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Co-optimization of Transmission and Other Supply Resources

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Co-optimization of Transmission and Other Supply Resources

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and

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EXECUTIVE SUMMARY AND RECOMMENDATIONS

ES-1. Overview

The purpose of this report is to describe and explain the benefits of using co-optimization for power system generation and transmission planning. Co-optimization models are computer-aided decision-support tools that search among possible combinations of generation and transmission investments to identify integrated solutions that are "best" in terms of cost or other objectives while satisfying all physical, economic, environmental, and policy constraints.

We review the state of the art in power system expansion planning tools including existing co-optimization models. We also summarize data and computational requirements of co-optimization models, specify design choices to be made in developing them, and describe methods for their validation. Three case studies illustrate potential applications and associated results of co-optimization and its benefits relative to planning approaches that optimize generation alone or transmission alone. Methods to address short-run resource variability and long-run uncertainties within co-optimization are described in some depth, given the centrality of these topics in planning for the future. Institutional concerns regarding co-optimization are explored, including confidentiality, public domain access, and potential roles of states.

Two central findings are as follows. First, co-optimization is useful where power utilities are vertically integrated because it identifies less costly solutions by considering the tight interactions of generation and transmission. Second, co-optimization is also useful within unbundled environments because it facilitates exploration of how generation dispatch and investment will respond to changes in transmission capacity, access, and congestion. This helps planners to identify grid reinforcements that encourage generation siting decisions that yield the lowest overall cost of power production and delivery. Co-optimization also facilitates integrated and simultaneous assessment of all planning alternatives, including supply-side options (bulk and distributed generation and storage), demand management, and transmission, so as to identify the most economically and environmentally efficient combinations.

Our findings imply that co-optimization is likely to be highly useful for system expansion planning, particularly within the Eastern Interconnection (EI). This is particularly important given the large transmission investments that are anticipated to promote interregional power trades and renewables integration. In the near term, there is immense value to applying research-grade co-optimization tools to the EI or its subsystems. Such studies would be highly beneficial because they would (1) further illustrate the benefits of co-optimization for industry-sized systems; and (2) facilitate exploration of several model design issues, including treatment of uncertainty and deployment on high-performance, paralleled computers. In the longer term, consideration should be given to developing commercial co-optimization applications that would incorporate operational constraints and variability to enhance model fidelity while conveniently interfacing with existing and newly developed data repositories.

ES-2. Definition

We recommend use of the following general definition for co-optimization in this document.

> *Co-optimization is the simultaneous identification of two or more classes of investment decisions within one optimization strategy.*

Here, "*classes of investment decisions*," in the context of electric systems planning, almost always include decisions to build generation and transmission. But they may include other types of decisions as well, such as demand-side solutions, decisions to install storage, or building of natural gas pipelines. "*One optimization strategy"* may consist of a formulation to solve a single optimization problem (e.g., minimize cost subject to constraints) or it may consist of a formulation to solve an iterative series of optimization problems (i.e., sequential yet coordinated generation and transmission planning).

The above definition is tool-focused; it refers to the operation of a particular kind of computational method. But it must be understood in the context of the planning process in which it is used. If co-optimization is used by a vertically integrated utility, then its main result is the identification of joint transmission-generation expansion plans that are lower in cost than expansion plans would be if transmission and generation plans were developed separately. However, co-optimization can also be used within used in utility regions that are no longer vertically integrated (unbundled) and where planning for transmission infrastructure is performed by one entity while planning of other classes of investments (e.g., generation) is performed by others. In particular, co-optimization is likely to be highly useful in an unbundled environment in which transmission infrastructure planning is separated from generation investment. In this case, the process in which co-optimization is used might be called "*transmission planning accounting for market response*" or "*anticipatory transmission planning*." Key results of co-optimization computations would include not just how generation dispatch and grid congestion would be affected by alternative network configurations, but also ultimately how availability of transmission could incent changes in generation mix and siting decisions. Because transmission investments usually (but not always) have longer lead times than generation, it is appropriate for transmission planners to anticipate how alternative network configurations will affect the attractiveness of different locations for plant siting, and the resulting effects on costs, prices, and emissions.

Thus, to complement the above general definition of co-optimization, we also define a second term that reflects the nature of the many planning processes under which co-optimization could be usefully applied:

Anticipatory transmission planning is a use of co-optimization to evaluate network investments while considering how generation decisions, both dispatch and investment, will respond to changes in transmission capacity, access, and congestion.

Therefore, co-optimization can benefit the planning processes of states and Planning Coordinators regardless of market structure or regulatory regime. That is, no matter whether the power industry is vertically integrated or unbundled, co-optimization can be an effective tool for states and Planning Coordinators to better understand various risks, benefits and costs when assessing resource options, and to identify improved integrated solutions.

ES-3. Benefits of Co-optimization and Anticipatory Transmission Planning

Co-optimization is a systematic approach to address critical questions in planning. One such question concerns the fundamental tradeoff that exists in many places between transmission investment and quality of renewable resources. In particular, how much transmission capacity would be needed to economically and reliably deliver the energy produced by remote high quality variable renewables, or is it more efficient to develop less efficient resources nearer to load centers? As another example, is it more economical/reliable to invest in remotely located large-scale thermal or hydro generating stations and provide long distance HVDC/AC transmission for power delivery, or would it instead be less costly and environmentally damaging to invest in locally distributed and variable generation resources in highly congested regions with limited availability of transmission right of ways?

Another such question concerns the diversity and flexibility value of linking power systems and markets. How much thermal generation capacity would be needed to reliably operate a power system with significant amounts of renewable energy? By more closely linking geographically separate markets, how would transmission investment increase the diversity of resources and thereby increase the capacity value and reduce the ancillary service requirements of the renewable resources? How much operating and planning flexibility do additions of transmission capacity provide, and how can that be compared to flexibility from traditional generation sources?

A final and crucial planning question concerns interaction of transmission and generation with emerging resources. For instance, how much generation and transmission capacity could be saved at the planning stage by more aggressive demand-side management and demand response programs?

In this report, we illustrate the use of co-optimization models to answer these questions by comparing co-optimization with more traditional generation-only or transmission-only planning processes in a series of case studies. One group of case studies considers simple three to four bus examples that transparently illustrate how co-optimization reduces cost. Other case studies are based on a thirteen-region representation of the US power sector, and quantify the benefits of co-optimization of inter-regional reinforcements under various scenarios concerning renewable energy policies and technology developments. Through these examples, we have documented how co-optimization can lower the total cost of electricity provision through:

1. savings of transmission and generation investment and operating costs;
2. more efficient decisions concerning generation retirements and uprates;
3. more appropriate treatment of variable resources;
4. efficient integration of non-traditional resources such as demand response, customer-owned generation, other distributed resources, and energy storage;
5. fuel mix benefits;
6. improved assessment of the ramifications of environmental regulation and compliance planning; and
7. reduced risk and attendant effects on resource adequacy and costs.

The simple examples show how co-optimization can yield a more balanced and economic mix of resources compared to transmission-only planning (transmission expansion subject to a fixed scenario of generation investment) and generation-only planning (generation investment subject to a fixed network). Generally, the lowest cost solution results from a combination of transmission and generation investments, and considering only one or the other results in unnecessarily higher costs and emissions, and perhaps even a deterioration in reliability. The interactions between plant siting and transmission routing decisions can be complicated and surprising. Sometimes investments in transmission defer the need for new generation capacity investments, while in other situations, development of costly local generation is preferred to building cheaper or more efficient generation in remote locations plus the transmission necessary to access it. These phenomena can occur on radial networks, and become even more complex on looped grids, even for our three to four bus examples.

In our national applications, we find that, under some assumptions about renewable technology and cost developments, full co-optimization can save up to 10% or more of total generation and transmission costs compared to generation-only planning, and 5% or more compared to transmission-only planning given an assumed fixed pattern of generation investment. These savings are larger in magnitude than the transmission investments themselves, demonstrating the critical role of transmission in economically integrating renewable energy. The savings occur because co-optimization can result in appreciably different patterns of investment than generation- or transmission-only planning. The results show that the most profitable locations for renewable and nonrenewable plant investment strongly depend on where grid reinforcements are made. Differences of 50 GW or more in regional capacity expansion are sometimes found. Conversely, the cost-minimizing transmission investments are very different if a fixed scenario of generation expansion is assumed than if possible shifts in generation siting in response to transmission additions are considered.

The examples also illustrate two different types of co-optimization. The most efficient (but computationally challenging) type considers generation and transmission investment simultaneously. The other iterates, first expanding generation with a fixed grid (generation-only), then second expanding transmission given the first generation expansion solution (transmission-only), then back to generation-only, and so forth. We find that compared to generation-only planning, the iterative process can reduce costs quite significantly. However, after five iterations, this process yielded a plan for expanding interregional transmission in the US that is still $22 billion more expensive (present worth of generation and transmission costs) than the co-optimized plan, a difference of 1.3%. By comparison, the amount of transmission investment in the Eastern Interconnection in 2012 was approximately $3 billion, an amount that is expected to grow significantly in coming years.

That application also illustrates a major benefit of co-optimization. Full co-optimization spent approximately $60 billion more on transmission, but saved $150 billion (in present worth) compared to a solution in which generation was first planned, and then transmission was planned to deliver that generation. That is, there was a 2.5 benefit/cost ratio for the incremental transmission investment. Forty percent of the generation cost savings were derived from reductions in generation capital costs from more efficient generation siting and mixes, and 60% were variable cost savings. Thus, traditional transmission planning processes, which do not consider changes in generation siting and capital costs, miss a potentially very important benefit of transmission.

ES-4. General Recommendations on Model Development and Demonstration

Because of the many benefits of co-optimization that we have illustrated and quantified with our simplified models, we recommend that EISPC initiate efforts to develop a co-optimization tool for long-term electric systems planning. Although various research-grade co-optimization tools already exist, none have all of the features necessary to satisfy the long-term needs of the EISPC. We expect that the benefits available from such a tool would far outweigh the costs of developing it.

As an initial step, we also recommend that one or more Planning Coordinators or States collaborate with a research group to apply an existing co-optimization tool using detailed data from their region to quantify the benefits of co-optimization in a realistic setting. Such a study would reveal more precise estimates of co-optimization benefits than are possible from our simple three and four bus examples and US model. The study would also provide more information on the effort required to apply co-optimization, and on the insights that could be obtained.

ES-5. Recommendations on Tool Design

Development of a co-optimization tool that can be used in an actual planning setting requires a number of design decisions. These decisions often involve choosing between model fidelity (realism) and computational intensity. The following summarizes the most critical of these design decisions as well as our recommendation in each case.

1. *Pre-processing step:* We recommend a pre-processing step be included that would prepare data for input to the co-optimization tool. There are a number of functions that could be included in this pre-processing step, but the most important of them is identification of candidates for new transmission circuits that the co-optimization tool should consider.
2. *Co-optimization solvers:* The co-optimization tool should avoid use of nonlinear optimization solvers and instead rely on highly efficient linear continuous optimization solvers and/or linear mixed-integer optimization solvers. Nonlinear solvers cannot handle as large of a problem, and take longer to execute.
3. *Network model:* There are three choices for a network model, AC-flow, DC-flow, and transportation ("pipes-and-bubbles") flow. Of these, we recommend use of the DC-flow network model as it provides good fidelity for MW flows for a modest computational burden.
4. *Resource and transmission options:* The co-optimization tool should allow for selection from multiple resource and transmission technologies. Resources should include fossil-based and renewable-based generation, demand-side technologies, and various types of storage. Transmission technologies should include both AC and DC lines, each at multiple voltage and capacity levels. AC transmission capacity should be modeled as a function of distance between substations having voltage control equipment. DC transmission should include technologies employing line-commutated (thyristor-based) converters and technologies employing voltage-source converters. Simple demand response programs, such as critical peak pricing or peak-time rebate programs, can be practically and realistically modeled as programs that trigger an amount of demand reduction if price exceeds a threshold.
5. *Multiyear representation:* The co-optimization tool should have the ability to represent a given time frame (e.g., 20 years) as a sequence of multiple periods (such as 2 years) such that optimal timings can be identified for each investment.
6. *Policy representations:* There are many policies that profoundly influence power sector investment decisions. These include environmental policies on the federal, state, and local levels that address air pollution, once-through cooling, facility siting, and greenhouse gasses; market design features, such as capacity markets and regulatory preferences and incentives for particular resources; and the effects of regulatory policies on the attractiveness of transmission investments considering rate-of-return regulation and, in special circumstances, merchant transmission. Because of their profound effects, these policies should be explicitly represented in co-optimization models.
7. *Outputs:* The tool should not only identify economically and environmentally attractive near-term investments in transmission, it should also provide information on prices and costs, and their distribution among regions and market participants. This can be helpful in

understanding where generation siting would be most attractive, and who benefits from transmission expansion. Because users and stakeholders will have many objectives, such as lower power prices, emissions, regional job creation, and fuel supply security, another design decision is what objectives should be optimized. A co-optimization tool could be designed to have more than one objective function, and thereby be used to identify a set of solutions that represent a range of tradeoffs among objectives. This tradeoff information could inform negotiations among the interests involved in transmission planning, and so multiobjective capabilities should be built into co-optimization models.

In addition to the above decisions concerning tool design, there are several other considerations that will become increasingly important in the future, and should therefore receive consideration both in designing new co-optimization methods and in research on the topic.

1. *Handling uncertainty*: The past four decades shows that power system planning is subject to profound long-run uncertainties in policy, technology, fuel costs, and load growth, and that surprises are sure to be in store for power system planning in the future. It is possible to conceive of uncertainty in terms of parametric uncertainty around an expected value (local uncertainty). For instance, one might expect 1% demand growth ±0.5% over the next 10 years. Uncertainty can also be conceived in terms of dramatic shifts that significantly change the future (global uncertainty), for instance, we might expect natural gas prices to rise to only $7/MBTU over the next 20 years, or we may expect natural gas prices to rise to $15 over the next 20 years, or a policy change may occur related to certain resource (e.g., nuclear). It is possible to develop co-optimization tools that handle both types of uncertainty, but at a significant increase in computational burden.
2. *Value of transmission expansion:* The co-optimization tool should be able to assess all categories of benefits that transmission brings. These include (a) energy market efficiency enhancement; (b) ancillary service market efficiency enhancement; (c) emissions reductions; (d) increased network integrity (or "insurance" value) for multi-element contingencies; and (e) enhanced competition in bulk power markets.
3. *Generation flexibility*: Some RTOs recognize the need to explicitly incent operational flexibility. As renewable penetration increases, this issue will grow in importance. Therefore, co-optimization should include the ability to impose flexibility (e.g., ramping capability) requirements on resource portfolios as a function of net load variability. Modeling operational reserve requirements and proper modeling of the costs of fossil-fuel unit cycling would need to be considered.
4. *Transmission operations*: In theory, a co-optimization tool could consider operational issues such as system dynamics, reconfiguration, switching, right of way and voltage support, whose implications for planning may become more important in the future.
5. *Multi-sector modeling:* The electric system influences and is influenced by the performance of other infrastructure systems. Among these, the natural gas pipeline system is today perhaps the most consequential, but the passenger transportation system

will become more influential as it becomes more electricity-dependent. Including the ability to represent interdependencies between these other infrastructure systems and the electric system is likely to be important in the future.

6. *Advancements in computational efficiency:* Even a conservatively-designed co-optimization tool is computationally demanding. Developing a co-optimization tool with the ability to run on high-performance parallel computers will be very useful. Advanced optimization/decomposition algorithms could facilitate the consideration of long-run uncertainties as well as a greater range of load and renewable operating conditions. One particular aspect of co-optimization modeling that could benefit from such advancements is the treatment of operational constraints and variability. Current models usually focus on the "big picture" of expansion planning without including a great deal of operational details. This is in part necessary because of limitations in the size of models that present solvers and computers can handle. However, as computation capabilities improve, larger models with more realistic operations become possible. The need for better operations models is also driven by the deployment of smart grid technologies such as demand response, microgrids, and electric vehicles, which mean that the operations of the future electricity power systems could be very different from today. Improved representations of operations could also include unit commitment considerations or storage optimization.
7. *Market structure:* Although the deregulation process of electricity market began long ago, the market is still not fully deregulated. The current status quo is that vertically integrated regulated utilities and unbundled deregulated markets exist side by side. The implications of their co-existence for co-optimization, especially of interconnections between different systems, need to be better understood.

The first issue, that of uncertainty, receives particular attention in this report. Traditional planning methods have typically applied simple and ad hoc methods to address power system uncertainties. These methods have served the industry relatively well in the past. However, the industry is increasingly challenged by the needs to address a large number of new issues, including the growth of distributed power systems, uncertainties concerning the location of new energy resources and the retirement of older generators, integration of large amounts of variable energy resources, more dynamic loads, increasingly stringent environmental regulations driving changes to the generation portfolio, and long lead times to construct major facilities. These issues have led to significantly more complex and less predictable power systems and raised the question of whether existing planning methods are adequate. In particular, existing methods cannot quantify the economic value of flexibility and adaptability of transmission plans. As an example, some transmission investments might leave more options open than other investments for resource interconnection in the future because the regions they access might have a larger variety of resources. The option value associated with such flexibility can be important in transmission planning, but is not considered by present planning models, whether co-optimized or not. It is necessary for co-optimization model formulations to explicitly consider multiple future scenarios, and how future decisions might anticipate or adapt to them, instead of simply running analyses on many different scenarios.

ES-6. Data requirements

Co-optimization tools require more input data to run than generation- or transmission-only models alone. Building co-optimization models is a data-intensive task requiring significant effort to collect, maintain and share data without violating network security and organizational confidentiality standards. However, to the extent that the data sets required by co-optimization is more detailed, consistent, and of higher quality than data used by other models, it can also benefit more focused analyses. In particular, the incremental data for co-optimization could potentially facilitate improved analyses of demand response, energy storage, energy efficiency, distributed generation, variable-output resources, capacity additions, uprates, and retirements, capacity degradation, and fuel prices. The benefit of better data for those studies might by itself justify the incremental cost of data for co-optimization planning.

We recommend development of data repositories for use with co-optimization tools, if such tools are developed. These data repositories should include characteristics of existing and already planned infrastructure, characteristics of infrastructure options from which the tool will select, and future conditions.

In developing these data repositories, it is important to capture geographical variability in infrastructure data. There are such variations in (1) availability, quality, and investment cost of renewable resources such as wind, solar, and biomass; (2) investment and fuel expenses for non-renewable resources such as coal and natural gas; and (3) investment costs of electric transmission. These variations should be reflected in the data set. It is precisely these variations in costs over space that co-optimization takes advantage of in order to lower costs relative to traditional generation- or transmission-only planning.

In addition, co-optimization modeling inevitably involves *data aggregation* in order to reduce the model size and computational burden involved in regional infrastructure planning. This implies a need for the various entities involved to share data and identify regional boundaries for resource aggregation (e.g., to account for transfer capacities).

ES-7. Institutional Considerations

A well-designed planning process for generation and transmission that uses co-optimization needs to identify the needs of state regulatory and planning bodies, balance competing objectives of concern to stakeholders (such as cost, reliability, and environmental impact), and help allocate scarce resources among potential investment choices. Our analysis of the institutional issues associated with co-optimization concludes that robust co-optimization-based planning methods, reflecting the interests of local jurisdictions in the region, would likely be more effective in relieving regional transmission congestion and ensuring long-term resource adequacy. Such planning processes should provide a formal role for state governments and thus facilitate active participation by state officials: utility regulators, energy offices, consumer advocates, and environmental regulators, as appropriate to each state. It should also involve consumer and citizen interests as well as market players to guide the planning process. These are requirements under FERC Order 890, and co-optimization tools can facilitate informed involvement by stakeholders in this process.

Another institutional issue is co-ordination across different markets or regulatory jurisdictions. As the discussions over FERC Order 1000 have shown, there is strong interest in coordinating regional planning efforts in order to facilitate integration of renewables and lower the cost of power to consumers. Those discussions also show how difficult it is to achieve such coordination given our federal, devolved system of government and the diversity of institutions involved in planning. Institutional developments under Order 1000 should be followed closely to identify lessons that would be useful for conducting co-optimization studies. Co-optimization tools that encompass multiple regions will yield better estimates of the benefits of coordination of operations and investment across regions, which supports Order 1000's objectives.

A final issue is: who can interact in the planning process that utilizes co-optimization software and associated data? In unbundled markets, it is the case that generation owners are restricted to only the transmission information that is on OASIS and are limited in the communication they can have with transmission operators and planners. But yet co-optimization by definition considers interactions between generation investment and transmission reinforcements. It can be fairly asked: how can the need for separation be reconciled with the need to represent interactions and to have extensive data on both generation and transmission? We believe that the data necessary for informed co-optimization can be obtained and used by transmission processes overseen by utilities, states, and RTOs, but that restrictions on permissible communications will need to be understood and respected in those processes.

1 INTRODUCTION

1.1 Motivation

Optimization models have long been used to aid federal and state government agencies as well as utilities to plan electricity supply and to evaluate the economics of potential transmission investment. While the established practice is to plan supply resources first, and then to plan transmission, assessing both simultaneously to provide an integrated plan is capable of identifying attractive solutions that may not otherwise be considered. Doing so is becoming more important, due to, first, the increasing penetration of variable-output renewable resources, energy storage, distributed generation and demand response, and to, second, the need for interregional energy transfers to take advantage of diverse and remote sources of power. With hundreds of billions of dollars anticipated to be invested in sustainable energy sources and the transmission needed to access them, it is essential that transmission investments are made efficiently.

In particular, to provide better decision support for planners and regulators, planning models are needed that optimize transmission investment while simultaneously considering tradeoffs with investments in electricity supply and demand resources, while recognizing potential bottlenecks in natural gas supplies. In a vertically integrated planning environment, such models could be used for more efficient planning and investment in all resources and transmission, capturing to a greater extent the value provided by transmission [103,18]. In an unbundled environment, these models would instead be used by transmission planners to anticipate how network investments change incentives for the siting and sizing of investments in various types of resources. Recently, advances in mathematics and computer science have made it practical to formulate and solve such models, which are called co-optimization models[1]. Several have been applied for planning and policy analyses.

This Whitepaper demonstrates that co-optimization can produce more economic transmission results than can be achieved with existing state-of-the-art tools. Specifically, the Whitepaper demonstrates that planning transmission without considering how generation and other resource investment could adjust in response to the changed network configuration may result in overall higher costs to consumers. Similarly, this Whitepaper provides examples that lower-cost and greater reliability can be achieved with co-optimization of all resource alternatives.

There are two major reasons why co-optimization is essential in order to maximize the economic benefits and minimize the environmental impacts of transmission system expansion. One is that local generation and demand response can substitute for transmission in meeting future power

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[1] In states where the power sector is unbundled, the term "co-optimization" is a slightly misleading characterization of these models, since the transmission owner would not use such models to optimize resource investment, but instead to simulate the decision process of resource owners.

needs of customers. Thus, transmission reinforcements are not necessarily the least-cost means of meeting those needs (considering both economic and environmental costs). Second, siting of new generation, including renewable sources, is influenced by the availability of transmission, so that different transmission expansion plans will ultimately result in different patterns and even mixes of generation investment. Consequently, the benefits of transmission expansion should consider not only fuel savings resulting from reduced transmission congestion, but also capital cost savings from more efficient generation investment. These fundamental reasons for co-optimization are recognized not only by researchers (e.g., [119]) but also by RTOs/ISOs who mandate consideration of such resource interactions in transmission planning (such as the California ISO [4]).

This recognition of transmission's interaction with other resources has motivated the development of co-optimization methods by researchers and their first applications to important transmission planning and policy problems (such as [44,86,110,124,142,149]). There are no overviews available of these models, although there exist thorough reviews of the formulation and application of generation expansion (e.g., [50, 126]), electricity market models [138], and models for transmission planning (e.g., [83]). However, because of the growing recognition of the benefits for co-optimization and the expanding literature and methods in that area, an overview is needed of approaches to co-optimizing transmission, generation (including distributed and variable renewable resources), loads (including demand response and more traditional demand-side management programs), and/or natural gas pipelines. This White Paper responds to that need. In particular, the purpose of this White Paper is to provide an up-to-date and in-depth assessment of the present and potential capabilities of existing or readily developed co-optimization models relative to alternate transmission planning approaches. The focus of this assessment is on meeting the needs of the Eastern Interconnection States' Planning Council (EISPC) for a public domain model with reasonable data requirements, and an assessment of the potential benefits of co-optimization modeling.

1.2 Scope

This document begins with a review of modeling approaches presently used for resource planning and co-optimization, both implemented and proposed (Section 2), followed by implementation requirements for co-optimization software including data requirements, computing needs, and time requirements for model development and initial validation (Section 3). We next describe the need for, and theoretical benefits of, co-optimization compared to traditional planning methods and provide several illustrative examples which also serve as a basis on which to address validation protocols (Section 4). Uncertainties (such as fuel costs, ramifications of potential environmental regulations, load growth) are large and growing in importance in resource and transmission planning, and should be addressed by co-optimization models. Approaches for doing so are reviewed in Section 5. We then turn to confidentiality concerns and other institutional issues, including the potential role of the states in developing databases and applying co-optimization models, and the advantages and disadvantages of having co-optimization models in the public domain (Sections 6).

The report closes with recommendations for next steps, including in terms of model and data acquisition, model testing, and (if applicable) model improvements (Section 7). The purpose of these recommendations is to help EISPC foster and produce consistent and coordinated direction to the regional and interconnection-level analyses and planning that should benefit not only EISPC members, but all the market participants and electricity consumers, and to meet our nation's long-term electric power needs.

2 REVIEW OF PRACTICE, METHODS, AND NEEDS OF RESOURCE PLANNING MODELING AND CO-OPTIMIZATION

2.1 Introduction

The purpose of this section is, first, to review present practices of modeling for resource planning and transmission planning (Section 2.2). This is background to our subsequent discussion of co-optimization: its definition,

2.2 Review of Practice and Literature of Resource Modeling

Power system expansion planning encompasses generation expansion planning (GEP) and transmission expansion planning (TEP). Power system expansion planning would often consider issues such as when to build, how much capacity to add, what type of generation is needed, and where to locate new facilities. The role of system planners often goes beyond providing a plan with good economic incentives that satisfies reliability requirements. Planners would have to satisfy other objectives and constraints such as minimizing operation and maintenance costs, increasing the resiliency in the system operation, minimizing environmental impacts, and satisfying investment risk constraints.

Where generation and transmission are vertically integrated, generation and transmission expansion studies are carried out by the same entity. It was customary to consider transmission planning cases once a generation expansion plan was set. Two reasons accounted for separate expansion planning studies [140]. First, generation made up the great bulk of investment, typically more than 80%-90%. Therefore solving the GEP problem first by deciding on types of generation investment and then sites, considering general transmission costs among other factors, and subsequently using that generation plan as an initial condition for the TEP problem was an acceptable planning process. It was generally believed, often with justification, that additional cost savings that could be wrung from co-optimizing generation and transmission would be relatively small. For example, when the new generation technology was nuclear or large hydro, severe siting constraints generally dictated the location of plants, and transmission costs were a relatively minor consideration. Many coal facilities were sited at the mine mouth, which also constrained transmission facilities.

