovation: Coordinated Expansion Planning

Status and Research Challenges

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Status and Research Challenges

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Abstract

To attain least-cost generation, transmission, and delivery of electricity at a reliable level, close coordination between generation and transmission operation and planning is fundamental. Optimizing these sectors in isolation can miss integrated generation and transmission solutions that are cost-optimal while meeting reliability targets. Before the introduction of competition, the level of coordination was sufficient—but competition forced separation of the generation and transmission functions, even within vertically integrated utilities. Nowadays, generation companies act independently, dealing at arm's length with transmission planners. However, different groups (transmission planners and generation planners), within the same region—or even company—and across regions need to coordinate and anticipate others' decisions to attain better global long-term development. The same needs are emerging in integrated systems where unaffiliated distributed resources are appearing at the grid edge. Such unbundled and distributed systems are also fraught with uncertainties, which, if inadequately considered, will lead to plans that are not resilient and cannot adapt in a way that maintains economic and reliable operations.

These challenges, referred to here as the coordinated expansion planning (CEP) problem, have come into focus over the last few years for several reasons, including deeper penetration of renewable energy sources, integration of emerging storage technologies, electrification of the transport sector, increased interdependencies with other sectors (for example, gas), and increased distributed generation in distribution grids. These changes result in increased short- and long-term uncertainties as well as a need for increased modeling fidelity to represent temporal dynamics more accurately (for example, hourly or sub-hourly intertemporal couplings in expansion models). These challenges, together with the progress in computational resources, have prompted the development of sophisticated tools able to produce expansion plans that not only approach system optimality, but are also flexible and robust against the various planning and operating uncertainties.

This report provides an in-depth view of the state-of-the-art methods and tools to produce coordinated expansion plans. In addition, it identifies the research and development needs for the new generation of coordinated expansion planning models and tools.

The report begins with some introductory concepts and a general layout; it is followed by several sections that cover specific aspects of the CEP problem. Together the sections give an integral perspective on the ongoing and future research efforts on the CEP problem. However, each section has been written to be read independently, if the reader is interested only in a particular aspect of the problem.

Keywords

Adaptive planning
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Generation expansion planning
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PRIMARY AUDIENCE: System operators and planners (generation and transmission)

SECONDARY AUDIENCE: System operation and planning researchers, strategic analysis staff at utilities, regulatory technical staff

KEY RESEARCH QUESTION

The objective of this report is to identify a research and development agenda that would, upon execution, bring expansion planning software applications to a maturity level to enable their day-to-day use within electric infrastructure planning organizations.

RESEARCH OVERVIEW

This work investigated and summarized the state-of-the-art methods and tools to perform coordinated expansion planning. Attention was given to the most important aspects of the problem, including the need to increase operational modeling fidelity; reduce computational burden; enhance the accuracy of transmission system representation; provide explicit modeling and representation of distributed energy resources; account for electricity market perspectives on coordinated expansion planning; include the ability to represent uncertainty, weather impacts, interdependencies with other sectors, and resiliency; and provide the capability to evaluate the suggested expansion plans from multiple perspectives.

KEY FINDINGS

- The advantages of the coordinated expansion models over alternatives, in terms of cost savings while maintaining reliability, are demonstrated to be important.
- It is possible to include chronological series and intertemporal couplings to explicitly account for flexibility and storage, though at the expense of computational burden.
- Several important drivers that increase computational burden are identified along with the methods or research conducted to reduce computation time.
- Methods that allow modeling with increased spatial and temporal resolution are identified, and their advantages over existing approaches are shown.
- Explicit representation of distributed energy resources either as variables or parameters is now possible in expansion planning models.
- Electricity market perspectives for the coordinated expansion problem can be modeled, including features such as scarcity pricing, reliability services pricing, and implications of market failures for CEP.
- Methods for modeling global and local uncertainties are proposed and assessed.

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EXECUTIVE SUMMARY

WHY THIS MATTERS

EPRI members and the general audience for this report will clearly see the benefits of coordinated expansion planning, regardless of whether their relevant planning functions are unbundled. In addition, the need to increase spatial and temporal fidelity as well as chronology and intertemporal linkages are described, and new methods are introduced to tackle these new challenges. Both transmission and generation planners can benefit from these research findings—the use of a coordinated expansion planning tool or approach to supplement the planning process can identify least-cost investment solutions not otherwise considered while reducing study time and effort.

HOW TO APPLY RESULTS

Ideally, interested members could assess the benefits of performing coordinated expansion planning in their system through tailored studies. These would allow assessing both the qualitative and quantitative benefits from this type of expansion tool as well as using them as advisory plans or possibly actual expansion plans. EPRI is aiming to develop a supplemental project in this area to apply results and will continue research in this area through its Grid Planning (P40) program from 2020. Related issues on flexibility and resource adequacy are also covered in the Bulk System Variable Generation/DER Integration Program (P173).

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PROGRAMS: Planning Grid, P40; Bulk Power System Integration of Variable Generation, P173

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Section 1: Introduction

Electric power system infrastructure includes generation, transmission, and distribution system components. Because such infrastructure is capital-intensive with long lifetimes, planning decisions must be assessed carefully before they are made. *Expansion planning* is a general term that refers to the processes and procedures associated with this assessment and subsequent decision. Expansion planning is performed over a certain future time period, typically between 10 and 40 years; this period is known as the *decision horizon*. The ultimate aim of expansion planning is to identify optimal (in the mathematical sense or better in the practical sense) build-out of resources over time as well as expected system evolution. Such expansion planning is modeled and examined in terms of technologies, amounts, locations, and timing that result in minimizing the present value of revenue requirements (or costs in a restructured environment), including capital costs of new investments plus fixed and variable production cost over the decision horizon. Central to this aim is that the infrastructure investments are generally composed of multiple technologies, and so the investment result, when combined with existing technologies, can be considered as a technology portfolio. Coordinated expansion planning software applications facilitate this process by providing information on how alternative investments enhance or restrict the flexibility of the grid to respond to possible long-run technological, economic, and policy developments. This process also allows explicitly responding to key planning challenges of integrated energy networks[1].

The objective of this report is to identify an R&D agenda that would, upon execution, bring expansion planning software applications to a maturity level to enable their day-to-day use within electric infrastructure planning organizations/sectors. This agenda is described in terms of 12 research thrusts. Section 2 presents an overview of the problem and efforts to attain optimality. Section 3 describes the need for increased fidelity for representing system operations via production cost modeling. Section 4 addresses the tradeoffs between modeling fidelity and computational intensity and identifies ways to reduce compute time. Section 5 outlines various approaches for efficiently representing transmission investment; it also addresses the need to update the models throughout the decision horizon as investments change the network topology and associated operating conditions. The expected growth of distributed energy resources (DER) motivates Section 6, where recommendations are made regarding the need to include the effects of distribution systems and unplanned DER growth within a co-optimized generation, transmission, and distribution expansion planning application. Section 7 describes market perspectives and the implications on the formulation of the expansion planning objective functions. To account for the fact that the expansion planning application must necessarily address the future, Section 8 identifies ways of handling deep, long-run uncertainties that would significantly impact the system performance considering the expansion alternatives chosen. Section 9 describes the need to incorporate weather data to characterize weather uncertainty in the planning process, a need that becomes more pronounced as wind and solar penetrations increase; Section 9 also addresses the need to capture increased uncertainties associated with the effects of climate change. Section 10 recognizes coupling between investment decisions for electric infrastructure and investment decisions associated with that of other infrastructure sectors, particularly natural gas, transportation, and water. Section 11 recognizes that resilience, i.e., the power system's ability to withstand high-impact, large-scale events such as those associated with natural disasters, space-weather, cyber-security, cascading, and policy redirects, is heavily influenced by investments, and therefore should be addressed within an expansion planning application. Section 12 identifies ways that expansion plans can be independently tested and validated. Section 13 concludes.

[1] More details are available at http:\\integratedenergynetwork.com

Section 2: Problem Overview and Optimality

Coordinated Planning and Independent Planning

Coordinated Expansion Planning (CEP) models (which fundamentally co-optimize resource options in planning framework; see callout box), are a major improvement compared to traditional expansion planning models, and are likely to yield improved plan recommendations. Co-optimization connotes simultaneous consideration and comparison of the ability of different interacting transmission and resource options to meet the needs of consumers. These interactions include substitution possibilities, in which different alternatives compete to serve the same need, and potentially attain better results. For example, transmission and local generation and storage can substitute for each other to meet peak demand in a load pocket, or storage located at a wind plant and transmission can substitute for each other in delivering remote renewable energy. Complementary interactions can also occur where, for instance, storage enhances the value of variable renewables to the market, and so each is more attractive in the presence of the other.

Only by considering how all the alternatives interact within the context of the entire bulk power system can the net benefits of particular investments be fully assessed. For instance, typical transmission planning methods assume a scenario of generation build-out, and compare variable production costs of alternative network reinforcements. However, this "reactive" transmission planning process overlooks potential generation capital cost savings that could result from shifts in generation mix and investment locations that are made possible by the transmission reinforcements. Not only is generation-transmission substitution not considered, nor is generation-transmission complementarity—it is quite possible that optimal transmission investments would make more rather than less investment in generation attractive. It is unlikely that a particular generation scenario is the optimal set of generation investments under the best transmission investments; only by optimizing generation and transmission investments together can the planner have assurance that the least-cost combination (i.e., generation plus transmission expansion cost) can be found.

Co-optimization

The term "co-optimization" generally refers to the simultaneous consideration of more than one class of alternatives. Thus, "co-optimization" in the context of electricity spot markets refers to simultaneous determination of both energy and ancillary services schedules in a single run of a market model. Meanwhile, in the context of long-term planning, it has usually referred to simultaneous optimization of transmission and generation investments, and more recently has expanded to encompass storage, demand-management, and other resources.

However, "co-optimization" does not mean that in fact the "optimal" combination of alternatives will be recommended by the model. Any model is an approximation, and approximations inevitably introduce error; as famously stated by George E. P. Box, "all models are wrong, but some are useful." Common approximations that can lead to suboptimal solutions include: simplifications of operation models, such as reduced network models or approximate unit commitment constraints; restricted sets of alternatives; finite time horizons; consideration of too small a set of short-run operating conditions (wind, load, hydro, etc.) and long-run technical, economic, and policy scenarios. Any co-optimized (also referred to as "coordinated") expansion planning (CEP) model recommendations must be tested against more detailed production and reliability simulation models to check whether the CEP model's assessment of the recommended system's performance is reasonably accurate. Furthermore, the planner should simulate variants of the recommended plan to see whether other plans would perform better. Thus, "usefulness" of the necessarily imperfect CEP model is its ability to identify potentially cost-effective combinations of transmission and resources for further testing and refinement.

As a demonstration of the substitution effect, Table 4.33 of [1] reports optimization of interregional transmission in a 13 region model of the U.S. power system for the years 2020-2060. Two types of planning processes were simulated:

- Reactive transmission planning, where first a generation build-out scenario was defined by optimizing generation expansion subject to the existing grid, followed by a transmission-only optimization subject to that expansion. Thus, transmission investments are justified only by production cost savings, Figure 2-2a.
- Full co-optimization of transmission and generation mix, Figure 2-2b.

The reactive plan showed a present worth of $1766B of costs, divided between generation investment ($992B), generation operations ($719B), and transmission investment ($54B). Meanwhile, full co-optimization dropped total costs to $1679B, distributed among generation investment ($931B) and operations ($632B) and grid investment ($116B). Compared to reactive planning, the incremental $62B of transmission investment saved $61B of generation investment and $87B of production costs. This lowered total costs by almost 6%, comparable to the total transmission investment. This is illustrated in Figure 2-1.

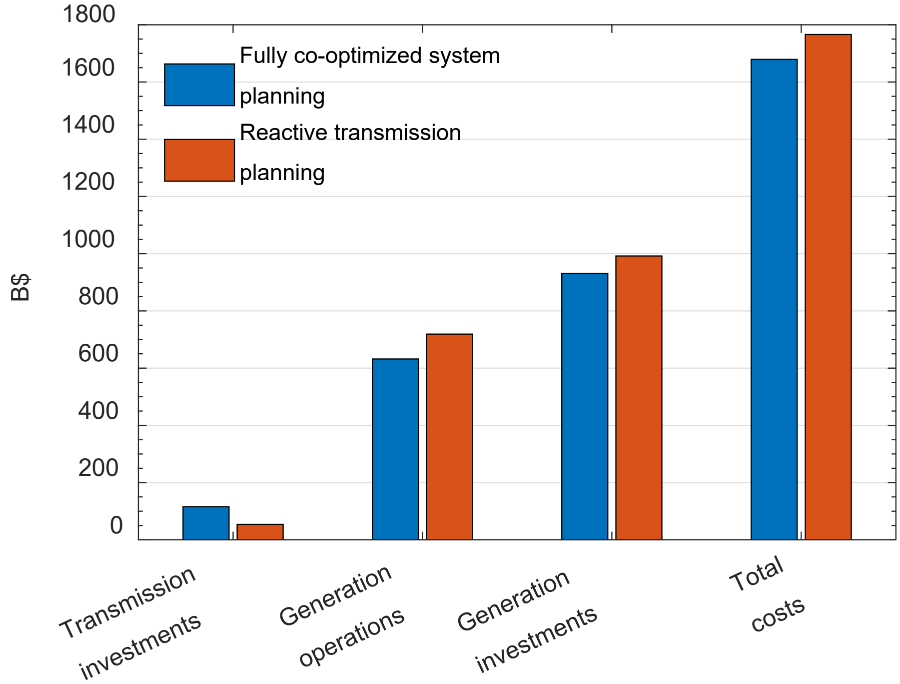


Figure 2-1
Comparison of costs of co-optimized and reactive transmission solutions in a study of a hypothetical U.S. national grid [1]

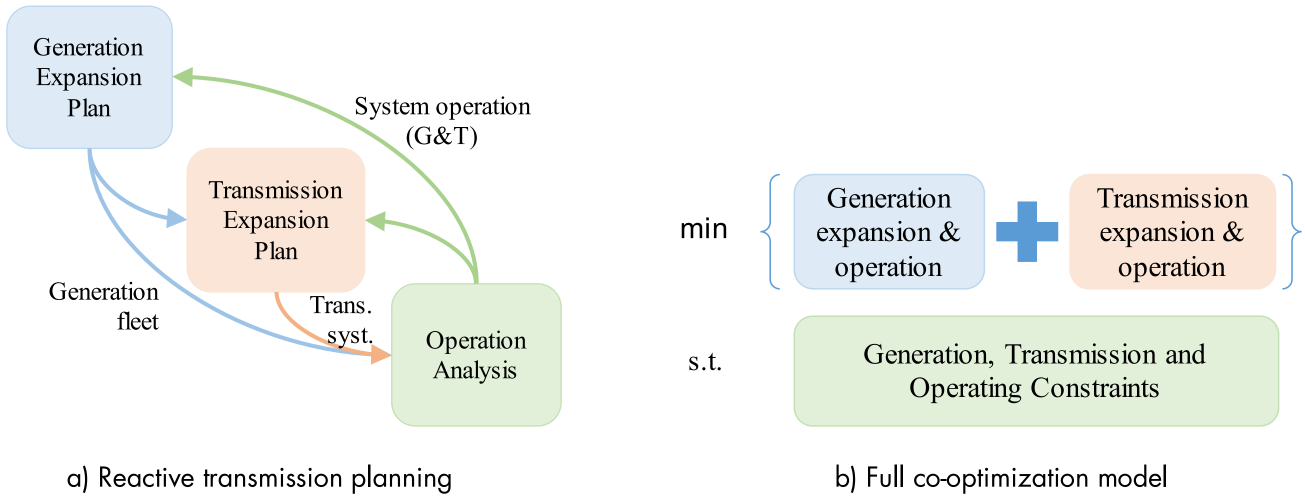


Figure 2-2
Traditional and co-optimized expansion planning models

However, complementary effects can also occur. In reference [2], an example is shown in which co-optimization instead increases generation investment relative to reactive planning; in that application to the Eastern Interconnection, co-optimization expands transmission investment by $8B, facilitating a 51 GW increase in the amount of wind installed by 2030, mainly in remote locations. These increased investments are more than paid for by large savings in production costs.

Many but not all the cost reductions resulting from co-optimizing rather than reactive planning can be achieved by iterating back and forth between separate models for transmission and supply investment. We call this "iterative co-optimization/coordination," which is the closest to coordinated expansion planning in practice and that still has room for improvement. For instance, in the U.S.-wide example just cited, if generation is re-optimized against the reactive transmission plan (i.e., the $54B investment), and then the new generation investment scenario is used to re-optimize transmission, total costs fall from $1766 to $1752 as a result of an additional $16B transmission investment. However, this is still well above the co-optimized system's costs of $1679B. Further iterations result in relatively minor improvements. Indeed, it is relatively easy to prove mathematically that the iterative approach cannot guarantee achievement of the cost reductions achieved by full co-optimized solution [1].

In either case, coordinated expansion results in appreciably more transmission investment, as shown for instance in Figure 2-3b, where more than twice as much interregional transmission is constructed (see Figure 2-1 for a breakdown of costs for this study). This strongly suggests that reactive transmission planning understates the value of new transmission.

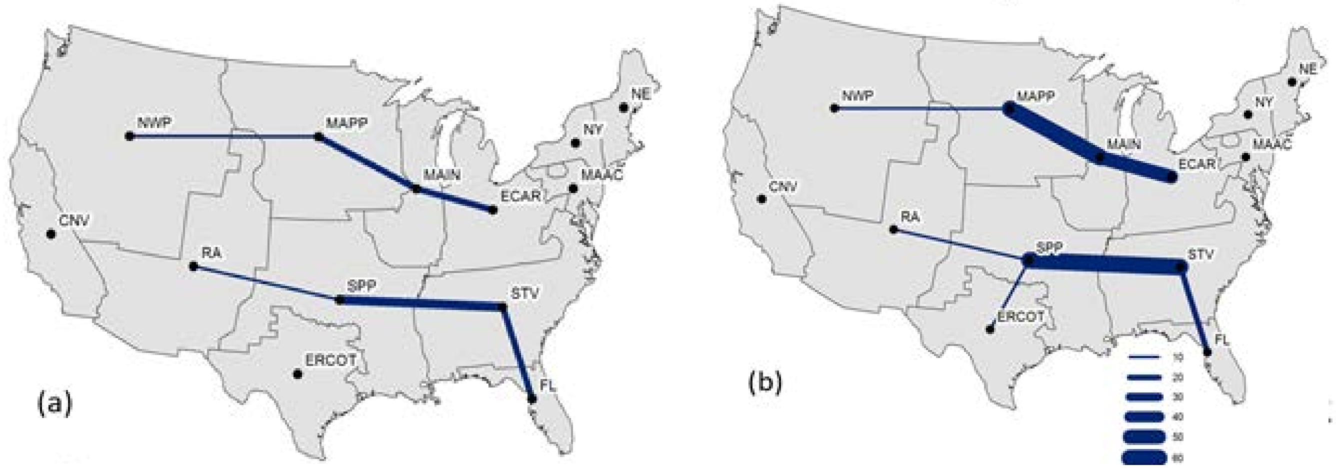


Figure 2-3
Comparison of (a) reactive and (b) co-optimized transmission solutions [2a-1]. (Cumulative transmission additions; line thicknesses are proportional to GW transmission additions between 2010-2030) [1]

The Relevance of CEP in Structured Spot Markets

Proactive Planning in an Unbundled Context When Generation Is Driven by Fundamentals

A common issue raised with CEP, at least in the transmission-generation context, is that the unbundled markets that exist in much of the U.S. assign the responsibility for transmission and generation planning to different entities. However, as clearly articulated by the California ISO [3], among others [4], transmission planners should proactively anticipate how the mix and location of generation investment will respond to grid reinforcements because the lead time for transmission is much longer than for investments in natural-gas-fired or renewable power plants.

Alternative grid designs will, for instance, change locational marginal prices (LMPs) and, in the case of capacity markets, local prices for capacity, altering siting incentives. Although generation mix and siting is a function of renewable resource availability, gas prices, gas pipeline locations, and access to land and water, transmission availability is also crucial. Transmission reinforcements can increase the value of remote resource development, while inadequate transmission can enhance the attractiveness of sites within load pockets. Thus, transmission planning and generation siting are tightly linked, and transmission planning should recognize this fact. Consistent with [1], [4], we use the terms "anticipative" or "proactive" planning referring to transmission planning that accounts for reactions of market players.

Mathematically, a single CEP with an objective of maximizing net economic benefits (equal to benefits to consumers minus all transmission and resource costs) can be shown to be equivalent to a situation in which a planner chooses one subset of investments in order to maximize net benefits, accounting for the reactions of a perfectly competitive market for all other investments. In the most likely circumstance, the CEP will be used by a transmission planner who wishes to maximize market efficiency, subject to a competitive market for resource investments and operations. For instance, a decomposition of the CEP problem based on the Dantzig-Wolfe principle[2] shows a transmission planner sending signals, which are interpreted as "transmission prices" (i.e., dual variables of master problem), to the market, which responds with an optimal mix of supply and demand options, under the assumption of competitive conditions.

Thus, efficient planning of a fully integrated utility is equivalent to anticipative/proactive transmission planning in competitive markets. This is a perspective

[2] Dantzig–Wolfe decomposition is an iterative algorithm for solving linear programming problems with special structure.

that has been accepted by regulators, including the California Public Utilities Commission in its review of the CAISO Transmission Economic Assessment Method (TEAM) [3].

Concerns with Proactive Planning in Unbundled Markets

As a first concern, we note, however, that even though transmission investments may take longer to plan than generation, some transmission entities feel obliged to implement a generation-first approach, in which indicative commitments to build new generation are then used to justify transmission additions. This approach can involve significant risk for both generation and transmission. First, needed transmission may be significantly delayed or may not be large enough to accommodate the generation. This is what happened in West Texas prior to the construction of Competitive Renewable Energy Zone (CREZ) lines, and in China a similar situation (albeit in a more centrally planned system) likely contributes to large amounts of constrained-off wind. Second, transmission may be built based on announced generation that does not materialize, resulting in underutilized assets. The longer lead times for grid reinforcements, together with siting and permitting uncertainties, exacerbates these risks, which can be lessened by adopting a proactive transmission approach.

As a general statement, use of CEP by an entity assumes that the CEP model is a sufficiently accurate representation of how other entities will react to the first entity's decisions. Although no projection of reactions will be completely accurate, the assumption is that fundamentals together with recognized policy constraints will be an important driver of generation siting and mix selection in the future, and can be largely captured in the CEP model. Furthermore, it is assumed that understanding how those fundamentals and policies will interact with grid reinforcements to alter future generation patterns will provide useful estimates of how transmission expansions will result in shifts in generator capital investment and resulting capital cost savings or operational efficiencies.

There is, however, the risk that the transmission planner miscalculates the reaction of generators to transmission reinforcements. Using CEP cannot guarantee that anticipated generation builds materialize, rendering the transmission investments less useful. Nonetheless, if the reactions of generators are uncertain because of identifiable risks in fuel markets, environmental rules, demand growth, or other fundamentals, then a stochastic or uncertainty-based CEP can be used to efficiently evaluate and prepare against those risks. Such a planning model would include multiple scenarios, one for each of several plausible combinations of these drivers, and would recommend near-term transmission projects that are beneficial across a range of possible futures [5]. Studies have shown that if generation responds to market fundamentals (whether ISO markets or otherwise), then there can be large benefits to evaluating and preparing against those risks using stochastic CEP [6], [7], [8], even when a small fraction of the plausible scenarios are considered. (In Section 8 below, alternative means of including long-run uncertainties in CEP are described in detail.) However, research is still needed to establish the benefits of using CEP models that assume market-driven generation responding to market fundamentals where the drivers of new generation investment are highly uncertain.

Of course, market response to grid expansions can only be estimated. More sophisticated CEP models are possible where instead of a perfectly competitive market, transmission planners can instead anticipate market investments in a situation in which there are market failures, such as incomplete market risk, scale economies, market power, transmission tariffs not based on LMPs, policy interventions, and seams issues. These are discussed in Section 7, below.

Another concern about using the basic CEP for planning is that transmission entities have objectives distinct from those of generators, so that recognition of how market-driven generation investment and dispatch decisions will react to grid reinforcements is important to accomplishing their objectives. Planners in the U.S. (e.g., the ISO/RTOs) as well as elsewhere (e.g., TSOs in Europe) are faced with higher-level policy objectives such as deeper penetration of renewable generation, which could conflict with zonal-level planning and operation concerns, as such integration may increase flows of power and congestion across seams. Economic views of such situations and their solutions could differ across zones in the U.S. or across nations in Europe.

CEP, in this context, can guide system planners on investments that are optimal, or closer to optimal, at a regional, national, or supranational level. Because market participants in some regions are unbundled with dispersed responsibilities, higher-level and local objectives will be imperfectly aligned; consequently, the upper (higher) level's optimal decision when made considering the lower (local) level's response can be no better than what economists call a "second-best" solution. That is, it is the best (in terms of upper-level objectives) that can be achieved given the constraint that the system is not integrated, and may in fact differ from the overall social optimum [9]. Mathematically, the CEP problem in that case should be phrased as a multilevel optimization, recognizing that the lower level may make decisions according to criteria that diverge from the upper level's objectives. As mentioned above, models have been proposed for this purpose and are discussed in Section 7, but to our knowledge they have not been implemented because of their computational complexity.

If through basic or multilevel CEP models, improved grid configurations are identified, then coordination between the upper and lower levels, and between different zones on the lower level could be reconciled through transfers among jurisdictions (e.g., [10], [11]). In implementing such transfers, tradeoffs between maximizing market efficiency and minimizing compensation payments could be evaluated.

Recent research [12], [13] has addressed possible uses of CEP models to identify optimal transmission reinforcements that benefit multiple regions relative to what might occur if regions do not coordinate; to quantify the benefits accruing to each region as a basis for cost allocation; and to identify those investments that would require involvement by a supra-regional entity in order to overcome barriers to cost-sharing. The extent to which decentralized approaches involving relatively limited exchanges of information could be used to incent efficient transmission investments that benefit multiple transmission planning entities is an open question for research.

Further complicating matters, some types of assets that can address transmission problems can earn market returns in order to offset some costs and provide incentives to fully participate in the market, but would require some regulated payments in order to be compensated for some of its transmission-like functions. As an example, the FERC requires ISOs to evaluate "storage as a transmission asset" when storage provides transmission services; there are difficult questions about whether and how such assets can also be valued as market assets and incented to provide value to the market at the same time [14].

R&D Issues on CEP Adoption Modeling Frameworks

Power system expansion modeling should strive to reflect the technical and economic relationships among various market participants. Their interactions lead to the creation of generation and transmission assets, and the particular institutional and market structures in place provide incentives that need to be recognized. Interestingly, while generating companies, transmission companies, and system operators have been extensively modeled, LSEs have been given relatively little attention in CEP literature. Given the growth of demand response together with distributed storage and generation, along with the changing nature of LSE incentives driven by ever-evolving wholesale market designs and retail regulation, the representation of all economic agents in CEP needs to be improved. Improved representation of the dynamics among market players that lead to capacity investment would make CEP modeling more realistic and therefore increase its value to potential users.

There are two research directions that could support this improved representation. First, in modeling the interests and strategies of participants in electricity markets, CEP models should address the calculation of incentives for efficient participation, also called "incentive compatibility." Incentive compatibility is when financial incentives make participation and investment profitable when such participation would increase the overall economic efficiency of the market, while at the same time discouraging participation and investment when it would not benefit the market as a whole. There are several levels of incentives. For example, regulators (FERC, state PUCs, and ISOs) provide investment incentives in wholesale markets in the form of rates-of-return and permitting, and encourage cooperation among neighboring systems, as in FERC's Order 1000. In turn, transmission owners and operators provide incentives for building and siting assets by their interconnection rules, pricing for transmission services, and creation of zones for acquiring ancillary services. Meanwhile, retail ratemaking provides critical incentives for distributed energy production.