However, transmission costs and siting considerations have grown in importance recently for several reasons, increasing the desirability of co-optimization. First, siting and permitting extra high voltage (EHV) transmission lines has only become more expensive and politically contentious. Second, natural gas-fired facilities make up the great bulk of thermal generation investment today; they are less capital intensive, have much more siting flexibility because of the well-established and extensive gas network, and often use dry cooling technologies, so that water constraints are less of a siting constraint. Third, although the best locations for renewable resource development are sometimes just as limited as potential sites for nuclear plants in the

1960's and 1970's, they are more diffused in space with individual wind farms and other facilities being much smaller than nuclear units. It is recognized that the best renewable resource sites in the United States are remote from the largest loads, requiring expansion plans to consider tradeoffs between remote, high-quality resources requiring substantial transmission investment and lower-quality, nearby resources Fourth, industry restructuring has increased the economic incentives for interregional transmission motivated by fuel savings, as consumers, power marketers, and utilities have strong incentives to access the cheapest sources of power, and the benefits of coordinated operation of utilities become more apparent. These benefits can be particularly large when variable renewables make up a very large fraction of new generation, since a greater diversity of type and location of renewable sources will improve the overall availability of renewable energy. For instance, rather than taking advantage of only the best wind resource, in terms of average power, it is optimal to distribute wind development over a large area, even if it means using some lower quality resources, because wind output is not perfectly correlated between different locations.

As a result of these trends, the incentive to consider co-optimizing GEP and TEP has grown, and this incentive would be enormous if it would lead to even a very small savings in power system planning and operation costs. However, co-optimized GEP and TEP problems posed significant computational challenges; computer resources available to planners before 2000 were incapable of supporting the solutions of co-optimization models. Fortunately, recent advances in computation methods have provided satisfactory solutions to co-optimized GEP and TEP problems with reasonable computation times, so now realizing savings by using co-optimization is a real possibility.

In this section, we review classic and widely applied methods for generation expansion planning (Section 2.2.1), after providing background on the context of generation expansion. These, together with the transmission planning methods discussed in Section 2.2.2, provide the foundation for true co-optimization. In Section 2.2.3, some of the literature and methods of co-optimization are reviewed as background for the more detailed consideration of specific co-optimization methods in Section 3. In that section, we differentiate between national and large regional models that are used for policy analysis and assessing the economics of large interregional power transfers, and more focused and detailed transmission planning. The former use aggregations of the grid, while the latter usually represent individual circuits.

2.2.1 Generation planning models

2.2.1.1 Introduction: The changing needs for generation investment models

Models for generation expansion planning were one of the first applications in the 1950s. Linear programming is method of optimization in which the values of the decision variables are chosen to maximize or minimize a linear objective function subject to linear equality and inequality constraints that define what values of the variables are feasible. Early proposals for co-optimization models, based on linear programming of simplistic "pipeline" (transshipment) models, were featured in a standard electricity economics textbook [133]. At the same time, dynamic programming formulations of generation capacity expansion models were popular (for instance, the IAEE's WASP [141]). Dynamic programming is a type of optimization algorithm that finds optimal solutions by considering a sequence of easier problems.

The clients for these generation planning tools were publicly and privately owned vertically-integrated utilities whose planning decisions were subject to various degrees of state and/or federal regulatory oversight. Utilities adopted these models as means of responding to questions received in the regulatory process, while intervenors used them to challenge the data and conclusions of utility studies. The tools became increasingly elaborate through the 1980s and the Integrated Resource Planning era of the 1990s [38]. For instance, they expanded the range of resources considered from traditional thermal plants to include intermittent renewables, storage, energy efficiency, and demand response.

However, the restructuring and unbundling of the power industry since then has shifted the focus from comprehensive planning of the entire system to focused financial analyses of the risks and cash flows of individual generation investments. The generation investment problem is now more complex in several ways. First, the planning problem is exposed to much more uncertainties in input data, such as load forecasts, price and availability of fuels, construction lead time, economic and technical characteristics of new generating techniques, governmental regulations, and transmission. For example, not only is the future load level uncertain, most generation companies nowadays cannot take their market share for granted as the result of competition with other generators as well as other independent power suppliers. Second, in the planning process several conflicting public and private objectives must be addressed. Objectives could include maximizing profit, maximizing system reliability, minimizing emissions of greenhouse gases, or minimize investment risks. These objectives are likely to conflict with each other. Third, large scale integration of renewable energy will have a profound impact on the economic, environmental, and perhaps reliability performance of future system operations, which requires new tools for production cost simulation and reliability evaluation. Fourth, as the result of increasing competition, interregional trade makes up an increasing fraction of supply in many regions, and so needs to be represented in planning models. Fifth, the changed market structure alters the way that generation owners evaluate investments. In the deregulated system, vertically integrated utilities get a pre-determined rate of return on the authorized rate base, subject to prudency reviews by regulators. In the electric market, the generation owner (GenCos) bear the risk of uncertain energy, capacity, and ancillary services revenues from the electric market as well as fuel and construction cost uncertainties. So for deregulated generators, the objective of generation expansion planning shifts from minimization of (production cost + investment cost) to maximization of (generator revenues – investment cost).

However, even where the power sector is completely unbundled, integrated models that comprehensively consider the mix and amount of generation investment in region still play an important role in policy analysis and transmission planning. Policy makers use integrated models to simulate how the generation market might react to changes in regulation, technology, or economic conditions, while infrastructure planners use them to project the benefits and costs of transmission investment. Because many co-optimization models can be viewed as extensions of traditional generation capacity planning techniques, we next review models used today to analyze the potential configuration and performance of generation systems.

2.2.1.2 Overview of generation expansion planning models

The classic generation expansion planning (GEP) problem is defined as the determination of the best size, timing, and type of generation units to be built over a multi-decadal planning horizon, to satisfy anticipated load growth. The investment criterion was normally minimization of the sum of capital investment and operation costs subject to various constraints. A generic form of the GEP problem is as follows:

Minimize the discounted sum of future investment and operating costs

Subject to:

> Total Energy production of all units = Demand for each time period in each year
>
> Unit energy production ≤ Unit capacity for each generating unit, in each time period in each year
>
> Loss of load probability ≤ LOLP requirement in each year

The user must input assumptions about how load, fuel costs, efficiency, and technology availability change over time. The result is a schedule of generation additions over the years y, and estimates of dispatch costs in each period t in each year. Even though this schematic formulation disregards important considerations such as transmission, unit commitment constraints, and environmental restrictions, it does address the major questions of cost, fuel choice, technology and system reliability.

A high level description of the generation expansion procedure is illustrated in Figure 2-1, which describes a process in which separate reliability and production (operating) costing models are used to evaluate proposed portfolios of generation assets. The above optimization problem can be viewed as the integrated and automated consideration of a wide range of generating unit sizes, types, and timing, including consideration of investment and production costs and reliability, resulting in the recommendation of a plan that minimizes the cost objective and meets all constraints.

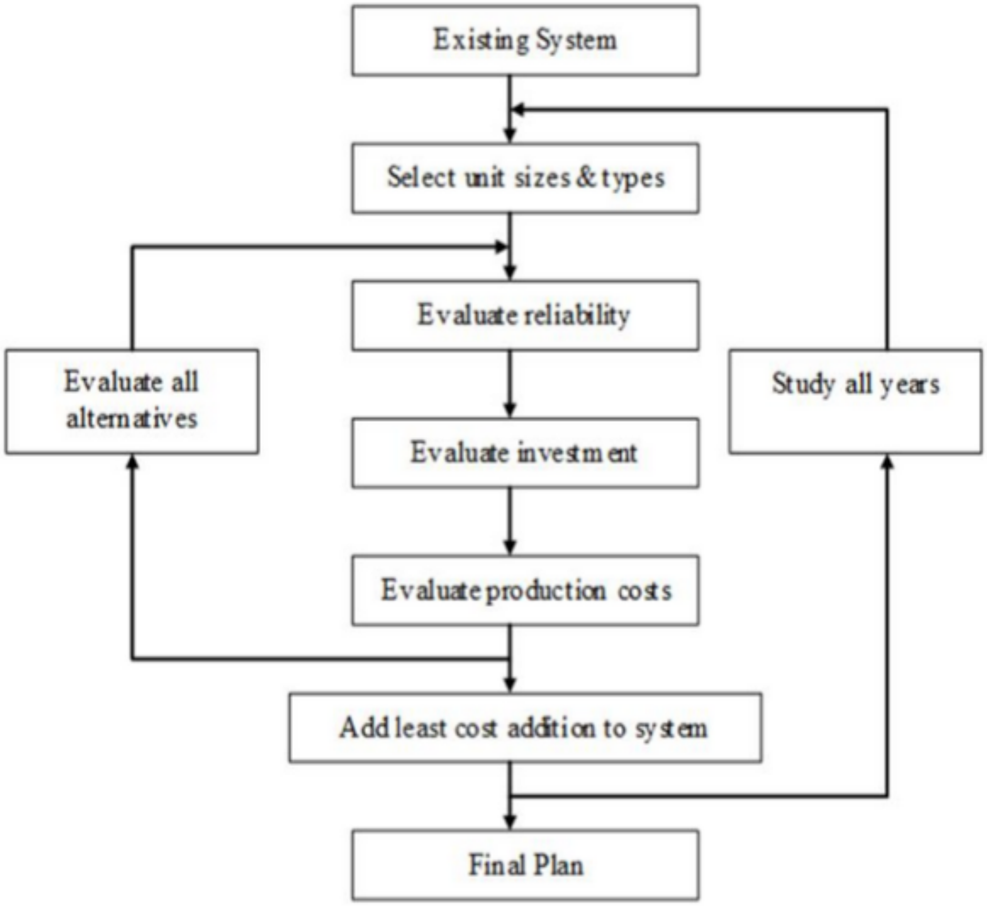


Figure 2-1. Generation expansion planning procedure [126]

Generation expansion planning is a challenging problem because of the large-scale, long-term, non-linear, and discrete nature of generation investment. Many commercial-grade system planning tools have been developed that differ in terms of solution algorithm, formulation of operating sub-problems, modeling granularity, and numerous other features. There are three main types of planning tools for generation capacity expansion: reliability, production costing, and resource optimization, as shown in Figure 2-2. Specific examples are summarized below. The focus of the present report is on optimization methods, since they are the basis of the co-optimization models we describe and apply elsewhere in the report.

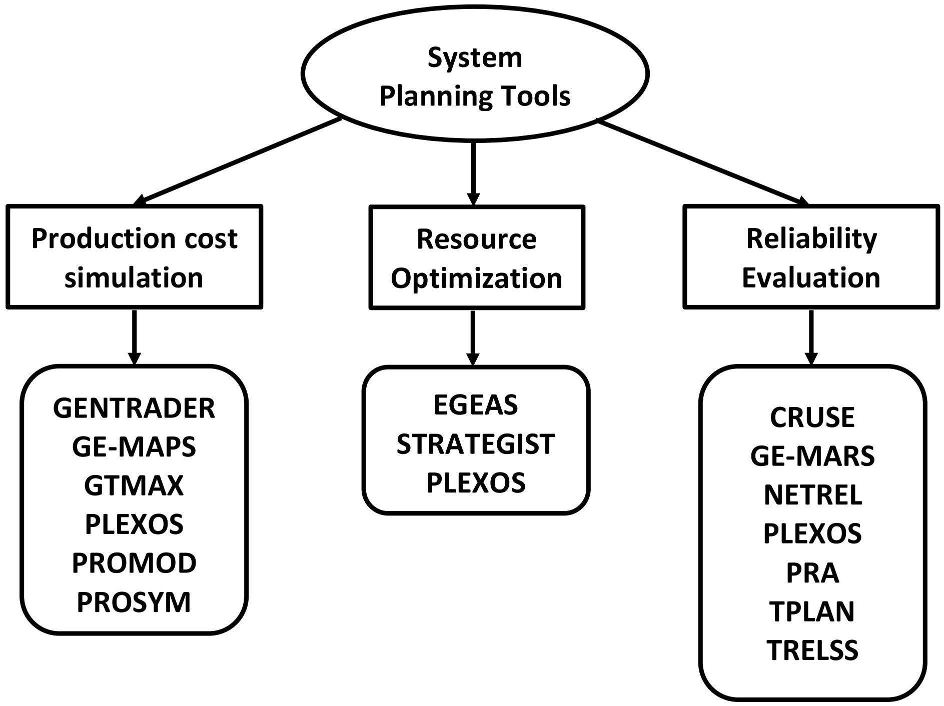


Figure 2-2. Classification of system capacity expansion planning tools

The tools can be further sub-divided into three categories: system models, modular packages and integrated models [62]. Their differences are illustrated below.

System models normally have only a database and some means to organize and/or analyze data. Such tools are generally not as comprehensive in scope as Modular packages. Figure 2-3 is a simplified system model.

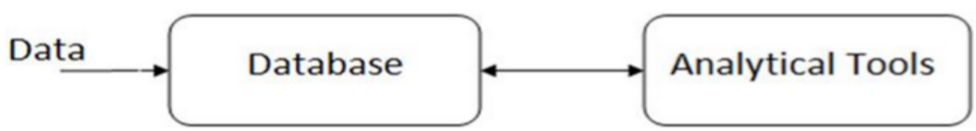


Figure 2-3. A simplified diagram of system model

Modular packages are integrated software packages that include modules for economic/reliability analyses, for projecting system load growth, or for balancing energy supply and demand. In the planning process, the users might not need to use all of the modules. They can select to use any module according to their need and nature of the problem. A simplified diagram of modular packages is shown below in Figure 2-4. Each module communicates directly with the data base; coordination of the modules is accomplished by the output of one module altering the data base, which is then read by another module.

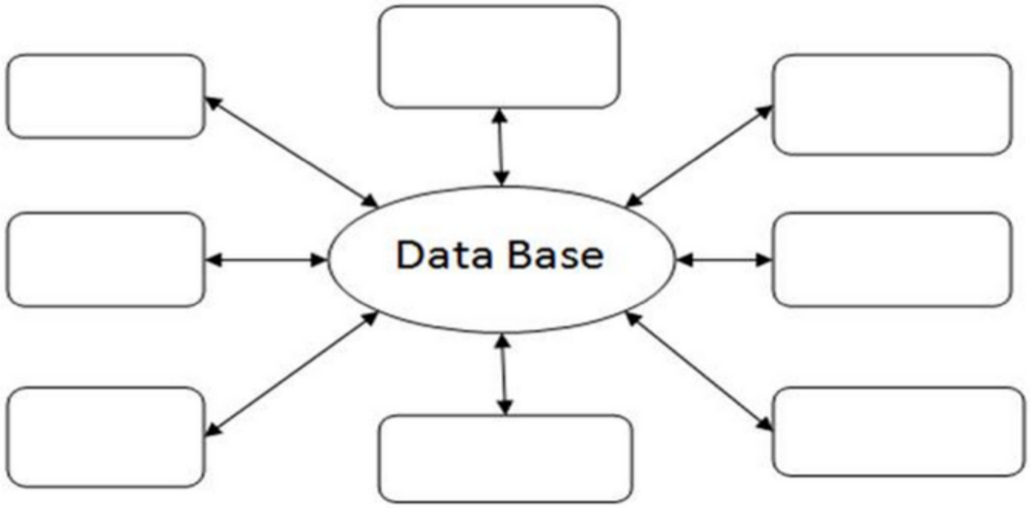


Figure 2-4. A simplified diagram of modular packages

Integrated models solve different aspects of the planning problem simultaneously. They often cover energy-economic-environment interactions. Figure 2-5 is a simplified diagram of integrated models. In this case, the modules are not distinct, nor do they communicate separately with the data base. Instead the data is input to the integrated system, and the modules are then solved simultaneously and together,

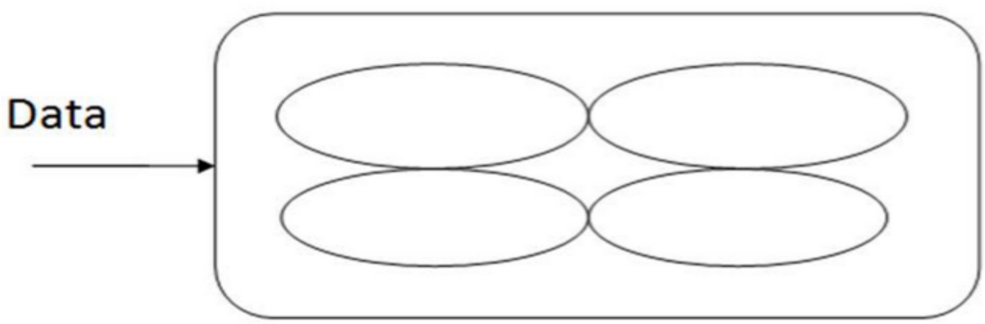


Figure 2-5. A simplified diagram of integrated models

However, the comparison and classification of different tools is not straightforward, as tools are often designed for specific purposes and distinct markets. For example, the underlying economic structure varies from model to model. Further, documentation of the assumptions of commercial packages is often deliberately vague to safeguard proprietary ideas.

2.2.1.3 Production cost simulation tools

Production cost programs have become the workhorse of long-term planning [64]. These programs perform simulations of how a pre-specified set of generation investments (and sometimes transmission investments as well) are operated, resulting in performance indices such as total fuel costs, emissions, and various reliability indices. Some simulation models consider operating hours in chronologic order, in which case they become unit commitment models. The unit commitment solution determines a day-ahead (or weekly) schedule for minimizing the cost of fuel for supplying electric power and starting-up/shutting-down generating units while satisfying the prevailing constraints listed below [121]:

- Hourly Load balance
- Hourly generation bids
- System spinning and operating reserve requirements
- Minimum up and down time limits
- Ramp rate limits of units
- Generating capacity constraints
- Startup and shutdown characteristics of units
- Fuel and multiple emission constraints
- Bilateral contracts
- Must-on and area protection constraints

Since thermal generators cannot instantaneously start-up or adjust generation outputs, the increased variability in net load that results from renewable penetration can stress power systems and increase costs. Other simulation models emphasize computational efficiency using load duration curves (including so-called Baleriaux-Booth methods). A load-duration curve re-orders operating hours from highest to lowest net demand, thus losing information about how load ramps up and down. However, computation of plant-by-plant generation output is easily (if inaccurately) calculated by “stacking” generators under the duration curve. Start-up costs and ramp limits are difficult or impossible to consider by such models, but when generation mixes had low renewable penetration, this mattered less. Although production cost models usually make use of optimization, it is for performing dispatch, and not for selecting generation investments. Production cost programs often incorporate reliability evaluation in addition to economic models. A representative list of commercial grade production cost models include: GenTrader [37], MAPS [10], GTMax [68], PLEXOS [104], PROMOD [107], and PROSYM [108].

2.2.1.4 Reliability assessment tools

Like production costing models, reliability assessment tools are evaluative only. That is, they do not identify optimal investment plans but just evaluate the performance of pre-specified sets of generation investments, sometimes in combination with transmission investments. Their focus is on the ability of a defined system to meet load under specified conditions.

Both deterministic and probabilistic tools are heavily used in the planning process. Deterministic tools include power flow, stability, and short-circuit programs, and assess whether a combined generation-transmission system operates satisfactorily under specified conditions and contingencies. Probabilistic tools compute indices such as loss-of-load probability, loss of load expectation, or expected energy not served for a pre-specified investment plan. They consider probabilities of satisfactory performance over a range of load and equipment outage conditions, rather than one scenario at a time like the deterministic models. Probabilistic tools are most often applied to generation systems without considering transmission, although probabilistic reliability tools do exist for combined generation-transmission systems. A representative list of commercial-grade reliability evaluation models include CRUSE [81], MARS [85], PLEXOS [104], TPLAN [131], and TRELSS [132].

2.2.1.5 Resource planning tools

Classic resource optimization models select a minimum cost set of generation investments from a range of technologies and sizes to satisfy constraints on load, reserve, environmental concerns, and reliability levels [51,133], as summarized above (Section 2.2.2). However, even though [133] summarized a linear programming-based co-optimization model, commercial generation expansion models often do not represent transmission, or if they represent it but do not consider the possibility of new transmission investments.

A representative list of resource optimization models includes EGEAS [48], PLEXOS [104], Strategist [146], and WASP-IV [141]. They, along with models proposed by researchers, use a variety of optimization algorithms to solve the generation planning problem, such as:

- mixed integer linear programming [38], in which both continuous and discrete (0-1) decision variables are considered. Discrete variables can be used to model the fact that generators are only available in a few sizes.
- dynamic programming [100],
- decomposition methods [16,41,129] which divide the problem into separate design (plant sizing) and operations problems. An example is Benders decomposition, in which the operations subproblem is used to estimate not only total operating cost for a trial solution, but also the marginal cost savings that would result from increases in capacity; that

marginal information helps guide the design problem towards a more efficient trial investment plant.

- neural networks [143], which are particularly flexible methods for statistical fitting of input-output relationships,

- network flow models [94], which are particularly easy-to-solve linear optimization models,

- genetic algorithms [35], which attempt to identify better solutions by randomly changing values of the decision variables of trial solutions and then using a competitive "selection" process to determine which trial solutions will "survive" and produce "offspring" by further random changes, and

- stochastic optimization [9,111], a type of optimization that attempts to identify solutions that do well across a range of possible assumptions or scenarios about, for instance, load growth or fuel prices.

Most commercial grade models focus on supporting investment decision making and are employed by utilities, GenCos, and TransCos, while others are national policy analysis tools which are used by government and other organizations to understand the impacts of potential policy changes.

Resource optimization models incorporate simplified production costing models as a subproblem, and often reliability evaluation as well. Figure 2-2 above classifies common commercial system capacity planning software. Table 2-1 below summarizes some of the attributes of more commonly used packages. For instance, the packages differ in their treatment of transmission. A DC optimal power flow (OPF) formulation linearizes the nonlinear AC equations when calculating transmission-constrained dispatch, and may or may estimate resistance losses.

Table 2-1. Attributes of some resource planning tools

	Resource planning tools			
Features	**PLEXOS**	**GEM**	**EGEAS**	**Strategist**
Model category	Integrated model	Integrated model	Modular packages	Modular packages
Transmission constrained	Yes	No	No	No
Geographic scope	Regional	Regional	Regional	Regional
Algorithm	Quadratic programming, Mixed integer linear programming, Dynamic programming, Stochastic programming	Mixed integer linear programming	Generalized Benders decomposition, Dynamic Programming	Dynamic programming
Economics / Reliability	Both	Both	Both	Both
Objective	Multiple objective functions	Least cost	Least cost	10 different objective functions
Methods to represent system load	load duration curve or chronological	load duration curve	load duration curve	chronological load in twelve typical weeks per year
Plant retirement decisions	√		√	√
Transmission Loss	DC OPF, quadratic losses	only losses on HVDC	No	quadratic loss function
Market transactions	√	√		
Reliability evaluation method	Monte-Carlo, N-x contingencies	N-1 contingencies	Monte-Carlo	Monte-Carlo

2.2.2 Transmission planning models

2.2.2.1 Overview

The primary purpose of Transmission expansion planning (TEP) is to determine the least-cost transmission additions to meet load from a defined set of generation facilities and/or exchanges, subject to reliability constraints. New transmission lines can provide voltage support and improve system reliability, as well as interconnecting new generation units and accommodating increased long-distance exchanges. Costs might include just transmission investment costs, but increasingly include costs of generation investment and operations. These economic benefits are increasingly important in transmission decisions, as pointed out in Section 1. The reliability and economic benefits of a particular transmission upgrade change over time as the result of the changes in loads, generation and grid topology, so multiple years (as many as 20-30) need to be considered.

Historically and often currently, utilities were almost exclusively concerned with reliability and meeting NERC requirements with relatively little concern for their economic implications. More recently, for the reasons such as access to renewable resources, the economic benefits of new transmission facilities have become more important and have sometimes become the major driver. However, projects that were primarily intended to satisfy a reliability problem will almost certainly have economic benefits and vice versa. Understanding the shorter and longer-term reliability and economic benefits of facilities has an important bearing on the receptiveness of customers to pay for these facilities.

In the traditional regulated utility environment, vertically integrated utilities operate the whole electric system and make investment decisions for both generation and transmission additions. Transmission expansions can be justified if there is a need to build new lines to connect cheaper generators to meet the current and forecasted demand or new additions are required to maintain or enhance system reliability, or both. In the traditional transmission planning model, the capital investments are often justified by the need to meet reliability requirements to serve the current and forecasted load. As cost is often used as a criterion to evaluate investment alternatives, and various reliability criteria must be met, the traditional transmission planning problem is normally formulated as a cost minimization problem with reliability as a constraint [144].

Figure 2-6 provides a schematic of the traditional "generation first" transmission planning process in which a vertically integrated utility first devises a generation plan, and then plans transmission to accommodate the generation investments.

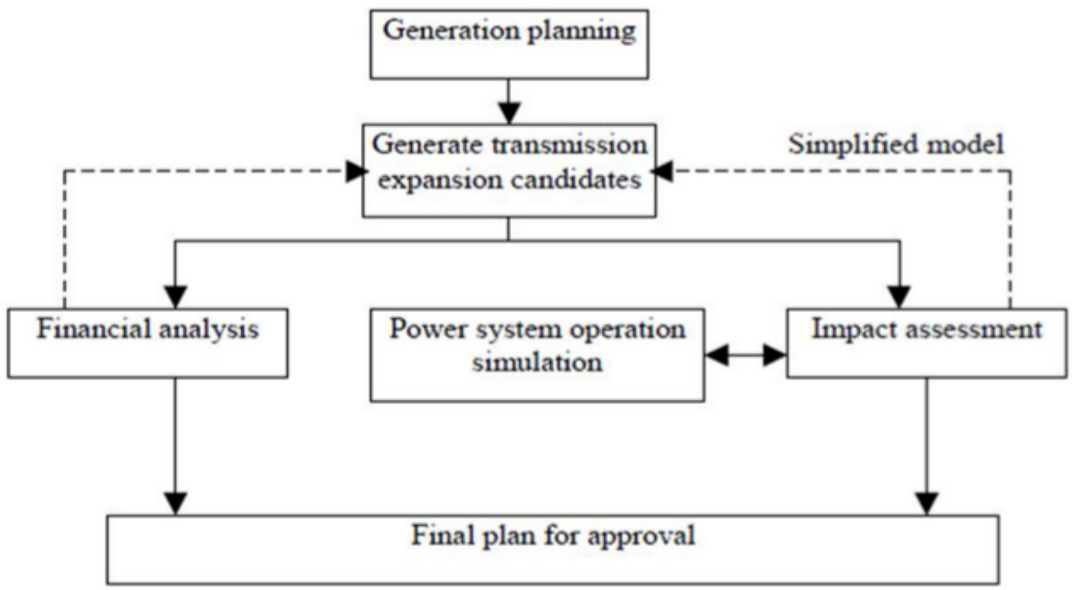


Figure 2-6. Transmission expansion planning procedure (from [126])

In the restructured power industry, transmission expansion planning encompasses many economic and engineering issues, including the facilitation of competition among generators [4]. As the results of the issues arising in the new system structure, many aspects of planning problems are being re-evaluated and new methods are being proposed to address them. Responsibilities are often split between transmission owners, who propose projects, and RTOs/ISOs, who often conduct independent economic analyses of those proposals [4]. It has been argued that the appropriate way to view the transmission planning problem is as a "transmission first" bi-level problem, in which planners of transmission infrastructure make decisions about where to make transmission additions, anticipating how generators will invest and operate in response to transmission availability and pricing [113]. In general, this is a very difficult nonlinear problem [36]. There is some literature that takes iterative approaches to solving this game between the transmission "leader" and generation "follower", in which separate models for transmission and generation are coordinated (e.g., [113]). However, in the case in which it is assumed that transmission is efficiently priced (using locational marginal pricing), all markets are competitive, and generators react rationally to locational incentives, the bi-level problem can be reduced to a single optimization problem, which is more easily solved and is practical for real transmission planning. This naturally leads to co-optimization formulations of transmission planning problems, representing optimization of both transmission assets as well as the mix, location, and timing of generation investment (e.g., [142]). Co-optimization models are, of course, the focus of the present report.

2.2.2.2 The objectives of transmission expansion planning

As the paradigm of the traditional least-cost expansion criteria is not valid in the new market environment, there has been a debate on what criteria shall guide the transmission expansion decision making. Based on the decision maker's concerns, the objective function could be minimization of (production cost + investment cost), minimization of (congestion cost + investment), maximization of (consumer and generation surplus – investment cost), maximization of (TransCo's expected revenue – investment cost), minimization of investment risk, minimization of greenhouse gas emissions, or several objectives at the same time. These various kinds of objectives reflect the interests that different parties want to gain from the planning problem. Statutorily, entities such as state commissions have varying degrees of responsibility to ensure the lowest delivered cost reasonably possible while achieving a high degree of reliability. The Federal Energy Regulatory Commission (FERC) and North American Electric Reliability Corporation (NERC) have statutory obligations to ensure enough transmission lines are built to maintain system reliability. From the TransCos' perspective, they want a return on transmission investment cost allocation plans and revenues from the financial transmission rights, energy market, and bilateral contracts. TransCos also want to minimize their financial risks. From the ISO/RTO's perspective, they want to ensure that the electric system will be operating reliably. What is more, they also want to relieve transmission system bottlenecks, transfer economic generation from remote areas, promote competition in wholesale electric markets, lower system production costs, and decrease customer payments. From GenCos' perspective, they want a transmission investment plan that can deliver their generation resources without congestion. It is very difficult to satisfy all the above needs, which renders transmission planning a multi-objective problem.

2.2.2.3 Coordination with generation and load

As the planning for both generation and transmission is carried out by a single decision maker in the regulated industry, the transmission planner can obtain good information on generation expansion plans and loads. In the restructured environment, however, the authority that conducts transmission planning does not own the generation companies, so generation plans (and reactions to changes in network capabilities and costs) are uncertain. For example, when the Mid-continent Independent System Operator (MISO) plans transmission, the first step is to forecast the generation resource additions within the planning horizon. The imperfect information might produce imperfect expansion plans. Moreover, as generation projects generally have much shorter lead time than transmission expansions, new generation projects might be built after a transmission plan is finalized but before the line is ready to be operated. As the initial transmission plan did not take those generation projects into consideration, the transmission investment might no longer be optimal in terms of economic value or reliability requirements.

Symmetrically, transmission additions might affect the economic or reliability justification of a generation investment plan. For example, in U.S. Eastern Interconnection, most of the wind-rich areas are located in the Great Plains states, which are far from load centers. Where a co-optimization model might find savings in simultaneously developing remote wind and high capacity transmission lines to connect it to load centers, a generation-only model without such lines is likely to choose to develop local resources that tap existing regional transmission instead. Similarly, without existing, remote wind farms injecting power, a transmission-only model will likely decline to invest in new inter-regional transmission corridors. This chicken-and-egg problem helps justify the development and use of co-optimization models.

As another example of the interaction of transmission and generation decisions, the imminent retirement of a significant portion of the coal generation fleet and perhaps significant amounts of nuclear capacity as well will result in a need to interconnect new natural gas-fired generation. The cost and access conditions for this new transmission are a significant influence on plant siting decisions.

2.2.2.4 Transmission planning tools

Just like generation expansion planning, the transmission expansion planning problem can be phrased as a large-scale non-linear mixed-integer programming problem. That is, the objective function and/or constraints are non-linear, while some decisions discrete in nature (either build a particular facility or not) and are modeled as 0-1 variables. Many optimization techniques have been employed in the transmission planning optimization models, most of which are in the research stage rather than commercial software. These algorithms include

- dynamic programming [30],
- game theory [21],
- fuzzy set theory [127],
- expert systems [6,94],
- object-oriented programming [47]
- decomposition [41,42,43,44,129],
- heuristic methods [76], such as genetic programming.
- non-linear programming [147], and
- mixed-integer programming [5,142].

The two algorithms that were not previously defined are (1) fuzzy sets, which gauge the attractiveness of a plan by so-called “fuzzy” criteria that capture a user’s vagueness about what levels of a numerical criterion are desirable and (2) object-oriented programming, which allows users to interact with and build models by clicking and connecting “objects” on a screen, rather than write lines of code. Although most of these are research models, an exception is PSR's transmission planning package, a mixed-integer programming model that is now being applied by WECC [5].

2.3 Co-optimization

This section will review existing co-optimization models, and then lay out basic choices associated with designing a co-optimization planning model, and also will summarize advantages and disadvantages of each choice. It comprises following subsections. Section 2.3.1 presents definitions of co-optimization models. Then in Section 2.3.2, we review existing co-optimization models, differentiating between ones used for national- or regional-scale policy analysis, and ones used for detailed transmission planning. We then present a summary of selected existing co-optimization tools and their modeling features as a table. Detailed reviews of each of these existing tools are presented in Appendix II.

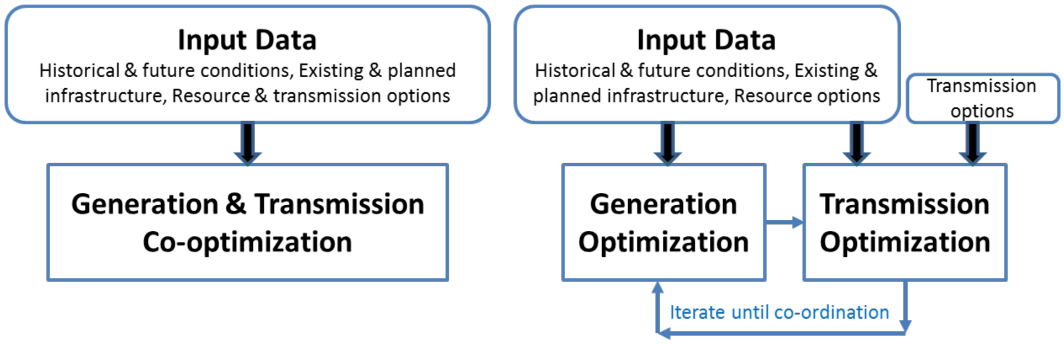
Following this review, we then turn to the choices that must be made when developing a co-optimization model. First, we discuss the choices associated with network representation (Section 2.3.3), within which for each choice the associated data preparation, investment decision options and the features of the model optimizer are discussed. Section 2.3.4 presents the choices available for resource investment options. Section 2.3.5 presents a discussion on other additional planning tool attributes such as end effects modeling and handling uncertainties.

2.3.1 Definitions of co-optimization

We begin with two definitions, which are depicted in Figure 2-7:

Definition A: Co-optimization is the simultaneous optimization of two or more different yet related resources within one optimization formulation. Unlike the traditional electric systems planning approach, where generation and transmission investment are typically identified in sequence (usually generation, then transmission), a co-optimized approach identifies them simultaneously. We assume in the remainder of this document that the co-optimization model is multi-period so that solutions include not only what, where, and how much generation and transmission to invest in but also when.

Definition B: Another perspective to co-optimization of resources is given by relaxing definition A to: "co-optimization is the optimization of two or more different yet related resources within one planning framework." Here the emphasis on simultaneous optimization within one formulation is relaxed, while still the objective is to comprehensively optimize all related resources within one framework. This can be achieved by introducing an "iterative approach" to the traditional sequential planning of generation and transmission, until a complete coordination between generation and transmission planning solutions exist. This approach to co-optimization relates to the current independent practices of generation and transmission planning organizations, and also allows for improvising the respective optimization tools to accommodate specific considerations for generation (e.g., economics, policies, futures) and transmission (e.g., reliability, control schemes) expansion planning respectively. While an iterative approach to co-optimize may reduce computational burden, it may not converge and provide global optimal solution.



(a) Definition A (b) Definition B

Figure 2-7. Co-optimization definitions

There are several challenging issues in the co-optimization of GEP and TEP. First, conflicting objectives: GEP can be driven by prices but the same principle may not apply to the TEP [110]. Second, power system constraints such as network flow limits, load demands, and reliability requirements link the two planning problems, which introduce an additional dimension of difficulty in finding feasible and practical planning solutions. Third, one of the main obligations of expansion planners is to facilitate a fair and competitive market. The planner also has to take into account uncertainties associated with renewable energy, non-traditional generation resources such as microgrids, fuel costs, component outages (such as transmission lines, plants, and transformers), and customer behavior including demand response. The co-optimization of GEP and TEP becomes much more challenging when contemplating the full range of uncertainties relevant to expansion planning.

Early versions of these models have been proposed as linear programs, and in the case of thermal power plants, versions of these models have been proposed back in the 1960s and documented by Ralph Turvey in his classic book on electricity economics [133]. However, those models did not address the effect of Kirchhoff's voltage law (KVL) on transmission (i.e., parallel flows), thus distorting calculations of flows and overstating transmission capacity.[2] Transmission

[2] Kirchhoff's Laws include the Current and Voltage laws. The former says that there is a current balance at any node (bus) in a network, with inflows equaling outflows. The latter says that the net voltage drop around any loop in a network must be zero. In the linearized DC load flow model, the analogies to these laws are, respectively, that the net inflow of power to any bus is zero and that the sum of the products of power times reactance around any loop is

capacity is overestimated because models that disregard KVL implicitly assume that flows can be routed to avoid congestion, which is not possible in the absence of FACTS devices such as phase shifters.

A separate strand of work has been power plant siting models that choose specific locations for power plants and transmission lines, subject to assumptions concerning generation mix. A flurry of activity in this area was the result of President Carter's National Coal Utilization Assessment, and is summarized in [50] (for a more recent review, see [53]). These models, however, tend to treat generation and transmission investment as continuous variables, and also ignore Kirchhoff's voltage law.

Very recently, there have been several applications of generation-transmission co-optimization models at two scales. One scale involves detailed representations of AC load flows, or linearized DC load flow approximations, of actual high voltage transmission facilities as they interact with potential generation facilities within a single utility service area or other (relatively) small regions. The other scale encompasses large regions (e.g., WECC, the European Union) and uses linearized DC load flow approximations of aggregations of transmission facilities, as well as simplified representations of generation technologies (using classes of technologies rather than individual generating units with unique operating characteristics). The latter can be viewed either as simplifications of smaller scale methods that are applied to larger regions, or, alternatively, as improvements upon regional siting models and other long-used tools (such as ICF's Integrated Planning Model [60]) that build in more detailed sub-regional representations and replace transshipment ("pipeline", "pipe and bubble") representations of transmission with more realistic linearized DC load flows.

2.3.2 Review of co-optimization models

2.3.2.1 National policy tools

The generation planning tools mentioned in Section 2.2.1 are mainly designed for analyses of regional power systems, while the following tools are mainly employed by governments and regulatory bodies to study the power system on an inter-regional, interconnection, or even national level. For instance, USEPA and USDOE use national models with (highly) simplified representations of interregional transmission constraints. Some of these models, however, are used to assess the potential profitability of generation investments considering the reaction of the rest of the market. Table 2-2 below summarizes several national policy tools and their characteristics. Section 3 of this report summarizes several additional models that can be used for

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also zero. One result of these laws is that power travels in parallel paths between sources and sinks, and another is that given a set of sources and sinks, the flow over any given line is completely determined and cannot be controlled. More generally, however, phase shifters and other FACTS devices can be introduced into a network, which allows for partial control of flows.

co-optimization at the national or large region level; the models in that section tend to have more detail on power system transmission and generation, and less on other energy forms than some of the comprehensive models in Table 2-2 (especially MARKAL and NEMS).

There are three key differences between planning and national policy tools. First is the level of spatial aggregation. National planning tools have low spatial resolution. For example, in some global versions of MARKAL, all of Europe is represented as a single node; while in IPM, there are on the order of 10-20 regions representing the United States. However, in many regional planning tools, the regional aggregation is user-specified, normally containing much more detail. For example, PLEXOS can operate at 3 types of geographical units: regional, zonal, or nodal.

The second key difference is the user. National planning tools are mainly (but not solely) used by regulatory bodies and governments, while regional planning tools are widely used among utilities, ISOs, and many consulting firms.

The third key difference is that national tools often explicitly consider price formation in fuel markets, such as the coal and natural gas supply curves considered in IPM. In contrast, regional tools take fuel prices as fixed input assumptions, and instead treat the electric power system itself in much more detail.

Table 2-2. National policy and planning tools [59, 60, 104]

		National Energy Modeling System (NEMS)	ICF Integrated Planning Model (IPM)	MARKAL/ TIMES	PLEXOS	WASP-IV
Output		Optimal electric and other energy sector investments & operations	Optimal generation investment	Optimal electric and other energy sector investments & operations	Optimal electric and natural gas sector investment and operations	Optimal generation investment plan
Optimization model	Objective function	Equilibrium model (not optimization)	Minimize cost	Minimize cost	Minimize cost	Minimize cost
	Stochastic scenarios	√		√	√	√
	Formulation	Modular	Linear program	LP, generalized network	LP, MIP	Generalized network, modular
Forecast horizon		20-25 years	20-25 years	Unconstrained	10-50 years	30 years
Sustainability	Greenhouse gases	√	√	√	√	√
	Other emissions	√	√	√	√	√
	Fuel depletion	√		Partial (step supply curves)	√	
Reliability					Loss of load, N-x	Loss of load
Energy represented	Primary energy sources	√	Natural gas, coal supplies	√	√	
	Electricity	√	√	√	√	√
	Liquid fuels	√			√	
Transportation	Freight	√		Only fuel demand		
	Passenger	√		√		

2.3.2.2 Co-optimization models for detailed transmission planning

Co-optimization models are considered in detail in Section 3, but we summarize some basic features here.

The transmission expansion planning problem is typically regarded as a nonlinear, highly complicated problem. These complexities justify application of advanced optimization algorithms such as the branch-and-bound method for mixed integer programs, Benders decomposition, and heuristics such as genetic algorithms.

Co-optimization models that attempt to tackle the computationally difficult aspects of transmission planning date back to 1970s where linear mixed integer programming models were proposed [114]. Nearly all of these were research efforts, and have not been implemented as commercial software. A Benders decomposition-based approach was developed to separate and coordinate the investment problem and operating subproblems [102]. Reliability issues were assessed in terms of customer interruption functions in co-optimization models [77], allowing tradeoffs between outage, investment, and operating costs. However, earlier models were oversimplified and thus deemed impractical for market-based generation and transmission expansion planning.

Additional research efforts in the last two decades were made to address the co-optimization problem in electricity markets. In general, co-optimization is viewed as a bi-level optimization problem for generation and transmission and iterative approaches have been widely used to coordinate the two planning problems [2,88,92,118]. For instance, Baringo and Conejo [7] presented a bi-level stochastic co-optimization model and transformed it into a single-level mathematical programming with equilibrium constraints. It was shown that transmission expansion decisions significantly affect wind power capacity expansion even though investment cost in transmission expansion is much lower than that in wind power capacity.

A variety of market features and complications have been included in proposed co-optimization models. A recent study in [129] presented a co-optimization model that incorporated transmission congestion costs. It was shown that distributed generation could mitigate congestion and defer transmission investments. A follow-up study in [130] proposed a co-optimization model which accounted for incentives offered to independent power producers (IPP). Reference [48] introduced a multi-area co-optimization model with short-term power system operations strategies. It was demonstrated that the proposed model could offer considerable economic benefits in power pools. A follow-on study in [65] presented a microgrid-based co-optimization model which incorporated investment and operation costs of local microgrids into the co-optimization objective function. It was shown that considering microgrid investments in the co-optimization problem could provide significant reliability and economic benefits. In addition,

[110] proposed a capacity payment mechanism in the co-optimization model for transmission and generation facilities.

Uncertainty has been a focus of much research in co-optimization. Stochastic programming was applied in [80,111] to simulate random outages of system components. It was demonstrated that even simple co-optimization models could result in significant savings when optimizing transmission and generation assets. Stochastic programming was also applied by [142] to consider alternative scenarios of future economic, regulatory, and technology developments. However, in comparison with the deterministic co-optimization models, the stochastic models may lead to higher investment costs since additional generating units and transmission lines would have to be installed to handle uncertainties.

2.3.2.3 Summary of existing co-optimization models

This section presents a summary of the detailed review performed on some existing co-optimization tools using Table 2-3.

Table 2-3. Summary of existing co-optimization models

Model Name	Developer	Trans Investments	Optimizer	Time-step/ Horizon	Sectors
NETPLAN	Iowa State University	Pipes Continuous	LP (simultaneous multi-period optimization)	Hourly or monthly or yearly/ 40-years	Electric, Fuel, Transportation
Iterative gen-trans Co-optimization	Iowa State University	AC/ DC Binary/ Continuous	Iterative LP (gen.) and MILP (trans.) / Bender's decomposition for large problems	Hourly or monthly or yearly/ 40-years	Electric
Meta-Net	Lawrence Livermore National Lab	Pipes Continuous	Market equilibrium model	Hourly/ Yearly (sequential if multiple years)	Electric, Fuel, Transportation
COMPETES	Energy Research Centre of the Netherlands	AC/DC Continuous	LP (iterative to solve nodal balance and linearized DC model)	Samples of hour / Yearly (sequential if multiple years)	Electric
Stochastic Transmission Planning	Johns Hopkins University	AC Binary	MILP (non-iterative) / Bender's decomposition for large problems	Hourly or daily/ 50-years (multi-stages)	Electric
ReEDS	National Renewable Energy Lab	DC (single stage lag in line impedance	LP (multi-stage multi-period optimization)	Samples of hour/ 40-years (2-year sequence)	Electric

		update)			
PLEXOS	Energy Exemplar LLC	AC/DC Lines Interfaces	MIP, Stochastic Optimization	Chronological or Duration curves	Electric Natural Gas
Prism 2.0	Electrical Power Research Institute	Pipes Continuous	General equilibrium economy model (iterative to equilibrate couplings)	Samples of hour / Yearly (sequential if multiple years)	Electric, Fuel, Transportation
REMix	German Aerospace Center DLR	AC/DC Continuous	LP (static investments at beginning)	Hourly/ multi-year	Electric/Heat
SWITCH	University of California, Berkeley	Continuous	MILP (non-iterative); modeled through AMPL; uses Cplex	Sampled hours in sampled days/multi-year	Electric
LIMES	Potsdam-Instituts für Klimafolgenforsch ung	Continuous	LP	Aggregate hours (6 hours per time slice) in sampled days/40-year	Electric
GENTEP	Illinois Institute of Technology	AC/DC Binary/Continu ous	MILP / Bender's decomposition	Hourly or monthly or yearly/ multi-years	Electric (includes microgrid)

The detailed reviews of above models are presented in Appendix II. The reviews cover the following aspects of each of the tools, namely, the infrastructure sectors modeled, the types of infrastructure investment decisions made, the computational model, the associated optimizer and solvers, and other planning attributes such as network modeling (AC vs. DC vs. pipes-and-bubbles), optimization time steps, how uncertainties are handled, and the modeling of demand-side options. The reviews also present the development status of each tool, along with their limitations and possible improvements. We note that these existing co-optimization models differ in how they model each of the attributes that were discussed in Sections 2.3.1-2.3.4.

Table 2-4 presents a summary of few other planning tools which are not among the models reviewed in Appendix II but are extracted from the publication [20]. These tools are highlighted here because they are capable of performing long-term investment planning in the energy sector (including electric generation and transmission network) over a wider geographical region. In contrast, we do not consider software that assesses a single plant's economics or that analyzes energy supply only for the heat/transportation sector or small-scale micro-grid/community.

Table 2-4. Summary of other generation and transmission system planning tools

Tool	Computational Method	Tool Description	Developer	Time-step	Sector
BAL-MOREL	Partial equilibrium model	Open source electricity and district heating tool	Open source (Danish tool)	Hourly	Electric/ Heat/ Transport
E4cast	Equilibrium model	Energy projection, production, and trade	Australian Bureau of Agricultural and Resource Economics	Yearly	Electric/ Heat/ Transport
EMCAS	Optimization using agent based electricity markets	Creates techno-economic models of the electricity sector	Argonne National Laboratory	Hourly	Electric/ Transport
IKARUS	Linear cost-optimization scenario model	Bottom-up cost-optimization tool for national systems	Institute of Energy Research at Research Centre, Germany	5 years	Electric/ Heat/ Transport
MARKAL /TIMES	Equilibrium model	Energy-economic tools for national energy-systems	International Energy Agency	Hourly-monthly/ samples	Electric/ Heat/ Transport
MESSAGE	Partial equilibrium model	National or global energy-systems in medium/long-term	International Institute for Applied Systems Analysis (IIASA), Austria	5 years	Electric/ Heat/ Transport
ORCED	Equilibrium model	Simulates regional electricity-dispatch	Oak Ridge National Laboratory (ORNL)	Hourly	Electric/ Transport
PERSEUS	Multi-periodic linear programming	Family of energy and material flow tools	Institute for Industrial Production, Universität Karlsruhe	36-72 slots (days) per yr	Electric/ Heat/ Transport
WASP	Optimization	Identifies the least-cost expansion of power-plants	International Atomic Energy Agency	12 LDC per year	Electric

2.3.3 Network representation - Model fidelity

In this section, we are summarizing the pros and cons of the different choices one has in representing the network within a co-optimization model. These choices include modeling fidelity, i.e., in decreasing levels of fidelity- an Alternating Current (AC) model, a Direct Current (DC) model, a network flow model, or a hybrid model. Each of these modeling brings in a number of benefits to system operation management and planning, and with enhanced fidelity comes the associated computational complexities for solving the resulting optimization problem.

2.3.3.1 AC power flow model – Optimizer, investments and data

Optimizer: An AC model consists of complete representation of real and reactive power flows in the transmission network governed by electrical laws, which is expressed in terms of a non-linear function of network states, namely bus voltages and angles, and network parameters (impedances). The AC optimal power flow (ACOPF) problem is formulated as an economic generation dispatch problem with network security constraints. The comprehensive formulation enables simultaneous management of real power (P) demand with voltage (V) and reactive power (Q) requirements, which are otherwise accomplished by proxy methods or multi-stage planning approaches with relaxed versions of ACOPF that are applied in the current operational and planning environment. Along with the non-linear power flow relations in the ACOPF, the continuous generation expansion variables and integer transmission expansion variables make the co-optimization a Mixed Integer Non-Linear Programming (MINLP) problem, a very complex optimization problem to solve.

A complete mathematical formulation of ACOPF based generation and transmission planning model (ACOPF-GTEP) is presented using equations (1-12) in Appendix I.2. The ACOPF-GTEP problem is a non-convex MINLP problem due to the presence of integer variables and non-linear relations (shown in equations (2, 3, 4, 5, and 8) of Appendix I.2). The above described problem is according to co-optimization definition-A, i.e., simultaneous optimization of generation and transmission expansion. If the co-optimization definition-B is adopted, then the problems can be broken into NLP model for generation expansion and MINLP of reduced size for transmission expansion. Nevertheless, even without considering the network expansion part, the ACOPF itself is an extremely difficult non-convex optimization problem to solve with convergence and computation related challenges, which makes it impractical to apply in real world applications [17]. Studies are yet to convincingly quantify the added value of co-optimizing voltage and reactive power flows (i.e., better resource utilization, pricing & global welfare maximization) against the severe computational deadlocks such models pose.

Algorithms: Though extremely challenging, such models are not unsolvable and many techniques are being explored. Typically such nonlinear optimization problems involve iterative methods with basic steps including [17]: choosing an objective function to optimize, choosing an initial solution x_0 at k=0, choose a search direction d_k, choose an appropriate step size s_k to update the solution vector x_k, and repeating this search until convergence criteria is met. There are numerous methods for each of these steps, which thereby differentiate the many available solvers or algorithms for solving such non-convex/non-linear problems and their convergence rate (i.e., linear or faster than linear), numerical stability and computational properties. Some of the available methods for unconstrained non-linear optimization problems are conjugate gradient method, quasi-Newton method, Newton's method, Gauss-Seidel method, and steepest descent method. In the case of constrained non-linear optimization problems, Lagrangian Function is used to transform them into unconstrained dual (Lagrange multipliers) optimization problem. Iterative methods including penalty and augmented Lagrangian methods, barrier or interior point methods, sequential linear programming and quadratic programming methods are often used to solve such generalized Lagrangian functions. The expansion problems with integer variables render the problems even more difficult, and are generally attempted to solve using variations of branch and cut methods in combination with above mentioned methods for NLP. MINOS, IPOPT, SNOPT, KNITRO and CONOPT are some of the commercially available solvers for such MINLP and NLP problems.

Model Relaxation: There are several ways in which the MINLP formulation of ACOPF-GTEP model can be relaxed to models with reduced complexities [148]. One way to simplify the model is by using a decoupled power flow formulation or removing the reactive power flow parts altogether (corresponds to equations (5) and (10) in Appendix I.2), while still capturing the interactions between bus voltage magnitude and real power transfers.

Another way is to use binary variable instead of integer decision variable, thereby changing the decision from how many transmission lines to be built to whether or not a candidate transmission be built. This replaces the integer variable with multiple stages to a variable with two stages (0 or 1), thereby reducing the problem complexity. The relaxation of ACOPF-GTEP full model using binary decision variables are shown using equations (13-18) in Appendix I.2. The relaxed model using binary variables allows for further relaxation of the complex MINLP problem using a disjunctive formulation based on the big "M" method [148], thereby making it a MILP problem. A further relaxation of the model is by using a continuous decision variable for transmission investment, as shown by equation (19) in Appendix I.2.

Investment options: The investment options in a multi-period ACOPF-GTEP model are:

1. Generation: where, when and how much of different technologies to be invested.
2. Transmission: where, when, how many transmission lines to be invested (if integer), should there be investment in a particular line (if binary).
3. AC transmission technologies: The ability to choose between different voltage levels for AC transmission can also be embedded by designing candidate arcs with appropriate arc operational and investment characteristics (i.e., cost, losses, capacity) for respective KV levels, and each will its own binary decision variable.
4. FACTS devices: Investments in FACTS (series and shunt devices) can be considered in ACOPF formulation, as shown by equation (20) in Appendix I.2. These shunt devices help in providing the required reactive power and regulating the system voltage within

specified security limits. Long distance real power transmission over AC lines involves a commensurately high reactive power transfer, which causes a drastic decrease in bus voltage at the receiving end (load centers) and thereby inhibits the power transfer capability and causes voltage stability issues. Therefore considering FACTS devices within the formulation allows weighing the available options and deciding whether to invest in more transmission or reinforce the existing transmission using FACTS at the load side.

Data preparation: The data required to run a co-optimization model basically includes data pertaining to historical and forecasted system conditions (mainly related to real power load patterns and variable generation), system topology, operational and physical characteristics of existing and planned electric infrastructures, available options for generation and transmission investments and their operational and investment attributes, and finally the scenario descriptions. With AC formulation, the additional data required will be pertaining to reactive power and voltage, which include generator capability curves, reactive power limits, and voltage set points; transmission line apparent power rating and complex impedances; bus voltage limits; and cost of FACTS devices.

2.3.3.2 DC power flow model – Optimizer, investments and data

The direct current (DC) OPF problem is a linearized approximation of the power injection formulations of ACOPF problem, which has been very prevalently used in real-world operating and planning applications. The DC model basically consists of two relations, real power flow which is directly proportional to angle difference (in radians) and reactive power flow which is directly proportional to bus voltage difference (shown by equations (21-22) in Appendix I.3). Typically, the power system operations are cost optimized for real power flows and meeting the real power demand, and hence only equation pertaining to real power flow (also known as B-theta model) is used in practical market and planning applications.