Bringing together the literature on CEP modeling with the economic literature on incentives (as described in [15]) could provide theoretical frameworks that are practical and effective for encouraging efficient mixes, locations, and types of investment. The following ideas are core in incentive theory. Conflicting objectives and decentralized information, which are key characteristics of electricity system governance, are two integral ingredients. Another core idea is that each market party—consumers, LSEs, system operators, grid owners, or generation investors—pursue their private interests, which are shaped by incentives. Though the incentive theory paradigm has limitations, its practical application would be a step towards increasing relevance and effectiveness of CEP models.

Improved modeling of distributed resources is a second direction. How market design and retail rate-making affect investment in such resources needs to be anticipated, and their implications for the economics of grid reinforcement need to be understood. The possibility of significant two-way flows between transmission and distribution makes this need all the more pressing. The divergent economic incentives facing distributed resources that are behind-the-meter versus those that are directly connected to the distribution system and not subject to retail rates is a particularly important issue in incentive design and CEP modeling. Better modeling and, ultimately, improved incentives for these resources could lead to more efficient planning and utilization of network assets.

Section 3: Production Simulation Representation

A coordinated expansion planning (CEP) application seeks to optimize an economic function, the objective function, over an extended period of time, the decision-horizon, where the decisions focus on investments and retirements in terms of when (which years), where (what buses, what circuits), what technologies (e.g., wind, solar, combustion turbines, storage), and how much (capacity in MW). The objective function is a composition of investment costs plus production costs over the decision horizon.

A key feature of any CEP formulation is that total production costs over the decision horizon must be computed for each considered investment plan. The production costs include the fixed (FOM) and variable (VOM) operation and maintenance costs. Appropriate computation of production costs requires increasing levels of fidelity as wind and solar resources increase their presence in the grid. The reason for this is due to the increased amount of flexibility services required as wind and solar resources grow. In the following subsections, we define flexibility services, we show their centrality to the EP function, and we describe how the need to accurately assess them influences the design of a new generation of EP applications.

Flexibility Services

A previous EPRI report provides a broad definition of flexibility - the ability to adapt to dynamic and changing conditions, for example, balancing supply and demand by the hour or minute, or deploying new generation and transmission resources over a period of years [16]. When considering flexibility in CEP, some of the most relevant services include: (1) frequency response: 0-20 seconds following loss of generation to avoid low frequency dips and/or low steady-state frequency levels [17]; (2) frequency regulation: continuous steady-state frequency control to maintain frequency-control metrics [18]; (3) contingency response: capacity reserves having the ability to compensate for loss of generation within 1-15 minutes [19]; and (4) load following (or ramping): the ability to compensate for 5-min to multi-hour ramps [20], [21]. We add a fifth (5) planning reserve provision: capacity reserves to satisfy the annual peak [22]; although not typically considered operational in nature, its inclusion in expansion planning is addressed through the production simulation function.

Flexibility Services and CEP

The need for and the provision of flexibility services must be well-modeled in the next generation of CEP applications, for two reasons. The first reason is the impending change in the ratio of energy and flexibility-service revenue streams. Historical electricity-market revenue streams have been dominated by the energy revenues, with a relatively small percentage derived from provision of flexibility services. However, this may change in the future as marginal costs of producing wind and solar energy drive down the energy component, while the increased demand for flexibility services (due to increasing wind and solar investment) drives ancillary service and capacity prices up.

The second reason motivating improved modeling of flexibility services with CEP applications is associated with the need to identify CEP solutions that are indeed feasible. Power systems can operate reliably only if flexibility services are adequately provided. Yet, many of the enablers of flexibility services, including fast-ramping generation, controlled demand, storage, AC transmission, and HVDC transmission, may produce expensive energy or no energy at all. Without appropriate modeling of the need for flexibility services and the extent to which each investable technology can provide them, a CEP model may identify physically unrealizable asset portfolios. For example, assuming wind and solar are least-cost energy producers, a CEP model that does not represent the need for and the provision of flexibility services will over-estimate the optimal level of wind and solar, or, in the case of policy targets, underestimate potential costs for integrating these resources.

Non-Chronological Operating Conditions

The design of the production simulation (PS) function (sometimes known as production cost modeling (PCM)) within a CEP application is complex, because the need to accurately capture flexibility services requires high-fidelity PS models. However, PS fidelity comes with a cost, as the most computationally intensive part of an EP application is the PS.

PS modeling within expansion planning has traditionally utilized non-chronological representation of operating conditions; as a result, the PS itself imposes no modeling requirements that linear programs (LPs) cannot handle. This is important as LPs are the least computationally-intense type of optimization problem. Here, we identify three non-chronological approaches:

- Approach N1: The earliest EP models, these, were formed around the generation expansion planning (GEP) problem. They convolved load duration curves with generation outage models based on merit-order commitment and block-loading dispatch to obtain the energy produced by each generation unit, and thus each unit's production cost, over the time period represented by the load duration curve. This approach remains valuable because it efficiently provides resource adequacy indices such as loss of load expectation. Running Approach N1 in parallel with other approaches is a computationally efficient way to obtain adequacy indices.
- Approach N2: Here, the PS applies a transmission-constrained economic dispatch to each operating condition represented. Here, computational efficiency is gained through temporal and spatial aggregation. Temporal aggregation is accomplished by clustering similar operating conditions to tens or at most hundreds per year (rather than 8760), using, for example, the *k*-medoids method. The clustering should operate on attributes that reflect similarity in terms of load, wind, and solar availability, and in terms of transmission flows. Spatial aggregation is accomplished via network reduction. Here, load may be distributed from an eliminated bus to the neighboring retained buses through the standard processing of Kron's method[3]. The same approach is not applicable for generation, however, since it is important to maintain each unit's identity and corresponding economic performance data. Therefore, a heuristic is used to identify the retained bus to which generation from an eliminated bus is transferred, e.g., the retained bus to which the largest percentage of load is transferred in the Kron reduction process.
- Approach N3: The third approach involves co-optimizing generation and transmission investments to capture the interdependency between them. In deploying CEP, the computational efficiencies obtained via temporal and spatial aggregation become paramount, because inclusion of transmission as an investment option increases the computational intensity, even under modeling simplifications (possible modeling simplifications for transmission investment are described in Section 4).

Approaches N2-N3 model flexibility services by imposing constraints as a function of each technology in the resource portfolio to ensure those resources can provide sufficient amounts of each flexibility service. For example, flexibility service #2 (regulation) may be imposed by requiring that the sum over all resources of the MW amount each resource contributes to up- (and down-) regulation exceeds the amount of up- (and down-) regulation the system requires for that operating condition. Units are then dispatched for energy between the headroom (and footroom) necessary to provide this regulation service. Although this approach of modeling constraints on flexibility services ensure that some flexibility services are available, the amount required is exogenously-specified, rather than determined by simulated need, and so may over- or under-supply. A design based on chronological operating conditions is therefore needed.

Chronological Operating Conditions

With infinite computational capability, the most rigorous design would be a CEP with an internal full-scale PS that operates on a full-size network model at 5-minute intervals of temporal granularity throughout the decision horizon[4]. Such a design may be worth considering as the state of the art improves. At this point, it seems prudent to design a procedure guaranteed to be computationally tractable, and then allow experience

[3] Kron reduction is a method used to reduce or eliminate the desired node without need of repeating the steps as in Gaussian elimination.

[4] To put things into perspective, with existing computing power, modeling at hourly intervals would be extremely intensive.

with this design to illuminate opportunities for more rigorous designs. The remainder of this section is written embracing this thinking.

Bearing in mind the existing computing limitations, the second set of approaches for representing PS within CEP applications improves by utilizing chronological representation of operating conditions. Recent publications in this area include [23], [24], [25], [26], [27], among others. The procedure is illustrated in Figure 3-1. Here, in step 1, an EP application generates a CEP solution on a reduced model. In step 2, the CEP solution is translated to a full-size network model. In step 3, a full-scale external PS simulation is run on the full-size network model, and violations are identified in step 4. In step 5, these violations are addressed by identifying reduced model constraints to add to the CEP. For example, observations from the PS indicating that evening ramps require load shedding imply that additional constraints should be imposed to reduce solar PV additions and increase combustion turbine additions.

A central feature to the design of Figure 3-1 is that there are actually two PS functions: the full-scale external PS of step 3, and another simpler one that is internal in the EP of step 1. The approach shown in Figure 3-1 is iterative; i.e., it continues iterating the Step 1 to Step 5 process until a convergence criterion is satisfied.

This approach is attractive because it remains computationally tractable for a high-fidelity external PS. Indeed, this approach is a crude form of decomposition (see Section 4 for additional perspective on decomposition). However, the solutions produced by the CEP, depending on the fidelity of its internal PS, may be far from feasible, generating multiple violations in the PS application, thus requiring several CEP-PS iterations before it converges to a feasible solution; indeed, it may not converge at all.

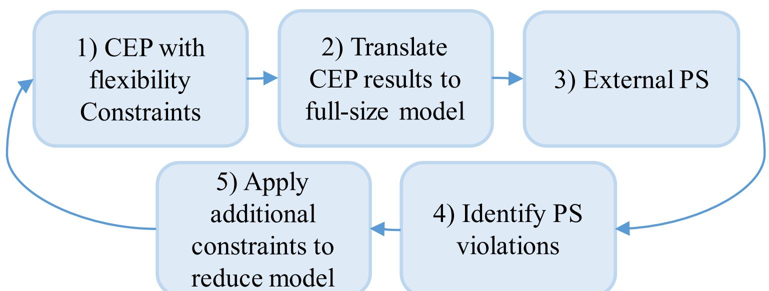


Figure 3-1
New CEP design

There are six R&D issues inherent to the CEP design of Figure 3-1, described as follows:

1. *CEP approach:* The CEP approach of step 1 can use a non-chronological (N1-N3) or a chronological approach (denoted with C). The advantage of using a non-chronological approach is speed per iteration. The advantage of using a chronological approach is fewer iterations and improved convergence properties. There are at least two different chronological approaches to consider.

   a. Approach C1: Here, operating blocks are represented chronologically, but the PS (and thus the CEP) application remains a linear program (LP) – see Section 4 for more detail. One important type of constraints that can be modeled are unit ramp-rate limits since they are captured simply by constraining the change that can occur from one operating condition to the next one. Constraints that are state-dependent cannot be modeled exactly as these require integers. The research should focus on how to relax or approximate each state-dependent constraint using continuous variables. Useful references on this topic include [26], [27].

   b. Approach C2: Here, again, operating blocks are represented chronologically, but the PS application is a mixed integer linear program (MILP), providing that the PS can have significantly increased fidelity. There are two reasons why this approach still requires the external PS: the action of the external PS allows some unit commitment (UC) constraints to be omitted in order to achieve a desired CEP solution speed; and the external PS operates on a full-scale model whereas the internal PS operates on a model that reflects temporal and spatial aggregation.

There are two ways where Approaches C1 and C2 may benefit computationally. One is by using both chronological steps and non-chronological steps. Another is by applying decomposition procedures; it is likely that decomposition must be applied for Approach C2, otherwise it may be tractable only if other model attributes are heavily restricted. See Section 4 for more on this issue.

2. *Modeling components with inter-temporal constraints:* The external PS application must account for components imposing inter-temporal coupling (e.g., minimum up and down times), and, to the extent that its modeling approach allows, the internal PS should as well. Traditional PS models are described in [28] and [29]. Reference [30] provides a high-fidelity storage model.

3. *Translation:* The translation of step 2 is necessary because the EP solves on a reduced network, but the external PS solves on a full-sized network. Thus, generation and transmission investments must be mapped from the reduced network of the CEP to the full-sized network of the PS. One way to do this is to map generation via rules (e.g., map new wind and solar to surrounding buses based on resource quality; map new gas to nearest bus with gas or coal) and transmission via a transmission expansion planning (TEP) application on the full-sized network after the new generation has been mapped. Although an exact TEP is a mixed integer non-linear program (MINLP), it can be modeled as an LP under some approximations (see section 4), in which case it is very fast even when run on a large network. A high level of fidelity can be achieved, with little additional computation, by iterating according to Figure 3-2.

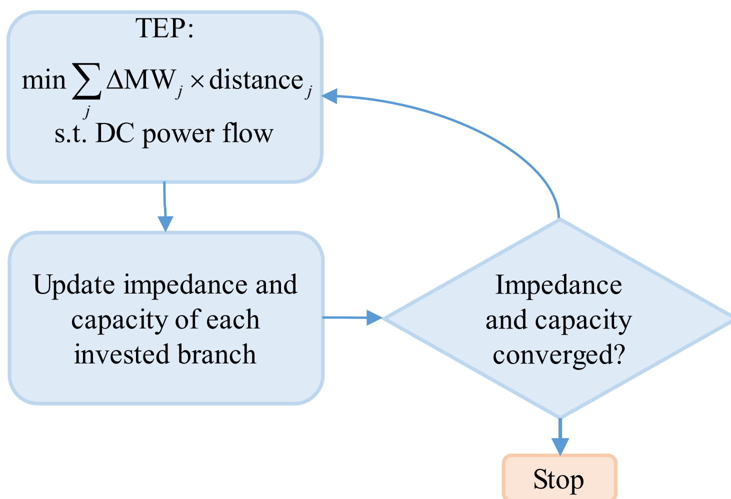


Figure 3-2
Iterative TEP for translation of transmission investments

4. *External PS interfaces:* Given the fact that excellent commercial-grade PS applications are available today, there is little need to develop one, i.e., the external PS of Step 3 in Figure 3-1 should be selected from among the available commercial PS applications. Once this is done, there remain two development efforts related to the external PS:

   a. A front-end interface between the step 2 translation function and the external PS must be developed. Assuming there is a PS model available for year 1 of the decision-horizon, then this interface applies the transmission and generation investments and retirements obtained from the Step 1 translator to the year 1 full-size model to obtain the year N full-size model.

   b. Following successful execution of the PS on the year N full-size model, a back-end interface needs to identify violations of constraints, and from these violations, identify new CEP constraints necessary to eliminate the violations. Intelligence within the external PS can facilitate this by identifying constraints having violations that trigger a load shedding function. If there is a high cost to load-shedding, then it may be possible to use Lagrange multipliers to identify the most important binding constraints to relieve.

5. *CEP-interface:* In step 5, constraints are developed to augment the CEP. This step must be capable of converting the violations associated with the full-size PS run to the reduced model of the CEP.

6. *Auxiliary functions:* The process of Figure 3-1 requires two auxiliary functions to prepare the EP data:

   a. Temporal aggregator: Recognizing similarity of days, 48-hour periods, or 1-week periods is necessary when modeling chronological conditions. This requires using inter-temporal attributes (e.g., a net load ramp over 2 hours) rather than static attributes. Reference [31] captures the essence of this issue.

   b. Spatial aggregation: Network reduction logic is essential.

R&D Issues on Production Simulation Representation

We summarize R&D issues on production simulation representation as follows:

1. Develop a flexible internal PS application that has capability of switching in and out various PS capabilities to enable high fidelity, on the one hand, or high computational efficiency, on the other. Such functionality will allow the researcher and practitioner to tune the internal PS application to achieve maximum fidelity allowable to remain computationally tractable.

2. Design and implement functionality for steps 2, 4, and 5 of Figure 3-1, which relate to how the EP and PS tools are linked together, and how constraints are added to the EP model.

Section 4: Computational Intensity

The coordinated expansion planning (CEP) problem as described already, particularly the co-optimized version, is inherently computationally intensive, and reduction in compute-time is usually obtained at the expense of modeling fidelity. In this section, we identify the CEP problem attributes that make it so compute-heavy together with various approaches whereby one may achieve improved modeling fidelity with minimal compute cost.

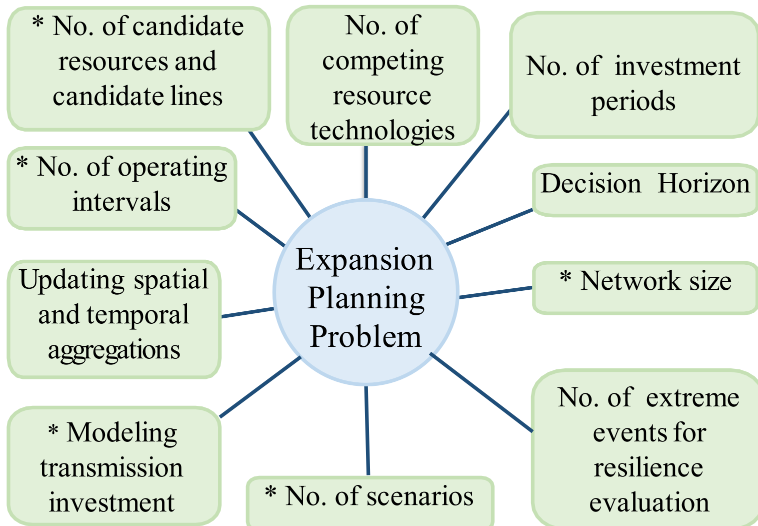
CEP Attributes and Computational Intensity

Figure 4-1 illustrates 10 different attributes that have significant influence on CEP problem compute-time. We provide a brief explanation of each one in what follows.

- *Network size:* The larger the network size, the larger the number of power flow equations in each operating condition. There are spatial aggregation methods that address this issue.
- *Decision horizon*: Longer CEP assessment duration (e.g., from 10 years to 20) motivates more investment periods and operating conditions.
- *Investment periods*: Increasing the number of investment periods increases the number of investment-related decision variables.
- *Investment candidates:* Investment candidates for resources (buses) and for circuits can include every bus and every circuit, or the number of decision variables can be decreased by allowing expansion at only a limited number of buses and circuits. It can be useful to screen candidates (particularly for circuits) using a fast, scaled-down CEP application (e.g., 1 period), thus reducing the number of candidates before running a high-fidelity CEP application.
- *Technologies:* For each resource investment candidate, and for each investment year, there is a decision variable required for each considered technology (e.g., onshore wind, offshore wind, solar PV, combustion turbine, combined cycle). Some technologies may have multiple options, each of which requires its own decision variable. For example, there may be various onshore wind turbine designs with their own unique investment costs, with some optimized for lower wind-speed regimes and others optimized for higher wind-speed regimes.
- *Number of operating intervals:* Independent of what type of PS method is deployed in the CEP, a user-specified choice of operating intervals is required. When using a non-chronological PS (see Section 3, designs N1-N3), the user specifies the number of operating blocks per year. When using a chronological PS (see Section 3, designs C1, C2), the user specifies the number of operating UC periods (e.g., 24 hours, 48 hours, or weeks) per year. In both cases, higher fidelity is achieved with a larger number of operating intervals but at an increased computational cost as each operating interval requires its own economic/network analysis - usually some version of an economic dispatch or a unit commitment assessment. There are temporal aggregation methods that address this.
- *Updating spatial and temporal aggregations:* Temporal and spatial aggregation depends on the resource locations, types, and amounts, together with network topology. These aggregations are typically performed using the year-1 conditions and not repeated. However, all aspects of the power system change throughout the CEP decision horizon. Updating spatial and temporal aggregations improves fidelity, but the update process requires additional computation. See Section 5 under "System dynamic production/reduction/expansion/translation."
- *Modeling transmission investment:* There are a few different ways to model transmission investment ranging from the low-fidelity, low-computational cost transportation model to the high-fidelity, high computational cost disjunctive model. This issue is further discussed in Section 5.
- *Number of scenarios:* When representing uncertainty, and thus when using some form of stochastic programming, the number of different scenarios (also known as futures) greatly influences the number of constraints and decision variables. For example, with only 11 uncertain variables, with two possible values for each, the number of possible scenarios is

2^{11}=2048. Current state-of-art stochastic or adaptive programs cannot handle this many scenarios, and so scenario reduction must be performed.

- *Number of extreme events for resilience evaluation:* Hurricanes, wildfires, earthquakes, tsunamis, and other natural disasters have created high interest in developing CEP models capable of identifying infrastructure investments that balance investment cost and resilience to these events. Although there is yet little published progress in this arena, it is clear that the number, nature, and modeling fidelity of chosen events will significantly impact computational intensity.



(* indicates there are existing methods and/or research efforts to reduce computation)

Figure 4-1
Influences on EP compute-time

Reducing Computational Intensity

Figure 4-2 illustrates that there are four dimensions to increasing the computational speed of the CEP problem; it also suggests that the effectiveness of deploying any one dimension interdepends with not only how each of the other three dimensions are deployed, but also the structure of the problem and its modeling granularity. We address each of these issues together with that of their interdependency in this section.

- *Optimization method:* There are three standard optimization methods for solving linear programs (LPs): the primal simplex, the dual simplex, and the (interior point) barrier method. It is difficult to predict which one is faster for a given problem, but there are guidelines based on problem attributes that suggest tendencies favorable towards one algorithm or another [32]. In addition, many of today's state-of-art solvers offer so-called concurrent optimization which, when invoked, solves the problem simultaneously on different cores using different algorithms, effectively handling the problem of uncertainty for choice of algorithm via excessive deployment of computational resources.

For mixed integer linear programming (MILP) problems, the almost-universal algorithm is the branch and cut implementation of the branch and bound approach, although the differences among implementations in terms of logic for identifying which LP algorithm to call in each step, and the details of each available LP, can result in wide variances in solve time.

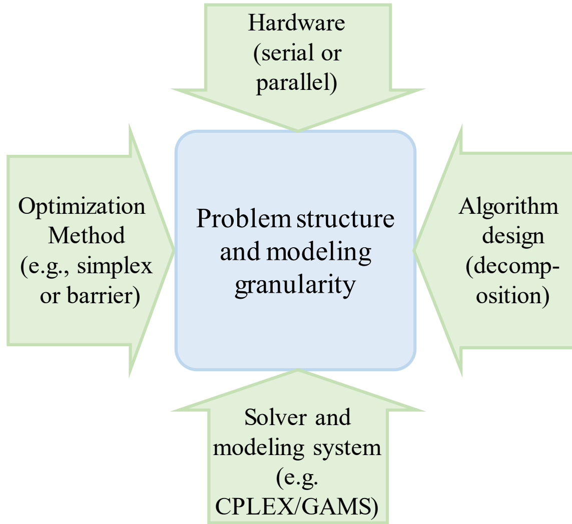


Figure 4-2
Dimensions of decreasing EP computational Intensity

- *Solvers:* There are various commercial solvers today, including, for example, CPLEX, Gurobi, XPRESS, MOSEK, and LINDO. MATLAB and Microsoft's Excel application also have solvers. There are some lesser-known solvers that provide particularly effective means of decomposition, including ADMM and DSP. Although many of these implementations use similar algorithms, they perform quite differently on different types of problems. For example, Figure 4-3 illustrates performance results for simplex and barrier LP algorithms among Gurobi, CPLEX, XPRESS, and MOSEK for one set of benchmark problems [33] (the ordinate is normalized average time)[5].
- *Modeling systems:* There are various commercial modeling systems that interface with the solvers, including, for example, GAMS, AMPL, AIMMS, and MPL. These systems, referred to as algebraic modeling languages (AMLs), link the domain-expert's conceptualization of their problem to the various algorithms instantiated in the solvers, via problem expressions that are similar to the mathematical description one uses when writing the problem objective function and constraints. Generally, the choice of modeling system does not affect the solution speed of the solver, but different modeling systems may enable easier development of certain algorithm designs. An approach similar to these modeling systems is to use a high-level programming language to formulate the problem for submission to the solver; the Python Optimization Modeling Objects (Pyomo) is such an approach, as is JuMP. In addition to providing all of the flexibility of a high-level programming language (Python in the case of Pyomo and Julia in the case of JuMP), these approaches have other specific strengths. For example, Pyomo facilitates stochastic programming problems for deployment in a decomposed, parallelized solution.

[5] Figure 4-3, developed by one commercial vendor, is provided for illustrative purposes only and should not be considered indicative of overall solver performances.

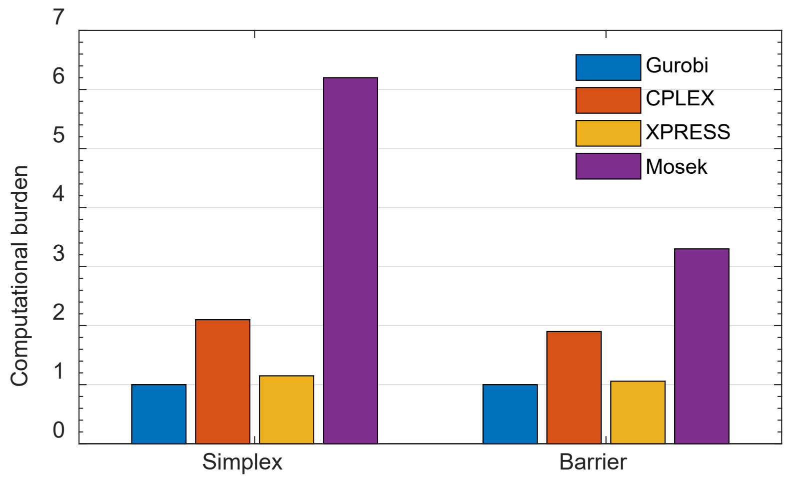


Figure 4-3
Solver performance results

- *Decomposition:* Decomposition methods solve a large optimization problem by breaking it down (decomposing it) into a single master problem with small subproblems. The underlying principle is that, if the problem's compute time is proportional to an exponential function of the problem size, then it is faster to solve many problems of small size than it is to solve one problem of large size. Problems with constraint matrices having block-angular structure, as illustrated in Eq. 4-1, are generally good candidates for applying decomposition. Such problems may have complicating variables (variables that appear in multiple subproblems, as is the case for the problem represented by Eq. 4-1) or complicating constraints (constraints that span multiple subproblems). The constraint matrix for the CEP problem can exhibit block-angular structure as a result of having close-to-independent time periods, and as a result, might be amenable to Benders [33], Dantzig-Wolfe [34], or Lagrangian relaxation [35]. The EP problem solved under uncertainty can exhibit block angular structure as a result of having close-to-independent scenarios, and as a result, is amendable to progressive hedging [36]. Hybrid decomposition deploys more than one method, e.g., Benders and Lagrangian relaxation [37]. Nested decomposition may be applicable where two decompositions are deployed, with one operating on the subproblem of the other [38], e.g., the higher level decomposition may operate on scenarios and the lower-level decomposition may operate on the time periods for each scenario. A decomposed problem when solved on a single core (the subproblems are solved sequentially) can obtain significant speed-up; in addition, the same problem when parallelized (the subproblems are solved in parallel) will generally obtain even greater speed-up. Modeling systems may facilitate decomposition; for example, GAMS will formulate the problem via Benders if variables are annotated as to which problem they belong (master problem or subproblem *k*). Another promising approach is to decompose by time period [39] or by geographical region [40] or by both.

$$\begin{bmatrix} \mathbf{a}_{11} & & & \mathbf{a}_{14} \\ & \mathbf{a}_{22} & & \mathbf{a}_{24} \\ & & \mathbf{a}_{33} & \mathbf{a}_{34} \end{bmatrix} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \mathbf{x}_3 \\ \mathbf{x}_4 \end{bmatrix} \leq \begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \mathbf{b}_3 \end{bmatrix}$$

Eq. 4-1

- *Parallelization:* Most of the solvers offer paralleled versions of their algorithms that are easy to deploy on multi-core machines. For example, CPLEX offers a parallelized version of its barrier algorithm; testing on a high-performance machine having 16 cores per node showed that an expansion planning problem that ran 22 hours using a single core took only 2 hours when parallelized across the node's 16 cores. Parallelizing across nodes is more involved but can also be done. It will be worthwhile to investigate a recent development of a parallel open-source software package to deploy decomposition methods particularly well-suited for solving stochastic mixed-integer programs [41].

R&D Issues for CEP Computational Efficiency

There are two main R&D issues inherent to the issue of computational efficiency, described as follows:

1. *Systematic solution implementation:* Given the various CEP problem attributes listed above that influence computational intensity, and given the various approaches listed above to relieve computational intensity, develop a systematic procedure to identify the solution design that solves the CEP problem most efficiently.
2. *Dynamic implementation:* The research question is to what extent can the systematic solution implementation be automated? We frame this question in two different ways:

    a. Given a particular problem size, what is the best solution design to use available computational resources in order to minimize compute time?

    b. Given available computational resources, what choice of problem attributes achieves the best tradeoff between modeling fidelity and compute time?