Optimizer: Though the DCOPF model in itself is a LP, an optimization realm which is quite advanced in terms of solution techniques and available stable solvers; the DCOPF based generation and transmission expansion problem (DCOPF-GTEP) is MINLP, a non-linear and non-convex problem with the introduction of transmission investment integer variables in the formulation. The constraints of this problem are shown using equations (23-29) in Appendix I.3, along with which equations (7, 9, and 12) in Appendix I.2 related to voltage angle and generation capacity should also be included. Again, with the use of binary decision variable for transmission investments and a disjunctive formulation, the MINLP model can be relaxed to a MILP. This disjunctive formulation based on big "M" method is shown in Appendix I.3 using equations (30-32). There are many stable solvers both commercial and non-commercial including CPLEX, Gurobi, LINDO, Mosek, GLPK, and lp_solve for solving MILP problems. Nevertheless, problems of bigger size, though solvable, are computationally intensive. The MILP formulation can be further relaxed to an LP problem by assuming the transmission investment variable as continuous. Such relaxed models with lesser computation may provide a way to screen the candidate locations or corridors, so that the full scale model can be run with reduced dimension.

Investment options: The investment options in multi-period DCOPF-GTEP model are:

1. Generation: where, when and how much of different technologies to be invested.
2. Transmission: where, when, and if there be investment in a particular line (if binary).
3. AC transmission technologies: The ability to choose between different kV levels of AC transmission can be embedded by designing separate candidate arcs for each voltage with appropriate arc operational and investment characteristics.

The downside of this DC approximation of non-linear AC relations is loss of model fidelity, in that the DCOPF does not incorporate voltage variables. Therefore, the resulting expansion solution has to be validated using a full AC model in order to assess its feasibility in meeting network security constraints. If there are violations of some reliability metric, then the DCOPF based MILP expansion problem has to be iteratively run with added constraints to have a proxy representation of security limits, until the expansion solution results in no more reliability violations. Some approaches are:

1. Impose limits on investment variables that are causing security limit violation (as done in [72]), which constrains MSC allocation amount in every iteration of reactive power planning problem in order to respect voltage magnitude limits).
2. Impose limits on decision variables' attributes, such as that modeled by St. Clair curves[3] for AC transmission line capacity with respect to distance. The curve limits the operational capacity of the transmission line for the same investment cost, in order to avoid voltage stability issues due to high transfers in long distance AC lines.
3. Using linear sensitivities to model constraints that incorporate management of network security limit within the overall optimization. For instance, linear sensitivities of bus voltage magnitude and voltage stability index with respect to generation and transmission expansion variables can be used to model the estimated impact of investments on network reliability, and appropriately optimize. This method also allows to incorporate FACTS devices' investments within the overall MILP based GTEP co-optimization. The linear sensitivities have to be updated before each iteration.

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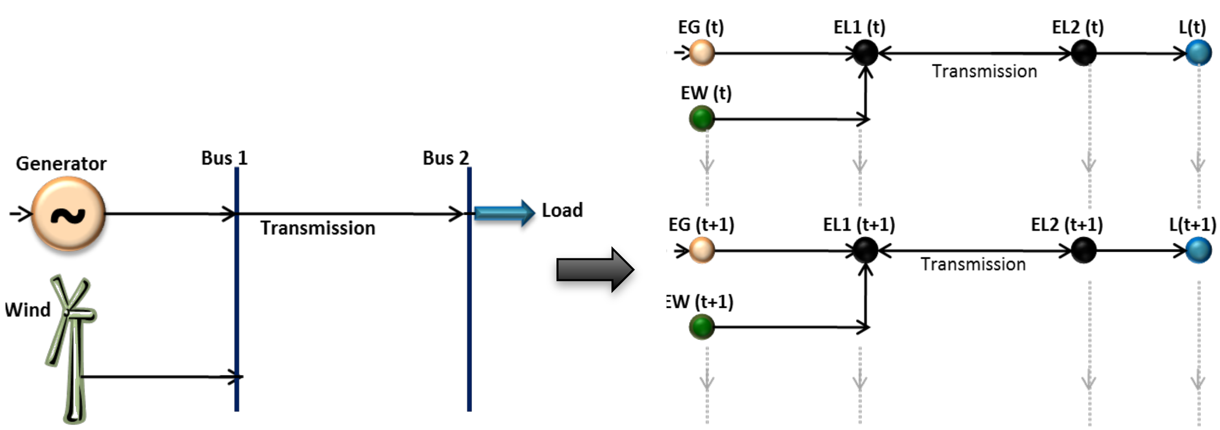
[3] These curves derived from empirical studies, also known as power-transfer capability curves, are used to estimate the maximum loading limits on transmission lines as a function of its length. The loading limits for various voltage levels are expressed in terms of Surge Impedance Loading of the line, and it takes into account thermal, voltage stability and angular stability limits associated with that line's loading.

Data preparation: DCOPF-GTEP model has lesser data requirements than ACOPF-GTEP model. Of the complete set of data mentioned in Section 2.3.3.1, data for network resistances, bus voltage limits, generator reactive power limits and voltage set points, transmission line reactive power limits and FACTS data (in most cases) are not required.

2.3.3.3 Network flow model – Optimizer, investments and data

In this model, the transmission network is represented similar to transportation pipelines, which move a commodity from one node to another node in the network subject to an efficiency parameter representing transportation losses. Such a model respects the nodal balance constraint at every node and transmission flow limits, but not electrical laws. Figure 2-8 shows network flow representation of a power network using one-line diagram for two connected periods *t* and *t+1*. It is to be noted that generation (modeled by arc EG_EL and EW_EL), transmission (modeled by arc EL_EL) and demand (modeled by arc EL_L) are all represented as arcs, with appropriate values for its operational and investment cost, bounds, and efficiency properties. Cost of power flows across all arcs are subject to efficiencies and capacity bounds, and the required arc capacity expansions are minimized by the network flow optimization.



(a) Power network (b) Multi-period network flow equivalent

Figure 2-8. Power system represented using network flow model

Optimizer: The network flow model based linear programming cost minimization formulation is shown in equations (33-36) of Appendix I.4, which minimizes the operating and investment costs. Since, both generation and transmission arcs are considered as transportation pipelines (with different properties), the only relation that governs this model is the nodal power flow balance equation (equation (34) in Appendix I.4).

The network flow based GTEP problem is easy to conceive and understand. Plenty of evolved algorithms are available to solve network flow class of LP problems. There is tremendous scope to speed up such problems using decomposition and parallelization methods [13], and advancements are being made in solving larger sized linear network flow problems using high performance computing [27].

Investment options: The investment options in multi-period network flow based GTEP model are:

1. Generation: where, when and how much of different technologies to be invested.
2. Transmission: where, when, and how much of transmission to be invested (continuous variable).
3. Transmission technologies: The ability to choose between different transmission technologies can be embedded by designing separate candidate arcs for each. However the differentiation can be made only with respect to operational and investment characteristics, and not based on equations governed by realistic electrical laws as can be done using AC and to some extent with DC power flow models.

Again, the downside of this approximation using a transportation model is increased loss of model fidelity, in that it does not incorporate voltage variables and the relationship of real power transfers with the bus angle difference and line impedance. The solution may see higher amounts of transmission flows than what could actually take place. Therefore, the resulting expansion solution has to be validated using a full AC model in order to assess its feasibility with respect to network security constraints. If there are violations of some reliability metric, then the expansion problem has to be iteratively solved with proxy constraints for enforcing security as discussed in Section 2.3.3.2, until the expansion solution results in no more reliability violations.

Data preparation: A network flow model has even lesser data requirements than a DCOPF-GTEP model. It will not require network impedances, bus voltage magnitude and angle limits, generator reactive power limits and voltage set points, transmission line reactive power limits and FACTS data.

2.3.3.4 Hybrid model

A hybrid model is one that may represent transmission lines with mixture of the above three described models. A typical and valid scenario of this representation may be consideration of both AC and DC transmission technologies in the model. In this case, DC lines are modeled as real power injections (positive and negative, as shown in equation (37) of Appendix I.4) at both the ends of the lines, which effectively translate to modeling it as a transportation pipeline. Therefore the resulting model will be either a hybrid of AC and network flow models or DC and network flow models.

Other situations where a hybrid model of transmission lines may be used are:

1. Study area emphasis: If a particular area alone is of interest within an interconnected power system, the transmission lines within that area may be modeled with high fidelity, while the lines external to the area may be approximated to transportation model with power injections into and out of the area.

2. Aggregated model: If a bigger geography is analyzed with highly aggregated generation and transmission capacities; then a transportation model may be used to assess the inter-regional bulk power transactions.

All discussions pertaining to optimizer, investment options and data apply accordingly to the hybrid model based on the combinations of choices made.

A high level summary of pros and cons for different network representation is presented in Table 2-5, and Table 2-6 provides pros and cons related to some of the commonly used optimization features. Depending on the choices, a hybrid model will have respective pros and cons.

Table 2-5. Pros and cons of network representation - Model fidelity

Choices	Pros	Cons
AC model	High P & Q model fidelity	Requires MINLP solver- excessive computation & data preparation
DC model	Good P fidelity, can use linear solver	No Q-V information (may need feasibility check using full AC model)
Network flow	Highest computational efficiency, reduced data preparation	No impedance effects, poor model fidelity

Table 2-6. Pros and cons of optimization features

Choices	Pros	Cons
Non-iterative	Obtains optimal solution	Excessive computation
Iterative	Faster, more flexible	Sub-optimal solutions; may not converge
Linear continuous	Very fast	Cannot capture discreteness in solutions
Linear mixed integer	Captures discreteness in solutions	Computation is significant

2.3.4 Network representation - Modeling coverage

There are at least two kinds of modeling choices that decide the degree of network coverage–

1. Sector/resource coverage: whether to represent any of the fuel (gas and coal) networks, flexible generation and demand side resources
2. Geographical coverage: how much of the electric network to represent (e.g., the region or the entire interconnection)

Benefits of representing increased model coverage are the ability to account for more investment options, and the costs of doing so are increased burden of data preparation and computational requirements.

2.3.4.1 Sector/resource coverage

In this subsection, we are describing the modeling and computational cost of including additional decisions within a generation/transmission co-optimization planning, including fuel network (coal, gas), demand response and storage.

Fuel network: The fuel networks are very much a part of energy sector. If one considers electric and transportation networks as the end-users in the energy sector, then the fuel networks can be considered as the source. Figure 2-9 shows a high level schematic diagram of an energy network, where three different yet interconnected subsystems are represented: coal, natural gas, and electricity sub-systems. The coal network can be modeled using information related to its production (CP) and transportation (1T). Similarly, natural gas network can be modeled using information on production (NP), pipeline transshipment (NT) and storage (NS) facilities. The flow limits of various arcs can be treated as the capacity of the different infrastructure components, and can be allowed to expand subject to investments.

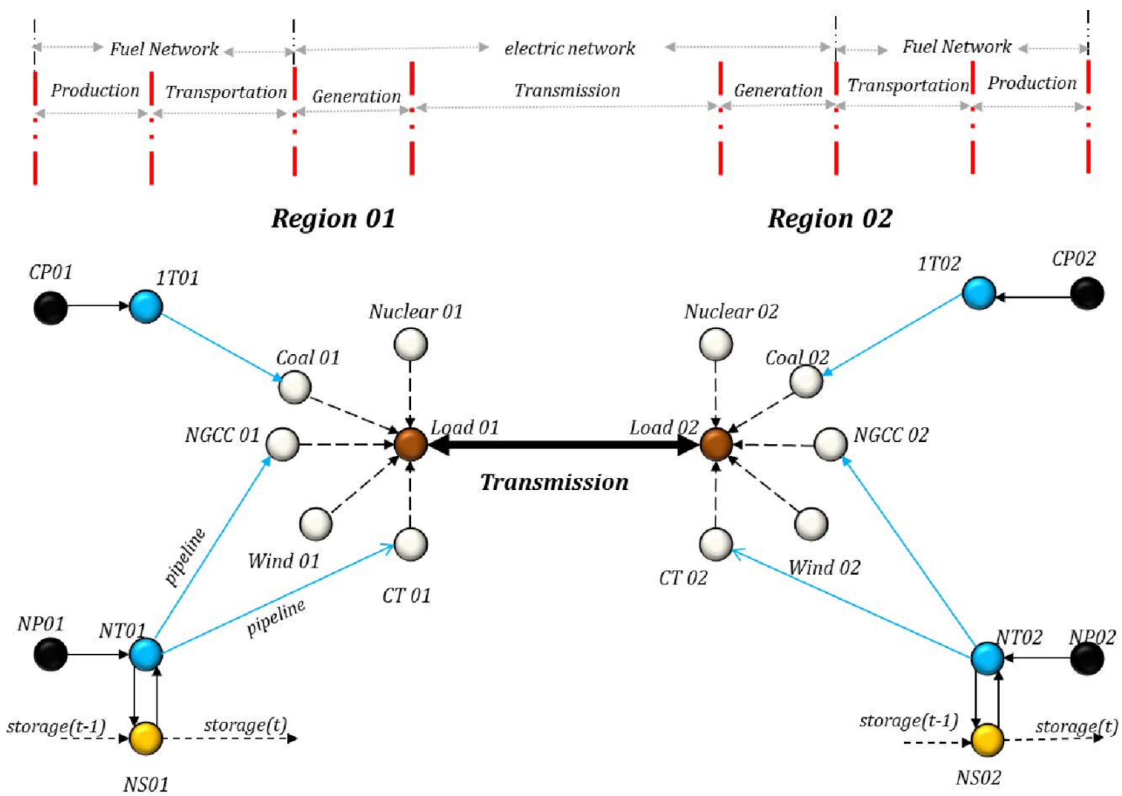


Figure 2-9. Fuel sources represented within energy sector [71]

Features of optimizer:

1. *Market equilibrium model:* A market equilibrium model is one that, though it models the interconnections between various source and end user sectors, optimizes the operations within each sector in isolation. The market equilibrium condition for each sector is satisfied, given the demand and supplier entities' bids. The demand from end-user sector is passed on to the source sectors, and finally each sector is at equilibrium with each other and marginal market prices are ascertained. Based on the modeling of bids functions, the model will be linear or non-linear. Typically such models are solved for hourly market operating conditions, and investments are made at yearly time steps.

   In this model the market constructs and the signals, including marginal prices of a particular resource, congestions and the economic metrics such as payback assessments, drive the investments. In a certain sense such market equilibrium models can be seen as market simulation tools, and not a tool that optimizes for investments considering the overall integrated energy sector.

2. *Linear programming:* Integrating the different pieces of the energy sector using a network flow model, allows for minimizing the overall cost of meeting energy requirements across all the interdependent sectors using a large yet interesting linear programming problem. Usually for such multi-commodity models, each sector's operations may be optimized at different time steps, typically dictated by the degree of variability in the respective commodity's value. Such optimization models provide perspectives on what the global energy policy strategies should be by representing infrastructure investments as decision variables to meet the integrated energy sector's requirements and not isolated requirements. Such models also provide signals to consider alternate market constructs. If the energy transfer medium such as natural gas pipelines and transmission lines are modeled using non-linear equations for a higher fidelity, then the optimization problem becomes NLP or MILP.

In any case, multi-sector modeling will increase the computational cost, and may require some degree of component/spatial aggregation (regions) within each sector and reduced temporal granularity for optimization.

Investment options: Apart from generation and transmission investment options, such a model further includes:

1. Gas pipeline and storage: where, when and how much to invest

2. Coal/oil transportation mode: where, when and how many of which mode (train, truck) to invest

A co-optimization model including all the sectors promises to provide notable benefits, as it optimizes considering overall energy needs. It opens up many opportunities to shape the future infrastructure portfolio or assess the merits in alternative strategies. For instance, Figure 2-10 shows the options available for generation expansion when both pipeline and transmission line expansions are co-optimized. Some interesting alternatives could be, natural gas generation can be sited close to the load with associated expansion in pipelines or sited far away from load center with associated expansion in transmission lines or a combination of both. Investments in transmission and natural gas units may also provide flexibility and support economic renewable integration. Therefore, a co-optimization tool that considers all these inter-related options may find expansion solutions with long-term benefits, emissions reductions and operational flexibility.

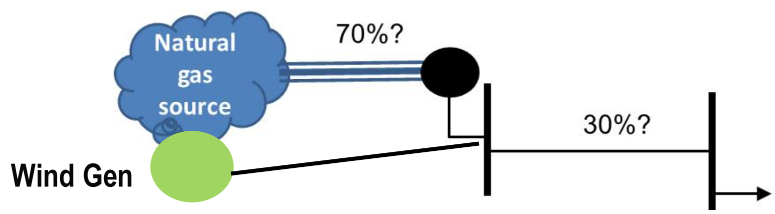


Figure 2-10. Tradeoff between pipeline/transmission investments

Data preparation: Increasing modeling coverage to include fuel networks will increase the burden of modeling and data preparation. The data preparation step may include a data aggregation step also for a spatially aggregated model, which will further require information on proper regional boundary demarcations and data filtering. Data additional to the electric network include fuel network topology and geographical characterization of investment cost, fuel cost and capacities. For instance,

1. The availability and quality of coal differs geographically, and so the availability, cost and transportation links for all varieties of coal may be required.

2. The gas imports/exports, pipeline and storage capacities could be characterized based on geography.

Storage technologies/demand response:

Storage technologies can be modeled by representing the three operations of a typical unit, namely, charging, discharging and reservoir dynamics. Conceptually a storage technology's discharge operation is similar to a generator operation and charge operation is tantamount to loading the system. The reservoir dynamics of storage must update the energy status periodically based on the current period's injections and withdrawal, subject to the charging/discharging (or round-trip) efficiencies and stored energy until the previous period. Each operation, charging and discharging will have their marginal costs, based on which they will be dispatched. Depending on the type of storage technology (based on their storage capacity), i.e., bulk storage (compressed air energy storage, pumped hydro, large batteries) or short-term (flywheel, superconducting magnetic energy storage, batteries), the grid services they provide differ. Bulk storage technology is able to provide a wide range of grid services through both its charging and discharging operations, namely peak shaving, regulation, spinning and non-spinning reserves. Short-term storage technologies are generally used for providing regulation services.

The modeling of demand response in a certain sense can be conceived as a special case of modeling charging side of storage, i.e., a dispatchable load. Demand side services can be provided from loads that are price sensitive, emergency interruptible, and also certain kind of storage systems like ice-storage.

Apart from providing good flexibility both these technologies provide very significant benefits in terms of economics and system reliability by virtue of their capacity, and have the ability to defer or replace any generation or transmission expansion plans. Hence their consideration within the overall co-optimization tool provides a wider solution space to the long term planning problem.

Features of optimizer for Storage: The optimization formulation depends on the kind of storage technology being integrated and the goal of the study. Some of the optimizer features that the storage integration can influence are:

1. *Inter-temporal constraints and simultaneous multi-period optimization:* A storage technology's reservoir modeling introduces inter-temporal constraints, and hence necessitates optimizing simultaneously over multi-periods in order to economically manage reservoir status while providing grid services through charge/discharge operations. The basic relation needed is that the stored energy at period t must comprise of energy stored up until period t-1 less any leakage, plus (less) the energy to be charged (discharged) at period t.

   Typically the requirement to simultaneously optimize multi-periods increases the problem size, which can be controlled by assuming a reasonable operating cycle (2-day or weekly) for storage with end/boundary condition on reservoir energy status.

2. *Time steps and operating states:* Depending upon the focus of the study, an appropriate optimization time step will be necessary. Apart from portfolio optimization, if the scope of the planning tool is to also assess the economic benefits of storage, then the tool should be able to model the ability to dispatch the storage for making profit from arbitrage opportunities [23]. In this case, an hourly (or even a sub-hourly) time step for optimizing the operations will be ideal to capture the strategic dispatch of storage with respect to price sensitivities.

   Furthermore, bulk storage technologies will have three states, namely, charge, discharge and idle. Based on the system conditions, the unit is usually in one of these states, which is decided by a unit commitment program that uses the unit's physical characteristics and start-up/shut-down costs. The unit commitment is minimally a MILP problem.

However, if economic assessment and high operational fidelity are not the criteria, then a simpler model that captures the basic storage relation as mentioned in point 1 above and assessed for certain samples of hourly system conditions (including peaks) will be a good beginning. This will enable co-optimizing storage along with generation and transmission resources, while also ensuring the optimization problem is LP.

3. *Short-term technologies:* While the above two points are mostly applicable to bulk storage technologies, a short-term technology with very limited energy capacity and ability to make very fast zero-cost transitions, and generally requires an assessment at smaller time scales (sub-hourly, say 5-minute dispatches) to assess their participation and profitability in providing regulation services. Though the problem remains an LP, it increases the problem size and may not be ideal for a long-term resource planning tool.

   However, if the required capacity for ancillary services is estimated and represented in the long-term investment planning tool [71], then such devices' capacity subject to their utilization factor [139] can be considered in the overall portfolio planning.

Demand Response: The second point discussed above for the storage technologies on the usage of hourly optimization time steps is also applicable to demand response modeling, when the DR modeling includes dispatching it based on system prices and representing the discrete states of an interruptible load. However, as mentioned in point-3, a model that incorporates the available MW on the demand side for load management, along with the appropriate $/MW price and capacity factor can use relatively longer optimization time steps. This will be a reasonable beginning to represent demand side resource in a long-term resource planning tool, considering the computing requirements. By representing important hourly samples of system conditions, demand side options' competitiveness in portfolio planning along with other generation and transmission options can be assessed.

Investment options: Apart from generation and transmission investment options, such a model further includes:

1. Storage technologies: where, when, how much of each to invest, i.e., configuration of charging, discharging and reservoir capacity.

2. Demand response: where, when and how much to invest

Since, demand response addresses the system flexibility needs at one of the sources that cause short-term and long-term variability, i.e., system load, it will compete against generation and transmission projects which may otherwise be needed for meeting peak system needs.

Similarly, storage technology providing energy services to the grid may displace the peaking units at the top of the generation stack, and by virtue of their competitive ramping rates may obviate the need to invest in fast ramping combustion turbine units under increasing renewable penetration. Bulk storage may also act as a virtual transmission access, when optimally sited close to demand along the congested transmission path [24].

A planning tool that models operational reserve requirements and monetizes the conventional fossil-fuel fired unit's cycling phenomenon will increase the value of storage and demand response among the available resource options.

Data preparation: Integrating storage and demand side options will increase the burden of modeling and data preparation. Data related to technology investment cost, life, and other operational attributes such as variable cost, capacities, efficiency, ramp rate, grid services and unit commitment related data (if needed) are to be prepared. For short-term storage, a good estimation of their long-term utilization factor is necessary. Data for a conventional unit's cycling and costs will be useful. Table 2-7 provides pros and cons related to modeling additional sector and resources.

Table 2-7. Pros and cons of network coverage - Sector/resource

Choices	Pros	Cons
Fuel network (coal, gas)	Investigate sector interactions (gas-electric)	Excessive computation and data preparation
	Integrated investment options	NLP if pipelines modeled using non-linear equations
Storage/demand response	Add flexibility, enhance wind penetration	Excessive computation and data preparation, Inter-temporal constraint for storage
	Investigate gen/trans investment deferrals	To capture arbitrage/ancillary, may require optimization at hourly (sub-hourly) time steps

2.3.4.2 Spatial granularity and geographical coverage

Depending upon the network spatial granularity (i.e., nodes at plant level, substation level, regional) and extent of geographical scope (i.e., inter-regional, national), different kinds of infrastructure related problems can be investigated.

When optimized at plant-level granularity, the geographical scope may be limited by the model size, required data and the associated computational complexities; however several other important operational strategies among the resource options can be considered, such as the optimal transmission switching [49] for mitigating operational issues. A transmission switching problem is a complex MILP optimization problem, like unit commitment, which provides operational solution that may defer the investments in generation and transmission. Studies done at this granularity level also allows for considering factors such as plant and transmission line maintenance scheduling and retirements within the overall planning.

To reduce the model size and computational burden involved in investigating infrastructure planning at national or interconnection wide geography, some level of system component aggregation has to be done. Such model brings in a variety of solution options by virtue of modeling the geographical variation in resource availability and economics, and hence helps in siting such capital intensive infrastructures with long life strategically for long-term economic and sustainability benefits. An aggregated model across wider geography also helps in assessing various futures and the portfolio, and provides valuable signals to develop policies and market constructs that help in the evolution of any particular beneficial future.

Irrespective of geographical coverage, the optimizer for a model depends upon the kind of decision options modeled. If only continuous capacity variables are considered, the model is LP; and if discrete variables are considered such as plant, transmission line investments/retirements and other operational decisions such as unit commitment and transmission line switching, then the model can become MILP and more complex. Table 2-8 provides a summary of pros and cons related to two choices of geographical coverage.

Table 2-8. Pros and cons of network coverage - Geography

Choices	**Pros**	**Cons**
Plant level	System level studies,	Excessive computation and data preparation for large models
	Decisions on generator starts, retirements & maintenance, transmission line switching	
Aggregated model	Studies on regional policies and planning trajectories	Data aggregation, regional boundary definitions
	Study interconnected systems/sectors	Plan implementation and benefit identification (cost allocation)

2.3.5 Additional planning tool attributes

2.3.5.1 End effects

The planning problem in reality is an infinite horizon problem. The infrastructure assets typically have long lifetimes, and hence in making an assessment among alternative choices, one must consider the operational value of assets over their entire lifespan, apart from considering their overnight investment cost. However, in addition to being computationally intensive, the solutions in the far out years are impractical due to future uncertainties and very insignificant money value, and hence simulation of such a long-term planning problem is truncated at a certain year. This induces anomaly in the end year investment solutions, termed as "end effects". The effect of truncation is that near the end of the simulation horizon generally assets with lower investment cost, irrespective of their operational cost, are favored by the minimum cost optimization model in order to reduce the objective function. There are at least four well-known approaches to mitigate this issue [40], whose pros and cons are summarized in Table 2-9:

1. *Extended simulation:* The most straight-forward and simplest way is to simulate for a longer duration, but report the results only for the desired horizon (T). Though this method will eliminate the end effects within the desired horizon by capturing the operational value of alternatives, it will necessitate heavy computation. The additional evaluation period is usually known as extension period, many applications typically choose about 30-40 years (MISO 2012). To simplify the evaluation, applications assume stationary conditions during these years, i.e., no increase in load and no new investments; but the investments made up until end period of desired horizon are simply evaluated against each other for their operational value.

2. *Salvage value:* The method truncates the simulation to desired horizon, but places a proxy value on all assets that are carried over from desired horizon into extended future. This proxy value is the undepreciated value of the asset at the final year of the simulation, which will be subtracted from the total cost-based objective function of the optimization problem. This will tend to reduce the bias created by the truncation towards infrastructure with low investment cost and lower lifespan.

3. *Primal equilibrium:* This method imposes an equilibrium condition on primal variables (x) after the desired end period. It assumes for an infinite horizon problem, there will be a finite horizon beyond which the decision variables attain equilibrium, i.e., they increase at the rate of growth in demand (λ), i.e., $x(T+t) = \lambda x(T+t-1)$, where $t=1... \infty$. The problem horizon remains as desired, but with additional constraints for t>T. This kind of model is more suited and intuitive for problems that have infinite resources for investments, $x< \infty$.

4. *Dual equilibrium:* This method imposes an equilibrium condition on dual variables (μ) after the desired end period. It assumes that the dual variables of the T stage problem increase in proportion to the assumed discount factor (α), i.e., $\mu(T+t)= \alpha\, \mu(T+t-1),\ t=1... \infty$. If the Lagrangian function of the primal optimization problem can be conceived, then it can be observed that all the constraints after period T till ∞ can be added into a single term with a common multiplier $\mu(T)$. This kind of model is more appealing, since in reality prices usually rise (except under temporal uncertainty) over time at an inflation rate. The model is applicable to problems with limited resources for investments, $x<x_{max}$.