Section 5: Transmission System Modeling

In this section, we address three issues related to transmission system modeling: transmission investment representation, dynamic production simulation/ reduction/expansion/translation, and loss modeling.

Transmission Investment Representation

Transmission investment modeling within the CEP problem may be achieved via implementation of what we call here as the full model. This model employs (a) the network relation **P = B'θ** where **P** is the bus injection vector, **θ** is the vector of bus voltage phasor angles, and **B**' is the negated imaginary part of the network Y-bus neglecting bus shunts; and (b) for each investible circuit, a flow equality and a flow inequality.

The network relation, the flow equalities, and the flow inequalities must account for investible circuits. We focus here on just the flow equalities and inequalities as these two relations serve to illustrate the difficulty associated with this formulation.

The flow equality is given by $P_{jk} = (B_{jk}^{\text{exist}} + Z_{jk} B_{jk}^{\text{invest}})(\theta_j - \theta_k)$. The flow inequality is given by $-\left(P_{jk,\max}^{\text{exist}} + Z_{jk} P_{jk,\max}^{\text{invest}}\right) \le P_{jk} \le \left(P_{jk,\max}^{\text{exist}} + Z_{jk} P_{jk,\max}^{\text{invest}}\right)$. Here, P_{jk} is the flow between buses j and k, B_{jk}^{exist} and B_{jk}^{invest} are the negated susceptances of existing and investible circuits, respectively, connecting buses j and k, θ_j and θ_k are the angles of the voltage phasors at buses j and k, respectively, and Z_{jk} is the integer variable indicating whether the transmission investment between buses j and k should be made ($Z_{jk}=1$) or not ($Z_{jk}=0$). $P_{jk,\max}^{\text{exist}}$ and $P_{jk,\max}^{\text{invest}}$ are the flow capacities of the existing and invested transmission circuits, respectively. The decision variables are the elements of **P**, the flows P_{jk}, the phasor angles θ_j and θ_k, and the investment indicators Z_{jk}. The investment indicators impose that the associated optimization is an integer program.

The difficulty associated with modeling transmission investment arises in the flow equality equations, where we observe that the integer investment indicator Z_{jk} multiplies the angles θ_j and θ_k. The presence of decision variable products means that the optimization is nonlinear. Given the presence of binary investment variable Z_{jk}, the transmission investment optimization is a mixed integer nonlinear program (MINLP). Such problems, being non-convex and nonlinear, are difficult to solve. A number of simpler models have been suggested; expanding from [42] we summarize them in increasing order of modeling rigor in what follows.

1. *Transportation model*: This model represents all circuits as pipes. One may also think of the represented circuits as DC lines. Although all circuits are capacitated, the effect of impedance on flows is not represented so that a pipe or set of pipes may carry flows (up to their capacity) with no physical influence on flows carried by pipes comprising parallel paths. This model replaces the network relation **P=B'θ** with the simpler one **P=Ae** where **A** is the node-arc incidence matrix and ***e*** is the vector of circuit flows; this model enforces nodal balance. There is no need for the flow equalities (and so there are no angle decision variables) or the investment variables Z_{jk}. The flow inequalities become $-P_{jk,\max} \le P_{jk} \le P_{jk,\max}$. The decision variables are the flows P_{jk} and the flow limits $P_{jk,max}$. The resulting optimization problem is a linear program and can be solved efficiently. The fact this this model does not account for the power flow that would be observed means it is more suited to understanding the potential for increased transfer between regions rather than build-outs of specific lines. It also may underinvest in new transmission as impact on parallel lines is not captured.
2. *Constant impedance model*: This model deploys the network relation, the flow equalities, and the flow inequalities of the full model, but drops the integer variable so that the flow equalities become $P_{jk} = B_{jk}^{\text{exist}}(\theta_j - \theta_k)$, and the flow inequalities become those used in the transportation model $-P_{jk,\max} \le P_{jk} \le P_{jk,\max}$. The decision variables are therefore the elements of **P**, the flows P_{jk}, the phasor angles θ_j and θ_k, and the flow limits $P_{jk,\max}$. This

formulation is a linear program and therefore computationally efficient. However, although flows are influenced by network impedances, this influence becomes increasingly inaccurate as more transmission is invested because the circuit impedances remain constant and therefore become inconsistent with the circuit's increased capacity. Because the larger capacity has impedances that are too large, the new transmission sees less flow; thus, this model tends to overinvest in transmission in order to achieve the flows that it requires.

3. *Hybrid model*: The hybrid model combines the transportation model with the constant impedance model in that existing transmission is represented as in the constant impedance model, but investments in a circuit are modeled with a pipe parallel to that circuit. Because the invested transmission can achieve flows up to its capacity without influencing parallel flows, this model tends to underinvest in transmission. However, this underinvestment may be less erroneous than the overinvestment of the constant impedance model. This model is a linear program.

4. *Iterative*: This model performs several CEP iterations using either the constant impedance model, the hybrid model, or both (either successively or alternatively). Following each CEP calculation, the invested transmission is converted to transmission with consistent values of impedance and capacity before another iteration is performed. This model is an iterative sequence of linear programs.

5. *Disjunctive*[6] *model*: In this model (also referred to as the "Big M" model), the flow equalities used include one for the existing circuit (terminating at buses *j* and *k*, numbered circuit *b*) $P_b = B_b^{exist}(\theta_j - \theta_k)$, and one for a parallel invested circuit (also terminating at buses *j* and *k*, numbered circuit *b+1*), $-M(1-Z_{b+1}) \le P_{b+1} - B_{b+1}^{\text{invest}}(\theta_j - \theta_k) \le M(1-Z_{b+1})$. Here, Z_{b+1} is a binary variable having value of 0 if the investment is not made and 1 if it is made. M is a large positive number so that, if the investment is not made ($Z_{b+1}=0$), the middle term becomes effectively unconstrained so that there is no relation enforced between flow P_{b+1} and $B_{b+1}^{\text{invest}}(\theta_j - \theta_k)$; if the investment is made ($Z_{b+1}=1$), the middle term becomes constrained from above and below to zero, imposing equality to zero, and $P_{b+1} = B_{b+1}^{\text{invest}}(\theta_j - \theta_k)$ is enforced. This model is a mixed integer linear program (MILP). This formulation is attractive in that it is equivalent to the MINLP of the full model, and standard MILP solvers are available to handle it. However, CEPs when modeled this way become quite computationally intensive, and, except for problems where the various attributes causing computational intensity have been severely limited, compute times using serial computing are impractical. It may be that compute times can be satisfactorily reduced for this formulation via a decomposed, parallelized high-performance computer implementation and/or by deploying optimization methods specialized for high-speed execution [43], [44]. Reference [45] extends the traditional disjunctive model to allow multiple parallel circuit additions between two buses, by using a decimal-binary transformation; this approach significantly improves computational efficiency when transmission expansion includes adding multiple parallel circuits.

System Dynamic Production Simulation/ Reduction/Expansion/Translation (PS-RET)

This section expands on the idea introduced in Section 4, under the subsection "CEP attributes and computational intensity" identified by the bullet "Updating spatial and temporal aggregations." Here, we describe a dynamic production simulation, reduction, expansion, and translation (PS-RET) process.

A CEP application is intractable on a large-scale planning model having tens of thousands of buses, using a production simulation (PS) of 8760 hours per year (or potentially even a higher temporal resolution to capture intra-hour effects). Thus, the CEP problem is spatially and temporally reduced to operate on a smaller size network with fewer operating intervals. Current state-of-art is to perform this spatial and temporal reduction once, for year 1 conditions, and then to run the CEP for the entire decision horizon (e.g., 10-30 years) using the reduced model, and then translate (in the terminology of Section 3) the investments back to the full model.

[6] The word "disjunctive" means "lacking connection" or "marked by breaks" which fairly characterizes a network where one is considering adding new circuits (i.e., new connections between nodes).

The problem addressed in this section stems from the fact that spatial and temporal reductions depend on the system conditions (load levels and location, generation levels and location, and transmission). Because these conditions change throughout the CEP decision horizon, the nature of the spatial reduction (which buses are retained) and temporal reduction (which time intervals are considered "similar" and aggregated) also change, causing the year-1-based reduction to be inconsistent with latter-year system conditions.

This problem motivates a dynamic process whereby spatial and temporal reductions are repeated throughout a receding horizon on an evolving topology and on evolving conditions. The term "receding horizon" implies, with each PS-RET cycle, that the entire decision horizon steps ahead in time by one "delta" (Δ). The duration of a Δ, user-defined, is typically one or more years. Denoting T as the number of years in the decision horizon, a dynamic PS-RET process is characterized as:

1. k=1
2. Year k:
   a. Perform spatial and temporal reductions using year k full model with translated results from years $t \leq k$ represented.
   b. Run CEP for years $k \rightarrow k+T$.
   c. Translate investments for years k to $k+\Delta$ to full network model and store years k full network model plan.
3. If $k+\Delta > T$, stop, else, $k=k+\Delta$, go to 2.

Figure 5-1 illustrates a dynamic PS-RET with T=10 years and Δ=5 years; there are two PS-RET cycles. Here, the first PS-RET cycle performs a CEP for years 1-10 and retains the investments for years 1-5; the second PS-RET cycle performs a CEP for years 5-15 and retains the investments for years 6-10. A useful side-benefit of the dynamic PS-RET process is that, because it performs CEP beyond the decision horizon (year T), it offsets so-called "end-effects" for investments made within years 1 and T that would otherwise result from the artificial termination of time at year T. The PS-RET process illustrated in Figure 5-1 is consistent with the Figure 3-1 process.

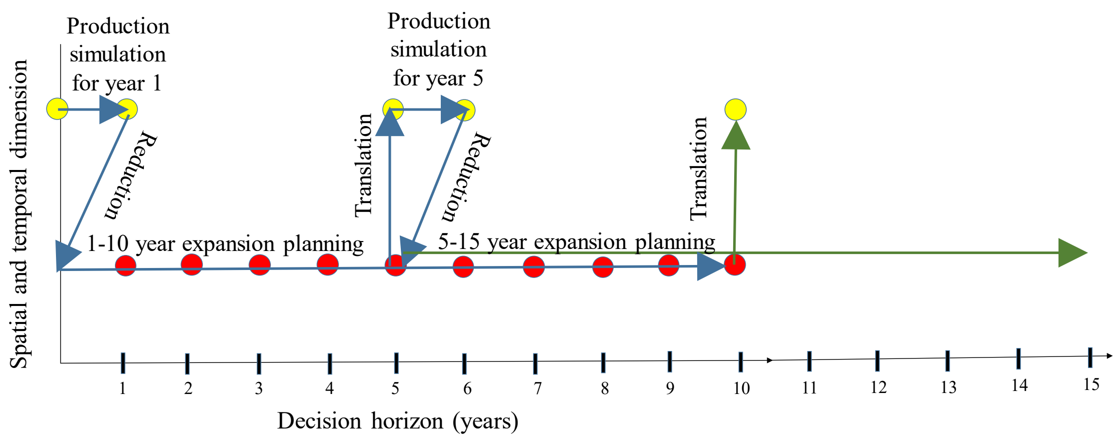


Figure 5-1
System dynamic production simulation/reduction/expansion/translation (PS-RET) process

Loss Modeling

Losses are particularly important to include in studies for which one wants to quantify tradeoffs between investment strategies that significantly affect them, e.g., high DER investments vs. low, or use of high-capacity interregional transmission vs. mainly local resources. The problem is, however, that losses are proportional to the square of the current flow (and when using the DC power flow, to the square of the real power flow), and so a piecewise linear approximation must be introduced in order to represent them in an LP or an MILP. There are generally two levels of modeling fidelity to be determined when deploying a linear loss model.

1. Number of segments: If the number of segments to the piecewise linear model is limited to one, then integer variables are avoided, and the model is an LP.

If two or more segments are used, then the model will be the more accurate but more computationally intensive MILP.

2. Relation to network model: The simplest approach is to include the approximation and cost of losses in the objective function. Incorporating losses within the network model increases modeling fidelity; the computational expense of doing so is not clear.

References [46], [47], [48], [49], [50] address this issue.

R&D Issues for Transmission System Modeling

There are three main R&D issues associated with CEP computational efficiency, described as follows:

1. *Transmission investment representation:* Barring some breakthrough on MILP solvers that would allow efficient use of the disjunctive model, there are two areas of investigation to pursue in developing a rigorous but fast transmission investment model:
   a. Screening: Elimination of some circuits from the list of candidates can be done efficiently, and it significantly reduces computation time associated with transmission expansion. The screening should be computationally fast; for example, a 1-period CEP could be run, and circuits seeing no investment could be eliminated. Alternatively, circuits can be eliminated from investment consideration if they have low "congestibility" based on the network Laplacian [51], a price sensitivity matrix [52], or an empirical distribution of transmission line power flows obtained from an 8760-hour production simulation where lines with congestibility below a certain probability threshold are eliminated. This would be an additional step in the PS-RET process illustrated in Figure 5-1.
   b. Iteration: The iterative method described above is promising; the research objective here is to identify the performance (in terms of time per iteration and number of iterations) of three designs: impedance model, hybrid model, and both. This approach would be used as the CEP of the PS-RET process illustrated in Figure 5-1.
2. *Dynamic PS-RET process:* The dynamic PS-RET process should be designed, implemented, tested, and then studies should be conducted to illuminate the sensitivity of solution stability and compute time to various parameters, e.g., the step-ahead Δ. There are two main R&D issues here:
   a. Network reduction: Network reduction using variants of Kron's method is effective although a heuristic is necessary for eliminating buses having generation [53], [54]. Recent work for DC power flow equivalents should be considered [55], [56], [57]. In addition, steps 4 and 5 of Figure 3-1, which identify violations in the external PS and construct constraints for the CEP, should be combined with the network reduction.
   b. Coordination logic: This logic coordinates the PS, the reduction, the CEP (and any CEP iterations), and the translation, and implements the receding horizon features of solution storage and step-ahead Δ.
3. *Loss modeling:* The approaches to model losses should be implemented and tested to identify the one that offers the highest fidelity with acceptable influence on compute-time.

Section 6: Representing Distributed Energy Resources

DER Representation

There are two philosophical approaches for representing distributed energy resources (DER) within expansion planning applications. Approach 1 identifies the physical needs of the bulk system (generation and transmission) as well as the distribution system. Approach 2 identifies the needs of the bulk system and captures the effect of DER and distribution systems on the needs of the bulk system, but it does not seek to identify the needs of the distribution system at the level that a distribution plan would require. Although success in managing computational intensity (per Section 4 R&D efforts) may make Approach 1 more viable, we embrace Approach 2, because distribution system planning requires modeling it at a granularity level that, when combined with bulk system representation, causes the CEP to become computationally intractable. Therefore, here we focus on G&T coordination, while representing the impacts of distribution, as opposed to full G, T & D coordinated planning. The latter modeling is a major challenge as outlined in EPRI's the Integrated Energy Network (IEN) initiative[7].

There are two high-level decisions to make in regard to modeling DER in a CEP application, as follows:

1. How many feeders and how many segments per feeder should be used in representing the distribution system at each load bus in the bulk system?
2. Should DER and distribution line investments be considered as decision variables or parameters?

We address these two questions in the remainder of this section.

Feeders and Segments

DER installations affect the need for bulk system expansion. There are two ways through which this influence is manifested: (1) energy and flexibility services displacement and (2) loss reduction. If DER is modeled as a decision variable, this influence may also come through (3) competing infrastructure investments.

- *Energy and flexibility services displacement:* DER displace the energy produced by resources at the bulk system level and therefore reduce the need for bulk system resources. DER also reduce the need for capacity at the bulk system level, but this influence is tempered by the extent to which DER are credited with capacity-providing capability by virtue of their tendency to be variable (if wind or solar) and less-directly controlled by the grid operator. DER may also displace frequency regulation, contingency reserves, and/or load following normally provided by bulk system resources if they have the control and communication capability to provide these services, and the distribution system is not a constraining factor.
- *Loss reduction:* Because DER are connected close to the load, initial DER installations tend to reduce flow from the bulk system into the distribution feeders and thus reduce losses. This tendency will begin to diminish at the point when net-supply from DER exceeds load in a given distribution system.
- *Competing infrastructure investments:* If the DER life-time cost (initial investment plus annual O&M) per unit service provided (energy and flexibility) is lower than that of centralized generation, then DER may outcompete centralized generation and reduce its need. It is often the case that energy efficiency (EE) and demand-response (DR) programs will indeed have this influence, although they are limited in the extent to which they may be deployed. On the other

[7] http://integratedenergynetwork.com/

hand, centralized resources typically outcompete distributed generation (DG) (rooftop solar, microturbines, and distributed storage) due to economies of scale achievable at the bulk system level, and so assessing high DG penetration levels typically requires imposing constraints to force their installation, or modeling them as parameters rather than decision variables.

Figure 6-1 illustrates a model that captures the above three ways that DER investments affect the need for bulk system expansion investments. In this model, the distribution system connected to each transmission-level load bus k is replaced by a single distribution feeder with N_k segments (or buses), where N_k is user-specified to be any number N_k=0 (load and DER investments are modeled at the high-side of the distribution step-down transformer), N_k =1 (load and DER additions are modeled at the low-side of the transformer), N_k =2 (load and DER investments are split between low side buses 1 and 2), or any higher number. All transmission buses in Figure 6-1 have distribution systems modeled with N_k =3, considered to be a minimum level of distribution segments that still achieves good modeling fidelity. With N_k ≥3, the following effects are captured:

1. the effect of DER on losses;
2. the need for feeder capacity expansion (due to either increased forward flows from load growth with little DER growth, or due to increased reverse flows due to very high DER growth);
3. the effect of distributing load and DER at different electrical distances from the transmission bus;
4. the performance of portfolios of options to provide support during high-load, low solar time periods (e.g., from the bulk system and/or from non-solar DER such as storage and microturbines).

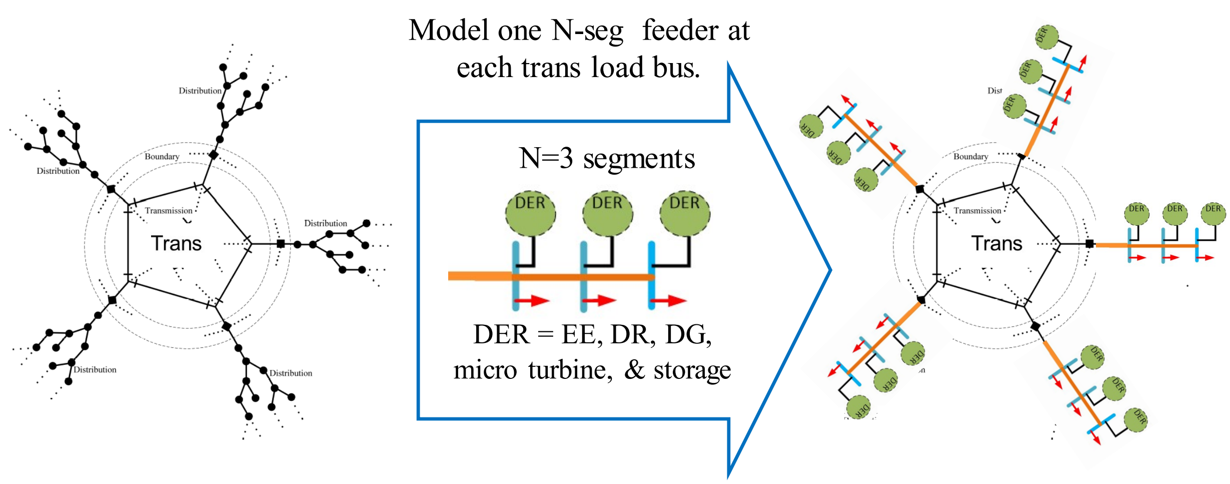


Figure 6-1
A Network modeling approach to capture the effect of distribution investment on bulk system expansion

Parameters of Decision Variables

DER are modeled using either parameters or decision variables.

In some cases, it may be preferable to model DER as parameters. This means that the growth rate of each DER type in the distribution part of the CEP network model is user-specified, i.e., exogenous to the optimization. Thus, DER growth is *assigned*, not *competed*, within the optimization. One reason why this can be appealing is that the decision to invest in DER is not made by the CEP user (generally a utility planner) but rather by a customer or customer group. This approach positions the analyst to react to the parametrically specified actions of DER investors.

Modeling DER as decision variables enables identification of socially optimal investment strategies. However, it assumes that DER investors make decisions in order to minimize their total long-term cost of energy, although we know this is not the case. Customers, for instance, may install rooftop solar not because it offers less expensive energy but rather to contribute to environmental objectives (e.g., CO_2 reduction) and/or to become autonomous from grid supply. In addition, this approach requires more complex modeling within the EP because it competes distribution investments (DER and feeder capacity) with centralized investments (generation, storage, and transmission). Although modeling DG is similar to centralized generation, modeling distributed storage and demand-side programs (EE and DR) requires that their actual cost structures (e.g., for EE, rebates per appliance; for DR, payments per demand reduction or shifted) be translated into a capacity-related investment cost and an operations-related energy cost. As previously indicated, from the system perspective, EE and DR are cost-effective expansion alternatives because they have low capital and operational costs compared to options that require built infrastructure[8]. This motivates the need to limit their investment to achievable levels.

R&D Issues for Representing Distributed Energy Resources

There are three main R&D issues associated with representing distributed energy resources in CEP applications, described as follows.

1. *Distribution network:* The CEP user should have a high degree of flexibility in representing the distribution network topology at each bulk system load bus. The following options should be available:
   a. Automatic feeder representation: As described above, at each bus k, the user should be able to specify the number of segments N_k, and the application should then automatically generate a feeder to use in the model that can approximate local conditions (e.g., rural, urban, large, small, etc.).
   b. Manual feeder representation: There may be some cases where the user desires to provide a unique representation of the distribution network; this option would allow for that.
2. *Modeling distribution line investment and losses:* These issues have been addressed in Section 5, but there, the focus was on transmission modeling. Modeling at the distribution level could be done in the same way. However, because the distribution representation is, in many cases, purely radial, it may be that line expansion and loss modeling can be done differently. For example, a radial distribution line may be represented with a transportation model, approximating losses as some percentage of the flows.
3. *DER models:* Models and appropriate data for DER technologies need to be developed. These would include storage, DR, and EE. It would also include DG, with focus on developing cost data associated with rooftop solar for residential and commercial/industrial facilities, natural-gas based micro-turbines, and anaerobic digesters fueled by agricultural waste.

[8] To date, there has been only one kind of energy efficiency program seeing widespread deployment: rebates to customers for purchase of high efficiency appliances. On the other hand, there are at least two broad classes of demand response programs: i) direct load control, and ii) time-varying rates. The latter can be further classified in terms of whether it is time-of-use pricing, real-time pricing, variable-peak pricing, or critical-peak pricing.

Section 7: Market Perspectives on Coordinated Expansion Planning

CEP in a World of Zero Marginal Cost Resources and Scarcity Pricing

As noted in Section 2, use of CEP in unbundled markets is equivalent to assuming that the transmission planner is anticipating the investment and operations reactions of a competitive energy market. As described in this section, this perspective can account for market failures, as well as the dramatic changes brought by large amounts of zero-marginal-cost variable renewables.

Scarcity and Reliability Services Pricing

In markets across Europe and the U.S., energy prices have been driven downwards by the rapid expansion of solar and wind capacity. Regulators, market designers, and especially market participants are asking how investments in needed resources can be supported in this situation.

A useful perspective on this problem can be obtained by considering a CEP that has two crucial features:

- Demand curves and curtailment penalties: If CEP considers price-elastic demand, in which higher prices result in voluntary reduction of loads, or involuntary curtailment with a penalty level that reflects the value of lost load, then market prices will rise during periods of scarcity. As the classic works by Schweppe, Caramanis, and their colleagues show (e.g., [58], [59]), such scarcity pricing can, in theory, incentivize the optimal mix of generation investment. In a market with frequent zero or negative prices as a result of renewables, the outcome will be price spikes during scarcity periods, signaling the need for investment.
- Co-optimized reliability services: If the needs for regulation, operating reserve, and (perhaps) ramping needs of a market are captured by explicit representation of the requirements for and supply of these commodities, and realistic penalties for any shortfalls, then these can be significant revenue streams for new investments. Incorporation of explicit demand curves for these services, in which marginal penalties for non-supply increase as the shortfalls grow, will allow scarcity to be reflected in market prices for energy, even if loads themselves are treated as fixed.

Under these assumptions, and with the addition of one mathematical condition, the cost-minimizing/benefit maximizing plan yielded by a CEP will be supported by the prices of the energy and other commodities. That is, every investment will earn revenues from the energy and reliability services markets equal to or greater than its investment and operating costs, where prices are calculated by the shadow prices of the market clearing constraints for the various commodities in the market. Despite the high frequency of zero or negative prices, there will be enough price spikes and high enough compensation for ancillary services that the right amount of each generation type, as well as storage and demand-side investments, will be fully compensated. (As an example of a real market that is using spot markets as the primary revenue source for generators, ERCOT has an energy-only market, where instead of capacity payments there is a high energy price cap of $9000/MWh. Ancillary services are purchased based on an operating-reserve demand curve that results in very high prices when such reserves are scarce; because that market is co-optimized with energy, energy prices will also rise.)

Under the right conditions, the theoretical result that spot prices for energy and ancillary services can support generation investment under certain conditions holds even if transmission is lumpy [58]. Given a transmission plan, such revenues will guide investment decisions in the rest of the market, which will auto-expand over time.

The mathematical condition is, however, a stringent one: that the CEP be a convex optimization problem. This means that its objective (if maximized) is concave, and the feasible region is convex. This implies that, for instance, all operating and capital costs must be convex functions of the decision variables (i.e., no scale economies), and that decision variables are all continuous (i.e., no binary variables). However, power markets are full of nonconvexities. Unit commitment, for instance, involves discrete on/off and start-up variables, and results in well-recognized gaps between prices and costs that are made up with uplifts. Larger wind farms are cheaper per MW than smaller farms. Thermal power plants can be built only in certain sizes.

If the CEP disregards the nonconvexities, for instance, by omitting discrete start-up variables and assuming capacity can be added in continuous increments, then its prices will, in theory, fully compensate new entrants. As mentioned above, this directly follows from the theory of convex optimization. Whether market prices will support optimal investment depends on the market design and the practical impact of the nonconvexities. In particular, there are acknowledged shortcomings in many spot markets that could result in economically desirable investments being financially unprofitable. Examples of these shortcomings include price or offer caps, lack of effective scarcity pricing, out-of-market dispatch, and interval durations that suppress price volatility and thus undervalue flexible generation. In an effort to provide more efficient incentives for investment, additional market features have been implemented in several markets, such as installed capacity markets, flexible ramping product, and operating reserve demand curves.

Thus, the basic theory outlined by Caramanis and Schweppe [58], points the way that investments identified by CEP would, in theory, be provided by the market. Complemented by fully-functional financial markets, in which those who desire long-term contracts or other hedges against short-term risks can buy them, well-designed short-term markets for energy and ancillary services can provide most or all the revenues needed for optimal investments from CEP. However, real markets have limitations, manifested as market failures which render this supporting-price result less credible and cast doubt on whether spot markets are likely to be enough.

CEP-Facilitated Long-Term Auctions

An alternative to dealing with the revenue issues that arise in markets with high renewables that are being discussed in some policy circles [60] is to expand the role of CEP models from one of suggesting transmission and other investments. In this proposal, the CEP would run auctions in which transmission and alternative resources would compete against each other by submitting offers which, if cleared by the planning model, would be awarded long-term contracts based on the shadow prices for the constraints in the model. Both existing resources and possible new investments would compete. The goal is to overcome a major market failure: the lack of a robust market for long-term capacity commitments. Investors whose offers are accepted would receive certain financial guarantees in exchange for obligations to maintain the existing resources or build the new ones. Transmission proposals that are accepted would also receive guarantees.

There are many details that would need to be worked out in order to make this proposal viable, and these are being discussed extensively at the time of this writing. Some of these issues include the following:

- What would be the relationship of settlements in the CEP-administered long-term market and spot markets? For instance, might payments for installed capacity markets be determined in the CEP-administered market with only obligations to make offers in spot-markets, like today's capacity markets? Or might some financial or physical energy supply obligations or options be created and automatically associated with winning offers?
- What would be the role of imbalances and how would they be settled, both in short-term markets and longer-term investment obligations?
- How would obligations be enforced, since bankruptcy might be a tempting hedge for new projects?
- How would long-run policy, economic, and technology uncertainties be factored into the auction?
- Who would be responsible for revenue inadequacies for the auction that could result from, for instance, load growth that does not materialize, or up-front payments to resources that are not built?

A compromise between a full Integrated Resource Planning-style (IRP) auction facilitated by a CEP model is a restricted model that allows resources, potentially including storage and demand-side measures, to compete head-to-head with transmission to meet capacity needs. Such a model would specify a needed amount of installed capacity by subarea within a balancing authority or ISO, adjusted for its expected load-carrying capability, and would allow capacity from one area to meet the need of another area. The value of energy and ancillary services would not be considered.

If this idea sounds familiar, it is because it is the idea underlying the capacity market of PJM, which is called the Reliability Pricing Model (RPM) [61]. Capacity requirements are defined by area, and various types of resources, adjusted by their expected forced outage rate ("EFORd") can meet those needs, and transmission limits between regions constrain exchanges. Transmission reinforcements, demand response, new and existing generation, and storage can all participate in the RPM auction, with the prices set by the intersection of supply curves constructed by offers with an administrative demand curve in each region. The awards are for 1 year of capacity payments three years in the future. It is theoretically possible to define variants of the RPM model that could, for instance, be used to make awards for longer periods of time or with longer lead times.

The Implications of Market Failures for CEP

As mentioned, the use of CEP models by planners in an "anticipative/proactive" mode assumes that decisions not under the planner's control can be predicted. If it is assumed that the latter decisions are made in a perfectly competitive environment, then the planner can use a CEP formulated as a single optimization model with an objective of maximizing net benefits, and achieve the same results as would be seen in the market.

However, there are many "market failures" that mean that, at best, the perfect competition assumption is a useful approximation and, at worst, the assumption results in large differences between the results and what is seen in reality. Some failures can miscalculate the changes anticipated by proactive CEP models. Several of these are discussed below, as well as ways in which CEP models can be adapted to account for them. One general approach to adapting CEP models is to simulate how generation, storage, and demand respond in an imperfect market by adding constraints or modifying costs in order to capture these deviations from perfect competition.

Nonconvexities

CEP models can account for nonconvexities when optimizing asset additions by including appropriate nonlinear terms, discrete variables, or other representations of nonconvexities in the model's objective function and constraints. The main difficulty mentioned is that the prices represented by the dual variables to the energy and ancillary service constraints are no longer guaranteed to fully compensate new entrants. The new entrants suggested by the model may not be fully compensated, while other assets may be more profitable than observed in the model.

Another, more practical difficulty is that nonconvex models are harder to solve. Recent research on supporting prices in non-convex power markets (e.g., [62], among others), albeit in the context of short-term power market operations, could be extended to a multi-level expansion planning framework, where "up-lift" payments could be endogenously computed so as to consider the trade off between such a regulatory intervention to improve market efficiency. This clearly requires further research.

Financial market incompleteness

The lack of markets for long-term contracts comparable in duration to the life of assets is thought to discourage investment in long-lived, capital intensive supply. In general, market incompleteness means that there are some classes of financial instruments for which there exist willing buyers and sellers, but no such instruments or means of exchanging them exist. This incompleteness may arise because of large policy or other uncertainties that make risks difficult to assess.

Particular manifestations of incomplete markets for risk are that market parties who cannot hedge risks will behave in a risk averse way in choosing investments; that the degrees of risk aversion will differ among market parties; and that market parties will act on their different beliefs about the probabilities of future scenarios. In contrast, in ideal complete markets for risk, the trading of hedges will result in investment choices being made according to a consistent set of risk preferences and beliefs revealed by the market valuation of risk instruments. An obvious shortcoming of CEP models is that they often assume no future long-term risks —i.e., a single future scenario of prices, technology costs, and policies— or if multiple scenarios are considered in a stochastic planning model, expected net benefits according to a single set of probabilities are maximized. Thus, there is no risk aversion modeled. Furthermore, market parties are assumed to have the same long-time horizon for planning (e.g., 40 years) and the same low rate of return (e.g., 5%/yr), while in reality investors often require short-payback periods and demand higher rates of return for riskier investments.

When such models are used for policy prescriptions or for anticipative/proactive planning, there then arises the question: how distorted are the predicted generation and transmission additions relative to what would unfold in markets characterized by agents with diverse risk attitudes and beliefs about the future? There have been some theoretical analyses exploring this bias (e.g., [63]) and trying to assess how the results would differ. However, these models are far from being practical for planning.

Environmental externalities

Environmental externalities can be represented in a CEP by adding objectives such as minimization of health effects from traditional air pollutants, minimizing land devoted to new facilities, or minimizing greenhouse gas emissions. Then the CEP can be used in a multi-objective manner to generate portfolios of resources and transmission lines that represent a range of priorities among those objectives [64], [65]. For instance, all objectives except one could be constrained to a desired goal, and the remaining objective optimized, then permuting the goals results in a "Pareto set" of multiple portfolios, each of which has advantages relative to the others. Such tradeoffs can also be generated by solving a CEP with an objective defined as the weighted sum of the individual objectives, and then varying the weights. Determining appropriate weights is a feature that requires future work.

An assumption of this multi-objective process if used in an anticipative/proactive manner is that somehow the environmental objectives are translated into taxes, limits, or other policies that promote cost-efficient achievement of the goal. More generally, policy constraints as actually implemented by local, state and federal agencies can be included in a CEP, and the assumption of the solution is that the markets efficiently comply with those policies. As an example, renewable portfolio standards (RPS) or other technology requirements can be inserted as constraints on the market [66].

Imperfect coordination among subregions

Another important market failure arises from inefficient coordination among neighboring regions. Because cost-efficient trades in energy and ancillary services are not consummated between areas, incentives for investments may be distorted. In a CEP, such inefficiencies arising at seams can be simulated by the simple expedient of hurdle rates between adjacent regions. In some cases, hurdle rates arise directly from transmission access charges, and can be quantified. But other less visible barriers to trades mean that effective hurdle rates may be much higher, and also more difficult to quantify. A knotty conceptual problem is how to interpret asset additions that are justified in a CEP in part because they reduce such hurdle costs. Are these real cost savings that should be credited to those assets' economics? Do they constitute real societal benefits? How will they be viewed by regulators?

Pricing distortions

Other imperfections, especially market power or inefficient transmission tariffs, in theory require a more complicated modeling framework called *bi-level modeling* in order to do anticipative planning, as mentioned above. If the transmission planner is the "leader" and all resources and demand are "followers", then the transmission model anticipates the solution from the inefficient energy market. For example, the first-order optimization conditions from the latter could be embedded as constraints in the former [67], [68], [69]. These conditions in general involve highly nonlinear, nonconvex equations.

It is therefore unsurprising that bilevel CEP models are computationally impractical for use in planning today because of the lack of efficient solvers for large-scale bilevel problems. Furthermore, bilevel problems in which the energy market involves market power require additional assumptions about how that market power is exercised. For instance, are the market parties playing quantity (output) strategies, bidding strategies, or are they implicitly or explicitly colluding? Such assumptions are difficult to validate, and planners and regulators are understandably reluctant to base investment decisions upon them.

The case of inefficient transmission tariffs is similarly problematic. For instance, energy prices may be set on a zonal basis, disregarding within-zone congestion. Transmission costs may be recovered based on annual interconnection charges that are differentiated based on MW-mile or similar calculations. This then poses a difficulty for an anticipative planner, since use of a single net-benefit-maximizing CEP would assume competitive markets that are responding to efficient transmission prices (i.e., LMPs). If transmission prices diverge strongly from LMPs, then the incentives for siting and even the mix of generation types may be distorted. Like the market power case, a theoretical solution is a bilevel model in which network charges are set by regulatory formula in the lower level (market) model, but this is only a gleam in the research community's eye at the moment.

R&D Issues on Market Modeling

In Section 2, we have mentioned the importance of understanding the incentives and strategies of various market participants, and the need for research on distributed energy decision making. Another desirable area of research is on the interaction of transmission assets and pricing with incentives for the location, mix, and timing of bulk supply investments.

U.S. wholesale electricity markets take a variety of approaches to address resource adequacy problems. Some rely primarily or entirely on incentives provided by spot energy and ancillary service markets, while others have implemented explicit requirements and incentives for generation capacity. The differences in designs imply different revenue streams for generators, and possibly very different incentives for where, when, and what type to build. The proactive planning philosophy of CEP modeling means that it is important to understand how these incentives interact with transmission availability and pricing to affect the efficiency of supply investment. There are several related topics that should be investigated.

1. Can differences in nature and timing of investment be explained in terms of the differences in wholesale market design? What are the impacts of short-run operating markets and financial transmission rights systems on long-term expansion incentives? What is the effect of capacity market designs on investment, and how can they be accounted for in proactive (CEP) planning?
2. What market designs incentivize better regional coordination across control areas, which should lead to (i) more effective integration of new renewables, (ii) lower operational costs, and (iii) more efficient investment?
3. Transmission costs are recovered through a combination of mechanisms, including congestion revenues, interconnection charges, and per MWh transmission access charges. How do the differences in mechanisms for allocating transmission charges impact supply investment?
4. How does risk aversion on the part of owners of transmission and resources?

Section 8: Uncertainty Models for Expansion Planning

Types of Uncertainty

Because the future is always uncertain, addressing uncertainty must be a part of any expansion planning process. In this section, we focus on global uncertainties, in contrast to local uncertainties, where the two terms are distinguished below.

- *Global uncertainties:* are uncertainties for which different values within the range of likely values produce significantly different results; examples include emissions policies, large demand shifts, DER penetrations, coal or nuclear retirements, extremes in fuel prices, precipitation changes (e.g., extended drought), and dramatic change in technology investment costs.
- *Local uncertainties:* are uncertainties characterized by a range of values a parameter may take under a global realization; for example, under a "low" load growth or fuel price scenario, the annual load growth may vary ±0.5 % and the annual fuel price change may vary ±1%. Similarly, wind or solar capacity factor may vary from year to year. Local uncertainties are also referred to as *parametric uncertainties*.

Figure 8-1 illustrates the relation between the two types of uncertainties, using demand growth as an exemplar.

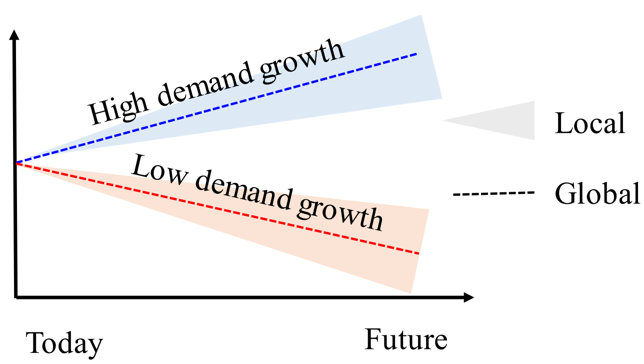


Figure 8-1
Global and local uncertainties

Perhaps the simplest approach to address global uncertainty is to assume a single set of values for all uncertain parameters, identify the deterministic expansion planning result, and then perform sensitivity studies to identify variations in those uncertain parameters. Another approach that has gained some interest among the regional transmission organizations is the so-called "least regrets" approach, which, as expressed in a recent California ISO (CAISO) planning document [70], evaluates "a range of plausible scenarios made up of different generation portfolios, and identifies the transmission reinforcements found to be necessary in a reasonable number of those scenarios." The Mid-Continent ISO has employed a similar procedure in developing its multi-value projects (MVPs) [71].

Although these approaches are useful for gaining insight, they generally depend on heuristics and subjective judgment. Of most importance, alternatives identified in these ways can differ significantly from alternatives identified based on optimization under uncertainty. Thus, it is highly beneficial to develop expansion applications that systematically account for global uncertainties.

Over the past few years, two approaches to performing expansion planning under uncertainty have emerged. We refer to the first approach as stochastic programming (SP) and the second approach as adaptive expansion planning (AEP). Although the two approaches are different in substantive ways, they also share similarities. We provide a high-level view of the two approaches in the next two subsections.

Stochastic Expansion Planning

Traditional deterministic or scenario-based transmission planning methods identify reinforcements that are beneficial under one set of assumptions, and then consider whether those recommendations would be altered if the assumptions are changed. For instance, if load growth accelerates, investment plan A may be the best, but if load growth remains low, then plan B might instead be preferred. Some more sophisticated versions of scenario-based planning might attempt to identify transmission investments that are recommended in most deterministic model solutions that result from solving one model for each scenario. However, a plan developed in this heuristic manner may have much higher costs than a plan that is developed considering all scenarios - and their relative likelihoods - at once, and recognizing the flexibility that a plan has to be adapted to surprises and changing circumstances.

Stochastic programming is an optimization-based approach that allows a planner to ask: what network reinforcements should be made now despite the uncertainties, and what investments should be deferred and possibly made later, considering multiple possibilities of what might happen and how the immediate decisions allow for a system to adapt to later changes? This decision structure is shown in Figure 8-2 as a decision tree, in which time proceeds from left to right. Three steps of the decision process are shown, consisting of two decision stages separated by uncertain scenarios. (In general, stochastic programming models can include more than three such steps.) The steps shown in the tree are as follows:

1. "Here and now" decisions, shown as the first square node on the left. These are made before it is known how longer-run uncertainties will be resolved. A choice (one set of transmission investments, for instance) is represented as one of the arcs leaving that node to the right. In the stochastic program, these possible decisions are represented by a set of first-stage decision variables.
2. Uncertain events, shown as round (or "chance") nodes. After the "here-and-now" decisions are made, the planner will next learn what scenario will occur. The arcs leaving the chance node to the right represent the range of possible scenarios (one per arc) of what could happen to long-run environmental policies, load growth, fuel prices, etc. Each of the scenarios has a probability.
3. "Wait-and-see" (or "recourse") decisions then follow. For each scenario, there is a decision node (square node) representing a set of scenario-specific second-stage decision variables that are decided after it is known which scenario has occurred. What choice is made in this second stage is conditioned on the scenario, which is mathematically implemented by defining separate decision variables for each scenario. As a result, the decisions made if, say, solar development costs fall dramatically can differ if instead a scenario occurs in which solar costs are unchanged as time progresses. Thus, recourse decisions allow the system to adapt to technology, economic, and policy changes embodied in the scenarios.

For simplicity, in Figure 8-2, only two alternative decisions are shown per decision node, and only two scenarios per chance node; actually, there may be a large number of decision alternatives and scenarios, respectively.

An optimal solution, or "decision strategy," for this problem is a single set of choices in the first decision stage (shown in Figure 8-3 as a red line from the first decision node) plus a set of choices for each of the scenarios that are considered in the second decision stage (shown as the red lines from the second set of decision nodes that are reached, given the first stage's decisions).

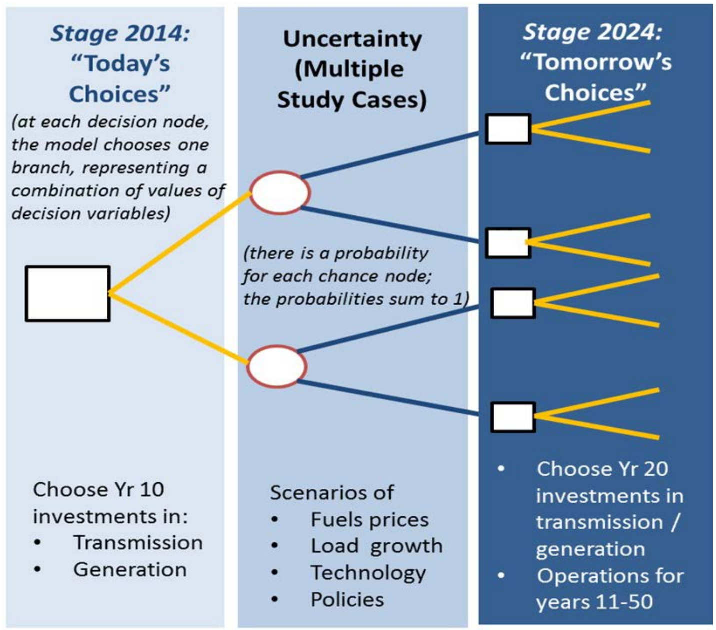


Figure 8-2
Decision tree schematic of the two-stage transmission-generation optimization

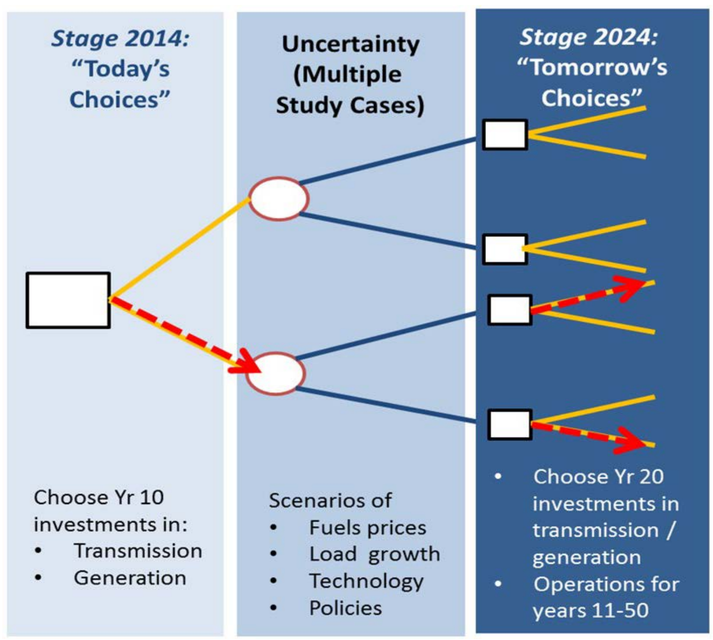
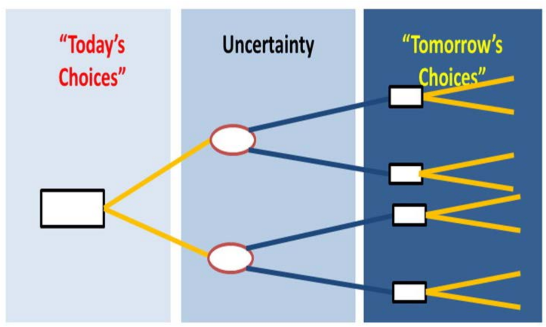


Figure 8-3
A solved decision tree, indicating which decisions are made in the first stage and, for each scenario, in the second stage

Mathematically, a stochastic planning method like the Johns Hopkins Stochastic Multi-stage Integrated Network Expansion model (JHSMINE) defines a single set of "decision variables" for near-term alternatives (such as WECC year-10 line alternatives, or possible generation capacity additions by type and location). In addition, multiple sets of variables are created for longer-term investments (such as year-10 candidate lines), one set for each scenario, representing how the system adapts to future conditions. Variables are also defined for resource operations and line flows for each of a number of representative load, wind, solar, and hydro conditions in each scenario starting at the time that first-stage additions come on line (e.g., years 11-20), as well as for the years after completion of second stage lines (e.g., years 21-50). The model then determines the combination of values that minimize probability-weighted cost across all the scenarios at once, accounting for how near-term additions affect system costs and benefits of later additions under each scenario.

Figure 8-4 shows how these variables relate to the decision trees of Figure 8-2 and Figure 8-3. The first set of variables (which we show as a vector X_1) are chosen in the first stage's decision node, while there is a separate set of second-stage variables (which we show as a vector $X_{2,s}$) for each of the scenarios S in the second stage. The second-stage variables include both the recourse decisions and all operations after the first stage's investments come on line. The mathematical statement is a standard "two stage" linear stochastic optimization model with a linear objective function ("Minimize the present worth of probability-weighted costs") that is to be optimized. Here, Figure 8-4 shows the model's objective function as a linear function, but nonlinear objectives are also possible. The input data (such as fuel and capital costs) are captured as function parameters C (vectors representing costs associated with the decisions X). Costs incurred in the second stage under a given scenario S are weighted by the assumed probability of that scenario p_s. Any stochastic model also includes constraints that limit the feasible values of the variables. There are two general types of constraints: one set limits the possible values of first-stage decisions, while the second set represents the relationships between first- and second-stage decisions. For instance, if a transmission line is built in a particular corridor in stage 1, a constraint might state that the line cannot also be built again in stage 2. Figure 8-4 shows these constraints as linear inequalities, but nonlinear and equality constraints can also be included. The constraints' input data is represented here by the matrices A and vectors B, which define the constraints.



$$\min\left\{\mathbf{C}_1\,\mathbf{X}_1+\sum_{s\in S}p_s\,\mathbf{C}_2\,\mathbf{X}_{2,s}\right\}$$

$$\begin{bmatrix}\mathbf{A}_{1,1} & \mathbf{0}\\ \mathbf{A}_{2,1,s} & \mathbf{A}_{2,2,s}\end{bmatrix}\begin{bmatrix}\mathbf{X}_1\\ \mathbf{X}_{2,s}\end{bmatrix}\le\begin{bmatrix}\mathbf{B}_1\\ \mathbf{B}_{2,s}\end{bmatrix}\quad\forall s$$

Figure 8-4
A two-stage stochastic program written in abstract mathematical form, showing the relationship of the first and second stage decision variables to the decision nodes of the decision tree

Adaptive Expansion Planning

The objective in adaptive expansion planning (AEP) is to identify a core set of expansion alternatives through the entire decision horizon that are beneficial relative to the entire set of specific future scenarios considered. There is, of course, a cost to making the core set of investments. The measure of how beneficial the core is relative to a single scenario is quantified by the cost of adapting the core to the conditions of that scenario via a set of adaptation decisions. Thus, the objective in AEP is to minimize the cost of the core expansions plus the cost of the adaptations, including operating costs.

We associate to the previous description some simple analytics, and some illustrations. Consider Figure 8-5, where x is a chosen plan in "investment space." That is, x is a vector where each element of the vector consists of a capacity addition in the generation resource or transmission circuit corresponding to that element. Assume that we identify the plan x deterministically, under a single scenario (i.e., a single specification on how we think the future will unfold in terms of all parameters that influence the decision-making associated with developing the plan). The cost of these core investments is CC(x). Then we execute the plan (i.e., we build the plant and incur the cost), following which we discover that our assumptions regarding the future were wrong, i.e., a scenario actually happens that differs from the scenario we used to design and build our plan. Thus, we need to change our plan, i.e., we need to adapt it. If we refer to the scenario that actually occurs as scenario k, then the change that we need to make in our plan, in order to make it feasible under scenario k, is designated Δx_k. Then the "point" in the feasible region of the "solution space" is designated x + Δx_k, as illustrated in Figure 8-5.

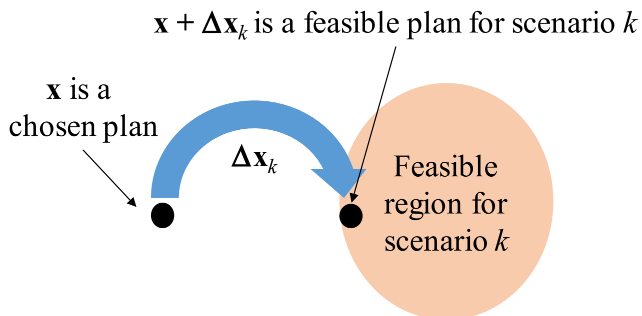


Figure 8-5
Conceptual basis for AEP

We now consider that the future is uncertain, and we believe any one of several scenarios can happen: k=1, k=2, ..., or $k=K$. Assuming we can obtain (or assign) probabilities to each scenario, p_k, then we desire to identify a core plan that minimizes the core costs plus the expected value of the adaptation costs. The formulation for this problem is:

$$\min\left\{NPV\begin{bmatrix}\mathrm{CC}(\mathbf{x})+\beta\sum_k \mathrm{AC}(\Delta\mathbf{x}_k)+\\ \sum_k p_k\ \mathrm{OC}(\mathbf{x}+\Delta\mathbf{x}_k)\end{bmatrix}\right\}$$

subject to:

Operational constraints
Reliability constraints
Environmental constraints *Eq. 8-1*

where:

- CC(x) is the cost of the core expansions x.
- AC(Δx_k) is the cost of adapting a plan x to a scenario k; i.e., it is the minimum cost to move x to a feasible design in scenario k.
- β is a multiplier on the adaptation cost that enables the analyst to control the relationship between robustness and core costs.
- OC(x+Δx_k) is the operational cost of operating the power system under scenario k. Operational cost is not a function of x because the core is not a scenario in itself.

The above problem formulation identifies a core expansion plan x that is "positioned" in solution space to minimize the cost of the core plus the expectation of the cost of adapting the core to all of the scenarios. In a sense, the identified core investment is centroidal to the deterministic investment for each scenario. Figure 8-7 illustrates three "investment trajectories," one corresponding to a scenario 1, another for a scenario 2, and a third, in blue, for the core. The yellow cylinders at each time t = 1, 2, and 3 of the decision horizon represent the adaptation necessary at those times to make the core feasible under each respective scenario.

Figure 8-7 illustrates the solution to the AEP problem for a value of β=1. In Figure 8-6, this solution is contrasted to another solution for a value of β=4. The effect of the larger value of β is to make the adaptations appear more expensive so that the solution chooses a larger core (the blue region), increasing robustness at a higher core cost.

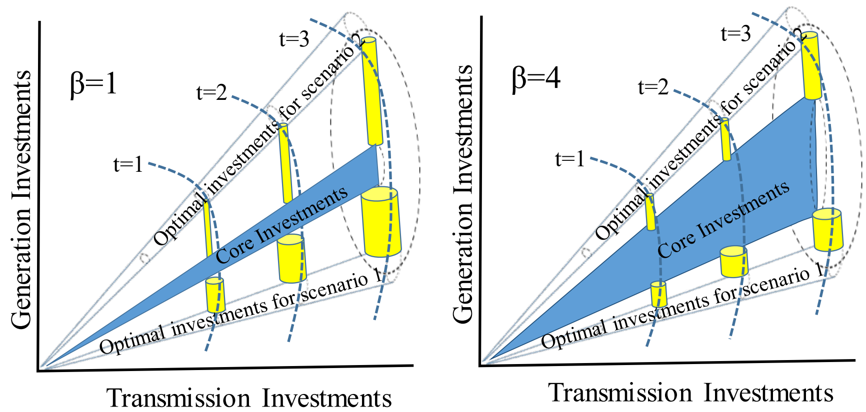


Figure 8-6
Compassion of AEP solutions for β = 1 (left) and β = 4 (right)

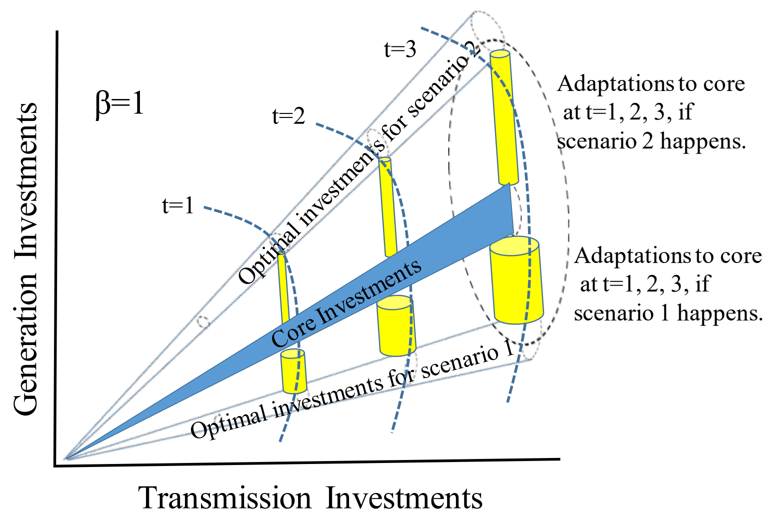


Figure 8-7
Conceptual illustration of AEP

Scenario Selection for CEP

It has long been recognized that the presence of large uncertainties in future economic, technologic, policy, and climatic conditions can make a large difference in optimal resource and transmission plans. In general, planning for an infrastructure that is large in scale, costly, and long-lasting requires careful consideration of the various uncertain conditions that may arise in the future. For instance, for transmission planning, this includes multi-decadal uncertainties in, e.g., load growth, advances in distributed generation and FACTS technologies, fuel costs, environmental rules, and renewable mandates. Ignoring these uncertainties can result in underutilized investments or missed opportunities [72], [73], [63]. A popular way to deal with such uncertainties is to consider multiple possible realizations of these variables, or "scenarios", as well as decisions that can be made later to modify the system in response to learning and changing conditions.