Table 2-9. Pros and cons of the various approaches to mitigate end effects

Choices	Pros	Cons
Truncation	Simple, flexible	Excessive computation
Salvage value	Light computation, relatively simple	Does not capture operational values easily
Primal equilibrium	Suited when resources unrestricted	Adds computation, convergence issues
Dual equilibrium	Light computation, practical appeal, relatively flexible	Implementation requires some knowledge of optimization

2.3.5.2 Screening methods and optimization interval

Screening methods are generally employed to focus on particular aspects of a broader problem, or develop interesting scenarios for planning, or reduce computational requirements in identifying the most interesting solutions within a very large solution space (which may warrant further attention). Table 2-10 provides pros and cons of two typical methods that help screen the solution space for the most insightful ones.

Table 2-10. Pros and cons of screening methods

Choices	Pros	Cons
Manipulate investment options/bounds	Simple, develop generation scenarios, identify candidate transmission (copper sheet method)	Risk of missing solutions or being not credible
Model relaxed to LP	Identify candidate locations, less computation	May bind the relaxed variable closer to binary, low fidelity

The problem of planning capital intensive infrastructures that operate for long term generally cannot be justified based on short-term benefits alone, but rather must also consider long-term impacts on economic competitiveness, environment, and resilience. Such studies are usually done for extended time horizons over which the effects of investment decisions are studied in order to relate their impact on the environmental changes (which usually take years to decades to manifest). This does not mean that decisions are to be made for that time frame, but rather, that decisions made for a shorter time frame are understood in the context of a long-range plan, and that impacts of those shorter-term decisions are well understood. Associated with the modeling of such long-term infrastructure planning problems, there are three kinds of simulation/optimization time intervals (going from shortest interval to longest):

1. *Optimization time step:* This is the time interval at which operations within a sector are modeled, i.e., hourly (like a day-ahead market) or monthly or yearly time steps. Typically inter-temporal operational relationships are modeled to relate successive time steps.

2. *Evaluation period:* This is the time period over which the operations are optimized, and investment decisions are made. For a multi-commodity model (i.e., fuel, electricity…), within one evaluation period the operations for each sector may be modeled at different time steps, typically dictated by the degree of variability in respective commodity's value. For instance, a coal network with reasonably stable prices may be optimized at yearly intervals, while natural gas and electric networks may require more granular time steps. A long-term optimization problem typically has multiple evaluation periods (usually yearly) over which network investments are optimized (also termed as multi-period optimization problem).

3. *Optimization period:* This is the period over which an optimization program is executed to optimize the overall long-term infrastructure investments. Typically it involves multiple evaluation periods interconnected successively. If the optimization is done simultaneously for all the evaluation periods within the planning horizon, then we call it as single optimization period. If the planning horizon is broken into many intervals (cycles), each consisting of multiple interconnected evaluation periods, which are optimized in a rolling manner (i.e., sequentially feeding the results to another), then we call this multiple optimization periods. Usually this kind of model is constructed to accommodate dynamic changes in futures and parameter inputs between rolling periods.

Figure 2-11 shows these three kinds of intervals using the arrows at the bottom, and three kinds of planning frameworks using the rectangular boxes. The arrow at the beginning of each evaluation period denotes the investment decisions. While each framework has a particular optimization time step at which operations are modeled, the differences are in evaluation and optimization periods. The framework 1 consists of single evaluation period within a single optimization period. Since the decision of how much and what to invest are made once for the entire horizon, and the solutions do not provide temporal information of when to invest, this framework is also known as static optimization. Framework 2 consists of multiple evaluation periods solved simultaneously within a single optimization period, whereby the temporal information of when to invest is also captured (denoted by solid lines between multiple evaluation periods). Framework 3 consists of multiple optimization periods solved sequentially (denoted by the dashed arrow feeding period t solution to period t+1), where within each optimization period there are multiple evaluation periods solved simultaneously (denoted by strong connections). Framework 3 is also known as dynamic/rolling planning, since it offers the possibility of updating the continuously evolving planning attributes such as infrastructure cost, and resource availability.

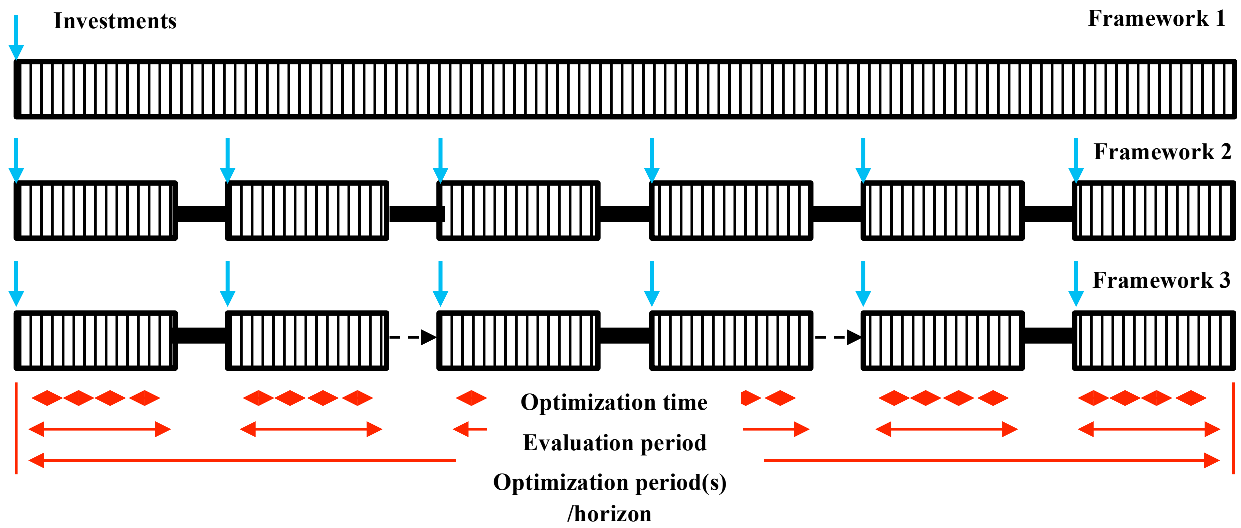


Figure 2-11. Optimization time intervals and planning frameworks

Table 2-11 presents pros and cons of three planning frameworks based on optimization/evaluation period choices. Table 2-12 also presents pros and cons, but for different choices of optimization time steps within the evaluation periods. In a certain sense, the choice of optimization time step may also act as a screening parameter, since it helps to condense the details involved in large long-term optimization problems and help find the relevant solutions at reasonable computation.

Table 2-11. Pros and cons of optimization/evaluation period choices

Choices	Pros	Cons
Single evaluation period/ single optimization period	Very fast	No temporal information
Multiple evaluation periods/ single optimization period	Achieves optimal solutions	High computational burden; decisions use future information
Multiple evaluation periods/ optimization periods	Reasonable computational speed, realistic about future info	Solutions are sub-optimal

Table 2-12. Pros and cons of optimization time step choices

Choices	Pros	Cons
Chronological hourly	Model starts, load-wind correlation and variability, inter-temporal constraints, assess arbitrage value of storage	Computation intensive for long-term problems
Hourly samples	Capture important hourly/seasonal information, reduces computation	Possibility of missing critical information in the sampling process, and miss phenomenon such as energy arbitrage, ramping and so on
Monthly/ yearly	Suited for long-term, inter-regional integrated sectors planning	Data aggregation (e.g., use LDC), small-time scale phenomena not captured

2.3.5.3 Handling uncertainties

Power system operational and investment planning problems typically face many uncertainties related to system conditions and component outages. At the operational time frame, planning against uncertainty is done through generation scheduling and commitment processes that ensure enough supply/demand side reserves. A long-term planning problem must also account for such operational reserve allocations appropriately [26, 69,124].

However apart from these, planning tools must also be able to handle longer term uncertainties related to future evolutions, which can be classified as local and global uncertainties. Local uncertainties can be parameterized by probability distributions or uncertainty sets around a point defined by a scenario. Examples of local uncertainties include shifts in load growth and investment costs or fluctuations of fuel prices. In contrast, global uncertainties are those that cause a significant impact on the evolution of the system. Examples of global uncertainties are the implementation of emissions policies, dramatic shifts in demand, or public rejection of a certain type of resource. A set of realizations on global uncertainties is appropriately thought of as a future scenario. In long-term planning, one generally creates a number of scenarios and then develops plans that are robust and perform acceptably in all scenarios. Table 2-13 provides pros and cons of certain choices and methods to handle uncertainties in long term planning.

Table 2-13. Pros and cons of choices to handle uncertainties

Choices	Pros	Cons
Deterministic	Fast, simple	Not robust
Component outages	Solutions more robust	Computational
Local uncertainties- Parametric uncertainty in conditions (e.g., demand, fuel prices, variable generation)	Provides increased solution robustness	More computational, ascertain probability distributions
Global uncertainties- "Large" uncertainties (e.g., \$4 N gas vs. \$10 N gas, CO_2 tax or not, 0.5% vs. 3% demand growth)	Provides increased solution robustness	More computation, data gathering more complex

3 IMPLEMENTATION REQUIREMENTS FOR CO-OPTIMIZATION MODELING

This section addresses several important practical issues associated with implementing co-optimization models, including data needs over and above traditional planning studies (Section 3.1), computational requirements (Section 3.2), the steps that are required to obtain the data and execute co-optimization models (Section 3.3), and finally time needed to develop and validate those models (Section 3.4). These sections draw on the authors' experience, informal conversations with the user community, and the literature.

3.1 Incremental Data and Their Benefits

Data availability and quality play a key role for any model development efforts. While, generally speaking, the electricity sector has extensive amounts of data available, ranging from generation to transmission and to consumption, the data requirements for constructing co-optimization models of high fidelity still pose significant challenges. The goal of this section is to review data issues in detail. Section 3.1.1 identifies the data used in current transmission planning processes; while Section 3.1.2 identifies incremental data needs for running co-optimization models, and provides a detailed summary of all the data required, including the desired data resolution and possible data sources.

3.1.1 Data for current long-term planning

The Eastern Interconnection encompasses large geographical areas that have multiple entities responsible for long-term generation and transmission resources, including both regulated and deregulated utilities, and independent system operators. Different entities have different planning processes, and consequently, different data requirements. Generally speaking, there are three types of planning processes, as summarized in [113]: reactive planning (RP), proactive planning (PP), and co-optimization planning (CP). Co-optimization can benefit states and Planning Coordinators regardless of their market and regulatory structures, as we have emphasized in the introduction and conclusions to this report.

Reactive planning refers to the practice of planning generation resources first, followed by transmission planning. Such a practice is common among regulated utilities, as described in [144] and through our discussion with several vertically integrated utilities in the Eastern Interconnection. In the reactive planning procedure, key data for transmission planning are the present transmission network topology and characteristics (e.g., transmission line voltage), forecasted peak load, and existing and planned generation resources. The last two pieces of information, load and generation, are usually passed along from the groups responsible for generation planning within the same utility company. The transmission planning in the reactive planning process is usually conducted through static analysis of load flow and power system feasibility, through the widely used commercial software, such as PSS®E from Siemens or other comparable tools. The input data for such analysis usually consist of bus data (base voltage, types of the buses, etc.), transmission line data ("from" and "to" bus, resistance, reactance, etc.), real and reactive load at each bus (either under peak conditions, or for a range of hours), generators (bus locations, real and reactive power limits) and transformer data.

The process of proactive planning, which has been used by several system operators/RTOs, usually requires running a production-costing model with detailed transmission network modeling, which would require more data than reactive planning. One widely used production-cost model is PROMOD IV® from Ventyx, a subsidiary of the ABB Group [107]. Transmission network data in the format used by PSS®E can be directly imported to PROMOD IV®. However, production-cost models need more detailed data on the supply side, including power plants' heat rate curves, fixed and variable O&M costs, availability, reserve capability, emissions rates, fuel costs, and, for some models, unit commitment constraints (minimum production levels, minimum-up/down time, ramp rates). For planning models that account for transmission contingencies, some transmission infrastructure performance data are needed such as Mean Time Between Failures (MTBF) and Mean Time to Restore (MTTR). For transmission planning, potential corridors are often identified first before running the production cost model. The planning process may be iterated several times between identifying potential transmission expansion projects and conducting feasibility and economics analysis of the power generation system.

The co-optimization planning problem attempts to find the least-cost combinations of candidate generating units and transmission lines for supplying the load forecast and satisfying prevailing operation and planning constraints. (However, in a world with increased penetration of demand response, load forecasts may lose some of their usefulness, and the goal will shift to maximizing market efficiency, being the net economic benefits to all market participants [4].) The objective comprises investment costs and salvage values for new resources, operation costs of generating units and microgrids, and the cost of unserved energy. The co-optimization expansion planning objective is subject to prevailing operation constraints, such as the limits on generation, fuel, ramping, emission, etc., and transmission network constraints.[4]

A decomposition approach could be applied to coordinate the operation and planning constraints as part of the co-optimization scheme (see Section 3.2.2, below, for further details). The decomposition would separate the planning problem into a co-optimization of generation and transmission, a short-term operation subproblem (which checks the transmission network constraints in the proposed plan) and an economic operation subproblem (which finds the

[4] A demonstration of a co-optimization process by the Australian Energy Market Operator using the commercial package PLEXOS can be found at http://www.aemo.com.au/Electricity/Planning/National-Transmission-Network-Development-Plan/Assumptions-and-Inputs.

optimal system operation based on the proposed plan). If the feasibility or the optimality check fails, constraints are generated by the corresponding subproblems and added to the next iteration of co-optimization of generation and transmission in order to try to move the investment problem towards feasibility. This iterative process will continue in an attempt to identify a secure and optimal expansion planning solution.

3.1.2 Incremental data needs

The data requirements for generation-transmission planning based on co-optimization would include all the data for the proactive planning process, plus the investment costs for new generation and transmission resources (and other resources such as demand response, distributed generation, and microgrids). For projects of a vertically integrated utility, such data shall be available within the utility. For other Planning Coordinators, such data are generally available from data vendors, such as Ventyx and Platts, as well as from certain specialized consulting firms. In summary, while in general all the data to conduct a co-planning process exist in the power sector, it may require tremendous effort to collect all the data from multiple sources. It may need additional effort to link data from different sources properly, such as linking existing and potential generation resources, forecasted demand, and demand-side resources down to the bus level in a transmission network. To help provide an overview of the data needed for generation-transmission co-optimization, a table (Table 3-1) that summarizes the categories of data needed and their potential sources is provided in Section 3.1.3.

3.1.3 Benefits of incremental data

As discussed before, more detailed, consistent, or higher quality of information are necessary for co-optimization modeling. Collection of such information will incur additional costs and manpower that would have to be justified. Part of the justification could be the potential benefits of co-optimization, in terms of more efficient and effective transmission plans and generation mixes. We described these benefits in our example applications in Section 4, below.

However, the incremental data needed for co-optimization models would also benefit other planning analyses. Such information could potentially foster improved analyses in more focused studies to support resource planning and investment, including studies of demand response, energy storage, energy efficiency, distributed generation, variable-output resources, capacity additions, uprates and retirements, capacity degradation, and fuel prices. As an example, Table 3-1 below shows how typical co-optimization planning data (discussed above and summarized in Table 3-3) can be utilized for sensitivity analyses in the production costing simulation of a power system with variable wind energy.

Table 3-1. Illustration of the use of co-optimization planning data for power system simulations

Scenarios		Wind Capacity (GW)	Wind Energy (TWh)	Wind Energy Contribution (%)	Production Cost ($ Billion)	Average Production Cost ($/MWh)
No Wind		0	0	0	217.5	45.64
Wind capacity factor $CF \geq 40\%$		230.5	845.2	17.67	130.4	27.25
$CF \geq 30\%$		481.5	1,596	33.37	86.8	18.14
All Wind		580	1,816	38	77	16.10
Fuel Price Sensitivity	20% Lower	230.5	845.2	17.67	118.9	24.87
	10% Lower		845.2	17.67	124.7	26.06
	10% Higher		845.2	17.67	135.7	28.36
	20% Higher		845.2	17.67	141.7	29.63
Wind Gen. Sensitivity	20% Lower		676.1	14.14	143.7	30.03
	10% Lower		760.6	15.9	136.8	28.59
	10% Higher		929.7	19.44	130.4	25.99
	20% Higher		1014	21.20	124.3	24.80
Load Sensitivity	20% Lower		845.2	22.07	64	16.73
	10% Lower		845.2	19.62	91.6	21.27
	10% Higher		845.2	16.29	178.5	34.65
	20% Higher		845.2	15.12	245.9	44.54
Carbon Cost Sensitivity	Low Carbon Cost with 40% Wind	230.5	845.2	17.67	406.8	84.97
	High Carbon Cost with 40% Wind	230.5	845.2	17.67	638	133.3
	Low Carbon Cost with 30% Wind	481.5	1,596	17.67	285.7	69.68
	High Carbon Cost with 30% Wind	481.5	1,596	17.67	448	93.59
Load Management	No Wind Energy with Load Shedding	0	0	0	208.7	44
	Min 40% CF Wind with Load Shedding	230.5	845.2	17.81	123	25.9
	Min 30% CF Wind with Load Shedding	481.5	1,596	33.53	80.6	16.97

3.2 Computational Requirements

This section will discuss the computational requirements for using co-optimization models. Generally speaking, such co-optimization models belong to the classes of Linear Programming (LP), Nonlinear Programming (NLP), Mixed Integer Linear Programming (MILP), or Mixed Integer Nonlinear Programming (MINLP), with LP having the least computational demands while MINLP has the most.

Large-scale LP models in general can be well handled by the state-of-the-art commercial optimization software packages, including CPLEX (IBM), Xpress-Optimizer (FICO) and Gurobi Optimizer. However, NLP and/or MIP co-optimization models can include more realistic modeling options. But they are much more difficult to solve because of the great variety and amount of variables and constraints. This section differs from other sections of this report (especially the co-optimization literature survey of Section 2.3) in that it describes other advanced methods not yet used in practice that have the potential to expedite and improve the efficiency of whatever modeling approaches are deemed to be the most worthwhile. In the following, first we will discuss the difficulties facing users of complicated co-optimization models, and review the status quo on computing approaches. Then we will briefly discuss some methods for the nonlinear programs and models involving both expansion planning and market equilibrium problems. After that, we will focus on decomposition algorithms that divide large planning problems into more manageable pieces, and high-performance and parallel computing.

3.2.1 Difficulties, challenges and opportunities on computing requirements for co-optimization models

Co-optimization models include both transmission expansion planning and generation planning for multiple years/decades and multiple locations/regions. This leads to many computational difficulties due to the fact that the details of power systems can greatly increase the size of the problem. In addition, nonlinearity and integer variables and uncertainties can add additional layers of complications. As is discussed in Section 3.2, modeling of transmission flows by itself can be a very difficult non-linear program (e.g., ACOPF). After adding investment expansion decisions, the problem becomes an even harder mixed-integer nonlinear program. However, the linearized DC approximation to load flows is a practical and generally sufficiently accurate approach for simplifying the nonlinear AC problem while still maintaining model fidelity. In many studies, DC OPF is used to model power transmission, and is adequate except under relatively rare highly stressed conditions in which voltage constraints are in risk of violation. In addition to non-linearities, there are difficulties related to integer variables, dynamics, uncertainties, and the sheer size of the optimization problems.

In order to understand what the greatest cause of difficulty for particular co-optimization problems might be, we first discuss the types of models used in co-optimization of transmission and generation. The primary types are listed as follows,

- Linear models, nonlinear models, mixed integer models, and models with equilibrium constraints
- Dynamic models vs. static models
- Stochastic models vs. deterministic models
- Large-scale models when considering a big system including both transmission and generation expansions

Linear models are the easiest type to handle, because there exist very powerful and efficient commercial software packages, as mentioned. However, when the size of the problem becomes very large (potentially tens of millions of variables because of the large number of buses, load scenarios, plants, etc.), solving the problem could be very challenging even with the most advanced computers and software packages (e.g., several days in [115]). This is usually due to the limited memory space in the computers relative to the number of variables and constraints in the problem. In the following, we will discuss current approaches in this respect. Because the current techniques for mixed integer programs are mainly based on their linear relaxation (i.e., where the integer or binary variables are allowed to take on fractional values), software packages for linear programming are also those popular for solving mixed integer programs. In order to model the dynamics of changing environments (especially over multiple years), dynamic models are sometimes used. This is usually dealt with by adding more time stages (discrete dynamics). In reality, there exist many uncertainties related to future parameters such as costs, demands, capacities, etc. (see Section 6, below). However, there are methods for explicitly introducing uncertainties in the models such as stochastic or robust models, but these become yet more difficult to solve due to the size increase and additional constraints.

Therefore, all types of problems will become more difficult to deal with when the scale increases and dynamics and uncertainties are introduced. A universally adopted approach to deal with problems caused by the scale of the optimization is to simplify these assumptions and solve a comparatively easier problem, even though model fidelity and precision may be compromised. Simplification approaches include:

- Aggregation of input data and model variables (e.g., [115])
- Simplification of dynamics and uncertainties (e.g., [115])

Approaches to modeling aggregation include:

- Location aggregation (e.g., aggregated region(s) instead of exact locations) (e.g., [106])
- Time period aggregation (e.g., multiple year instead of daily data) (e.g., [122])

Examples of model simplifications include:

- Operational details simplification (e.g., unit commitment might not be modeled in expansion planning)
- One-time expansion planning (e.g., avoiding the dynamic of the market or policy changes over years)
- Deterministic input data (e.g., using the expected wind output or peak loads)

Model aggregations and simplifications are effective for reducing computational complexity. However, models then lose fidelity and accuracy to some extent. Thus, it is desirable to solve large-scale and complicated problems. In the next subsection, we will discuss details on how decomposition methods can be used to deal with large-scale/dynamic/stochastic co-optimization models in the next section.

Meanwhile, nonlinearities present many challenges even with advanced software packages. A handful of nonlinear solvers can be used through widely available packages for setting up optimization problems (such as GAMS, Matlab, and AIMMS); example nonlinear solvers include CONOPT, Barron, and PATH.

An alternative way to deal with nonlinearities is through piecewise linear approximations (e.g., [151]). This is easiest to implement when the nonlinear terms in the functions involve single variables and, in the case of cost, the nonlinearities are upward bending ("strictly convex", which means the second derivative is positive). Then linear or mixed integer solvers can be utilized. In [151], the nonlinear function is convex and in the objective function, and then no integer variable is required. In cases of non-convex nonlinear functions (such as costs that bend downwards), binary variables are required to be added to the linear approximation model. Although the nonlinearity is eliminated, the newly-introduced integer variables still keep the problem from being solved easily. Furthermore, the more precision that is needed, the more integer variables need to be added and more difficult it is to solve. However, this might still useful because of the advance of mixed integer programming theory and software packages. Nonlinearities arising from games between two independent entities, one of which is optimizing considering the reaction of the other usually is addressed by using iterative methods. Iterative methods generally solve a simple problem at each time (e.g., the transmission planning, generation expansion, or a market equilibrium). For co-optimization models involving games (e.g., the market or general economy), iterative methods are used in a way where each player's optimization is solved iteratively with information of the optimal dual and primal solutions of other players and leaders' decisions. Iterative methods are usually easy to use and implement. However, for some problems it might be difficult to prove finite convergence in theory. In practice, computational results are often but not necessarily good. For this reason, approaches that directly solve the problem in one shot without iteration are increasingly popular [36] using, for instance, PATH.

3.2.2 Decomposition approaches for co-optimization models

In co-optimization models, both expansion and operation of transmission and generation assets must be considered. When solving these complicated models, some approaches break down the whole model into two parts: a transmission part and a generation part. For each part to be solved, the information of the other part (primal and/or dual solutions) is assumed to be known. The two parts are solved iteratively until no or negligible further improvement can be achieved by changing the solutions. (An example is provided in Section 4.3.4.) This method is easy to implement but may only find a suboptimal solution due to the presence of integer variables or complicated constraints. To further address the limitations of current commercial optimization solvers, we will discuss decomposition algorithms that hold great potential to efficiently solve large-scale co-optimization models. Some decomposition algorithms for co-optimization models are listed as follows,

- *Benders Decomposition*: a useful tool to help with large number of scenarios
- *Column Generation*: a useful tool for extracting good information from subproblems
- *Branch-and-Price*: a promising tool to solve multi-stage stochastic mixed integer programs

The state of the art optimization solvers (MILP or LP) can solve problems with reasonable sizes (e.g., a RTO deterministic expansion problem) within an acceptable amount of time. However, as the scale or size increases, the computational times increase exponentially or the problems are just too large-scale to be loaded into computers due to their limited memory space. Hence it is necessary to break down the largest scale problems into smaller problems that can be solved efficiently by the current solvers. Decomposition methods divide the original problem into smaller-size problems and assemble the information of the smaller problems in a way in which improvement at each step and convergence are guaranteed.

3.2.2.1 Benders Decomposition-type Decomposition

For stochastic programming expansion planning problems, dispatch costs for many individual hours or scenarios need to be simulated and incorporated in the model, which makes such models very large. To address the issue of model expansion resulting from by scenarios, Benders decomposition (BD) [11] is attractive due to its properties. A complete description of Benders decomposition can be found in Appendix A.III.1. Intuitively, Benders decomposition when applied to capacity expansion problems divides the problem into an investment/expansion problem (choose MW capacities of new plants or lines, for instance) and a set of operations problems. The expansion problem proposes trial system designs, and the operations problems then calculate the operating cost and shadow prices (in terms of operating cost savings) of additional capacity. The expansion problem is then re-solved, using (very loosely speaking) the shadow prices as guides to identifying a new solution. That is, the solution of the operation problem returns to the expansion problem information about what additional investments might be beneficial and which of the proposed investments haven't panned out. Through repeated iterations, the expansion problem makes better guesses, and under certain conditions, the process is guaranteed to converge to the overall cost-minimizing design.

As an example, two-stage expansion planning problems usually have the following structure as shown in Figure 3-1,

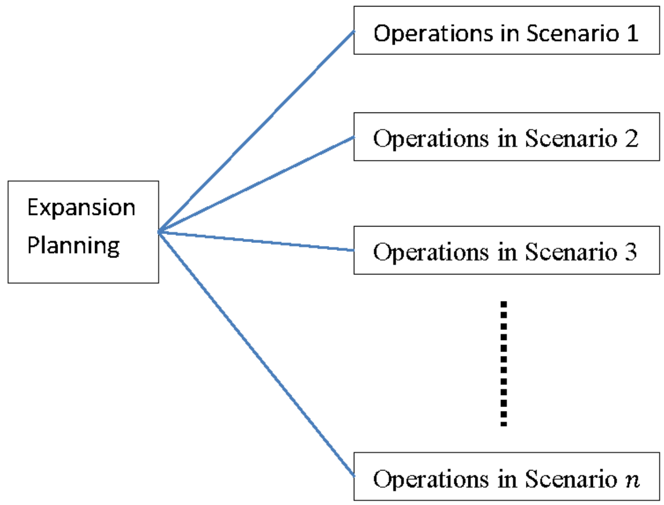


Figure 3-1. Structure of the two-stage expansion planning problems

Benders decomposition perfectly aligns with this structure. When the expansion decision is known, we can solve each operations problem separately, which is readily done because each is small. When applied to this structure, Benders decomposition is also referred to as the L-Shaped method [136]. This structure (Figure 3-1) is also a good fit for using parallel or distributed computing resources, which will be discussed in the high performance computing section. Although convergence of Benders decomposition is guaranteed in theory if the original problem has certain convexity properties, the main drawback of using Benders decomposition is that after rapid initial progress, the algorithm's convergence tends to slow. To this respect, numerous acceleration methods have been proposed to speed up the convergence rate. A short survey can be found in [151].