However, considering multiple scenarios vastly increases the number of variables and parameters considered, making stochastic programs hard to solve. As a result, many simplifications need to be made concerning network flows or operations. Thus, future models that aim to model more realistic conditions (e.g., AC power flow, unit commitment) will be even more computationally intensive. So there is a need to consider ways to keep the number of scenarios reasonable in order to achieve practical solution times, while still allowing the CEP model to consider a full range of long-run uncertainties as well as short-run operating conditions.

Scenario reduction methods have been widely studied in the field of optimization. Dupačová et al. [74] originally laid out the basis for a scenario reduction method based on probabilistic distances between scenarios. Heitsch and Römisch [75], [76] improved that work by proposing more effective forward-selection and backward-reduction algorithms. Hoyland et al. [77] suggested a different scenario reduction method that aims to match certain statistical properties of the original scenario set and the reduced scenario set.

Power systems has been a rich source of problems for stochastic optimization, so researchers in the field have had a keen interest in scenario reduction methods. The distance-based method has been popular. Gröwe-Kuska et al. [78] were the first to implement that method in a portfolio management problem for a hydro-thermal power system, while Morales et al. [79] proposed a variant that works better for electricity market problems. Carrión et al. [80], [81] applied the Kantorovich distance for a consumer's electricity procurement problem. Other methods such as clustering and importance sampling have also been used. Feng and Ryan [82] proposed to cluster the original scenarios in a generation planning model before performing the forward-selection algorithm in [75], [76]. Papavasiliou et al. applied their importance-sampling inspired method to multi-area stochastic unit commitment [83].

But despite the wide-ranging research on scenario reduction in the context of power systems, there has been little application to transmission expansion planning and CEP. In one exception, Yu et al. [84] propose a robust transmission expansion planning method with Taguchi's orthogonal array testing, but they consider only a narrow set of uncertainties, and not the full set of economic, technology, and policy risks typically of concern to planners. Also, there has been a lack of research that compares the performance of different scenario reduction techniques for a single power systems problem. A significant comparison work in power was done by Dvorkin et al. [85], who compare multiple scenario reduction techniques in the context of unit commitment. Sun et al. [86] present an objective-based scenario selection framework for transmission planning that can potentially be widely used for future research.

In the remainder of this section, a summary is presented of a comparison of the performance of four promising scenario reduction methods in the context of a CEP model for the Western Electricity Coordinating Council (WECC) region [87]. The four scenario reduction methods are compared within the framework of stochastic CEP. The methods analyzed include three existing methods: random sampling (Rand), importance sampling (IS), distance-based method (DB), and an additional method proposed in [87] called Stratified Scenario Sampling (SSS). The CEP model is an anticipative/proactive transmission planning model that considers new backbone lines and renewable interconnectors on a 328-bus reduced network. The transmission planner is assumed to correctly anticipate the reactions of generation investment and operations in a competitive market. The model is solved as a single large cost-minimizing mixed integer linear program, under the assumption that the generation market is competitive, and the transmission planner wishes to maximize net economic benefits. Each of the four scenario reduction methods is used to reduce a set of 20 scenarios. The basis for this comparison is the expected cost (present worth over 30 years) of the resulting CEP solutions quantified using the full set of 20 scenarios relative to the optimum based on a model with the full set. In particular, the first-stage (near-term) transmission investments from a CEP solution for a set of scenarios are imposed on the full stochastic CEP, which is then solved, allowing all generation investments as well as second-stage transmission investments to be optimized. This quantifies the increase in cost resulting from implementing the first-stage transmission decisions from a naïve model rather than the unconstrained optimum from the full 20-scenario model. This results in an index called ECNS (expected cost of the naïve solution) for each scenario reduction method.

The case study shows that by clever selection of scenarios, model size can be drastically reduced while preserving the benefits of stochastic programming, allowing the user to either add other features to the model or execute more runs more quickly. The performance of these methods was measured by comparing values of ECNS, first-stage transmission investment decisions, first-stage generation investment decisions, and reductions in solution time. The following are the conclusions of the comparisons:

- For scenario reduction, an intelligent reduction of the scenario set can be much more beneficial than simply adding a lot more scenarios. For example, random sampling of 14 scenarios from the original

20 performs worse on average than a DB scenario reduction method that reduces the original scenario set to just 3 scenarios.

- The DB method and the SSS-MM method both provide solutions with relatively little loss of cost-efficiency when compared to the full 20-scenario model solution. Furthermore, both methods greatly reduce solution times.
- The overall investment decisions obtained from using the DB method better match the optimum from the most complex model that utilizes the full 20 scenarios.

These conclusions do not necessarily generalize to other planning settings. Nevertheless, users of stochastic CEP are well advised to choose scenarios carefully, which will result in better near-term investment recommendations and faster models.

CEP Model Tuning: Which Model Enhancements Are Most Worth Making? (A case study)

CEP model users need models to execute within a reasonable amount of time while capturing system features that will make a difference in expansion decisions, especially near-term commitments. Not all desirable enhancements can be included, because the simultaneous consideration of multi-decadal time horizons, many load slices within the year, multiple long-run scenarios, and large interconnected regions means that, as noted earlier in this report, it is impossible to simultaneously consider 8760 hours per year, the full regional network, dozens of scenarios, and detailed unit commitment constraints. A CEP user needs to consider which system features should be modeled in more detail, and which can be safely neglected.

There is no standard advice that can be given, as the most critical features will depend on the system. However, there is a conceptual framework that can be used to consider the question. First, would a candidate enhancement likely change near-term investments in transmission or resources significantly? If not, then the enhancement is not important. Second, if near-term decisions would change, do those changes have significant impacts on net economic benefits or other objectives? If two model versions gave distinct solutions, but both solutions perform equally well, the enhancement has no economic (or other) impact.

In this subsection, a study applying the above framework to a CEP problem for the WECC region is summarized [88]. In order to illustrate how the economic value of enhancements can be quantified, that study compares three possible model enhancements:

1. Inclusion of five future scenarios (versus a deterministic/single scenario problem). The scenarios are five scenarios defined as part of the 2013 WECC Transmission Expansion Planning Policy Committee process [89], [90].
2. Inclusion of a linearized DC load flow model or hybrid model (versus a pipes-and-bubbles transmission model). The hybrid model is a new approach that retains a linearized DC load flow representation of existing circuits, which includes Kirchhoff's voltage law, but treats new lines as DC lines with controllable flow, which has significant computational advantages relative to the full DC load flow model.
3. Inclusion of 48 load slices per year to represent load and renewable variability (vs. 24 slices).

There are many other possible enhancements that could be considered, such as detailed storage modeling, unit commitment constraints, improved network reductions or larger networks, and the impact of N-1 contingency constraints or other reliability constraints. However, the comparison presented here suffices to illustrate how different enhancements can affect solution performance, and the framework for valuing the enhancements.

An economic metric called the *value of model enhancements* (VOME) can be quantified by comparing two solutions at a time, as in the WECC case study presented at the beginning of this section, a two-stage CEP problem that addresses transmission planning over 30 years subject to anticipating the reactions of competitive generation investment and operations. The first solution is the first-stage transmission recommendations from the simpler model. The second solution is the recommendations from the more complex model. Both solutions are tested using a model with all enhancements, allowing generator investments in each stage as well as second-stage transmission investments to be optimized subject to the fixed first-stage transmission investments. Generally, but not necessarily, the model with the enhancement will provide a better performing first-stage solution. For each enhancement, the improvement in performance (VOME) is quantified several times, making different assumptions concerning the presence or absence of the other enhancements in each case. Those improvements are then averaged, resulting in the VOMEs reported below in Table 8-1.

What the results of the table reveal is that the inclusion of uncertainty via multiple scenarios results in an order of magnitude greater improvement in the CEP model solution performance than adding an additional 24 hours or improving the network model

Table 8-1
VOME for Three Enhancements (Stochasticity, Hours, Network) and Associated Ranges (Billion 2014 U.S.$, present worth) for the WECC region

Enhancement:	Deterministic to 5 scenario stochastic	24 to 48 load slices per year	Pipes & bubbles to Hybrid network	Hybrid Network to DC-load flow
VOME ($B)	5.59	0.50	0.049	0.080
Fraction of total benefit	13.8%	1.24%	0.121%	0.198%

R&D Issues on Modeling Uncertainties

Uncertainties in expansion planning problems have traditionally been dealt with by sensitivity and scenario analyses, while researchers have proposed more systematic approaches based on stochastic programming, adaptive expansion planning, and robust optimization. In stochastic optimization, uncertain parameters are usually characterized by a limited number of realizations that are embodied in scenarios (as discussed in the example in the previous section), with assumed probabilities. Adaptive Expansion Planning also considers a set of scenarios.

On the other hand, because planners may prefer to avoid specifying probabilities, researchers have proposed using robust optimization [91], [92], [93], which does not assign probability distributions to uncertain parameters or require consideration of a few discrete scenarios. These methods instead use "uncertainty sets" (formed by ranges on uncertain parameters) and seeks to find the "min-max" solution. This is defined as the solution that performs the best (e.g., minimum cost), if the worst combination of uncertain variables occurs (e.g., maximum uncertainty). However, this high degree of risk aversion means that robust optimization can lead to solutions that are too conservative, resulting in larger system costs than other alternatives that consider the likelihood of materialization of the uncertainty.

Research on the following topics would result in methods that better combine the strengths of stochastic optimization while incorporating broader notions of robustness, and more fully reflect the profound uncertainties that face planners:

1. Most models are from the perspective of a single decision maker with a single view of uncertainty in the various parameters. But CEP under deep uncertainty needs to account for views of diverse stakeholders. While policy makers might worry about, for instance, energy security and climate risks, regulators and investors could be more concerned about technological change, tariff movements, and competitive pressures to varying extents. There can be disagreements on the amount of uncertainty, and especially the credibility and likelihood of extreme cases (see the discussion of resilience, in Section 11). Research on methods to consider varying viewpoints when defining probabilities and uncertainty sets, and demonstrations in realistic settings of whether and how such approaches can make plans more robust to disagreements would be valuable. A neglected type of

uncertainty whose implications have not been explored involves actions that might take place within subregions with the intent of obviating the need for transmission reinforcements; these actions might be driven by market fundamentals (in which case a well-formulated CEP should anticipate them) or might be based on vaguely defined considerations of "energy security" or "energy independence."

2. It is easy to define many economic, environmental, technologic, and social variables that are uncertain. In addition to disagreements that might arise concerning the degree of uncertainty in each, the extent to which different uncertain variables may be correlated or otherwise associated with each other may be speculative. Methods for defining several trajectories of several variables over the multi-decadal planning time frame that represent plausible but distinctly different outcomes are needed. The set of trajectories needs to span the range of outcomes that might be reasonably expected, and capture correlations of variables in a way that is consistent with theory, past observations, and/or expert judgment. On the other hand, the number of scenarios cannot be too large because of CEP model computational limitations.

3. We have presented two approaches in this section for performing co-optimized expansion planning under uncertainty. Whereas the SP approach is most effective for making the t=0 decision of what infrastructure to develop now, the AEP approach is most effective for laying out a long-term sequential plan of what to build. These approaches may well be complementary, but how to use them together within an electric systems planning arena needs illumination. Although there have been some efforts to this end [94], there is a need to embed these tools into industry practices in order to further this understanding. Research could also consider combining stochastic CEP and robust decision making (RDM) [95], which is distinct from robust optimization. Such a method might use CEP to efficiently define some potentially attractive near-term investments together with possible adaptations, and then apply ideas from RDM to thoroughly evaluate those strategies under many scenarios, and to identify ways to improve the robustness of those strategies.

4. Another possible direction is distributionally robust stochastic optimization (DRO) [96], also known as *data-driven optimization approach*. DRO does not assume full knowledge of probabilities of uncertain variables, but can take advantage of available information, such as means, ranges, or standard deviations, that might be available from historical data or expert judgment. Then one chooses a set of probability distributions, each of which is consistent with that information, and then finds a transmission plan that provides the best hedge against the selected set of distributions. The objective of the model is to minimize the worst-case cost associated with the worst-case distribution in this set. Like robust optimization, DRO is still a risk-averse approach, although it is likely to yield less conservative solutions [97]. There have been recent instances of its application in transmission expansion planning [98].

5. Computational tractability: Many of the approaches mentioned in Section 4 will facilitate the tractability of large-scale expansion planning models under uncertainty. In particular, mathematical decomposition methods could allow consideration of a larger number of long-run scenarios simultaneously with more rigorous technical detail in short-run operations problems, and therefore increase the accuracy of CEP optimization models.

Section 9: Weather Impacts

Electric power systems are changing at a rapid rate, and one of the fastest changing areas is the integration of renewable energy sources into the generation mix [99]; in particular, wind, solar, and hydroelectricity. These technologies comprise most of the existing and likely future renewables portfolio [100]. With the integration of these resources comes new benefits and challenges, which are directly linked to their primary energy carrier: weather. Therefore, weather variables need to be explicitly included in CEP models as accurately as possible to enable understanding of events that are important for system reliability as well as energy management for different technologies [101].

The impacts of weather affect different parts of the electricity system including: i) the supply side—the efficiency of the thermal power plants, both through air temperature and the withdrawal water temperature [102]; ii) demand side—the weather is a main driver of load [103]; iii) transmission and deliverability, for example, temperature and wind speed [104]. Additionally, extreme events also play a substantial role in expansion planning because the severity and duration of the events (locally) have significant technical and economic impacts [104].

The impact of climate change is superimposed to the weather phenomena that interact directly with the electricity system. The climate portion of the weather is difficult to decouple, but efforts are made to model its impact into CEPs in order to estimate more accurately the true cost of different scenarios and sensitivities [105].

This section discusses the ways in which weather data are used in CEP models and how efforts can be made to improve them. Further, the section discusses methods to include climate change into CEP models for either sensitivity analysis or pathway selection.

Resolution of Weather Data

Ideally, the weather data that is included in CEP models should be as granular as possible. However, as noted in previous sections, the granularity at which parameters in CEPs can be included is dependent on tradeoffs. That is, the higher granularity on one domain, the lower one should expect in another [106]. If the CEP is to investigate high penetration levels of renewables, then the tradeoff should be in areas that are not weather related, since these would diminish in importance over longer horizons. For example, modeling unit commitment (UC) with perfect accuracy is less important in a system with 90% renewables because there are fewer large-scale slow-starting power plants whose minimum operation requires stricter scheduling. This does not state that UC should not be included, but it is an area where complexity could be reduced in exchange for better granularity of weather parameters. Caution is advised since some parameters are, in fact, more important with deep penetrations of renewables, such as transmission topography, power flow, and storage modeling.

The best model would have high temporal resolution for the weather data (hourly or even 5-minutely) accompanying the appropriately matched geographic granularity (1-km, 3-km, 5-km, for example). This is because the "dispatch" of renewables is not a free variable; thus the modeling needs to constrain itself with the potential supply to be able to determine the system requirements to balance out those (weather-driven) fluctuations. It is important to keep the resolution of time and space consistent with the physical scales of the underlying weather model. It should always be remembered that from a weather perspective the data for a grid cell are an average over the temporal and spatial granularity.

For illustration, a 200-km spatial resolution and a 1-minute temporal resolution produces outputs for weather variables that are inconsistent. For the weather data to be consistent, information must be able to flow between weather model grid cells. Imagine the two corners of the 200-km grid cell: at a 1-minute resolution all points within that grid cell are assumed to be acting the same. In the next time step (1 minute later) the whole 40,000 km2 changes. This would be faster than any atmospheric wave can travel [107], and thus, is inconsistent. Users of CEP models should be skeptical of the weather data and understand the limitations and assumptions. We are focusing on numerical weather prediction (NWP) models for weather data because they are the main source of input parameters that can cover (without data gaps) whole electricity grid footprints. Theoretically, one could use actual power data, but they can be very sparse so they would need to be extensively extrapolated, and they are typically assimilated into NWP models [108].

Data Granularity and Temporal Extent

While the granularity is important when capturing weather in CEP models, the extent of the data is equally important. High granularity (e.g., 5-minute, 3-km) is not useful if it only covers a single day. Typically, the extent is chosen to be a calendar year. To incorporate more years and to smooth out extreme years, a "typical meteorological year" (TMY) is constructed [109], which includes the average of numerous years and can provide statistics on the variables. The main limitation of a TMY construct is that weather is not random; it is chaotic, which means that there is a deterministic process underlying the behavior and patterns. In general, the TMY loses the ability to recognize extreme events and/or multiple chain events. Further, when a TMY is used the correlations between variables are diluted based on the averaging of multiple data points. It is always the case that information is lost when averaging takes place.

Another method would be to use multiple, parallel, chronological weather years based on historical data. This, however, increases the computational burden, but facilitates the CEPs to recognize time-, space- correlated atmospheric phenomena. In effect, it is giving the CEP multiple (possibly equally likely) future weather years to solve. It is different from stochastic approaches, which could lose the important correlation effects, since weather is not random, and the chronological order of the events is based on a deterministic process. The advantage of the approach is that the user can select the number of years to solve for and weight them based on their regional climate. For example, if a grid is more susceptible to polar vortex constraints, the weighting for historical years with those events should potentially be higher, while systems that are constrained by summer cooling demand should weight years with hotter summers. It is important to keep several other years in the solve, because it communicates to the CEP that other time periods must be met economically as well. The weightings should be derived dependent on the local system. For large-scale CEP models that cover the U.S., the weighting should be unity because the system should operate under all conditions equally efficiently.

In the above discussions, it has been assumed that the weather data are chronological and includes all time-steps. This is not always the case in CEP models [110]. Furthermore, some CEP models use time slices. These reduce the CEP scheduling and dispatch portion of the model to only cover a subset of all the, e.g., hours of a year, as discussed in previous sections. This method can become inaccurate when considering high-resolution weather data because important events can be completely missed, or the time-slices could over-emphasize lower probability events. The description of when time-slices are important depends on the system, but it changes as the penetration of renewables increases. This is also true for electrification interdependencies discussed in Section 10. The process of time-slicing also removes sequential events that are evident in weather systems [111].

As pointed to earlier, there are always tradeoffs for model development, but best practice would be to incorporate as many time-steps and calendar years at the highest granularity of weather data into the CEP model as possible, considering the added computation burden this creates.

Wind-Specific Weather Data

Incorporating weather data is an important topic for CEP modeling (increasingly so). In this subsection we focus on what variables, and why, should be included to improve description of wind turbines.

The wind-speed-to-power relationship is given as [112], [113]:

$$P = \frac{1}{2} C_p(u,\rho)\ \rho\ A\ w^3 \qquad \textit{Eq. 9-1}$$

Where $C_p(u,\rho)$ is the coefficient of power (empirically derived), ρ is the air density, A is the rotor swept area, and w is the wind speed. It is therefore critical that density and wind speed are incorporated in the weather data to describe the wind power potential. The coefficient of power also should include data about weather conditions, but typically these are not included in CEP models and the impact is likely to be small on the scales of most CEP models.

Even though wind is included in most CEP model descriptions of wind energy, the density term is almost always assumed to be 1.225 kg/m3 (the value at mean sea level). This is because it is assumed to make little difference; however, this assumption does not hold for all cases. This is particularly true for the U.S. The density of the atmosphere across the U.S. ranges in average density (over a year) from 0.778 to 1.296 kg/m3. In other words, due to Eq. 9-1 an average power change of -37% to +6%. These values are averages, and can be much more (and less) throughout the year [114], [115], [116].

The wind speed that is usually incorporated in CEP models is at the hub height (the center of the nacelle). It is typically described in absolute values (i.e., direction is not a factor). It is a better approach to include the Rotor Equivalent Wind Speed (REWS) that can consider changes in direction of wind across the increasingly large rotor area. Research shows that this can alter the temporal behavior of the wind power as well as the amount of power available [114]. It is possible to go even further with sophisticated NWP data and include the tendencies of wind and density fluctuations, since the values for all these data are average. Including the tendencies can be impactful for ramp metrics and extreme events, but has much smaller impact over typical operating ranges than including REWS and density [115].

For wind energy, there are more variables that should be included to improve the representation of wind turbines for CEP models that are dependent on weather data. The most important of these are temperature and precipitation. The wind turbines have design parameters (as with any technology) and it is deemed unsafe to operate them when it is too cold or hot. Therefore, CEP models should include temperature, at hub height, to signal shut-offs. This can be incorporated directly into the algorithms to produce the wind energy potential or a parameter within the CEP to shut off, allowing CEP users to alter the temperatures at which shut-offs take place. Precipitation should be combined with temperature to provide the CEP with data about icing events and how to shut down for dangerous conditions. Most CEP models ignore these two variables (temperature shut off and icing shut-offs), but with an electricity grid with increasing reliance on these technologies, it is important to describe the timing and impact of wind turbines shutting down for expected weather. These variables are already critical because of polar vortex events that are occurring in regions with large penetrations of wind energy.

The weather variables that are specific for wind turbines (both onshore and offshore) should be computed near the turbine heights. The weather data should be able to be expanded to include multiple hub heights because as technologies advance, higher hub heights are feasible, i.e., 80 m, 100 m, 120 m etc., so they are different from those used by solar PV, for instance; however, it is crucially important that all the data come from the same source (model), because the correlation between these variables is necessary for investigation into how these technologies interact in a grid modeled by the CEP models [117].

Solar-Specific Weather Data

The variables required for solar power are the same regardless of the technology; however, how they are used is very different. The two main technologies discussed in this subsection are solar photovoltaics (PV) and concentrated solar power (CSP). Most other types of solar power reduce down to being quite similar to these two main categories. The main variables required for solar power are irradiance (global, direct, and diffuse), temperature, wind speed, and precipitation.

The conversion of solar irradiance to solar power is not covered in detail in this report, but in simple terms it involves the photoelectric effect whereby a photon of light excites an electron enough to “free” itself from its parent atom and flow within the semi-conductor [118]. In general, the higher the solar irradiance, the higher the power output; however, temperature and wind speed play a significant role in the efficiency of the panels. Even though the exact formulation of solar power conversion is complex, there is a relatively simple underlying relationship:

$$P \propto \frac{I}{T} \qquad \text{Eq. 9-2}$$

where I is the irradiance and T is the cell temperature.

For CSP, the process is simpler; the photons of light add energy to, e.g., steam to drive a turbine. The CSP plants can be coupled with molten salt storage (typically) and transfer this heat energy to the salts for use when less solar irradiance is available. Solar PV can use all components of irradiance to generate electricity, while CSP relies almost exclusively on direct (beam) irradiance [119].

To incorporate solar PV or CSP, the irradiance must be included in the CEP model. To produce irradiance fields may require additional work if these are not included in the NWP data. Details are not covered here, but it is documented research [120]. The irradiance fields give a better parameterization of clouds, panel heating, and reflected conditions. This reduces the estimated PV power available, as most NWP model outputs substantially over-estimate shortwave radiation at the surface.

Once the irradiance fields are available, they need to be applied to the prospective technologies. These should include the angle of the panels, the temperature of the panels, and the wind speed in the vicinity of the panels. These all require combining weather variables to compute the efficiency, and ultimately the potential power production at the solar facilities. The biggest impact is temperature on the panel and inverter efficiency. The inclusion of these variables, in general, make solar PV more realistic in the CEPs, and drive decisions about placement of the technology because temperature and clouds become a key factor in the overall (and instantaneous) electricity production.

In ideal circumstances, these computations occur within CEPs, but because the mathematics are complex, it is typically calculated exogenously to the CEP solve. Most of the weather parameters are fixed for the solar production, and so there is little benefit of including all the calculations within the CEP. To include the variable would allow selection of new technologies or different response functions to atmospheric variables without re-computing beforehand; however, this is computationally intensive and is likely best to be performed outside the CEP. This method then allows substitution of other data sets relatively quickly.

Weather models have a difficult time resolving cloud (particularly scatter) at high resolution. Additional satellite data being incorporated in the derivation of the solar irradiance estimates can greatly improve the accuracy of this weather variable [121]. With the addition of satellite data, compared with NWP alone, PV power estimates are between 5% and 16% more accurate at an hourly average basis [120]. Finally, the amount of snow is another weather variable that should be incorporated, which is very important for higher latitude and can cause solar to be zero, even in the event of irradiance being present. This alone can reduce the capacity factors, in absolute values, by as much as 5%.

The solar power variables should be computed at ground level. The best practice to increase the accuracy of the solar power estimates is to incorporate satellite data along with statistical methods to resolve clouds in more detail as they are the most critical parameter for reducing irradiance.

Hydroelectric-Specific Weather Data

For the hydroelectric power estimates, the main weather variable required is precipitation that passes through to the river flow system. The prime mover is the water, which is brought to the hydropower plants from precipitation that falls and then goes into the river system.

There is a complex process by which the precipitation gets into the river systems because of snow packs, vegetation, evaporation, and more. A typical CEP model includes hydropower that uses historical data for output from existing plants. By doing this, the assumption is that the hydropower should behave as it did in historical years in future years regardless of the generation mix that might be present [122].

One way to improve the flexibility of hydropower is to allow hydropower to utilize water as it did in the historical year, but also allow it to dispatch down, and continue the flow of water downstream. This method would be conservative with respect to uses of water other than power delivery, while ensuring that hydropower can be flexible in future systems.

Ideally, CEPs would track the water usage to ensure that new construction of hydropower can be described more accurately. The tracking would involve precipitation and river flow. This would need to be done before the integration with CEP due to its complexity. In the U.S. there is approximately 12-70 GW of new hydroelectricity power plant capacity available, some at new sites and some at existing sites (expansion). For other countries, the amount of new hydroelectricity can vary widely.

Electric-Demand-Specific Weather Data

For almost all CEPs, the electric demand is fixed or exogenous. Some CEPs allow for demand response (DR). The load growth aspects are typically given in terms of percentage growth assumed from extension of historical values or some user-specified amounts [123]. The load shapes for, say, hourly data would be correlated to historical data for advanced CEPs.

CEP models that reduce the demand to load duration curves or time slicing fail to accurately capture the impact of weather variables because of the strong correlation between the weather and the load profiles themselves.

To incorporate weather into the load profiles, the main variable to be extracted is surface temperatures, which feed into demand in terms of cooling (and heating) degree days (CDD & HDD). The shape of the demand is then correlated to the CDD and HDDs. Further, for even more sophistication the demand can be correlated to temperature changes.

The amount of impact of temperature on demand is related to the type of electric loads on the footprint. The impact of temperature increases with electrification, which is covered in the next section. Locations with high space heating through electricity are more sensitive to cold temperatures, while warmer climates are more susceptible to load increases for hotter temperatures. Further, temperature alters the demand if more electric vehicles (EVs) are integrated into the electricity system, since their charging needs are strongly influenced by changing temperature.

The variables for temperature should be included in the load shapes. These can be incorporated by correlating historical demands in each region to be studied to the historical temperature. This can be projected forward for new demands and different weather years including climate using the correlation factors [124].

Load growth related to temperature is impacted further by climate, which is presented in a following subsection. Otherwise, the historical correlated data are likely the best way to estimate future load requirements based upon temperature.

Thermal-Generation- and Transmission-Specific Weather Data

For thermal generation and transmission, as with electric demand, temperature is the most fundamental weather data required for accurate descriptions within CEPs.

For thermal generation, it is perhaps the only real weather variable required. The temperature impacts the efficiency of all heat engines. Therefore, when the temperature is higher the power plants are less efficient; in other words, they need to burn more fuel for the same power [125]. As an example, a combined cycle power plant loses 0.75% efficiency for every 1°C (1.8°F) above 5°C (41°F), so by 30°C (86°F) its efficiency is almost 20% below that at 5°C (41°F). For power plants that withdraw water, the secondary impact is the temperature of the water to be used for cooling.

To represent the temperature impacts on thermal generation, a CEP should include an efficiency curve for each plant based on temperature. This can easily be produced exogenously for the CEP and entered for each site at which existing or new thermal generation can be constructed [125]. The parameters are more appropriate if scaled so that the CEP users can change the factors to mimic improvements in technologies.

For the water withdrawal temperature, each thermal site should have a conversion for the river flow (i.e., mass of water) and the heating effect for the ambient temperature. This can be partly done external to the CEP, but best practice would require constraints within the CEP to change the water temperature as the water is withdrawn and added back to the channels. Currently, no CEP model incorporates this aspect of weather, in detail, because of the complexity with hydrology, the temperature, and the withdrawal rate.

The efficiency of thermal power plants from withdrawal and ambient temperature is somewhat captured in existing plants with their estimated heat rates, but for new plants for CEPs these parameters are largely missing, and would substantially improve the characterization of new thermal power plants built for future electricity systems.

For transmission, the weather variables required for accurate descriptions are temperature, wind speed, and solar irradiance. The highest impact variable is temperature. The higher the temperature, the higher the line losses for transmission and the lower the rated capacity of a transmission line. Wind speed alters the heating effect of temperature and solar irradiance, though both wind speed and solar irradiance are smaller effects than the ambient temperature [126].

The temperature can be applied to the transmission lines outside of the CEP model as parameters to those lines. For new transmission lines, the temperature would need to be available for the pathways. These temperatures can be transformed into the line losses, which is the actual variable that impacts the transmission lines for power flow [127].

Incorporating Climate Change Data

The way weather data penetrate CEP models and how these could be incorporated more effectively is highlighted in the previous subsections. However, as mentioned earlier, the way climate is changing is superimposed upon the weather data. This means that using historical data is adding uncertainty in planned future electricity systems.

The climate change data are not currently addressed in any available CEPs. The future weather could be dramatically different to historical weather because of climate change. To add climate data, the best source would be the Coupled Model Intercomparison Project (CMIP) data sets. The ideal would be to include all the CMIP scenarios for all of the representative concentration pathways (RCP) to adjust the historical weather data based on the climate values. However, this would be huge amounts of data. More practically, a subset could be used. Adding any climate model data would increase the uncertainty in the CEP, and this can be quantified by the delta between the RCP values and the historical data.

The historical weather data can be adjusted by aligning the climate data with the weather data year and computing the differences for future (and past) years. Under the various RCPs, the differences can then be multiplied against the historical weather year. Caution must be taken when aligning the geographic and temporal resolution of the different modeling platforms. The climate data are likely to be daily or monthly, so adjustments must be made to correctly nudge the weather data to future climates.

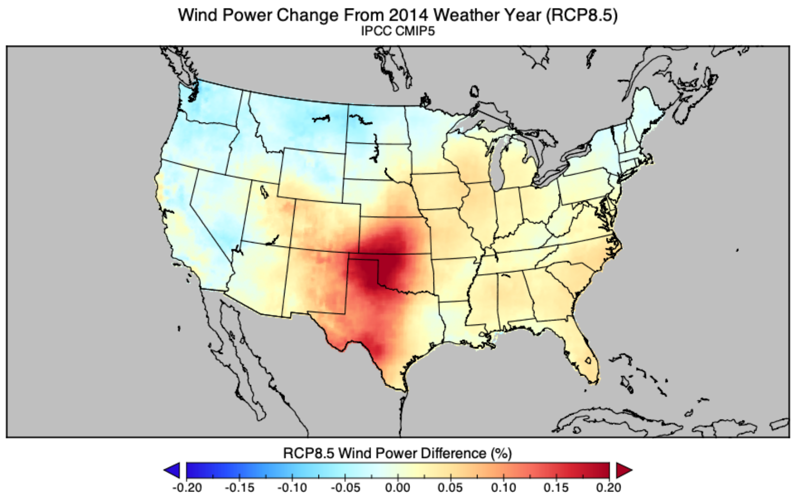
The weather variables that are easiest to adjust for climate are wind, solar irradiance, temperature, and precipitation. Fortunately, they are the most useful for integrating weather into CEPs. The adjustments should be made to the historical weather data and then all the inputs reprocessed for the CEPs that were discussed in the previous subsections.

The addition of the climate data adds more model noise because of the lengthy time scales involved and the uncertainty in the future path of GHG emissions. This would need to be quantified when displaying results from a CEP with climate nudging. The uncertainty can come in several forms. One that is obvious is that if the user decides a particular RCP, and the CEP is not global (and not full economy) there are implicit assumptions about the behavior of everything not included in the CEP.

For example, if RCP4.5 is assumed, and the CEP only covers the U.S., there is an implicit assumption that the rest of the world and U.S. economy decarbonizes to a level that emissions reach the RCP4.5 pathways (when added to the emissions from the studied grid). Another intrusion of uncertainty comes from the climate model data itself. The climate models are coarse and cannot resolve every aspect of the future atmosphere to 2050 or 2100; therefore, by adding these to historical data, the risk is that a future that does not happen is being planned for.

The best practice for determining the uncertainty and reducing it is to perform numerous modeling scenarios over a range of RCP nudged historical years and compute the differences and similarities to produce a most-likely pathway solution for each RCP. It is also possible to perform the method discussed stochastically using all the RCP model output to drive likelihoods for certain futures and allow the CEPs to solve around the probability distributions. This may be advantageous for robustness testing of electricity systems and computing the cost of inaction, adaption, or mitigation.

The introduction of climate data appears to have fairly consistent results. First, the generation assets must work harder to produce the same power compared with no climate change. Secondly, transmission lines need to be built (or upgraded) to higher capacities to be able to transmit the same amount of power compared with no climate change. Thirdly, the electricity demand increases, particularly for electrification of other sectors compared with no climate change. Fourthly, the wind and solar power resources are denuded to some degree because of the increased average temperatures compared with no climate change (see Figure 9-1). Finally, some of the impacts are localized, while others are more widespread, so the effects on each region are different.



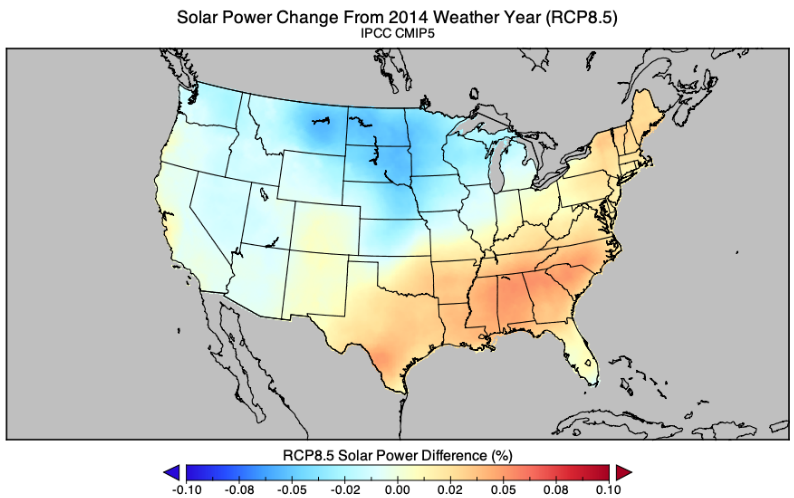


Figure 9-1
Change in U.S. Average Wind and Solar Potential Under RCP8.5 Conditions

R&D Issues on Modeling Weather

There are three main areas of research and development for modeling weather for CEPs. They all require higher granularity both temporally and spatially, which of itself is a difficult challenge to include in the modeling with a tractable solve time.

1. The first R&D area is improved representation of wind, solar, and water for the conversion to power. The technologies that depend on these resources must have high granularity and accuracy. In addition, the conversion from weather variables to power is critically important to refine. For example, inclusion of ramp rates, snow, ice, and temperature gradients for production is important for the CEPs to determine best siting. Further is the need for forecasts to be included. Developing efficient algorithms to compute power for new technologies based on similar weather variables is an area that is ripe for expansion.
2. The second R&D area is associating the demand and transmission ratings based upon temperature (and weather in general). Typically, most CEPs do not include this, but it will become ever more important in a world with higher renewable energy levels and increased electrification. The transmission component in particular needs detailed representation of the ratings along corridors based on the temperature, which is ignored in modeling. Due to the number of lines and the computation expense

for traditional power flow, new algorithms need to be efficient to apply these weather variables to these equations.

3. The final R&D area is building CEPs with detailed climate data included. The climate data should be superimposed upon the weather variables for future time (based on emissions released). The climate data are vast in terms of computing memory and add substantial computational needs for solving. Moreover, the climate data are ensembles, and research needs to be performed on best practices of which scenarios to include and how to incorporate the probabilities associated with those data.

The R&D issues for modeling weather are all related to providing the CEPs with more data on both the supply and demand sides for future time horizons. The additional data are not trivial to add into the modeling, but are related to other R&D areas because of the need for the CEPs to incorporate the chronological weather parameters in the dispatch portion of the models.

Section 10: Interdependencies with Other Sectors

The electricity sector is interconnected to many areas of the economy. In particular, there is substantial feedback between numerous sectors that could influence the performance of the electricity sector in the future.

When considering interconnected sectors, we refer to changes that result in feedback with electricity sector, not only dependent on the electricity sector. These linkages expand if parts of sectors are electrified (and decarbonized). For example, for the electricity grid today there are only two major interconnected sectors with electricity: the natural gas and water sectors. For future electricity grids, the interconnected sectors could expand to transportation, space and water heating, agriculture, and industry (via synthetic fuels) [117], [128].

With each of these sectors come complex interactions and emergent behavior that might change the most economical or logical way to solve the CEP problem. A full decarbonized energy system could take the form of the schematic diagram shown in Figure 10-1.

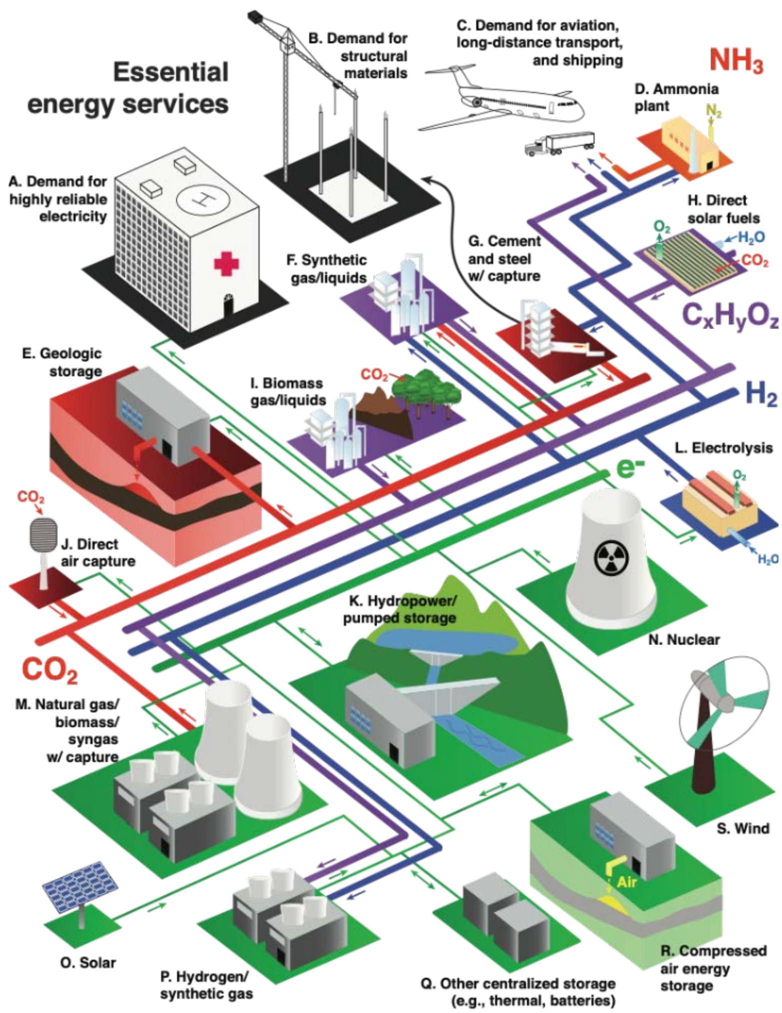


Figure 10-1
Schematic future energy system

Gas Network Infrastructure

The electricity sector includes many generation technologies, but one in particular is growing at an increasing rate: natural gas power plants. The increased reliance on natural gas power generation means that the electricity sector is becoming more dependent on the natural gas sector and infrastructure [129], [130].

The share of natural gas used for the electricity sector has doubled from 19.6% in 1997 to 38.8% in 2018. Figure 10-2 shows the change in electric sector natural gas use as a share by year. The increase in the electricity sector share has happened simultaneously with an overall increase in the economic dependency on the natural gas, since overall natural gas consumption rose by 31.8% over the same period. Thus, the electricity sector used 261% more natural gas in 2018 than in 1997.

Residential and industrial consumption of natural gas has (slightly) decreased over the period of 1997 to 2018, while commercial and transportation sectors have increased their usage. In particular, transportation increased its use of natural gas by 521%. These changes are noted because if electrification does occur, the ramifications of natural gas availability (and price) for the electricity sector become tied to the electrified sectors since they are dependent on the same (oil and) natural gas supply.

As with the electricity sector, the natural gas sector relies on heavy infrastructure to support the supply of fuel. There are pipelines (see Figure 10-3), storage facilities, and extraction sites across all of the U.S.. This infrastructure is critical to the electricity sector, and modeling efforts should incorporate the infrastructure to determine the benefits and risks of further co-dependencies between the sectors. The natural gas sector relies on the electricity sector to consume large shares of the natural gas production (now a majority); however, the electricity sector needs natural gas in a diverse portfolio due to the temporal behavior of demand.

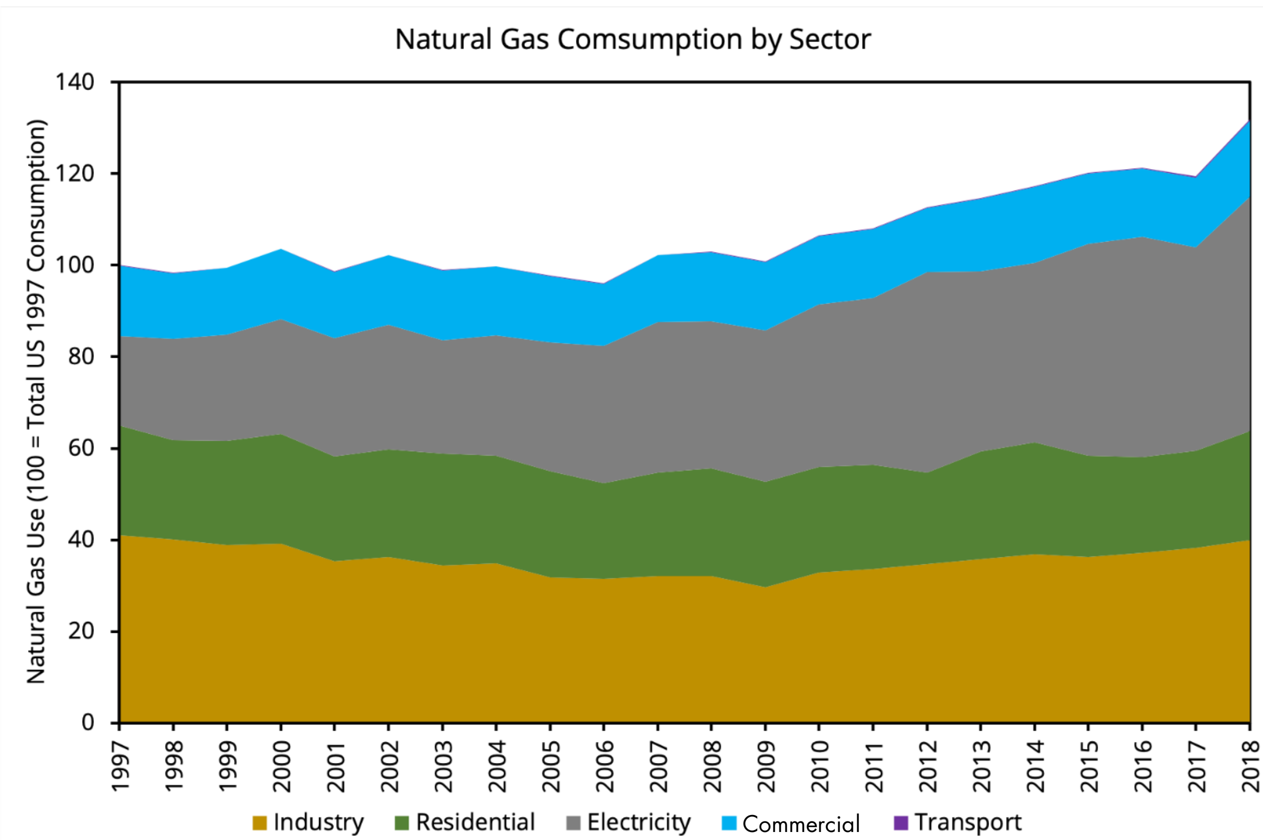


Figure 10-2
U.S. Natural Gas Consumption

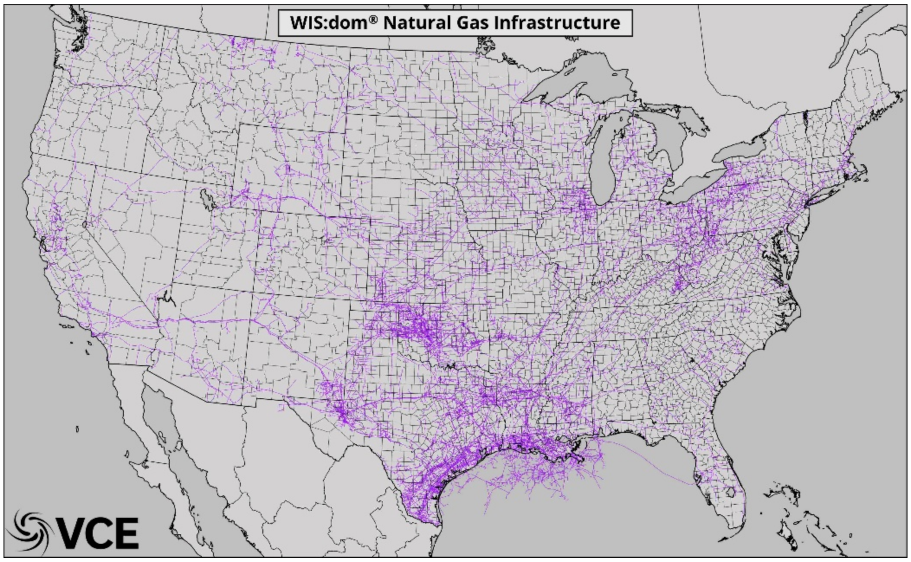


Figure 10-3
U.S. Natural Gas Infrastructure

Increased focus in modeling should be made around the market operations for natural gas and the requirements of the electricity markets. For instance, there could be a "shortage" of natural gas (as happens routinely in the Northeast) due to contracts and lack of coordination in the optimization of fuel supply but not due to gas availability, which then would manifest as scarcity pricing of electricity [131].

The optimization models should also include supply and demand elasticity for the natural gas. Most modeling uses static input costs that describe the price of natural gas for future years. However, if the electricity sector continues to use more natural gas (as a share), the supply and demand (temporally and geographically) shifts compared to the model that produced the price projections. Therefore, taking into account regional and national supply constraints, elasticity should be included to represent constraints and lag-times in infrastructure for natural gas. A simple elasticity function could look like:

$$GP_{r,t} = RM_{r,t}\ NGP_t + REM_{r,t}\ \Delta RGU_{r,t-1} + NEM_t\ \Delta NGU_{t-1} \quad \text{Eq. 10-1}$$

In Eq. 10-1, the regional gas price, $GP_{r,t}$, is an adjustment from the national average, NGP_t, by multiplying it with the regional multiplier, $RM_{r,t}$, and adding the elasticity component based upon the regional change in natural gas use, $\Delta RGU_{r,t-1}$, and the national gas use, ΔNGU_{t-1}. The elasticity functions, $REM_{r,t}$ and $NEMt$, would be empirically derived.

At present, the U.S. has a capability to store around 4,000 billion cubic feet of natural gas. If the storage was full, it would last approximately 2 months at average consumption levels. If transportation is electrified and more electricity is produced with natural gas, there would be a dual impact from lower oil demand and higher natural gas needs for the electricity sector. These dual-dependencies should be included in modeling the electricity sector decarbonization, since the storage infrastructure may need to expand dramatically to deal with the ebb and flow of electric demand.

If the natural gas and electricity sector were modeled in a co-optimized fashion, the risks would be determined; however, advantages and flexibilities would emerge. For example, with the natural gas infrastructure there is implicit longer-term storage than batteries. As noted, there is approximately 2 months of possible storage. Furthermore, if a co-optimized market emerged for natural gas pricing with electricity pricing, the economics of storage and pipelines may be altered in ways that could enhance the availability of natural gas during peak demand needs. For instance, a pipeline could charge by volume and time of day to ensure that supply is delivered and compensated appropriately.

Cooling Water Infrastructure

The electricity sector as it exists today relies heavily on the water infrastructure. About 99% of thermal conventional generation is cooled via water [132]. These are split between once-through and wetrecirculating/loop cooling. The main difference between the two types is that once-through has much higher withdrawals, while loop cooling has much higher consumption of water.

Since the electricity sector relies so heavily on the water infrastructure, modeling of the electricity sector should include it. However, this is a difficult task. Most of the infrastructure for water is not required all of the time. Predominantly, thermal conventional generation is sited near a fresh water source (typically a river), where the only infrastructure need is the piping to and from the river itself. Mother Nature takes care of the rest of the infrastructure needs.

Even though the current infrastructure seems like there is no need to model, there is growing consideration of the hydrological cycle to be included in the capacity expansion models, so that the amount of water available for the water-cooled power plants can be identified and determine if new plants can be added and if the existing plants can operate safely [133].

The modeling should begin with water availability and temperature for the power plants for the dispatch portion of the capacity expansion model. It can then be expanded to include water storage for plants to get extra water if it is restricted for some reason. Further, this would alleviate the "buy and dry" contracts that do exist in some parts of the U.S. [134]. The capacity expansion models should have the capability to recognize these constraints for expanding the electricity sector. Moreover, this parameterization assists in the modeling of hydroelectricity production, since the river flows being modeled are included.

The sector coupling that is included by considering water is predominantly hydrologic and agricultural. These again are indirect, but the constraints enforced by the water data would inform the availability of water for agriculture and other uses. The infrastructure component that might become important for flexibility is the water movement for irrigation and for drinking. These water sources are typically stored and pumped (using electricity) to where they are needed. There is an opportunity to use this movement of water (or fraction of) to incorporate more flexibility, if the systems were co-optimized [135].

Electrification and Decarbonization of Other Sectors

If the objective of a capacity expansion model is to enable investigation of load growth and/or decarbonization of the economy, then electrification must be considered [117]. The electrification of other sectors would fundamentally change the temporal profile of electricity demand. It would also, if the electricity sector was decarbonized, unlock deep decarbonization potential for those other sectors. With these possible benefits come some challenges for the modeling in terms of the interactions between the sectors that are already intertwined and incorporating new sectors that are currently almost entirely decoupled.

The GHG emissions from each sector in 2017 are shown in Figure 10-5. The figure does not include land-use changes or agriculture. Figure 10-5 shows that the electrification of transportation would have the largest impact on emissions, then industry, and finally commercial with residential. The GHG emissions associated with each sector caused by electricity production have been allocated to the electricity portion.

To consider electrification of transportation in CEPs there needs to be a determination of the parameters to define the loads and their temporal profiles. When considering the demands, the transportation sector should be split between vehicle types. Most simply they can be disaggregated by weight: light duty, medium duty, and heavy duty.

For heavy duty, one possibility is to consider hydrogen as an energy carrier. This would require the CEP to consider the production, transport, and storage of hydrogen. The way to parameterize heavy duty electrification would be to target an amount of hydrogen to be produced by region (e.g., county) over a specified period (e.g., month) and allow the CEP to co-optimize the production of the hydrogen (by building H_2 production facilities), transport of the hydrogen (H_2 pipelines, LNG trucks or tankers), and storage of the hydrogen (H_2 storage tanks or geologic storage) alongside the electricity system. The heavy duty vehicles would act as the sink for the hydrogen being produced. The CEP would be able to determine the price of the hydrogen based upon the build-out required and the cost of electricity to produce the hydrogen. See Figure 10-4 for a schematic of the hydrogen infrastructure that could be modeled in CEPs.

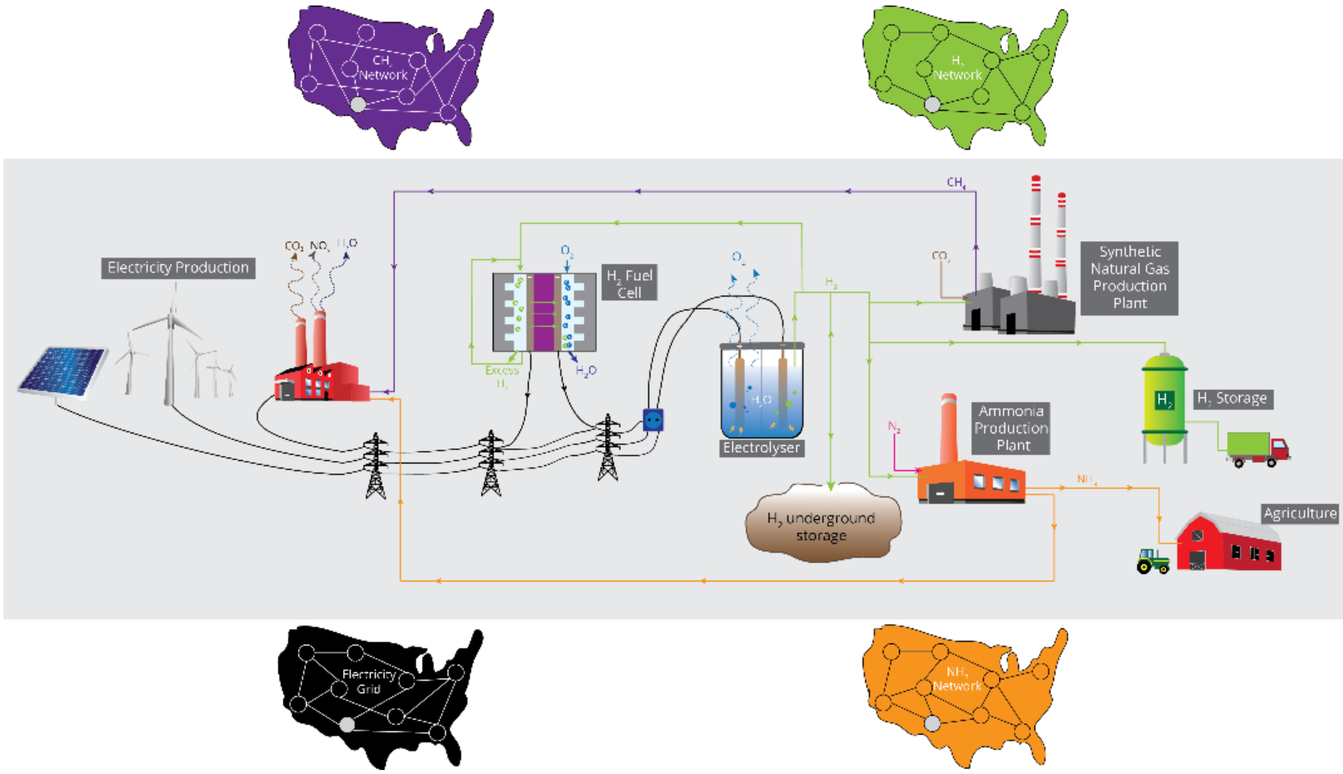


Figure 10-4
Possible U.S. hydrogen infrastructure by CEPs

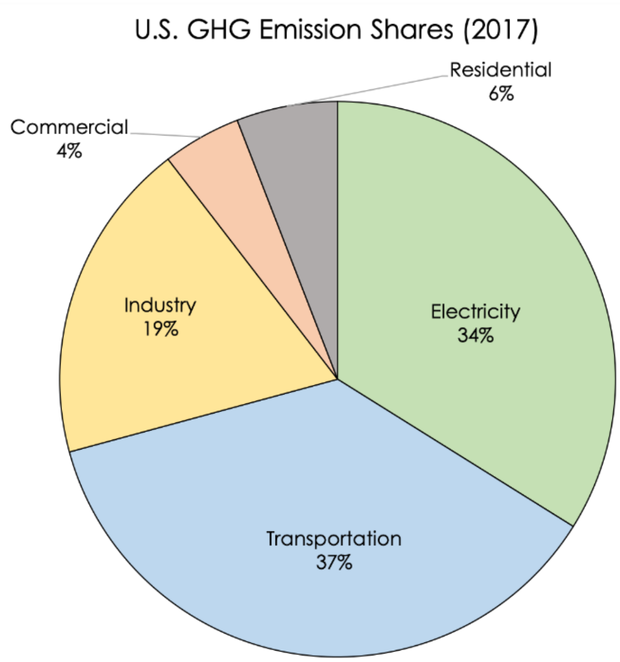


Figure 10-5
U.S. Greenhouse gas (GHG) emissions by sector

For the light duty and medium duty vehicles, the CEPs could consider direct electrification, that is, modeling the electric vehicles (EVs) and using electricity to charge the batteries directly from the grid. There are granularity trade-offs with the aggregation of EVs, since modeling every single EV would be computationally intractable within a CEP. Therefore, some pooling of demands and aggregated operation would be required, (e.g., [136], [137]). For a CEP with a nodal description, these could be aggregated to buses, and for a zonal description it could be county or RTO zone (essentially the resolution of the CEP).