The basic Benders decomposition method assumes linear constraints and continuous variables. However, co-optimization models sometimes violate these assumptions. Then variations of Benders decomposition have been developed and used. When the operating subproblem includes nonlinear constraints but still has a convex feasible region, generalized Benders decomposition [39] can be used instead (e.g., the generation expansion planning problem in [16]). (In a convex feasible region, all solutions on a line connecting two feasible solutions will also be feasible.) When the subproblem includes integer variables, the problem becomes much harder and Benders decomposition cannot guarantee convergence to an optimal solution. This is because the value function of the subproblem is neither convex nor continuous as in [14]. In this situation, the integer-L-shaped method in [75] can be used if the master problem has only binary decisions. In addition, particular improvements to the methods, such as disjunctive cuts and combinatorial Benders cuts, can also be valid methods in this situation. Meanwhile, for other non-convex cases, research is actively underway to develop efficient and effective algorithms based on the Benders Decomposition framework.

Another commonly used Benders framework is often applied for hydro-thermal power scheduling under uncertainty. In particular, for a multistage stochastic pure linear program, Benders decomposition can be nested through all stages while blended with simulation techniques. This method is also called Stochastic Dual Dynamic Programming (SDDP) [101]. This method is mainly composed of two major operations: forward simulation and backward addition of cuts. Simulations and cut additions can be implemented more efficiently in the high performance computing environment.

3.2.2.2 Column generation-related decomposition

Since column generation (CG) was introduced [22], it has been elaborated and adapted to solve a great variety of problems including large-scale linear programs, mixed integer programs, and stochastic programs. In this section, we will focus on how CG is used to solve MILP and multi-period stochastic programs that arise in the area of power system planning. A mathematical statement of the basic CG algorithm can be found in Appendix AIII.2. Intuitively, a "column" is one particular solution or set of values for the decision variables (such as 1000 MW of wind plus 500 MW of combustion turbines). In CG methods, very loosely speaking, candidate solutions are generated in sequence by considering, for instance, possible combinations of previously generated solutions.

Although originally developed for large-scale linear programs, CG algorithms have evolved to solve integer (mixed integer) programs and multistage stochastic mixed integer programs. Their applications include multi-commodity flow problems in [8] (which can be relevant to combined natural gas-electricity operations), airline crew scheduling in [137] and energy/power systems planning in [117] and [125]. Because most current solution methods for integer and mixed integer programming are based on linear programming, the convex hull[5] formulation implicit in CG methods can be more efficient since its linear relaxation is a better approximation of the convex hull of the original problem. As a result, CG is very useful when the number of feasible discrete decisions is far larger than the number of discrete decision variables.

However, the generation and inclusion of columns needs to be in accordance with branching rules/strategies used by the CG algorithm. This approach is usually referred to branch-and-price. This method is also a good fit for multistage stochastic expansion planning problem (e.g., [1,82,117,125]). In these approaches, the approach breaks up the large stochastic problem by solving a series of individual (and smaller) deterministic capacity expansion problems. This is done by relaxing the so-called nonanticipativity constraints, which couple the decision variables of different scenarios in the scenario tree, and force expansion decisions in any two scenarios to be identical through year y if the history (load growth, etc.) of the two scenarios are identical

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[5] A convex hull is a geometric concept, defined as the smallest convex region to contain a certain region (or to contain a finite number of points.

through that year. (That is, if scenarios A and B both have 2% load growth through 2025, then a planner cannot tell until after 2025 which scenario is occurring and so must make the same decisions through 2025 in both scenarios.)

This strategy is powerful when there are many integer or binary variables and many scenarios, which is often the case in power system expansion planning. Not only do plant expansion and line additions involve integer/binary decisions, but so do operations (i.e., unit commitment). In the expansion planning level, uncertainties come from input prices, load growth, new technology availability, and policy changes [57]. Furthermore, due to the rapid increase in renewable energy production, uncertainty has grown in the operational problems. Consequently, compared to the deterministic problem in Figure 3-1, Figure 3-2 presents a more nuanced problem structure that includes uncertain scenarios.

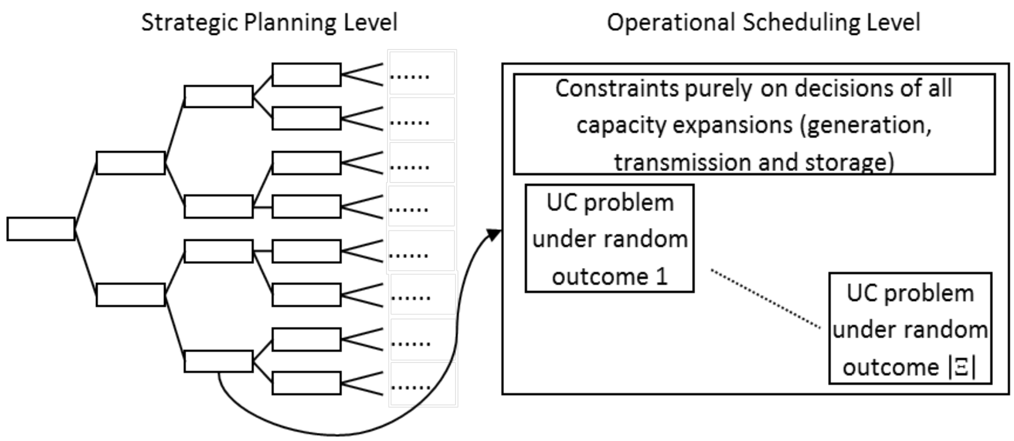

Figure 3-2. Expansion planning problem structure considering uncertainties in both levels [149]

To solve a complicated problem as shown above, an approach referred to as "nested column generation" can be used. Upon the decomposition of the stochastic strategic planning problem, another layer of decomposition needs to be performed on the operational problems. This is because the operational problems are still large-scale stochastic programming problems. Since both levels may include integer/binary variables, branch-and-price is a promising approach. In addition, more advanced formulations and methods based upon an approach called "disjunctive programming" are also the subject of active research.

3.2.2.3 High performance computing

High performance computing (HPC) usually refers to the use of supercomputers or clusters to solve complex computational problems. The computational tasks are usually achieved by the collaboration among many computers. For example, there is a central computing station that coordinates this collaborative work, and sends smaller tasks to the distributed computing resources, and then collects the resulting information, as shown in Figure 3-3. This structure nicely complements the application of decomposition algorithms. The central station is in charge of solving the master problem (such as the design problem in Benders decomposition) and sends either investment decisions (Benders) or prices (CG) to the subproblems that are individually solved on the distributed computers. In current practice (without HPC), the same computer needs to solve the subproblems in series, one by one. This consumes a lot of time since there might be many scenarios or subproblems. In many cases, this may be the main hurdle for solving the problem efficiently. While using the HPC environment, all the subproblems can be solved in parallel and the total computational time (on subproblems) can be reduced by as much as n times (where n is the number of subproblems or scenarios).

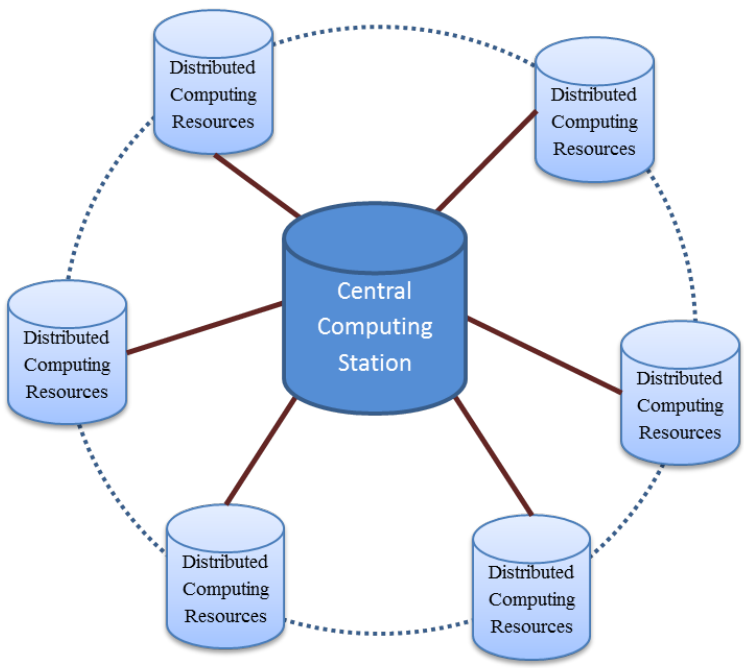

Figure 3-3. Distributed computing structure for decomposition algorithm

To further take advantage of distributed computing resources, a hierarchical structure can be constructed to facilitate algorithms based on nested decomposition. For example, the central station can be connected directly with sub-computing stations which, in turn, connect their own distributed computing resources. This is a good fit for decomposition algorithms that need to further decompose the subproblems. In addition, several levels of stations can be designed to accommodate more-complicated algorithms. To our best knowledge, high performance computing has not been widely used for accommodating decomposition algorithms in electric power planning practice. But much research is underway on the subject, which we believe will likely pay off in practical approaches for decomposition and solving very large co-optimization problems.

3.3 Steps Needed to Acquire Data and Execute Co-Optimization Models

This section has been developed through conversations with industrial generation and transmission planners. We describe how utilities and Planning Coordinators can develop and maintain databases necessary for using software that co-optimizes generation and transmission expansion (Section 3.3.1). These conversations also provided an opportunity to explore planners' view on the concepts, scope and requirements of co-optimization tools, and the general pros and cons of co-optimization, which we report in Section 3.3.2.

3.3.1 Data and information for co-optimization

Table 3-2 gives a synopsis of the kind of data required to run a co-optimization model, and summarizes some specific remarks that the experts we consulted made about them. This is provided for a quick perusal. Meanwhile, Table 3-3 is an expanded version of Table 3-2 and presents in detail data requirements and corresponding sources for obtaining these data.

Table 3-2. Synopsis of data and information needed to run co-optimization models

Categories	Required data	Specific remarks
Historical conditions	Hourly load & variable generation data, fuel prices, hydro conditions, bilateral transactions, generation forced & scheduled outage rates, transmission maintenance histories, inflation and discount rates, reserves for system adequacy, contingencies & flexibility, and imports & exports	Data for previous N years, load and variable generation data should be correlated with weather conditions or be weather normalized
Existing and planned infrastructure	AC network topology, AC circuit data, DC line data, fossil & renewable generation data, storage and demand response, and existing long-term bilateral contracts, contingencies (N-1 & N-1-1)	Operational characteristics, impacts of line length on its capacity if using DC model
Resource options	Generation, storage, demand response, and their maturation rate	Investment and operational characteristics of each option, geographical dependence of data
Transmission options	AC line, DC line, transformer, circuit breaker and voltage control equipment	Investment and operational characteristics of each option, candidate transmission investments
Future conditions	Forecasted system conditions, bilateral contracts, global scenario descriptions (policy, technology or load related)	Depends on planning horizon (with suitable end effects calculation), employ technique to choose a good set of global uncertainties

Table 3-3. Details of data and information to run co-optimization model

Data or information item		**How to obtain (source and comments for data collection)**
Essential	**Useful**	
A. Historical conditions		
Hourly load data for a previous year that is “normal” (has no strange events). Data for variable generation (VG) should “synch” with load data, i.e., they should be for same time period.	Hourly load data for previous N years; hourly weather data for previous N years,	**Source:** PI-Historian from EMS, Ventyx hourly data **Comments:** The load and VG data should be correlated with the weather patterns and thus, with each other. One way to do this is to use hourly load and VG data for a previous “normal” (has no strange events) year. But we also need to capture the systemic changes in load shape. Therefore, it may be necessary to develop a model for predicting synchronized load and VG data.
Fuel prices (coal, petroleum, natural gas, uranium) for previous year	Fuel prices (coal, petroleum, natural gas, uranium) for previous N years	**Source:** Energy Information Admin., Henry Hub, Market service providers
Hourly variable generation (use capacity factors only if hourly is unavailable) for previous year	Hourly variable gen (use capacity factors only if hourly is unavailable) for previous N years, and then weather normalize them, e.g., average them. Alternately, use N actual years as different “scenarios.”	**Source:** Pi-Historian from EMS, NREL (EWITS, WWSIS) **Comments:** Load and wind data should be correlated with weather patterns and so with each other. One way to do this is to use hourly load and wind data for a previous “normal” (has no strange events) year. But we also need to capture the systemic changes in load shape. Therefore, it may be necessary to develop a model for predicting synchronized load and wind data.
Hydro conditions for previous year	Hydro conditions for previous N years, and then weather-normalize e.g., average them.	**Source:** National Oceanic &Atmospheric Admin/ **Comments:** Alternately, use N actual years as different “scenarios.”
Bilateral transactions for previous year, unless all dispatch is to be represented according to economics. Hurdle rates (wheeling charges) should be represented between regions.	Bilateral transactions for previous N years	**Source:** OASIS databases **Comments:** Previous year bilateral transactions may be represented if they are thought to be representative of what will occur in the future.
Generation forced & scheduled outage rates (can be computed from gen forced and maintenance outage histories)	Gen hourly unit commitment for previous N years	**Source:** PI-Historian from EMS, GADS (NERC) **Comments:** Capture relationships between the seasons and maintenance scheduling in the co-optimization
Transmission maintenance histories for previous 5 years	Transmission cct forced outage histories for previous 5 years	**Source:** PI-Historian from EMS, TADS **Comments:** Transmission maintenance is generally off-peak and should be represented during that time. Forced outages can happen anytime but typical transmission FOR is 1% and so not very critical
Inflation and discount rates for previous year	Inflation and discount rates for previous N years	**Source:** U.S. White House Office of Management and Budget (OMB) **Comments:** ; Tag inflation to GDP. May have different rates for different organization types (e.g., IOUs vs. Public Powers) and for different regions

Table 3-3. Details of data and information to run co-optimization model (Cont.)

Data or information item		How to obtain (source and comments for data collection)
Essential	**Useful**	
A. Historical conditions (Cont.)		
Reserves to meet peak load and LOLE		**Source:** NERC, state PUCs, resource adequacy targets in Capacity markets. **Comments:** May vary by region or by state. Present variation is from 14.2% (MISO) to 18% (PJM)
Contingency reserve requirements for previous year, including which units contribute to those requirements and which do not.	Contingency records (N-1 & N-1-1)	**Source:** PI-Historian from EMS
Flexibility needs (regulation and ramping requirements for previous year)		**Source:** Estimate based on intra-hour load and VG variability, such that CPS-2 is met
Imports and exports for previous year, and whether it can be applied towards resource adequacy needs.		**Source:** PI-Historian from EMS
B. Existing infrastructure and planned infrastructure & conditions		
AC network data: topology, nominal kV at each bus.	Contingencies (N-1 & N-1-1) for gen. & transmission	**Source:** Production cost model
AC circuit data: kV level, impedance, continuous & emergency thermal ratings, rating adjustment for distance (St. Clair curves, i.e., loading limit given in multiples of SIL vs. distance), lifetimes (economic and operational), depreciation rate.	Xfmr taps, ranges of voltage cntrl equip, Var compensation (against voltage stability issues)	**Source:** Production cost model **Comments:** *Lifetimes:* Two types, economic and operational. Typically, they are 30 yrs and 70 rs for transmission. After 30 yrs of economic life, a depreciation rate for economic value is applied. *AC vs. DC model:* Need to capture the impact of line length on rating (voltage stability issues limit loading capability well before thermal rating). AC model can capture, but DC model requires explicit modeling for longer lines.
DC line data: type, bus terminations, ramp rates, continuous & emergency ratings, lifetimes	DC line reactive capabilities, whether it is voltage source converter or current commutated	**Source:** Production cost model
Fossil generation data: technology, P_{max} & P_{min}, block representation of heat rates, cycling costs, fuel types which can be used, emission rates, O&M costs, ramp rates, unit lifetimes (economic and operational), emission control support (different for different regions). Tax depreciation profile.	Q_{max}, Q_{min}, hot, warm & cold start-up costs & times, min. up & down times, hot & warm reserve costs, heat rate degradation as a function of use	**Source:** Production cost model, Ventyx data (captures geographic variation of these data, which is very important)
Renewable generation data: technology, P_{max} & P_{min}, emission rates, fixed O&M costs, ramp rates, unit lifetimes (operational and economic), operation histories, Tax depreciation profile.		**Source:** National Renewable Energy Laboratory
Storage data: technology, reservoir capacity, lifetime, grid services. For both charging and discharging: power limits, efficiencies, emission rates, fixed and variable O&M costs, ramp rates. Tax depreciation profile.	Start time & costs, heat rate degradation as a function of use (CAES)	**Source:** Production cost model, EPRI Handbook, Manufacturer data sheets (batteries)

Table 3-3. Details of data and information to run co-optimization model (Cont.)

Data or information item		How to obtain (source and comments for data collection)
Essential	**Useful**	
B. Existing infrastructure and planned infrastructure & conditions (Cont.)		
Demand response data: technology, P_{max}, P_{min}, ramp rates, fixed & variable O&M cost		**Source:** Production cost model, reports from load serving entities
Existing long-term bilateral contracts		**Source:** FERC
C. Resource options		
Generation, storage, and demand response data: same as for existing infrastructure, plus overnight cost per kW and lead time.		**Source:** Energy Information Admin., generator manufacturers, power plant design & construction consultants. **Comment**: Some data (overnight and variable O&M costs) depend on geographical location, and so regional multipliers may be necessary
Maturation rate for each technology		**Source:** Same as previous
D. Transmission options		
AC line data: kV level, impedance per mile, continuous & emergency thermal ratings, rating adjustments for distance (St. Clair curves, i.e., loading limit given in multiples of SIL vs. distance), distance between substations, overnight cost per mile, lifetimes and lead time.	Candidate transmission investments	**Source:** Conductor manufacturers, transmission design & construction consultants. **Comments:** Line and substation cost/mile depends on KV level. Also, overnight costs may depend on geographical location, and so regional multipliers may be necessary.
Transformer data: kV levels, impedance, cont & emerg thermal rating, cost, lifetime and lead time		**Source:** Transformer manufacturers, substation design & construction consultants. **Comment**: This data may be combined with CB and voltage control equipment data for a given substation design to form a single "substation cost"
Circuit breaker (CB) data: kV level, cost, lifetime		**Source:** CB manufacturers, substation design & construction consultants.
Voltage control equipment: kV level, cost, lifetime		**Source: M**anufacturers, substation design & construction consultants.
DC line data: type (VSC vs. .CC), kV level, continuous & emergency rating, ramp rates, overnight cost/mile, terminal costs, lifetimes, lead time	DC line reactive capabilities	**Source:** DC line equipment manufacturers, DC transmission design & construction consultants.
E. Future conditions (20 yrs)		
Forecasted conditions: hourly demand, fuel prices (coal, natural gas, uranium), possible variable generation locations & associated resource (wind/solar) quality	Planning horizon (forecasts needed for later years beyond horizon to adjust for "end effects")	**Source:** Market service providers, or compute using a forecasting algorithm. **Comment:** Hourly demand for future years may be obtained via scaling of a previous year's hourly demand profile. Alternately, a prediction model of synchronized wind and load data based on historical weather conditions should be developed for use in such planning studies
Bilateral contracts		**Source:** Use existing long-term bilateral contracts, and forecast future bilateral contracts using out-of-area price disparity
Scenario description: realizations (high/low) of global uncertainties such as cost of CO_2 emissions & cost, nuclear waste, fuel prices, demand growth, cost of each generation & transmission technology, inflation & discount rates		**Source:** Consider all combinations of global uncertainty realizations; reduce this number by choosing a representative subset of them.

3.3.2 Industry perspective on the scope of co-optimization and tools

This section reports perspectives that have been communicated to us from various leading practitioners of long-term generation and transmission planning regarding co-optimization. Their remarks are categorized into pros and cons of co-optimization. The "pro" comments also include several suggestions for what should—or should not—be included in co-optimization models. We report many of the observations as we recorded them, and do not try resolve the many disagreements and contradictions among the opinions expressed.

3.3.2.1 Pros of co-optimization and general advice

1. *Geographic cost variation:* Co-optimization is very useful given that the economies of generation options are highly varying across geographies. Therefore it will be economically beneficial to strategically expand generation and transmission simultaneously.

2. *Need for a robust tool:* Currently no tool is available that can co-optimize generation and transmission across multiple states (the previous point necessitates assessment over a wider-region), and simultaneously handle the decision complexities involved in such a problem. These complexities include:

    a. *Transmission candidates:* Many alternatives for transmission available (e.g., the MISO system has 60,000 nodes, and many candidate transmission lines to connect them), and there is a need to limit the alternatives.

    b. *Voltage ratings introduce discrete decision variables:* It is necessary to capture differences in characteristics of transmission lines at different voltage ratings, such as different costs of substation for 345 KV and 765 KV systems, respectively. Use of conventional continuous cost parameters expressed in $/GW-mile for transmission, analogous to the $/GW used in generation expansion, may not work.

    c. *Value of transmission expansion:* A generation and transmission co-optimization tool should be able to assess all the values transmission would bring to the system [103,18], apart from just production cost savings and emissions reduction related metrics, including:

        i. Value of transmission in reducing system congestion and losses;

        ii. Identification and quantification of parts of the network which incur savings and parts of the network which incur costs associated with each investment;

        iii. Accounting for system adequacy, and ancillary service/ramping service provision;

iv. "Insurance value" of adding transmission – i.e., adding transmission tends to mitigate the impact of multi-element contingencies, e.g., N-3, N-4, … etc.. An example is the economic value provided to southern California by the new Sunrise line, which was put in service in the summer of 2012 just after the San Onofre Nuclear Plant outage.

3. *Screening/evaluation tool:* The simultaneous optimization of generation resources and transmission will provide valuable insights into economically beneficial expansion plans, thereby serving as a good screening tool. The tool may also be used to evaluate and compare different solution strategies, i.e., proposed generation siting and transmission designs**.**

4. *Evaluating market constructs/design:* A co-optimization tool can be thought of as a pursuit to regulate the planning process towards an integrated resource planning paradigm, a move away from current deregulated market environment. The tool may provide signals to evaluate and perhaps improve the directions of current market constructs.

   - *Software underlying capacity markets:* The current market constructs may incent the adoption of certain solution strategies based on short-term economic signals (e.g., strategies for 1-5 year time horizon in terms of building local generation and demand response). However a long-term co-optimization model such as this can provide alternative options with a promise over longer horizons. Therefore, a co-optimization model considering generation, transmission and demand side options simultaneously over a longer time horizon may ideally underlie capacity market designs.

5. *Uncertainty and scenarios:* If a co-optimization tool is to be built, the following features (equally applicable to any planning tool) would be of interest to the industry planners:

   a. Handling uncertainty is important – e.g., uncertainty in natural gas and coal prices, load levels, and demand response.

   b. Many companies emphasize scenario analysis – the ability to gain insight of how a design performs under significantly different futures or scenarios is really important.

3.3.2.2 Cons of co-optimization

1. *Local DR program:* Local DR programs may obviate the need for additional generation and corresponding transmission. This may lessen the value of co-optimization, unless DR programs are considered to be an investment option in co-optimization.

2. *Transmission planning practices:* Transmission "only" companies deal just with transmission planning for their customers and others who own the generation. The generation owners make decisions about where and what kind of generation will be built.

Transmission companies design the transmission system to enable the generation and load choices of others. For such organizations, co-optimization may not be as useful as it would be for organizations owning both generation and transmission; yet, it may still be useful for determining future scenarios to study. This issue could be mitigated by developing the co-optimization tool in such a way so that the user would have the option of specifying or guiding the generation investments. The user would need to apply their own method for specifying or guiding generation investments, and it may be that such methods would differ depending on whether the service area of interest is within a traditionally regulated state or within a region served by an electricity market.

3. *Accounting for all design influences:* While co-optimization tools may propose possible transmission designs, its ability to find solutions that will actually get built is limited by influences in resource and transmission planning for which it would not account. Some of these influences include:
    a. *Influences in resource expansion:* Environment (air and water preservation), tax subsidies, policies, job perspectives, fuel access, and regional priorities/policies.
    b. *Influences in transmission expansion:* system dynamics, reconfiguration, switching, rights of way, and voltage support assessments.
4. *Data maintenance:* A data-intensive model requires significant labor to maintain. The value of the tool will need to be significant to justify such effort.

3.4 Time Requirements for Model Development and Validation

Developing any co-optimization model for practical application would likely be a long, arduous process. It is also a continuous process that would need to reflect updates on data and advancements in modeling and computation methods. Since most experience with co-optimization is in the research community, and because the process of developing commercial-grade software suite and research-grade models can be drastically different, it is difficult to provide an estimate for the time required for co-optimization model development in practice. That said, there are common steps required to develop any large-scale optimization model, whether research or commercial. We provide a time estimate for each step based on the experience of the team members, who have successfully developed co-optimization models as surveyed in Section 2.3.2.3 and Appendix II. The steps include:

- initial planning;
- data collection, processing and database construction;
- model construction;
- coding/debugging;
- testing; and
- validation.

The time estimates reported below assume that one person with appropriate technical background and experience is working on each task.

Initial planning: While the initial planning for developing a model may involve many subtasks, such as resource assessment and data collection, a central task will be to define the project scope. Several factors can affect decisions on scope. First, the scope is driven by the purpose of the modeling effort. For instance:

- Is the model to be used by policy makers for analyzing the impacts of environmental policies on the power sector?
- Or by system operators for system resource adequacy and reliability studies?
- Or by utilities for integrated resource planning?

Second, available resources confine the project scope. Examples of questions that must be addressed include: who are the domain experts and are they in-house or, alternatively, consultants who must be contracted? What data are on hand or could be readily obtained? What optimization solvers and/or proprietary planning software (Section 2.2) are available? What computing resources can be used? The time for the initial planning phase is highly variable depending on the complexity of the problem and the experience of the organization, and may range from one to six months.

Data collection, processing and database construction: The availability and quality of source data are of paramount importance for the success of any modeling efforts. As discussed in Sections 3.1 and 3.3 above, all the required data for constructing a co-optimization model exist. However, they are scattered in multiple places. In addition, certain data are confidential, while some others are proprietary, adding significant challenges in collecting all the required data in a timely fashion while staying within the project budget. A conservative estimate of collecting all the required data for the co-optimization to produce meaningful results would take six to nine months for a model covering the Eastern Interconnection. Merely obtaining the data is not enough, as the data has to be in the format that can be used by the planning model, and be of good quality. Hence, a data processing phase is needed after the data are collected. In addition, a database system is also required for passing the data to computer programs. The sophistication level of such a system could range from purely text files, to spreadsheet files, to SQL-based database management systems.

A rough estimate for initial data collection could be up to 9 months, dependent on the amount of proprietary and confidential data needed. For data processing and database construction, it may take up to one year and beyond. The lengthy time for data collection and processing, on the other hand, shall not be a deterrent for model development, as such processes can be performed in parallel to model construction. In addition, to test model validity, a small-scale, test data set can be developed first, independent of real-system data collection.

Model construction: The model construction phase contains two major tasks:

1. Establish the mathematical formulation for co-optimization models, if an appropriate commercial or research software package is unavailable; and
2. Choose an appropriate optimization solver or design algorithms to solve the resulting model.

The duration of the first task is mainly determined by two factors – the available domain experts and the sophistication of the model. The impact of the first factor is obvious, while the second factor refers to what features or functionalities are to be included in the model, which should be determined in the initial planning phase. The features, for example, may include some of the following:

- Is demand response is to be explicitly incorporated in the model?
- To what degree of sophistication are retrofit, retirement, and repowering options to be modeled?
- How are uncertainties (variability in renewable outputs and load, power plant and transmission line outages, long-run technological, policy, and economic uncertainties) to be represented in the model?
- How are energy storage, distributed generation, or microgrids to be modeled?