For the EVs to be included there are some important features to represent: first, the necessary charging and performance of the batteries that includes assumptions about driving behavior; second, the ambient temperature and its impact on the efficiency of the batteries as well as the temperature control of the cabin, and third, the amount of possible flexibility the charging could undertake to help the grid manage all the new demands for the EVs. The flexibility could be smart charging only (i.e., no injections back to the grid), or full integration that includes vehicle to grid (V2G) injections.

Figure 10-6 shows the daily and hourly demand profiles for local EV fleets. These normalized values can be multiplied by the annual electricity demand for vehicles, and the resulting profiles will estimate the new loads for that region. The hourly profile in the lower part can shift to the left and right depending on the rate structure and incentives in place for charging the EVs. The profile in the upper part represents a translation of weather and driving patterns as an average across the U.S. and converted from petroleum to electricity requirements for the same driving patterns. Considering Automated Vehicles (AVs) would result in considerably different profiles. The profiles in Figure 10-6 could be considered as the exogenous part of modeling the EVs. The endogenous part comes from the flexibility these new demands might have. For example, CEPs could allow the EVs to participate in programs that allow interrupted charging at a cost for the grid. The constraints to represent reality would be: leaving enough charge for daily activities, reducing the cost of energy for customers (i.e., if the customers lower power needs now, at a later time they must be provided the power at a lower rate), the EVs should be used as a last resort, and the energy should be provided by some time limit. An additional flexibility would be V2G, where the grid pulls power from the vehicles. This would be useful in emergency situations; however, it is typically more efficient to interrupt charging than draw power from the vehicles due to round-trip losses and battery degradation [138].

One area where V2G might become useful in the CEPs is when there is an overload situation, areas might "disconnect" from the grid and power themselves. This would be modeled as zero electricity draw from the grid, but being consumed from EVs locally. These should be modeled only for emergency events initially, but in the long run could be considered as part of the holistic operation of the system, particularly in distribution grids, e.g., [139], [140], [141].

The electrification of transportation either through direct connection to the grid via EVs or indirectly via hydrogen (and other synthetic fuels) can unlock huge potential GHG reductions and increased flexibility within the electricity sector; however, there are disadvantages and hurdles to overcome. The modeling should represent the need for building the new infrastructure and processing facilities including the costs and the possibility of new inflexible demands at those sites.

There is a clear need for transportation electrification to be modeled by CEPs because there is a surge of new EVs on the horizon, and this would unlock new customers (and load growth) for electricity suppliers. It also opens a possible pathway for deep decarbonization, since transportation is 37% of GHG emissions in the U.S..

The next area of electrification is the industrial sector. As shown in Figure 10-5, industry accounts for 19% of the U.S. GHG emissions. Most of the emissions from industry are related to energy production, through use of fossil fuels for the heat [142]. Within the industrial sector, under electrification, some portions will undergo "load destruction" because there will be a lower demand for their products. A primary example of this would be petroleum refinement if significant numbers of EVs are purchased. The important portion for a CEP to capture is the geographic disaggregation of the changes in demand (inside and outside the electricity sector).

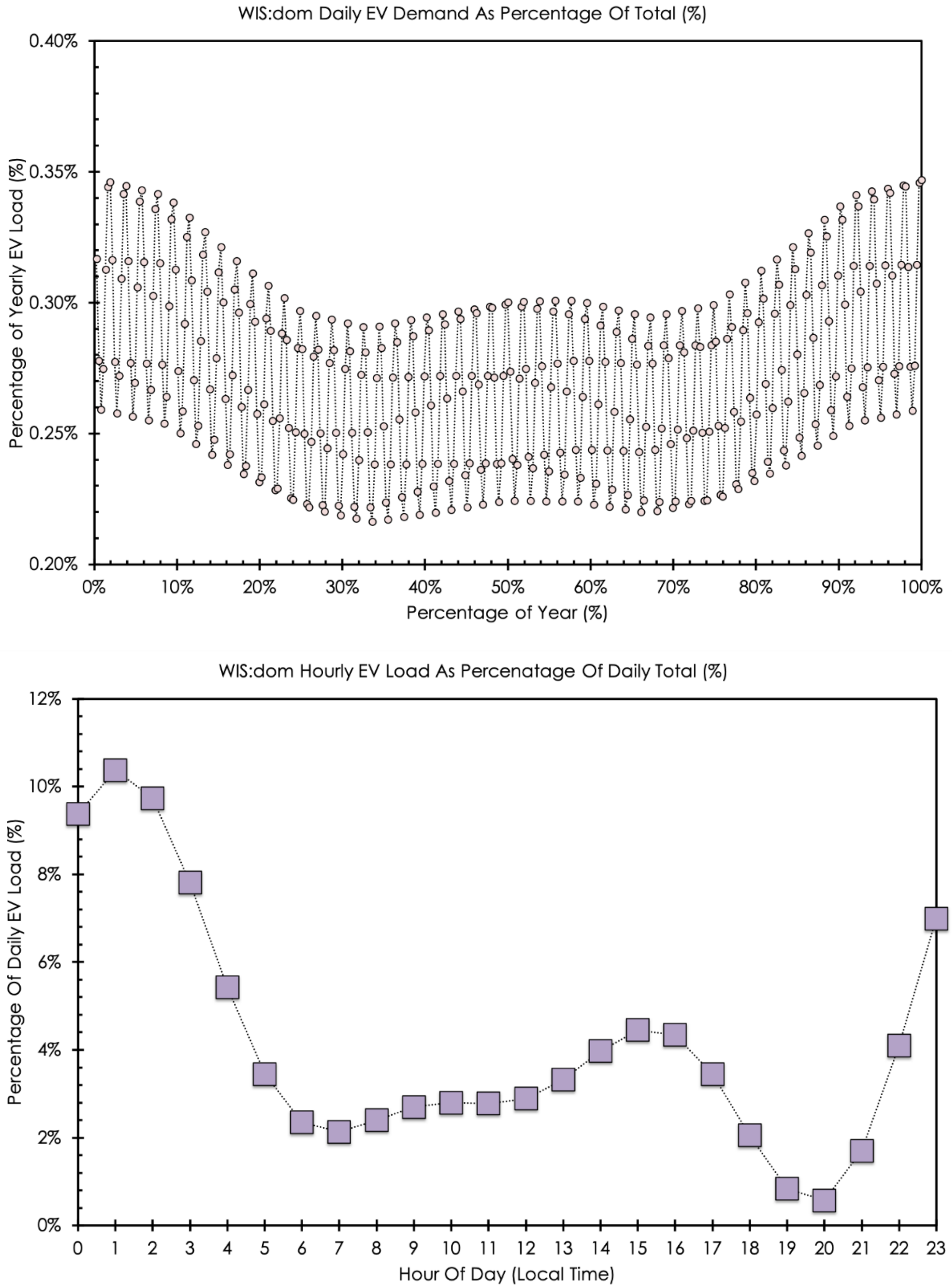


Figure 10-6
Input demand profiles for EVs at hourly resolution

Other areas in industry will potentially be electrified either via electricity directly or via hydrogen and other synthetic fuels (as shown in Figure 10-4). The exact values will depend on the industrial sector in each region. For example, iron/steel production could use recycled metal and an electric arc furnace along with hydrogen to produce nearly emission-free iron and steel. However, for virgin steel, carbon needs to be injected at the outset (to remove the oxygen bound to the iron), and currently this comes from coke. For a CEP to model this process, it would require some assumptions about recycling of old metals and the fraction of hydrogen versus electricity required to make the new iron and steel. There would need to be a calculation for the amount of "virgin" iron and steel being produced and how GHG emissions are accounted for. There could be carbon capture and sequestration (CCS) applied on this process, which takes additional electricity. Thus, the possible electrification of this portion of industry would require assumptions of rate of change and the energy intensity of these new loads. Some would be more costeffectively decarbonized without being electrified. Without the CEP knowing the costs associated with electrifying these different areas of industry, it would have no way of determining the tradeoffs. This is one area that is substantially lacking in all CEPs and is a difficult problem to overcome because of the low number of electrification possibilities for certain areas of industry.

The last remaining portion of Figure 10-5 that can be electrified is the residential and commercial sectors. These portions are the GHG emissions not attributed to electricity consumption in these sectors and are primarily driven by space and water heating. There are small contributions from cooking and other activities. For water heating, the electrification can happen via resistive water heaters or heat pump (HP) water heaters. Resistive water heaters use much more electricity than HP water heaters. It is more efficient, therefore, to convert other types of water heaters to heat pumps. These HP water heaters would enable flexibility about when and how to heat the water. This is partly because the HP water heaters typically have resistive backup that can be switched on to heat the water more rapidly, thereby absorbing excess generation that could be on the electricity grid. In addition, since the HP water heater has a higher efficiency, it typically runs over a longer time period than the resistive version and so there is more opportunity to shift the demand (lower amount of power for a longer period versus high power over a shorter period). Indeed, this becomes a vector in the CEP models for thermal storage of electricity.

The difficulty associated with electrifying the water heating is that it adds more demand in the colder seasons than the summer seasons. However, the HP water heaters become relatively flat, but flexible, base load that can be reshaped relatively easily to changing supply. This can be modeled in the CEP as an aggregation of the HP water heaters in certain regions (e.g., counties) and a certain percentage of them at any time can be used flexibly to assist with supply-demand balance (i.e., demand-side management; see for instance [143] on extracting flexibility from buildings).

To convert space heating in the residential and commercial sectors, a transition primarily from natural gas would occur. There are some locations where resistive space heating already exists, but the space heating sector is dominated by natural gas currently. To electrify these heating demands, either heat pumps (HP) for space heating or resistive heating can be adopted. Heat pumps are become more and more efficient and can be deployed across most of the U.S. Typically, it is desirable to have a backup heating source for very cold climates, either resistive or natural gas. This backup would be used in extreme cold conditions to keep the building shells at a comfortable temperature. Within the CEPs the electrified heating can be modeled in an aggregated manner (e.g., county-level) and the temperature across the aggregated level can be used with building statistics to determine the heating requirements for each time interval being modeled. By using the temperature profiles, the flexibility available can also be computed based upon what tolerable temperature variation can be accommodated at price points. This enables demand-side management of the space heating sector.

With the electrified heating come new electric profiles. In cold conditions, such as a "Polar Vortex," the heating demand can dominate all others. Further, in such situations, it can happen that there is little to no flexibility available because of the rapid heat loss from the building shells. It is important to model these in the CEPs because it enables the optimization to deal with the extreme conditions it may face with higher electrification of sectors. In doing so, the CEP may solve with different solutions within the other sectors. For example, it is possible that hydrogen could be used instead of HPs or resistive heating, thereby tapping into the new infrastructure that might come from the schematic in Figure 10-4.

Figure 10-7 shows a national aggregation of space and water heating demand for the residential and commercial sectors when it is entirely converted to heat pumps. The data have been normalized. It can be used as an input to CEPs along with the flexibility values for how much of these demands can be moved and for how long. These demands can only function in CEPs if there are chronological solves in the dispatch portion of the CEP. Demand-side management requires details on the shifting of demands and constraints on how long energy can be moved before being consumed for its original purpose.

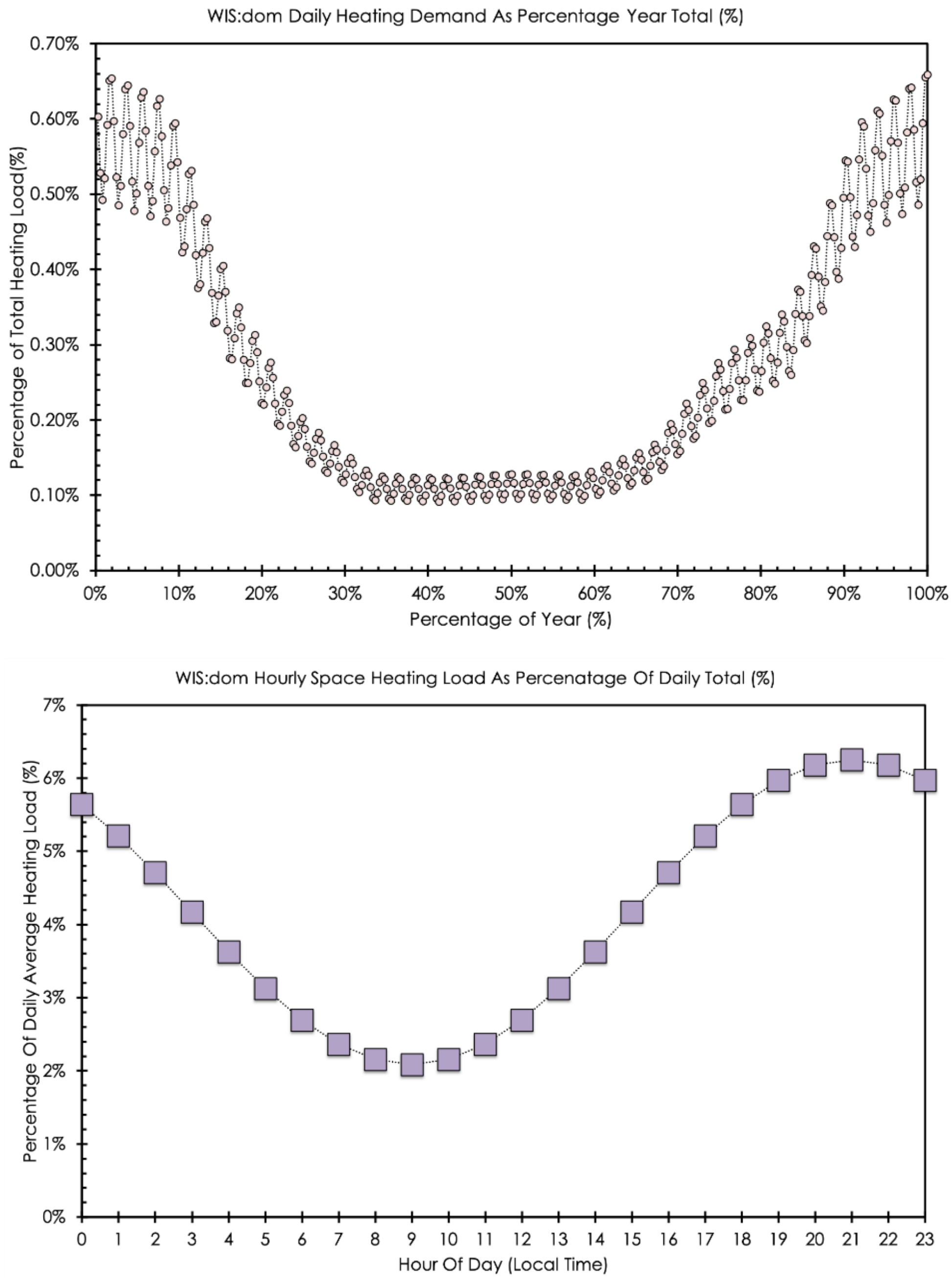
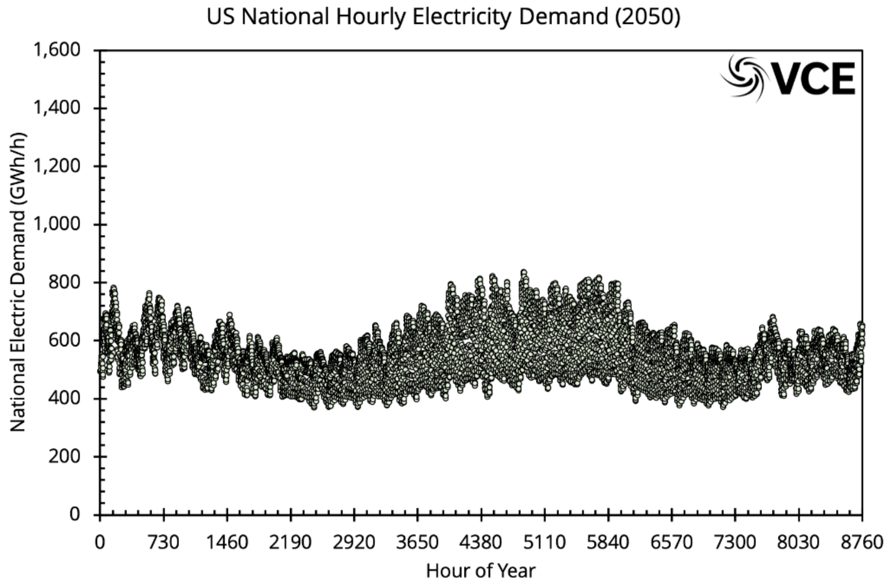


Figure 10-7
Input demand profiles for space and water heating at hourly resolution

Figure 10-8 shows the hourly national U.S. electricity demands for 2050 under minimal and extensive electrification. It is shown to illustrate how dramatic the change to the load profile can be over the hours, days, weeks, and seasons with the additional electrified loads. The change is more dramatic if energy efficiency is not incorporated. However, it does lead to more customers for electricity, which spreads investment over more units of electricity required. This may aid the transition to a lower emission economy.

In conclusion, the electrification of other sectors is a double-edged sword. On one hand, it unlocks the potential for economy-wide deep decarbonization, while on the other it completely alters the way electricity generation and demand interact. It does this in a few ways: the profiles are different diurnally and seasonally; the demand needed to be met is substantially higher; the demand side is much more flexible, which means that both supply and demand can be part of an optimized solution. The consequences for CEP modeling are that more granularity is required for the demand-side resources (i.e., loads, flexibility, locations, temporal profiles) because they now play a more integral part in the optimization. Further, the chronology of the demand becomes more important to correlate with the weather (and extremes of weather) because the demands are more sensitive to it changing. All-in-all, more weather-dependent, chronological, granular data are required in CEPs to handle the evolving electricity system.



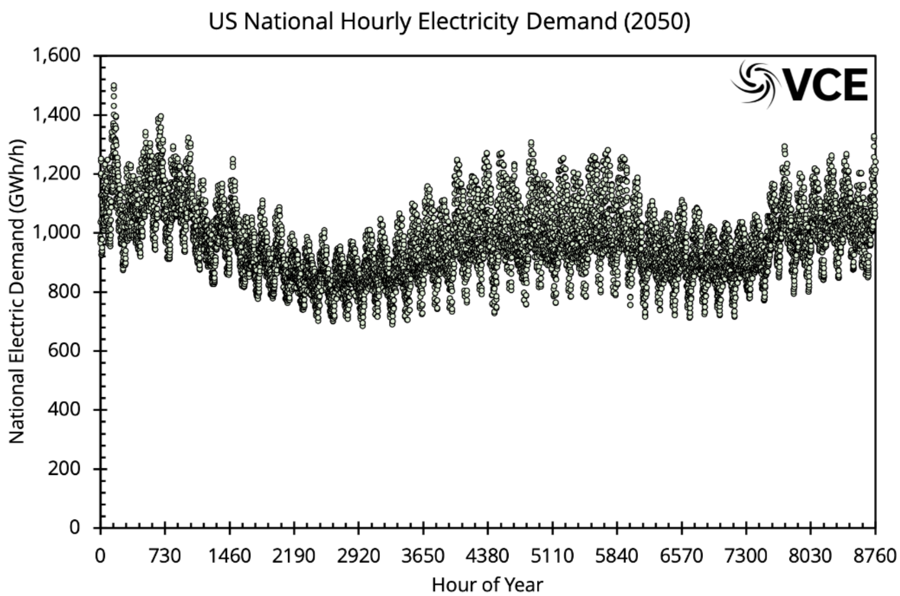


Figure 10-8
Hourly 2050 U.S. demand for monomial (upper) and extensive electrification (lower) futures

Multisector Modeling Approaches

Multisector models related to energy systems may represent any combination of the electric power system, the natural gas system, the water system, and the transportation system. Reference [144] provides a common categorization of such models into bottom-up models, top-down models, or hybrids. Bottom-up models are generally optimizers that identify technology portfolios over time to minimize costs; such models incorporate explicit, refined description of technologies and are generally preferred in engineering applications. A well-known bottom-up multisector model is the Times-Markal models, providing energy system evolution over a multi-period, long-term time horizon. The Times-Markal models are capable of multisector modeling via electric power, energy resources (coal, natural gas, petroleum, and renewables), and energy demand (commercial, industrial, residential, and transportation) [145]. The U.S. Environmental Protection Agency has maintained analysis capability with this application [146]. Another model, NETPLAN, provides integrated modeling capability of electric power, coal, petroleum, renewables, and both freight and passenger transportation systems; NETPLAN is distinguished by its modeling of transport/transmission associated with the various sectors as well as its ability to perform multi-objective optimization [147].

Top-down models are macroeconomic; they attempt to capture the performance of the energy-economic system rather than the behavior of individual firms. They usually include the influence of macroeconomic variables such as wages, consumption, and interest rates. One type of top-down model is the computable general equilibrium model; this model considers the economy as a relatively small set of supply and demand agents, which bring supply and demand quantities into equilibrium as each agent optimizes its own utility. For example, the General Equilibrium Model for Economy-Energy-Environment (GEM-E3) model, developed under the auspices of the European Commission, represents 21 individual sectors including electric power, natural gas, coal, oil, and transport (air, land, and water), among others [148], [149].

Hybrid models combine elements of bottom-up and top-down models. The U.S. Energy Information Administration uses the National Energy Modeling System (NEMS) to capture interactions between electric power, oil and gas supply, natural gas transmission and distribution, coal, renewable fuels, petroleum, and demand (residential, commercial, industrial, and transportation) [150]. NEMS is a partial equilibrium model, with each sector represented via a distinct module. NEMS is classified as a hybrid model because some modules employ optimizers and technology-rich bottom-up modeling capabilities, yet NEMS iterates through all modules until a macroeconomic convergence criterion is met [151].

Most multisector energy models developed to-date have been perceived as tools for driving policy decisions; in addition, the expanded modeling needs required to represent different sectors make these models computationally intensive. As a result, multisector models have been implemented at the national or regional levels and so have been less applicable for engineering decisions. This is changing, as the transportation sector becomes increasingly electrified, and electric grids increasingly loaded by the transportation system and interdependent with natural gas and water systems to supply electric system flexibility needs. Ultimately, the question answered by multisector expansion planning models is this: can infrastructure development plans be made more effective and less costly by coordinating expansion across sectors? In the remainder of this section, we provide insight into the nature of some central modeling features necessary for multisector representation.

Electric-Natural Gas Representation

Expansion of renewables and natural gas provides opportunity to co-optimize resource expansion with electric and gas transmission expansion. The various interdependencies can be observed by studying Figure 10-10 where the gas-fueled electric resource is represented by "G" and the wind plant is represented by "W", the blue triple line is gas transmission and the black lines are electric transmission, where line thickness is proportional to transmission capacity. The far-right bus is a large electric load center, relative to which the natural gas source and the wind plant are remotely located. Decision variables include gas generation and wind generation capacity and location, gas transmission capacity, and electric-line 1 and electric-line 2 transmission capacity. The location of the gas-fueled generation G could be close to the wind plant W, requiring short gas transmission but high capacity in E-line 1, or G could be close to the load, reducing capacity required for E-line 2. It is easy to see how these relationships can become more complex in a large-scale network with more natural gas sources, more load centers, and more wind and gas plant candidate locations.

This problem is addressed by developing an integrated gas/electric network model, where links between the electric and gas network models represent the combustion turbines and the combined-cycle power plants. Modeling the integrated electric and the gas network is accomplished by using the governing equations for power flow and gas flow, which are quite similar. In Figure 10-9, we observe at the top the DC power flow equation, which shows that the steady-state real power flow across a circuit is determined by the difference in voltage phasor angles between the terminating buses. Likewise, at the bottom, the Weymouth equation shows that the squared value of the natural gas volumetric flow rate through a pipeline is determined by the difference between the squares of the pressures between terminating nodes.

The susceptance defines the transmission line characteristics

$$B_{ik}\overbrace{\left(\theta_j-\theta_k\right)}^{\text{Voltage angles}}=\overbrace{P_{jk}}^{\text{Active power flow}}$$

The constant value defines the pipeline characteristics

$$C_{ik}\underbrace{\left(\pi_j-\pi_k\right)}_{\text{Squared pressures}}=\big(\underbrace{G_{jk}}_{\text{Gas flow rate}}\big)^2$$

Figure 10-9
Electric and gas flow governing equations

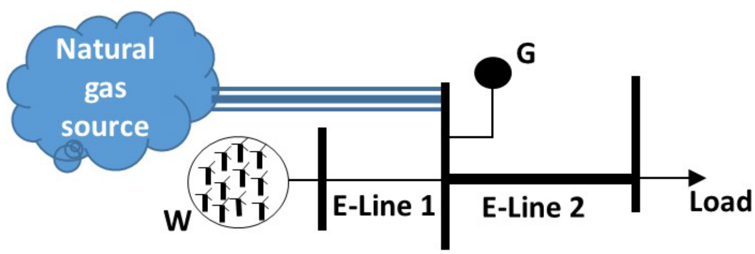


Figure 10-10
Illustration of electric-gas expansion-related interdependencies

The similarity of these two equations suggests that the expansion planning modeling methods described in Section 5 for the electric network may be applied to the natural gas network as well. Indeed, as in Section 5, the natural gas flow equality expression for candidate gas lines results in a nonlinear relation due to a product term arising from the binary investment variable multiplying the squared pressure terms, so that the optimization problem is a mixed integer nonlinear program (MINLP). In addition, the Weymouth equation contains the square of the gas flow rate, a nonlinearity not present in the DC power flow equation. Further, it is not possible to define the squared flow rate as a variable (as done for the squared pressures). This is because whereas squared pressures are not used elsewhere in the model, gas flow rates (and not squared gas flow rates) are needed for imposing gas balances at each node, ensuring feasible flows in each pipe, and converting to electric energy at each power plant. Addressing this issue requires linearization of the squared pressure and gas flow variables. References [152] and [153] illustrate this using a piecewise linearization method called *special ordered sets of type 2* (SOS2), [154]. Significant computational efficiency may be gained without much loss of modeling fidelity if the SOS2 method is applied only to the gas flow variables (and not the squared pressure variables). Finally, it is reported in [153] that modeling compressor and reduction stations to terminate natural gas pipeline expansion candidates is critical because otherwise, pressures become unrealistically low and over-expansion occurs.

Electric-Transportation Representation

As our various transportation modes diversify their energy source from an almost petroleum-only system to one that also utilizes electric energy, natural gas, and/or hydrogen, there is strong motivation to consider interdependencies between energy and transportation systems. For example, and as stated earlier in this section, the electric industry should know the level of grid decarbonization for which a specified transportation fuel portfolio results in a targeted net energy/transportation system carbon decrease. The electric industry should also be able to study the impacts on energy subsystem loadings of various transportation system expansion strategies, e.g., expanding high-speed rail or significantly increasing light-duty vehicle fuel efficiency.

Following the modeling approach described in [147], [155], [156], we consider the energy system as composed of the electric power subsystem, the natural gas supply and pipeline subsystem, the coal supply and transport (rail, barge, and truck) subsystem, and the petroleum supply and transport (pipeline, rail, truck, and tanker) subsystem; we also include the potential for a growing hydrogen subsystem. We further consider the transportation system as composed of the freight transportation subsystem (with rail, barge, tanker, and truck fleets) and the passenger transportation subsystem (with light duty vehicles, rail, and air fleets). Freight and passenger transportation subsystems have both mobile (the previously identified fleets) and fixed (highways, railways, river systems, and airports) infrastructure. We may model the energy and transportation systems as a set of interconnected, capacitated subnetworks evolving over time. Figure 10-11 illustrates such a model for three locations and two time periods, where for each time period, the top (pink) subnetwork represents the energy system, the middle (blue) subnetwork represents the freight transportation subsystem, and the bottom (yellow) subnetwork represents the passenger transportation subsystem. In general, the model would have thousands of locations and would span several decades with annual time steps. In this model, energy system demand is specified as node injections; in contrast, the transportation system demand is specified as link flows.

In using the model of Figure 10-11 to represent energy/transportation interdependencies, one must capture the loading of the transportation system on the energy system due to the use by light duty transportation technology of petroleum, natural gas, electric energy, or hydrogen, the use of petroleum and electric energy by rail, and the use of petroleum by airplanes, as illustrated in Figure 10-12 (hydrogen network not shown in the figure). Here, the energy used by the transportation system during a particular modeled time period is given by the product of the energy per-unit of transported commodity and the transported commodity per time period, with that energy demand split between the energy nodes at the locations of the terminating transportation path.

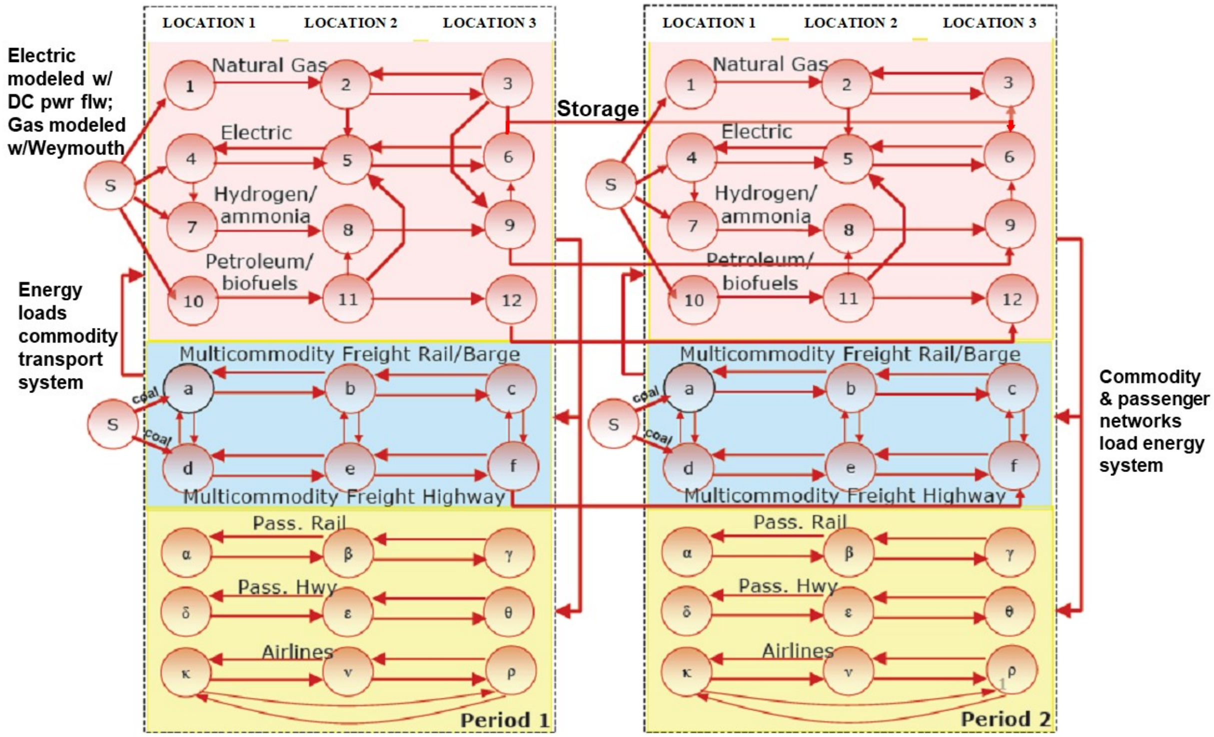


Figure 10-11
Interconnected, capacitated subnetworks for multi-period, expansion planning model of energy and transportation sectors

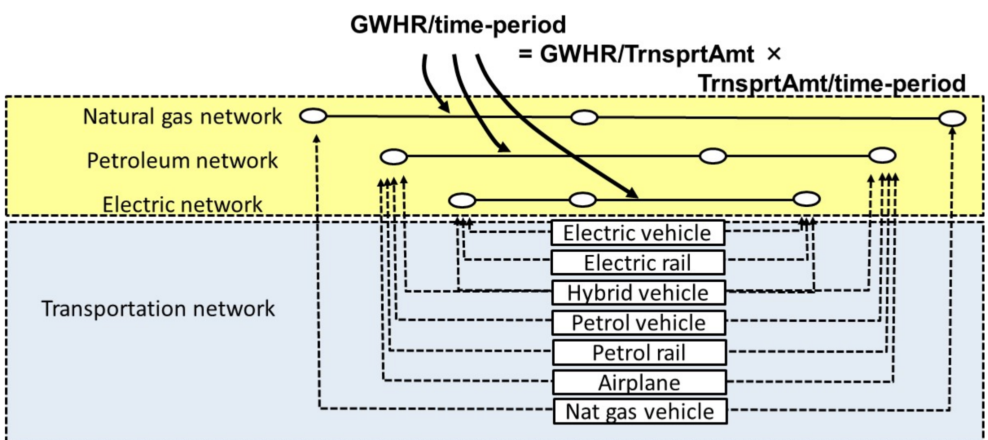


Figure 10-12
Transportation system load on energy system

Commodities transported by the freight transportation subsystem include, for example, agricultural products (e.g., grains and corn), chemicals, and gravel. They also include "energy commodities," i.e., commodities that are moved by rail, truck, and barge but may be converted to energy; such commodities include coal and bio-energy feedstocks and may be understood as the energy system loading on the transportation system. The flow of energy commodities must be included in the transportation freight subsystem model and in the energy system model, and both flows must be coordinated since they represent the same commodity but in different units.

Electric-Water Representation

It was mentioned earlier in this section that the water system could be a source of flexibility for electric power grids as wind and solar penetrations increase and thermal plants become less economically competitive and are retired. Indeed, there are two types of water systems that are particularly attractive in this way: water treatment plants (WTPs) and wastewater treatment plants (WWTPs). These two forms are attractive for three reasons: they represent a relatively large amount of load; they offer significant flexibility; and they are available throughout the year on a daily basis (although irrigation pumping may also be of interest, this type of load is only available for a few months per year and therefore does not satisfy the third criterion).

For example, in the region of the U.S. operated by the Midcontinent Independent System Operator (MISO), we estimate that the total nameplate capacity of WTPs and WWTPs is at least 1000 MW. Motors for pumping load consume over 90% of this load, and if 30% of it is available at any given moment for the provision of flexibility, this would provide 270 MW of flexible load. A typical weekday regulating reserve requirement in the MISO region is 400 MW, whereas 10-minute ramp-up requirements range between 10 and 1300 MW and 10-minute ramp-down requirements range between 70 and 1500 MW, and so a 270 MW contribution to these requirements would be significant. WTPs often utilize water storage tanks, many of which can gravity-feed water demand for hours before they require replenishment, and both WTP and WWTP have wait-time built into their processes, offering the ability to shift load by minutes or hours. And many new plants pump, at least in part, with variable speed drives, offering the ability to modulate load, a feature that is attractive for frequency regulation. Investment costs associated with initiating WTP and WWTP as controllable demands are likely low, as they would require only costs associated with their communication infrastructure.

The overall approach required is to develop a high-fidelity model of the operation of WTPs and WWTPs, including representation of water storage, temporal requirements of the water demand, the energy requirements of each step in the treatment processes, and any constraints, e.g., on minimum up and down times and specification on maximum and minimum levels for storage tanks. Such a model was developed in [157] and integrated with a power grid energy/ancillary-services dispatch test system in [158] concluding that the water distribution system offers significant flexibility to the power grid.

R&D Issues on Modeling Interdependencies with Other Sectors

There are four main R&D issues that result from this section.

1. Top-down/bottom-up: Determine the mutual benefits of these two modeling approaches and the extent to which they should be integrated for use via a hybrid model.
2. Multisector interdependencies for gas/electric and energy/transportation: Develop modeling capabilities that capture the effects of intersector loading in expansion planning, of particular importance when a sector (e.g., transportation) switches from one energy form (e.g., petroleum) to another (e.g. electricity). This work should draw upon the rich literature on natural gas/electric modeling and transportation/energy system modeling. This effort should pay particular attention to enhancing the fuel supply models used on the electric side and improving supply and demand elasticity on the natural gas side.
3. Multisector interdependencies for electric/water: There are at least two R&D issues here:
    a. Water temperature effects on thermal plants: Ensure that operation of existing thermal power plants as well as operation of candidate power plants respects water temperature constraints.
    b. Water distribution system flexibility: Water-related energy loads offering potential for grid-related flexibility services, such as WTPs and WWTPs, should be assessed to determine whether what they offer is effective and whether it may be a significant percentage of the future needs under high-wind/solar penetration levels.
4. Modular multisector code: A flexible code should be developed that enables user choice of which sectors to model and the fidelity level for each sector.

Section 11: Including Resilience

Beyond Credible Contingencies

The industry has traditionally designed and built electric infrastructure to satisfy co-called "credible" contingencies. These contingencies, generally including single- and double-component outages, are specified by reliability criteria, e.g., categories B and C of the North American Reliability Corporation's (NERC) disturbance-performance table [159]. However, there are additional disturbance types that can result in significantly increased societal costs for weeks and months. Traditionally, such events have been classified as NERC Category D events with the only requirement being to "evaluate for risks and consequences" [159]. However, such events do/can occur, and the resulting system performance is highly influenced by the size and capabilities of the installed equipment and the integration of this equipment via system design. The term "resilience" is used to refer to system performance following such events [160]. Reference [161] overviews this term and discusses various ways it has been defined and used with respect to electric system infrastructure, emphasizing that events of concern for resilience analysis and/or design are high-impact, low probability events. One definition, embraced by NERC [162], follows. "Resilience is the ability of an organization to resist being affected by an event or the ability to return to an acceptable level of performance in an acceptable period of time after being affected by an event."

The objective of the research described in this section is to build into expansion planning applications the ability to identify design strategies for electric infrastructure, at both T and D levels, to enable improved performance under such conditions. There are five key concepts to this work:

1. *Severe events:* Categories and examples of high-impact, low-probability events that drive resilience are as follows:

   a. Natural disasters: When the Katrina/Rita hurricanes occurred in 2005, over 80% of Gulf gas was shut-in, some of it for months, causing electricity prices to elevate well into the following year [163]. When the Maria hurricane caused power interruption in Puerto Rico in 2017, it took almost a year to rebuild the infrastructure [164]. Earthquakes [165], wildfires [166], and tsunamis [167] can have similar impacts. Likewise, geomagnetic disturbances can cause transformer failure and/or low voltage problems, as observed in the 1989 Hydro Quebec event, which resulted in high reactive power draw within transformers, tripping of seven static Vr compensators, and ultimate system blackout for over 9 hours [168].

   b. Cyber-security: A 2016 cyber-attack on a Ukrainian control center resulted in loss of 200 MW of generation capacity [169]; although the limited outage is not considered high-impact, the success of this attack indicates existence of high-impact potential.

   c. Cascading outages: There are many examples of cascading outages worldwide [170]. One of the most well-known of these is the 2003 Northeast U.S. Blackout, which was initiated by three generator trips over a 90-minute period, followed by a slow progression of six line trips over a two-hour period, ending with a fast series of multiple circuit and generator trips over a three-minute period [171].

2. *Event sets for resilience assessment:* A specific event will uniquely influence infrastructure operation, resulting in event-specific impacts and costs. However, there may be infrastructure design features that facilitate good performance across many, and possibly most, types of events. For example, network connectedness (ratio of number of branches to number of nodes) might be such a feature because it creates increased and redundant capacity to allow resource sharing across the network; enhancing it may occur via increasing parallel paths, or, from a higher-level view, using dual-fueled power plants. Identifying such features requires identification of sets that include multiple (~10) high-impact, low probability events, and studying various system features across these events to identify those features that facilitate good system performance.

3. *Resilience-oriented design:* The emphasis on this work is on identification of resilience-oriented design strategies, an emphasis born from the fact that expansion planning is an infrastructure design tool. Thus, we desire to incorporate within expansion planning tools the ability to identify good tradeoffs between cost, investments to facilitate normal operation, and investments to enhance resilience. However, we also recognize that the best resilience policies will be those where design and operational strategies borrow strength from one another.

4. *Operating conditions:* Investments to enhance resilience are identified under extreme event conditions; yet, they must also be competed against investments that facilitate normal conditions. This requires that the expansion planning application represent operating conditions within the decision-horizon to capture both extreme events and normal conditions. To enable the analyst to control the weighting of resilience-related benefits relative to expansion-related benefits, a parameter should be available to weight resilience costs within the objective function.

5. *Resilience upgrades:* Certain expansion investments increase capacity in a way that simultaneously enhances resilience. However, some resilience upgrades do not enhance expansion. This is because resilience is also improved by the ability of equipment to resist degradation. For example, transmission structures may be strengthened to reduce their failure probability during hurricanes, an action that enhances resilience but adds no capacity. This creates two problems that must be addressed within an expansion planning application. The first problem is that the resilience improvement must be characterized in a way that will enable cost reduction within the expansion planning application. Continuing with the example of upgrading transmission towers, this could be done by representing line capacity as a function of its outage probability, i.e., $C_k=(1-p_k)C_0$. Here, C_0 is the line's normal capacity, p_k is the line's outage probability (for the given event) when it is upgraded to resilience level k, and C_k is the line's capacity when it is upgraded to resilience level k. The second problem is that the relationships between resilience improvements and their characterizations within the expansion planning application are typically better-developed external to the expansion planning application. For example, fragility curves for a failable component relate a physical parameter such as wind-speed to the component's failure probability; different resilience upgrades result in different fragility curves. The availability of a wind speed distribution corresponding to the particular extreme event being modeled enables computation of failure probability through a Monte Carlo simulation.

R&D Issues on Resilience

There are three main R&D issues associated with representing distributed energy resources in EP applications, described as follows.

1. *Event-set composition:* The analyst must select a portfolio of specific extreme events to drive resilience evaluation. There is a need for developing criteria and guidelines for making this selection.

2. *Investment modeling:* Addressing resilience within expansion planning is of interest because expansions influence operational costs during both normal conditions and those conditions that result from extreme events (if this were not the case, the two problems should be addressed separately). Assets that provide benefits under normal conditions provide additional capacity, either for generation, transmission, or distribution. These assets may also provide benefits during extreme conditions. There are also assets that provide benefits only during extreme conditions; these are assets that decrease component failure probability during the extreme event but provide no additional capacity, e.g., replacing or reinforcing transmission or distribution line structures (e.g., new or additional guys) or strengthening support structures (stronger crossarms and insulator strings). There is an R&D need for identifying such resilience enhancements for each type of extreme event, to identify expansion options that benefit both conditions, and to ensure that the modeling effectively captures the benefit of each expansion.

3. *Extreme-event modeling:* Making investment decisions dependent on decreasing operational costs during both normal and extreme conditions requires that both sets of conditions be represented within the same optimization problem. There is an R&D need to develop this representation. One approach is to represent one year within the decision horizon as a year during which one extreme event occurs, an approach where the number of "extreme event years" equals the number of events in the extreme event set. This approach may inappropriately de-emphasize

normal conditions. Another approach is to identify a single year as an "extreme-event year" and repeat that year within the optimization for each event in the extreme event set. The availability of a parameter μ to vary the weighting on costs related to extreme events is important, to enable the analyst to shift emphases between investment benefits during normal conditions and investment benefits during extreme conditions.

Section 12: Performance Evaluation

Performance Evaluation Framework

An expansion planning application identifies future system expansions to minimize overall costs while satisfying constraints on operations, investments, and environmental impacts. Because the plan is generated within an optimization framework, it is assumed to be optimal, or at least good, and it will perform well subject to the conditions (including uncertainties) under which it was produced. Because of the EP computational intensity, those conditions must necessarily be limited. For this reason, we desire a computationally inexpensive way to test and evaluate a plan, and to compete one plan against another, under conditions independent of the ones for which each plan is generated. In effect, we need a sort of "virtual lab bench" on which we can experimentally test each theoretic (computed) plan, i.e., we need a fair and objective way to evaluate plan performance.

Considerations for Performance Evaluation Tools

There are six main concepts that should underlie the development of a performance evaluation tool:

1. *Out-of-sample conditions:* The tool must have the ability to expose the plan to a wide range of conditions, at least some of which were not modeled in the development of the plan.
2. *Monte Carlo simulation:* The tool should be able to automatically repeat the evaluation, so that each repetition exposes the design to a different set of out-of-sample conditions. If the out-of-sample conditions are generated based on distributions associated with the uncertainties, this becomes a Monte Carlo simulation.
3. *Recourse:* The tool should have an ability to apply a form of recourse if the plan is infeasible under the particular conditions to which it is exposed. Perhaps the most common recourse function is load shedding; however, load shedding by itself may not serve as a realistic recourse option under particularly severe, long-term conditions for which further investment is necessary. Therefore, it may be preferable for the tool to provide two kinds of recourse: load shedding and rebuilding. The tool should have the intelligence necessary (perhaps through an optimization function) to choose from among the recourse functions, depending on the conditions encountered.
4. *Lead-time:* The amount of lead-time necessary for a reinforcing/rebuilding is important because it determines the extent to which load shedding will serve as the (short-term) recourse function. There are two important years associated with implementation of lead-time: decision year d, and operational year o. The decision year d is the year the decision to reinvest is made. The operational year o is the year the reinvestment first becomes operationally available. With lead time l as the time required after the decision year before the reinvestment becomes operational (lead-time includes construction time), the operational year is given by o=d+l. During years between the decision year and the operational year, recourse may be necessary, and if so, load shedding becomes the only recourse option. Although zeroing lead-time is unrealistic, it significantly reduces the need for load shedding.
5. *Performance measure:* The performance measure for each plan, exposed once to a single set of out-of-sample conditions, is total cost, including revenue requirements of the original plan (the plan being evaluated), the costs of any new assets, and the operational costs throughout the decision horizon including any load-shedding cost. The performance measure for each plan, run as a Monte Carlo simulation, is the average costs over all runs.
6. *Computational speed:* To enable multiple out-of-sample exposures (and thus the Monte Carlo evaluation), it is essential that the tool have low compute time. This goal is achievable because each exposure is a single trajectory through time, i.e., each exposure need not account for multiple scenarios. Thus the compute time for a single exposure is equivalent to that of a deterministic evaluation.

Folding Horizon Simulator

A performance evaluation tool was developed and reported first in [172] under the name of folding horizon simulator (FHS) and then was further developed in [94]. Figure 12-1 is a flow diagram of one FHS iteration. In each iteration, a *T*-year trajectory of global uncertainty realizations is obtained via two-state discrete time Markov chains. To decide whether the design needs reinvestments to the circumstances proposed by the Markov chain, a robustness test is performed by simulating multiple times a production cost model (plus constraints that depend on the global uncertainty realizations) using random data generated from realizations of local uncertainties. This test reduces the cost of the final plan since reinvestment might be unnecessary when the design passes the test. Success or failure is determined by the expected energy not served percentage, which we define as the expected ratio between the total energy not served and realized energy demand. When the test is not passed, a single period planning model is run to determine both reinvestments needed and their corresponding cost. Since reinvestment decisions are implemented, the initial plan has partially changed and therefore must be updated. This recursive updating process is known as folding horizon. The system is exposed to different Markov chain trajectories so as to get stable statistics related to the reinvestment cost. Markov chains are used to model the evolution of each global uncertainty.

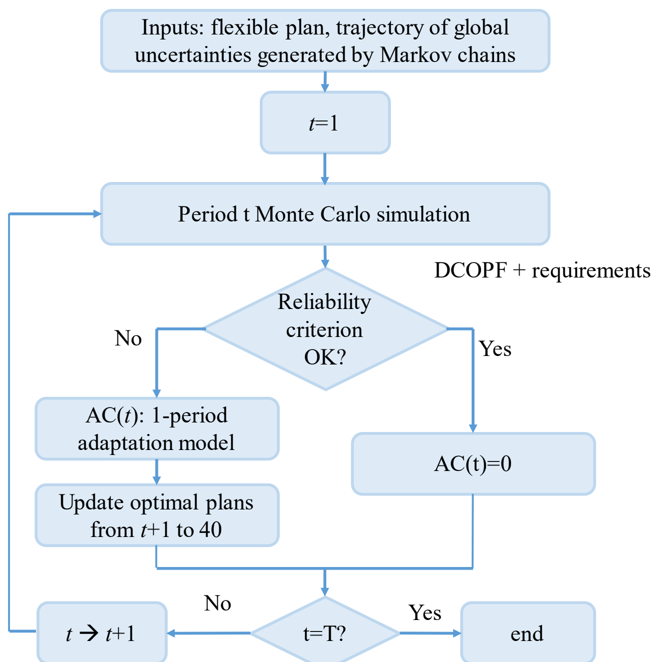


Figure 12-1
One FSH iteratio

R&D Issues on Performance Evaluation

A central R&D issue regarding the FHS is the determination of the best reinvestment strategy and the use of the load shedding cost. There are two issues:

1. Robustness indicator: As an indication of the robustness of the plan, should the load shedding cost be used or the reinvestment cost or both?
2. Backward or forward reinvestment: Should the reinvestment to correct the load shedding violation be made for the year in which the violation occurred (a backward reinvestment) or the following year (a forward reinvestment)?

Efforts in [140] used both the load shedding cost and the reinvestment cost as indicators of robustness, and it implemented a backward reinvestment step. R&D should take place to compare this approach with one that uses only the reinvestment cost as the robustness indicator, where the reinvestment cost is performed backwards in one case and forwards in another.

Section 13: Conclusions

This report has investigated and summarized state-of-the-art methods and tools to perform coordinated expansion planning (CEP), as well as the required R&D agenda that can further the maturity of these tools. This research can serve to bring the CEP software application to a maturity level to enable their day-to-day use. The research on CEP methods and tools is itemized in different research thrusts, and the main conclusions are as follows:

1. The need and advantages of CEP models are demonstrated through comparisons of co-optimized frameworks against conventional static reactive approaches as well as iterative transmission-generation methods. It is shown that CEP models are able to capture expansion alternatives that are more cost-effective than those attained by the static or iterative approaches. The relevance of CEP models as well as potential concerns are discussed for both centralized and unbundled plannng environments.
2. The presented CEP methods and tools are designed to respond to the ever-changing nature of power systems. That is, these tools acknowledge the need for increased temporal and spatial granularity in their scheduling model. This is in order to capture flexibility needs and services in systems with deep penetrations of renewable energy sources, as well as storage devices. While non-chronological models are less computationally intensive, they could fail to capture relevant temporal behavior. On the other hand, chronological models are more accurate but at a greater computational expense. Between these two extremes, the most suitable model needs to be chosen for the system to be explored and its expected futures.
3. This report also identified the factors and their attributes that affect computational intensity. Additionally, the methodological, algorithmic, and technical (e.g., hardware) dimensions of decreasing computational intensity are discussed.
4. The models used to represent transmission investment in CEP models are presented. Also, given the differences in the horizon for transmission & generation investments, and the scheduling of the system; a method that reduces temporally and spatially the system to run the CEP, and then performs detailed assessment of system operation on the full system model is presented. The model changes from a reduced version to a full version on a cyclic fashion, for a desired time step. This cyclical reduction and expansion of the model method increases the accuracy of the solution while keeping the complete formulation tractable.
5. With the emergence of new technologies and distributed energy resources (DER), it becomes necessary to model distribution grids with greater granularity. Since DER and the capacity expansion of the low voltage grids could offset or distort the needs for large-scale generation and transmission, a method that explicitly represents the desired depth on feeders and segments is proposed, in which the effect of these in the expansion plans of the system is captured.
6. The impacts of market failures are identified for the cases in which CEP operates in unbundled systems. Focus on cases in which energy prices are driven downwards by zero marginal cost generation and scarcity and reliability services pricing is explicitly considered. The lack of a robust market for long-term capacity commitments could also be considered by means of long-term auctions facilitated by the CEP process. Other implications of market failures for CEP are also considered.
7. Modeling global and local uncertainties is fundamental for planning purposes. By explicitly modeling global (i.e., long-run) uncertainties, the planner is considering possible recourse actions that could be used to accommodate deviations from the expected outcomes, minimize expansion costs, and avoid expensive mistakes. The deterministic models lack this capability, and the use of such models could mean that adaptations to deviations from forecasts will be significantly more expensive. Meanwhile, modeling local uncertainties (i.e., short-run) allows investing in technologies that are agile enough to provide the required system flexibility. This is becoming crucially important as the penetration of renewable energy sources (RES) deepens.

8. Power systems are increasing their share of renewable generation over time. The primary energy carrier (e.g., wind, solar irradiance, etc.) for these resources intrinsically depends on weather. Thus, accurately capturing the behavior of these resources, as well as the impact of climate change on planning horizons, is important to determine the actual power production of these resources as a function of time and location. Similarly, load and the performance of thermal generation exhibit a high dependence on weather. These variables should be captured at adequate temporal and spatial levels of granularity.

9. The electric system is increasingly interdependent with other systems (e.g., gas, water, and transport, among others). In order to attain globally efficient expansion plans for the combined sectors, coordination is fundamental. The CEP should therefore extend its scope to capture the impacts of its expansion plans on other sectors, as well as how its performance is affected by the expansion plans of other sectors. In the long term, coordinated expansion planning across sectors may be beneficial and/or necessary.

10. Resiliency is a fundamental design factor to be considered in power systems. This includes the ability to respond to various human-driven or natural events. These have consequences in power grids that go beyond credible contingencies, and therefore it is necessary to design a system that can operate and recuperate from these events easily. This is fundamentally a new line of research in power systems operation and planning.

11. Given an expansion plan, its performance needs to be evaluated considering out-of-sample conditions. These include both short-run operating conditions and long-run scenarios that are not considered in the planning model. Evaluating these would allow determining the quality of the expansion plan to implement recourse actions and accommodating to new conditions, as well as the lead-time for its implementation. Different metrics including adaptation cost, revenue requirements, and operating cost over the horizon are considered to determine the quality of the plans. Ideally, these performance assessments should be fast in order to explore multiple out-of-sample exposures.

EPRI will use the findings of this report to support development of long term research in this area, focusing on the above points. Next steps include detailed examination of existing toolsets, in order to identify gaps for future work, as well as case studies demonstrating various CEP methods.

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