Once the mathematical formulation is established, it will be known what optimization categories the model belongs to: linear programming, nonlinear (but convex) programming, mixed integer linear programming (MILP), stochastic programming (SP), or even dynamic programming (DP). The optimization categories dictate whether off-the-shelf optimization solvers could be directly used. For example, linear programming, convex quadratic and MILP models may be solved by CPLEX (IBM), Xpress-Optimizer (FICO) or Gurobi Optimizer. Even so, the scale of the models or their complexities may render the commercial solvers ineffective or unusable. In such cases, specialized algorithms (either to utilize the special structures of the problems at hand, or simply to utilize high performance computing) are needed, as discussed in Section 3.2, above. For other model categories (SP or DP), specialized algorithms have to be developed, as few commercial solvers are available[6].

The length of the model construction phase can be highly variable. The formulation stage may take one to several months; while the algorithm development stage may take less than a month if commercial solvers are usable, to up to a year if new algorithms need to be designed.

Coding/Debugging: The duration of the coding/debugging phase is mainly determined by five factors:

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[6] There are certain commercial optimization suites, such as GAMS and AIMMS,that can handle certain types of stochastic programming problems (such as stochastic programming with recourse constraints). However, there is relatively little documentation on their abilities to solve large-scale power system problems.

1. available human resources (and their competence level);
2. if new algorithms are to be developed;
3. coding language to be used;
4. database system; and
5. reporting requirements.

The third factor, the coding language to be used, is largely determined by the second factor. If only commercial solvers are to be used, the coding effort (excluding the effort involved in creating reports from the optimization model's solutions) only includes translating the mathematical formulation into computer languages and passing data (extracted from a database system) to the solver. In this case, not only the major programming languages, such as C/C++, Java, FORTRAN, are all suitable, but some specialized modeling languages are available as well, and they may significantly simplify and shorten the coding process. Such modeling languages include AMPL, GAMS, AIMMS, OPL (bundled with CPLEX), and Xpress-Mosel (bundled with Xpress-Optimizer), to name a few.

These specialized optimization modeling languages have several advantages compared to general purpose programming languages. First, they are much easier to use when coding optimization models, as their syntax and semantics closely resemble the mathematical notation optimization and, in some software, human language. Second, it is easier to pass data to an optimization solver through a modeling language that is designed to do so. Third, it is generally easier to debug with programming languages.

On the other hand, specialized modeling languages also have disadvantages, such as they may use more computing resources (such as memory) and are generally slower than general programming languages (such as C/C++). Further, if new algorithms have to be developed, then a general programming language is likely to be the only option, as the programming capability of the modeling languages are in general very limited. As a result, the time estimate for coding/debugging efforts can be highly variable, ranging from a few weeks for simpler models with read-to-use, off-the-shelf solvers, to multiple years for model, algorithm and database development for specialized, state-of-the-art models for which only research-grade code is available.

Testing: This (sometimes called verification) refers to the process of error finding, which differs from validation, to be discussed below, as validation is about the fundamental validity of the mathematical model. It is also different than debugging, as debugging is simply to ensure that a computer program can be compiled, while testing is to find errors in the modeling results after a model run is complete. Errors can come from multiple sources, including modeling errors (such as omitting a variable in a certain constraint), coding errors, and data errors. This is another lengthy process, especially for co-optimization models, due to their scale and complexity. A rough estimate for the testing phase is approximately six weeks to months, depending on whether specialized or general modeling languages are used. Specialized languages facilitate testing because of their easy-to-use interfaces and their orientation towards optimization problems.

Validation: This refers to the process of validating models to ensure accurate and credible outputs. This phase has to follow the testing phase, when the modelers have tried their best to ensure that the model is error free. Error free, however, does not necessarily mean that the outputs from the model are automatically correct. There may be fundamental modeling flaws (such as how renewable energy is modeled, how demand is modeled, etc.) or input data errors (such as mismatch among supply, demand, and transmission buses). The common practice of validation includes comparison to well-established results of similar studies and backcasting, which is to use historical data as input data and see if the model produces reasonable solutions compared to real-world realizations. Scenario analysis could also be used for validation purposes, as they could reveal if the model behaves reasonably with changes in input parameters. A very approximate estimate of the validation phase is of three to six months.

4 APPLICATIONS: CASE STUDIES OF CO-OPTIMIZATION BENEFITS AND VALIDATION

4.1 Introduction

This section utilizes three different research-grade tools, GENTEP, NETPLAN, and the JHU software, to illustrate co-optimization of transmission and generation. The illustrations are performed on simplified power systems that were chosen because they enable intuitive understanding of the solutions provided by the software. Section 4.2 utilizes GENTEP, developed at Illinois Institute of Technology, in a series of illustrations on three or four bus networks to illustrate benefits of co-optimization. Section 4.3 utilizes NETPLAN, developed at Iowa State University, and JHU software, developed at Johns Hopkins University, on a 13 bus network to address validation protocols for co-optimization software.

4.2 Potential Benefits of Co-Optimization: Some Simple Examples

4.2.1 Introduction

While co-planning of large-scale generation and transmission infrastructure is rare in the United States due to independent ownership of generation resources, co-optimization modeling can still provide valuable information to transmission planners. Compared to decoupled optimization (transmission-only, generation-only, or iteration between the two), co-optimization models that simultaneously solve for transmission and generation return solutions that are less expensive in total [113]. In this section, we present simple numerical examples of how co-optimization models, in comparison to traditional transmission-planning or generation-planning models, would benefit the planning processes. The potential benefits of the co-optimization models that are considered include:

1. savings on both transmission and generation resources;
2. consideration of retirements and uprates;
3. treatment of tradeoffs between transmission and other resources, considering how variable resources affect those tradeoffs;
4. efficient integration of non-traditional resources such as demand response, customer owned generation, energy storage/including pumped storage, and other distributed resources;
5. optimization of fuel mix benefits; and
6. improved assessment of the ramifications of environmental regulation/compliance planning.

These benefits are illustrated in a series of numerical examples based on three or four bus networks. These examples are solved using a co-optimization model GENTEP [120,66,65]. GENTEP is configured to produce transmission-only or supply-only solutions as well as full co-optimization, thus providing meaningful demonstration of the benefits of co-optimization through benchmarking and comparison.

4.2.2 Summary of optimization approaches: Generation, transmission, and co-optimization planning

Figure 4-1 shows the structure of the GENTEP model that is used to solve the various examples in Section 4.2.3. A detailed explanation of GENTEP is provided in Appendix II. The core of the GENTEP model is the co-optimization of investment in generation, transmission, and microgrids, which we call the "master problem." By setting either the generation capacity or transmission capacity to predetermined fixed values, generation-only and transmission-only planning can be simulated; if both are allowed to vary within the model, co-optimization is the outcome.

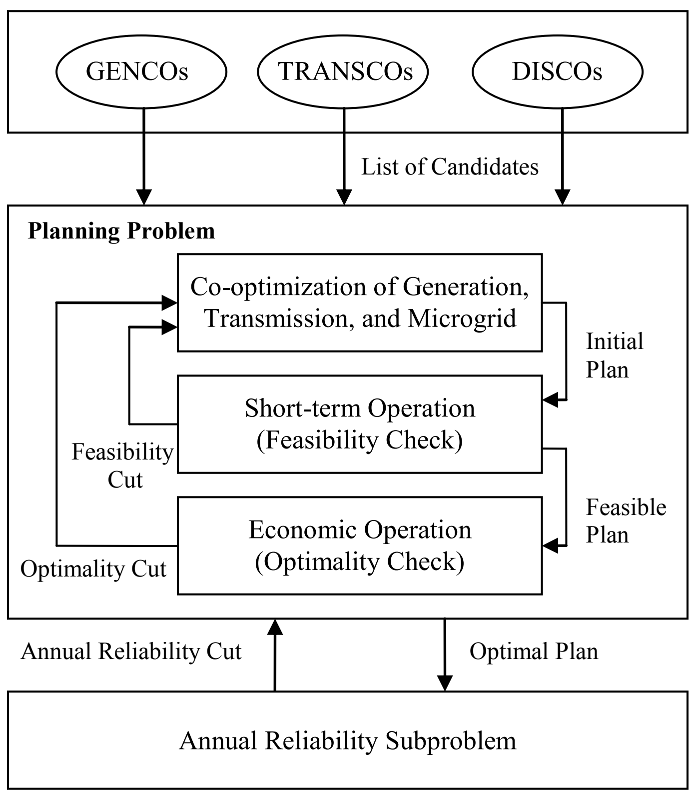

Figure 4-1. Schematic of GENTEP methodology for co-optimization

The master problem has the following structure:

Objective function: Minimize investment cost

Subject to constraints:

- Availability of capital investment funds
- Maximum capacity level of units and lines in a planning year
- Maximum number of units and lines to be added in a planning year
- Projected starting year of construction

Output: Annual installation status of candidate generating units and transmission lines

There are two subproblems that return important information to the master problem about the performance of the investment plants: the Reliability Subproblem and the Operation Subproblem. The former subproblem is structured as follows:

Objective function: Minimize mismatch between load and generation

Subject to constraints:

- Power balance
- Unit dispatch limits
- Line flow limits

Output: Reliability status

The Operations Subproblem, in turn, has the following structure:

Objective function: Operation cost minimization

Subject to constraints: Same as Reliability Subproblem

Output: Optimality status

The three versions of GENTEP (generation only, transmission only, and co-optimization) are used in the following section to solve a series of examples that illustrate the six types of benefits of co-optimization. In every case, we consider one year of operation (8760 hours), and assume that the same load applies in every hour. Some of the analyses below consider line or generator outage contingencies. In those solutions, GENTEP's objective function only includes costs from the base (no outage) scenario; however, a constraint generation procedure ensures that the generation is dispatched in the base scenario so that the system can be redispatched in a contingency such that expected amount of load that is unserved in the contingencies does not exceed an upper bound.

4.2.3 Analyses of benefit categories

4.2.3.1 Benefits category 1: Savings on both transmission and generation resources

The first type of benefits from co-optimization concerns the savings in costs of both investment and operations of the combined transmission-generation system. We illustrate those benefits by considering three examples below: a generation-only optimization, a transmission-only optimization, and a co-optimization. They are applied to different problems, so their costs cannot be directly compared; however, they illustrate the scope of each of the three problems, and the co-optimization example illustrates the consideration of transmission and generation tradeoffs. In the examples of this subsection, it is assumed that all transmission and generation equipment is 100% reliable; this assumption is relaxed in later examples.

Generation-Only Optimization: In Figure 4-2, we show the three bus network that connects two existing generators and two potential generators; the generation-only problem consists of choosing which (or both) of those generators to build, and how to operate them, subject to the existing network. So in this example, transmission is not expanded. The relevant generator, transmission, and load data are provided in Tables 4-1 – 4-3.

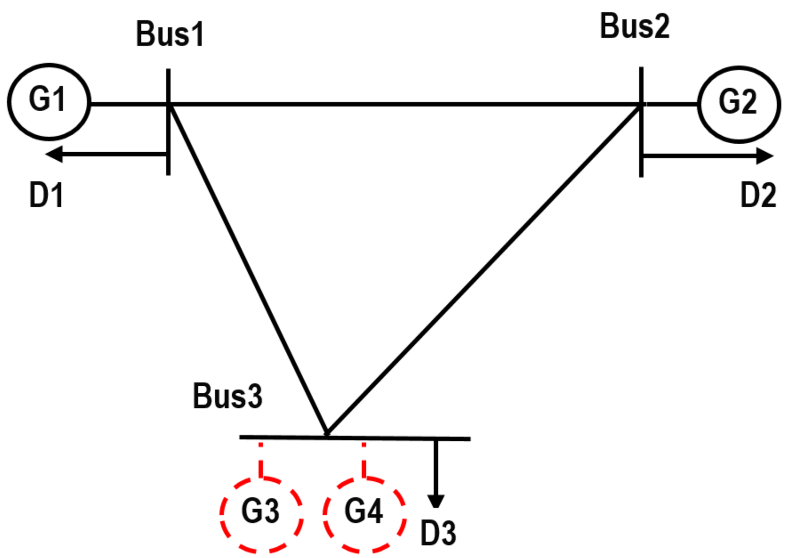

Figure 4-2. Network configuration for benefits category

Table 4-1. Generator data for benefits category 1, generation planning only

Unit	Min Capacity (MW)	Max Capacity (MW)	Fuel Cost ($/MWh)	Investment cost ($/yr)
G1	50	250	10	-
G2	60	200	10	-
G3	60	300	8	5,000,000
G4	60	300	10	4,000,000

Note: All investment costs in this table are annualized costs.

Table 4-2. Line data for benefits category 1, generation planning only

Line	From bus	To bus	Reactance (pu)	Capacity (MW)
L1	1	2	0.1	50
L2	2	3	0.1	100
L3	1	3	0.1	50

Note: The reactances are used in a linearized dc load flow model in GENTEP; the units are in “per unit” (pu).

Table 4-3. Load data for benefits category 1, generation planning only

Planning Year	D1 (MW)	D2 (MW)	D3 (MW)
1	100	300	100

In the generation-only planning problem, the existing units in the base case cannot satisfy the load, so new units must be added. The optimal solution to this problem is obtained in 3 iterations of GENTEP. The optimal solution adds new generator 3, though it has a higher investment cost than generator G4. The resulting solution, including dispatch and load flows, is shown in Figure 4-3. The total cost is $44,420,000/yr.

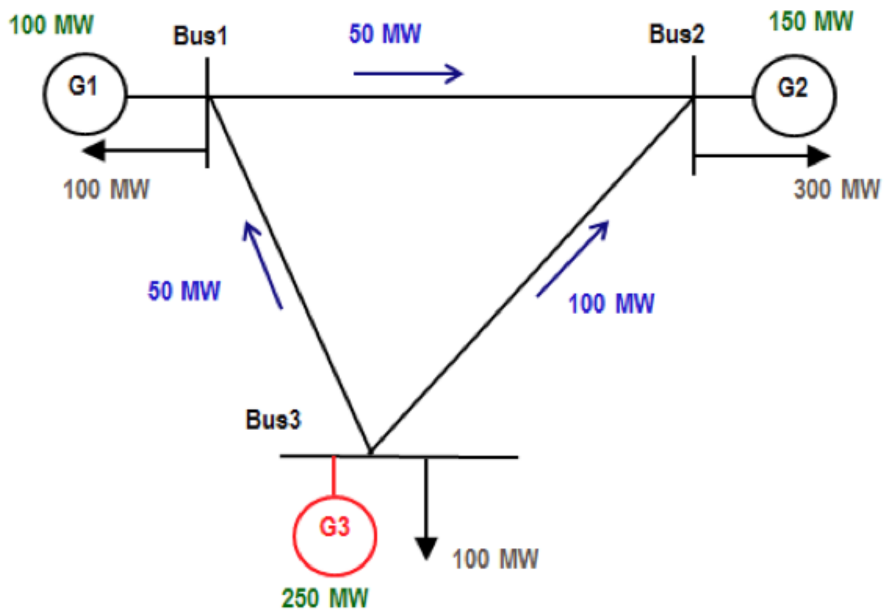

Figure 4-3. Solution for benefits category 1, generation planning only

Transmission-Planning Only: We now turn to transmission-only planning. Figure 4-4 shows that the two transmission alternatives that can be used to interconnect a new generator at Bus 4. The objective function of the model includes only transmission investment costs (since generator G3 is assumed to be built, it is a sunk cost) and variable costs for the generator. Tables 4-4, 4-5, and 4-6 provide the data.

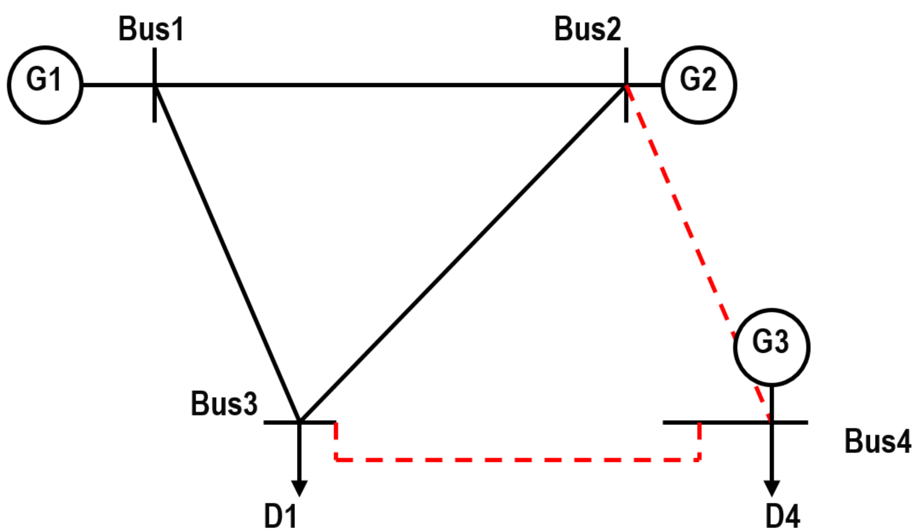

Figure 4-4. Network configuration and potential transmission alternatives for benefits category 1, transmission planning only

Table 4-4. Generator data for benefits category 1, transmission planning only

Unit	Min Capacity (MW)	Max Capacity (MW)	Fuel Cost ($/MWh)
G1	50	150	10
G2	100	200	8
G3	50	100	10

Note: Generator dispatch is constrained to be between the minimum and maximum values stated.

GENTEP obtains the optimal solution for the transmission-only planning model in three iterations. It chooses to install just one of the two lines, as shown in Figure 4-5. Line 2-4 is installed though it has a higher investment cost than the candidate line 3-4. The installation of Line 2-4 allows higher generation from the more economic Unit 2; hence it reduces the operation cost, and this reduction is greater than the expense of the line. The total investment and operating cost is $37,536,000/yr.

Table 4-5. Line data for benefits category 1, transmission planning only

Line	From bus	To bus	Reactance (pu)	Capacity (MW)	Investment cost ($/yr)
L1	2	4	0.2	100	6,000,000
L2	3	4	0.2	100	5,000,000
L3	1	2	0.1	150	-
L4	2	3	0.2	100	-
L5	1	3	0.1	150	-

Table 4-6. Load data for benefits category 1, transmission planning alone

Planning Year	D1 (MW)	D2 (MW)
1	200	200

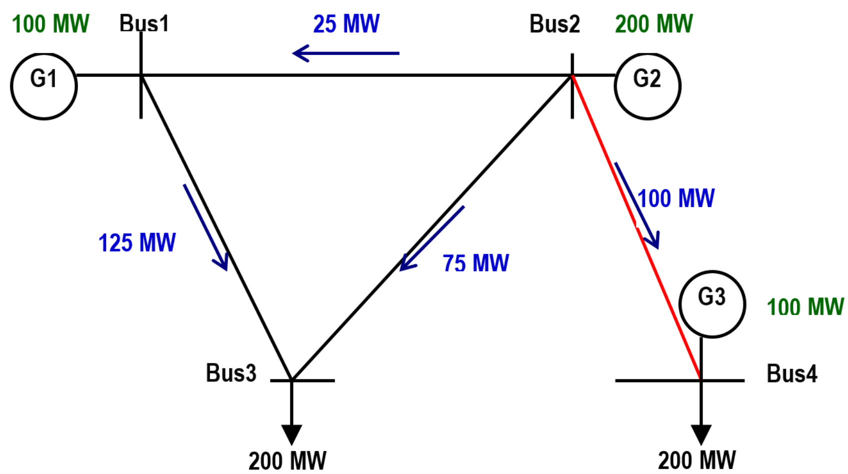

Figure 4-5. Solution for benefits category 1, transmission planning only

Co-optimization: The final of the three solutions illustrates how both generation and transmission alternatives can be considered at the same time by GENTEP. Figure 4-6 shows the network that is considered: one line can be built, and investment in Generator 3 is also a possibility. The two existing generators would be sufficient to meet the load if transmission is added; however, the line capacity from bus 2 to bus 4 is inadequate to meet bus 4's load. Thus either a new generator or a new transmission line is needed. There is a tradeoff that only co-optimization captures: more transmission investment means that generation investment can be avoided.

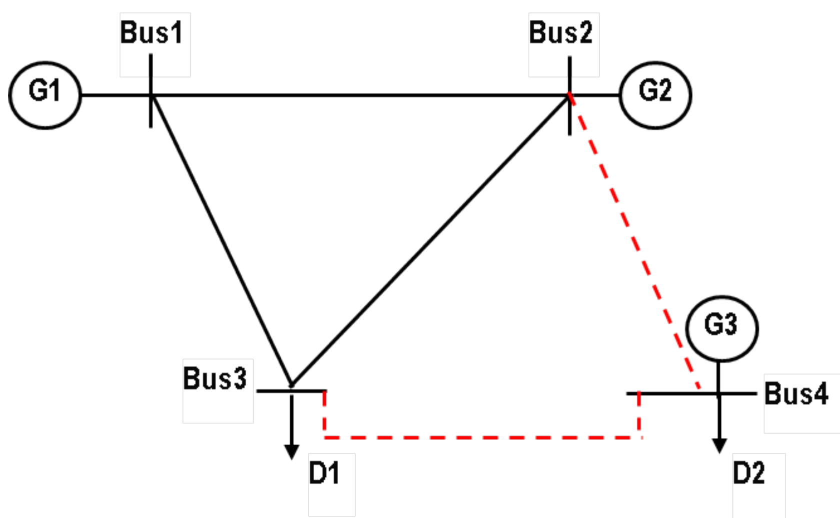

Figure 4-6. Network configuration and potential transmission and generation alternatives for benefits category 1, co-optimization

Tables 4-7 and 4-8 show the generator and line data; the assumed loads are the same as in the transmission-only planning problem above.

Table 4-7. Generator data for benefits category 1, co-optimization

Unit	Min Capacity (MW)	Max Capacity (MW)	Fuel Cost ($/MWh)	Investment cost ($/yr)
G1	100	250	8	-
G2	100	250	8	-
G3	50	150	10	4,000,000

Table 4-8. Line data for benefits category 1, co-optimization

Line	From bus	To bus	Reactance (pu)	Capacity (MW)	Investment cost ($/yr)
L1	1	2	0.1	200	-
L2	2	3	0.2	200	-
L3	1	3	0.1	200	-
L4	2	4	0.2	100	-
L5	3	4	0.2	150	5,000,000

GENTEP is used to perform co-optimization of generation and transmission expansion planning in this example. Table 4-9 shows the progress of the iterations of the algorithm, which converges in three iterations to the solution shown in the last column. In the optimal solution, only the new line between buses 3 and 4 is installed, and the new generator is not needed. This plan has a lower cost than any plan which would include building the generator. Thus, if we had done a generation-only expansion plan with transmission capacity fixed at the existing level, the result would have been a higher cost (the solution shown as Iteration 2), which cost 2% more than the most efficient solution. Although the new line has a higher capital cost than the new generator, it is chosen because it enables more extensive use of the existing units, which have relatively low variable costs. Figure 4-7 shows the resulting optimal investments and operations.

Table 4-9. Co-optimization solutions by iteration for benefits category 1 analysis

	Iteration 1	Iteration 2	Iteration 3 (Final)
Investment of G3 (1=yes)	0	1	0
Investment of L5	0	0	1
Dispatch of G1 (MW)	-	145.82	200
Dispatch of G2 (MW)	-	154.18	200
Dispatch of G3 (MW)	-	100	0
Total investment + operations	-	33,784,000	33,032,000
Convergence	-	1.576%	0.026%

Note: "Convergence" is the % difference between the upper and lower bounds of the objective function as calculated by the Benders decomposition algorithm used by GENTEP. Under certain mathematical conditions, when the divergence between the bounds goes to zero, the resulting solution is proved to be the optimal solution to the original problem. However, for practical problems, the user chooses a threshold for convergence so that the algorithm quits when the divergence is less than the threshold.

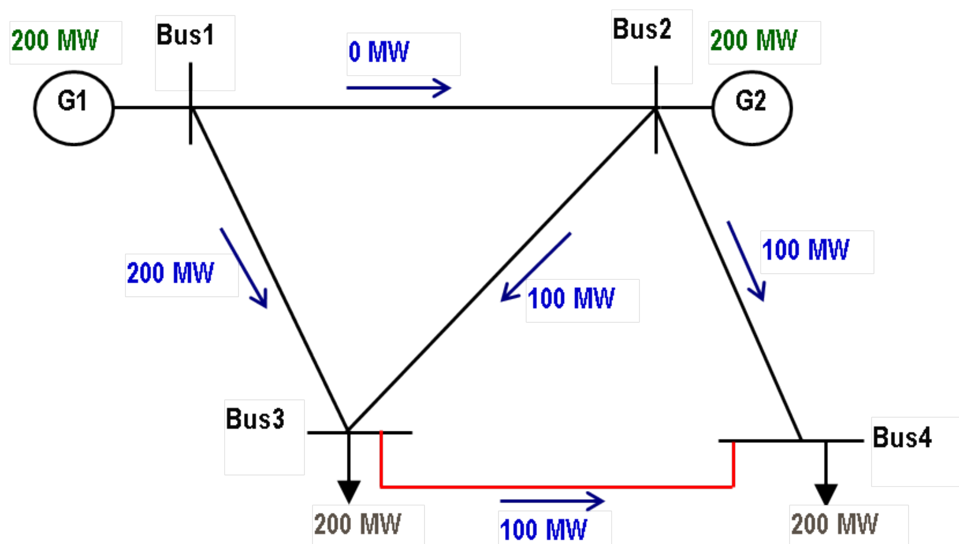

Figure 4-7. Solution for benefits category 1, co-optimization

4.2.3.2 Benefits category 2: Retirements

This example illustrates how co-optimization results in lower costs when existing units are retired. In particular, this example shows a case in which co-optimization is the only way to obtain a feasible plan that meets reliability criteria, while generation-only and transmission-only planning fail to do so. We also consider system reliability by using the Reliability Sub-problem of GENTEP to consider random, or "forced", outages of generators and transmission lines, whose probabilities are described by the "forced outage rate" assumptions in Table 4-10. As a result, there is a nonzero probability that load cannot be met, so our results will include a quantification of the expected energy not served (EENS). The model imposes an upper bound on the EENS. We set this bound to 5% of the load, which is equal to 109,500 MWh in one year when the hourly load is 250 MW, as it is in this example.

(Note that the dispatch and EENS costs associated with any scenario involving a generator or line outage are not included in the cost function of the optimization. Instead, GENTEP simply checks all contingency cases to ensure that the EENS does not exceed the upper bound, and if necessary systematically adjusts the base (no contingency) case in order to meet that bound. All flows reported in the tables and figures of this section are for the base case without any outages; flows, generation, and load unserved for contingency cases are not reported.)

More generally, retirement of existing generators can be considered as a decision alternative that can be modeled in both the generation-only and co-optimization models. Although we do not illustrate that case, in general, co-optimization would result in lower total costs than generation-only when such alternatives are considered because the transmission network can be optimized together with the new configuration of generation investment and operations.

Figure 4-8 shows the possible network configurations and generation sites, while Tables 4-10, 4-11, and 4-12 provide generator, line, and load data.

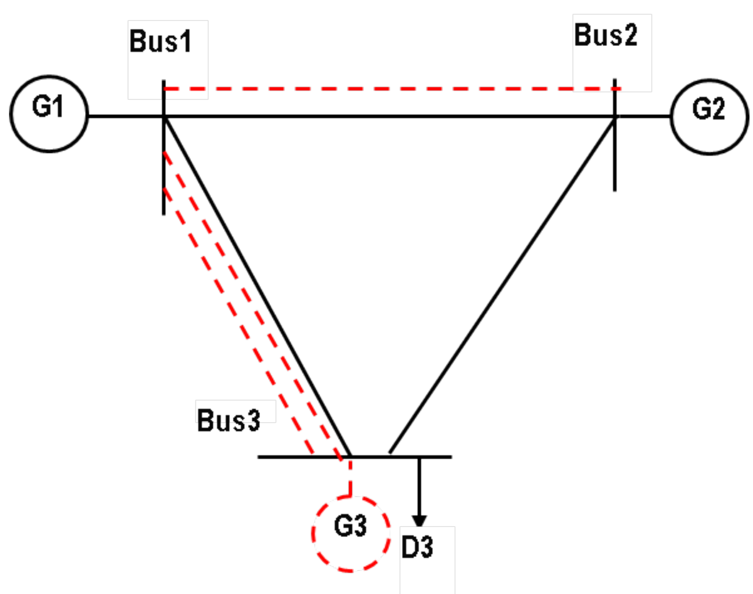

Figure 4-8. Network configuration and potential transmission alternatives for benefits category 2 analysis: Retirements

Table 4-10. Generator data for benefits category 2: Retirements

Unit	Min Capacity (MW)	Max Capacity (MW)	Cost ($/MWh)	Investment cost ($)	Forced Outage Rate (FOR)
G1	0	150	8	-	0.04
G2	0	150	12	-	0.04
G3	0	100	9	5,000,000	0.04

Note: The FOR is defined here as the probability that the generator is unavailable in the simulated hour. Outages of different generators are assumed to be statistically independent.

Table 4-11. Line data for benefits category 2: Retirements

Line	From bus	To bus	Reactance (pu)	Capacity (MW)	Investment cost ($/yr)	FOR
L1	1	2	0.1	50	-	0.01
L2	1	3	0.1	50	-	0.01
L3	2	3	0.1	100	-	0.01
L4	1	2	0.1	50	3,000,000	0.01
L5	1	3	0.1	50	3,000,000	0.01
L6	1	3	0.1	50	3,000,000	0.01

Table 4-12. Load data for benefits category 2 analysis: Retirements

Planning Year	D3 (MW)
1	250

If Unit 2 is retired, then neither generation planning nor transmission planning can achieve a feasible solution. The lowest EENS that either can achieve exceeds the assumed 5% EENS criterion. However, co-optimization does find a feasible solution by installing Lines 5 and 6, and generating Unit 3. In this case the EENS is about 4% of the load which amounts to an LOLE of 14 days per year in this hypothetical example. Thus, with the retirement of Unit 2, co-optimized planning is needed to achieve a feasible solution. Table 4-13 and Figure 4-9 document that solution.

Table 4-13. Three solutions for benefits category 2 analysis: Retirements

		Generation Planning	Transmission Planning	Co-Optimization
Investment State	**G3**	-	-	1
	L4	-	-	0
	L5	-	-	1
	L6	-	-	1
Dispatch of G1 (MW)		-	-	150
Dispatch of G2 (MW)		-	-	RETIRED
Dispatch of G3 (MW)		-	-	100
Planning Cost ($)		INFEASIBLE	INFEASIBLE	29,396,000
EENS (% of load)		-	-	4.24

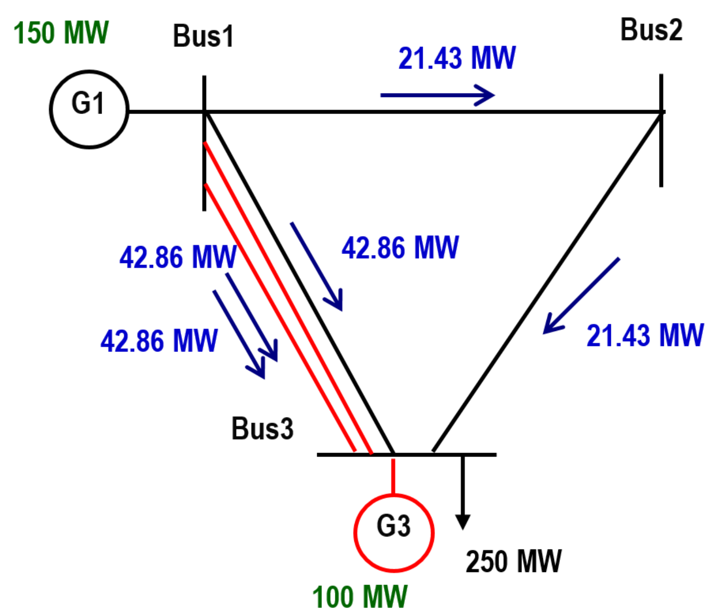

Figure 4-9. Co-optimization solution for benefits category 2 analysis

4.2.3.3 Benefits category 3: Treatment of variable resources

This example includes variable resources in the generation mix and shows how co-optimization can lower costs. The assumed network is displayed in Figure 4-10, and Tables 4-14, 4-15, and 4-16 document the generation, transmission, and load data. Note that a 100 MW wind farm (G4) has been installed at bus 1 (with capacity factor of 30% and variable operational cost of $2/MWh). We do not explicitly model variation in wind output in this simple example, but this is readily accommodated by GENTEP or any co-optimization model.

Table 4-17 shows the three solutions. In the generation-only planning model, the load is supplied but the wind generation at G4 could not be dispatched due to network limitations. The transmission-only model does allow for dispatch of wind. Under co-optimization (whose solution is also shown in the Figure 4-11), both Line 6 and generation Unit 3 are installed; the new line enhances transfer of wind generation. The resulting solution is more than 2% lower than the transmission-only solution and 7% lower than the generation-only solution.

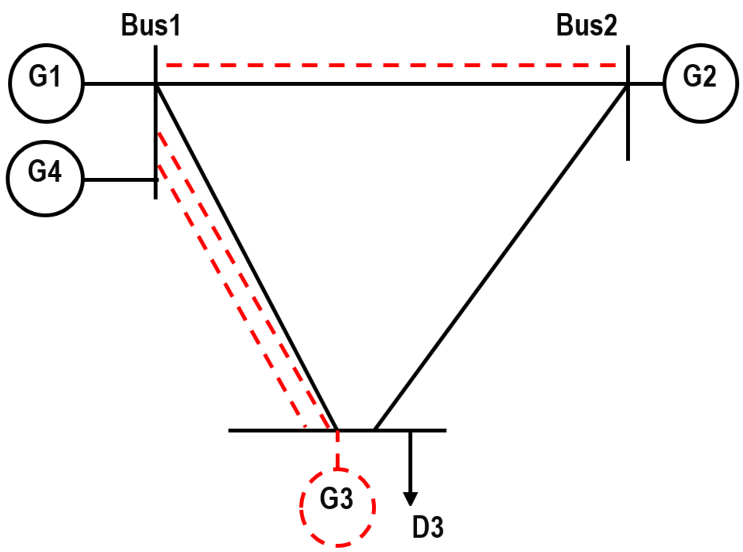

Figure 4-10. Network configuration and potential transmission alternatives for benefits category 3 analysis: Treatment of variable resources

Table 4-14. Generator data for benefits category 3: Treatment of variable resources

Unit	**Min Capacity (MW)**	**Max Capacity (MW)**	**Cost ($/MWh)**	**Investment cost ($/yr)**	**FOR**
G1	0	150	8	-	0.04
G2	0	150	12	-	0.04
G3	0	100	9	5,000,000	0.04
G4	0	100	2	-	0.04

Note: G3 is a wind resource with capacity factor 0.3, and therefore only produces 30MW despite a 100MW capacity.

Table 4-15. Line data for benefits category 3: Treatment of variable resources

Line	From bus	To bus	Reactance (pu)	Capacity (MW)	Investment cost ($/yr)	FOR
L1	1	2	0.1	50	-	0.01
L2	1	3	0.1	50	-	0.01
L3	2	3	0.1	100	-	0.01
L4	1	2	0.1	50	3,000,000	0.01
L5	1	3	0.1	50	3,000,000	0.01
L6	1	3	0.1	50	3,000,000	0.01

Table 4-16. Load data for benefits category 3 analysis: Treatment of variable resources

Planning Year	D3 (MW)
1	250

Table 4-17. Three solutions for benefits category 3 analysis: Treatment of variable resources

		Generation Planning	Transmission Planning	Co-Optimization
Investment State	**G3**	1	-	1
	L4	-	0	0
	L5	-	1	0
	L6	-	1	1
Dispatch of G1 (MW)		0	70	70
Dispatch of G2 (MW)		150	150	50
Dispatch of G3 (MW)		100	-	100
Dispatch of G4 (MW)		0	30	30
Planning Cost ($)		28,652,000	27,199,200	26,571,200
EENS (% of load)		3.373	3.326	1.526

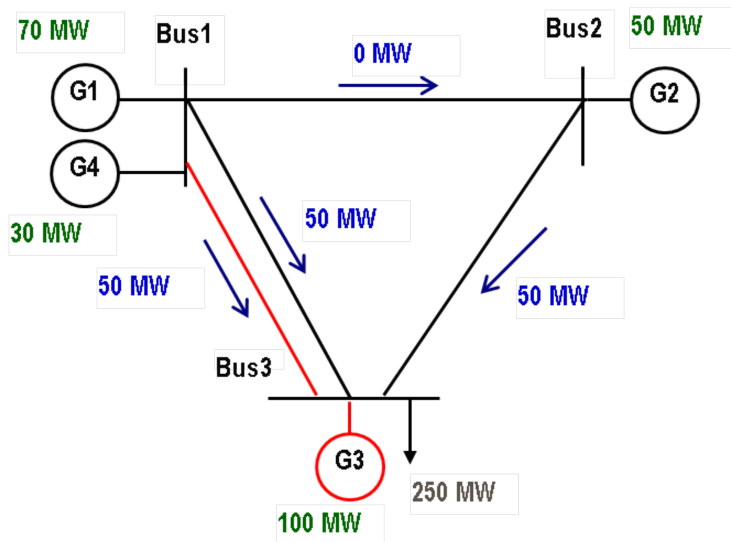

Figure 4-11. Co-optimization solution for benefits category 3 analysis: Treatment of variable resources

4.2.3.4 Benefits category 4: Efficient integration of non- traditional resources

Non-traditional resources can include demand response, customer-owned generation, energy storage, and other types of distributed resources. In this example, we illustrate the consideration of 25 MW of load reductions in each hour due to energy efficiency, which is a 10% load reduction. This could also be viewed as 25 MW of demand response by consumers, whose bid is low enough that it is accepted by the ISO, or as a load reduction by consumers which is due to the local use of distributed generation at bus 3.

With the exception of the demand reduction program, the load and transmission assumptions are the same as those in the previous example. Figure 4-12 shows the transmission and generation investment alternatives, and Table 4-18 provides the generator data.

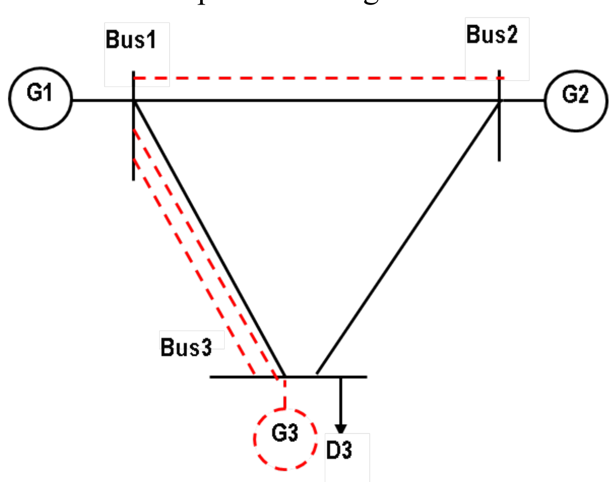

Figure 4-12. Network configuration and potential transmission alternatives for benefits category 4 analysis: Treatment of demand reduction

Table 4-18. Generator data for benefits category 4: Treatment of demand reduction

Unit	Min Capacity (MW)	Max Capacity (MW)	Cost ($/MWh)	Investment cost ($/yr)	FOR
G1	0	150	8	-	0.04
G2	0	150	12	-	0.04
G3	0	100	9	5,000,000	0.04

In the co-optimization solution (shown in Table 4-19 with the generation-only and transmission-only plans), both Line 6 and generating Unit 3 are installed as shown in Figure 4-13. Thus, co-optimization modifies both the generation and transmission systems. With the reduced load, generation planning would be more economical than transmission planning, unlike the previous wind example. However, co-optimized planning is better than either generation or transmission planning alone, with both lower cost and lower EENS.

Table 4-19. Three solutions for benefits category 4 analysis: Treatment of demand reduction

		Generation Planning	Transmission Planning	Co-Optimization
Investment State	**G3**	1	-	1
	L4	-	0	0
	L5	-	1	0
	L6	-	1	1
Dispatch of G1 (MW)		25	125	125
Dispatch of G2 (MW)		100	100	0
Dispatch of G3 (MW)		100	-	100
Planning Cost ($)		25,142,000	25,271,200	24,464,000
EENS (% of load)		2.432	3.088	0.687

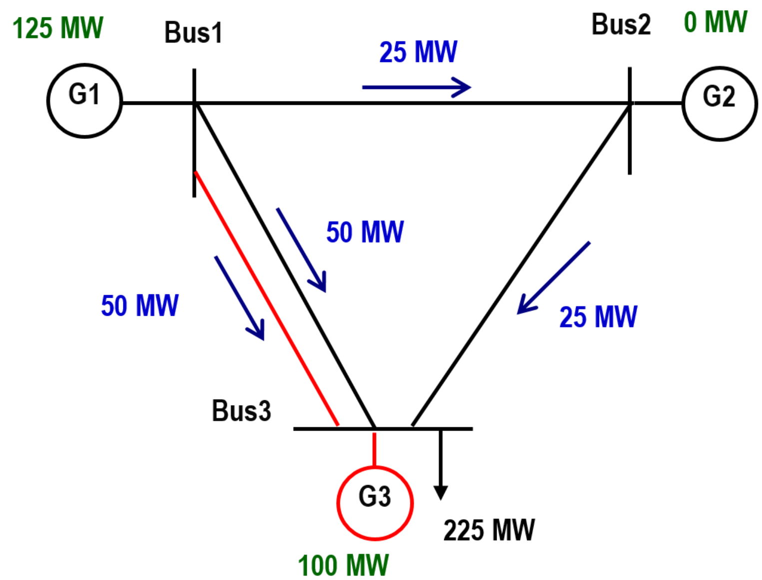

Figure 4-13. Co-optimization solution for benefits category 4 analysis: Treatment of demand reduction

4.2.3.5 Benefits category 5: Fuel mix benefits

This example illustrates the benefits of co-optimization when there are a mix of fuel types, in this case both thermal and wind. Line and load data are the same as the previous case. However, the 150 MW thermal unit in bus 2 is replaced with a 100 MW thermal and a 50 MW wind unit, as shown in Figure 4-14. Table 4-20 shows the new generation mix.

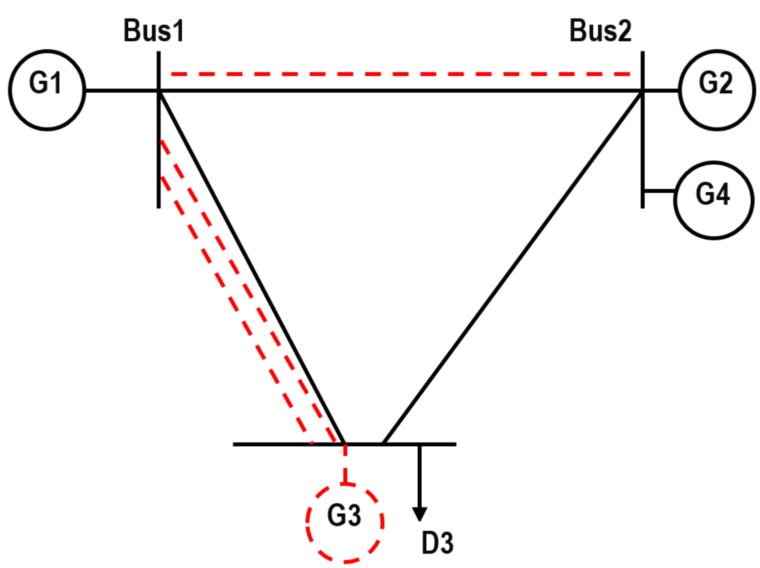

Figure 4-14. Network and generator investment alternatives, benefits category 5 analysis: Fuel-mix benefits

Table 4-20. Generator data for benefits category 5: Fuel mix benefits

Unit	**Type**	**Min Capacity (MW)**	**Max Capacity (MW)**	**Cost ($/MWh)**	**Investment cost ($/yr)**	**FOR**
G1	Thermal	0	150	8	-	0.04
G2	Thermal	0	100	12	-	0.04
G3	Thermal	0	100	9	5,000,000	0.04
G4	Wind	0	50	2	-	0.04

Solutions are shown in Table 4-21, and the co-optimized solution is illustrated in Figure 4-15. Like the previous example, investments in generator 3 and Line 6 are optimal, but only co-optimization results in that solution. Co-optimized planning reduces the planning cost and EENS compared to both generation-only and transmission-only planning.

Table 4-21. Three solutions for benefits category 5 analysis: Fuel mix benefits

		Generation Planning	**Transmission Planning**	**Co-Optimization**
Investment State	**G3**	1	-	1
	L4	-	0	0
	L5	-	1	0
	L6	-	1	1
Dispatch of G1 (MW)		0	100	100
Dispatch of G2 (MW)		100	100	0
Dispatch of G3 (MW)		100	-	100
Dispatch of G4 (MW)		50	50	50
Planning Cost ($)		24,272,000	24,396,000	23,768,000
EENS (% of load)		3.417	3.775	1.439

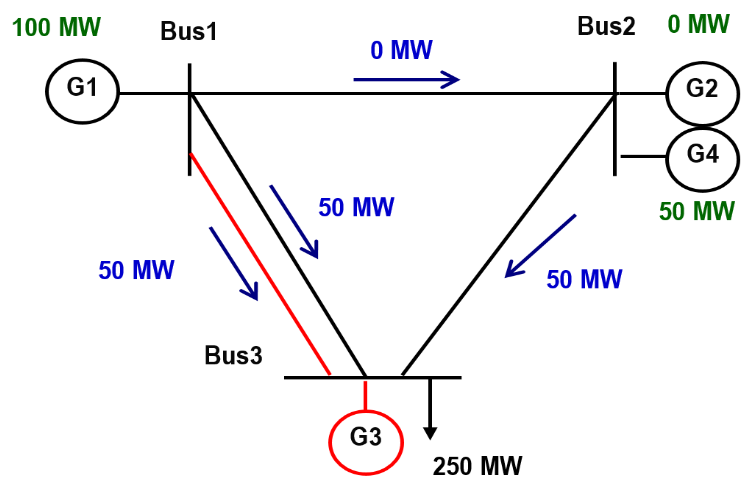

Figure 4-15. Co-optimization solution for benefits category 5 analysis: Fuel mix benefits

In Table 4-22, the above solutions are compared with a set of solutions based on all thermal generation. Addition of wind generation reduces overall costs for all three models, and EENS for transmission planning and co-optimization. The largest improvements are obtained when co-optimized planning is used (15.56% planning cost reduction and 19.78% reliability improvement). Thus, in this case, co-optimization allows for more effective integration of low variable cost renewable power.

Table 4-22. Comparison of all thermal and thermal + wind solutions for each planning procedure (generation, transmission, and co-optimization), benefits category 5 analysis

		Generation Planning	Transmission Planning	Co-Optimized Planning
All Thermal	**Planning Cost ($)**	28,652,000	28,776,000	28,148,000
	EENS (% of load)	3.393	4.134	1.794
Fuel Mix (Thermal + Wind)	**Planning Cost ($)**	24,272,000	24,396,000	23,768,000
	EENS (% of load)	3.393	3.775	1.439
Planning Cost reduction (%)		15.28	15.22	15.56
EENS reduction (%)		0	8.68	19.78

4.2.3.6 Benefits category 6: Improved assessment of the ramifications of environmental regulation/compliance planning

In this example, shown in Figure 4-16, we consider CO_2 emissions, with generators 3 and 4 having less than half the emissions of generators 1 and 2. A CO_2 emissions constraint is added to GENTEP, so that cost is minimized subject to that constraint, as well as the already defined constraint on EENS. We tighten that CO_2 emissions constraint as much as possible in each of the three models, resulting in the solutions provided in Table 4-23.

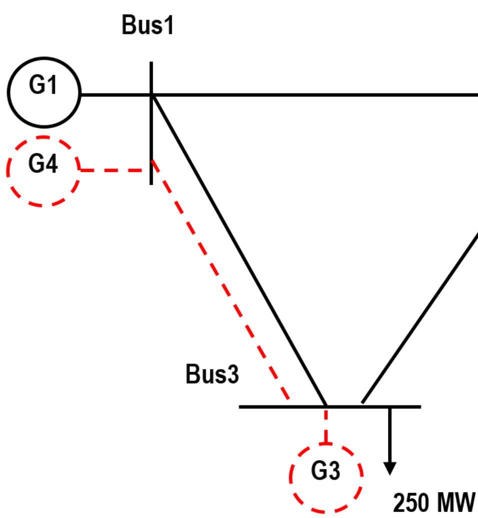

Figure 4-16. Co-optimization for benefits category 6 analysis: Environmental planning

It turns out that co-optimization allows for the greatest emissions reduction. Using transmission planning, the model is infeasible if the emission limit < 212.5 tons/hour, while an emissions constraint below 164.5 tons/hr results in infeasibility for the generation only model. Meanwhile, the co-optimized planning is feasible for an emissions limit of 116.5 ton. In that solution (Figure 4-17), low-emission Units 3 and 4 are installed and dispatched instead of Unit 1. Line 5 is installed to allow for greater dispatch of Unit 4.

Table 4-23. Generator data for benefits category 6: Environmental planning

Unit	Min Capacity (MW)	Max Capacity (MW)	Cost ($/MWh)	Investment cost ($/yr)	FOR	CO_2 Emissions (ton/MWh)
G1	0	150	8	-	0.04	0.85
G2	0	150	12	-	0.04	0.85
G3	0	100	10	5,000,000	0.04	0.37
G4	0	100	10	5,000,000	0.04	0.37

We tighten that CO2 emissions constraint as much as possible in each of the three models, resulting in the solutions in the Table 4-24. Co-optimization allows for the greatest emissions reduction. Using transmission planning, the model is infeasible if the emission limit < 212.5

tons/hour, while an emissions constraint below 164.5 tons/hr results in infeasibility for the generation only model.

Table 4-24. Three solutions for benefits category 6 analysis: Environmental planning

		Generation Planning	Transmission Planning	Co-Optimization
Investment State	G3	0	-	1
	G4	1	-	1
	L4	-	0	0
	L5	-	1	1
	L6	-	1	0
Dispatch of G1 (MW)		0	100	0
Dispatch of G2 (MW)		150	150	50
Dispatch of G3 (MW)		0	-	100
Dispatch of G4 (MW)		100	-	100
Planning Cost ($)		28,776,000	29,528,000	35,776,000
Emission (ton)		164.5	212.5	116.5

Meanwhile, the co-optimized planning is feasible for an emissions limit of 116.5 ton. In that solution (Figure 4-17), low-emission Units 3 and 4 are installed and dispatched instead of Unit 1. Line 5 is installed to allow for greater dispatch of Unit 4.

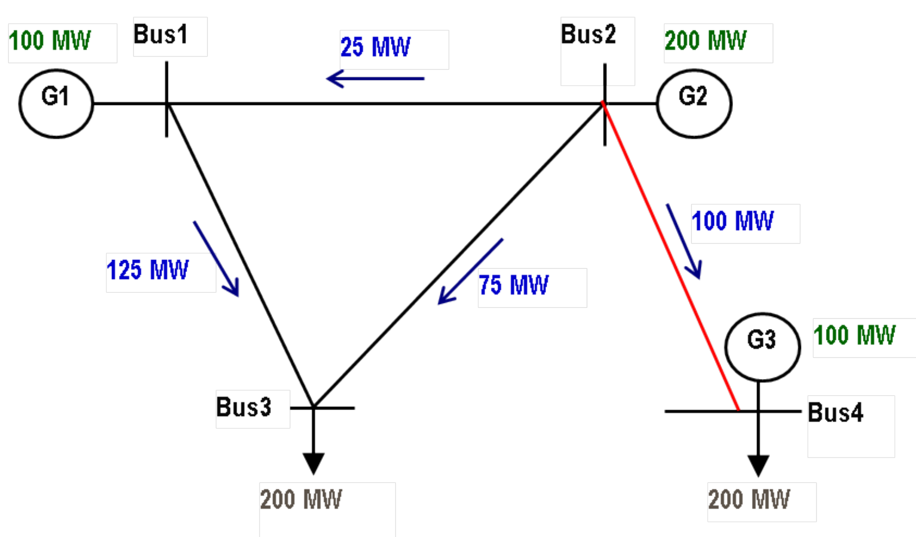

Figure 4-17. Co-optimization solution for benefits category 6 analysis: Environmental planning

4.2.3.7 Benefits category 7: Improved assessment of the resource adequacy

In this case, the existing generation capacity, shown in Figure 4-18, is sufficiently larger than the load, but transmission line limit would constrain the flow so that not all of that generation is deliverable. The generator data are shown in Table 4-25. The co-optimized planning shown in Table 4-26 resolves the issue, i.e., increases the network transfer capability, decreases planning cost, and improves reliability. The solution is depicted in Figure 4-19 in which Line 6 and Unit 3 are installed. In this case, there is no need to install Line 5. Line 6 enhances transfer of low cost power of Units 1 to the load at bus 3.

Table 4-25. Generator data for benefits category 7: Resource adequacy

Unit	Min Capacity (MW)	Max Capacity (MW)	Cost ($/MWh)	Investment cost ($)	FOR
G1	0	150	8	-	0.04
G2	0	150	12	-	0.04
G3	0	100	9	5,000,000	0.04

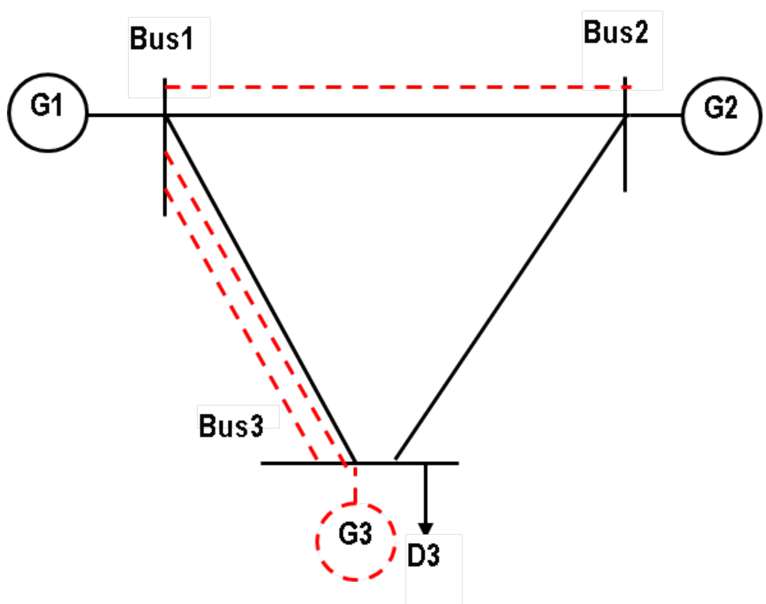

Figure 4-18. Co-optimization solution for benefits category 7 analysis: Resource adequacy

Table 4-26. Three solutions for benefits category 7: Resource adequacy

		Generation Planning	Transmission Planning	Co-Optimized Planning
Investment State	**G3**	1	-	1
	L4	-	0	0
	L5	-	1	0
	L6	-	1	1
Dispatch of G1 (MW)		0	100	100
Dispatch of G2 (MW)		150	150	50
Dispatch of G3 (MW)		100	-	100
Planning Cost ($)		28,652,000	28,776,000	28,148,000
EENS (% of load)		3.329	4.134	1.794

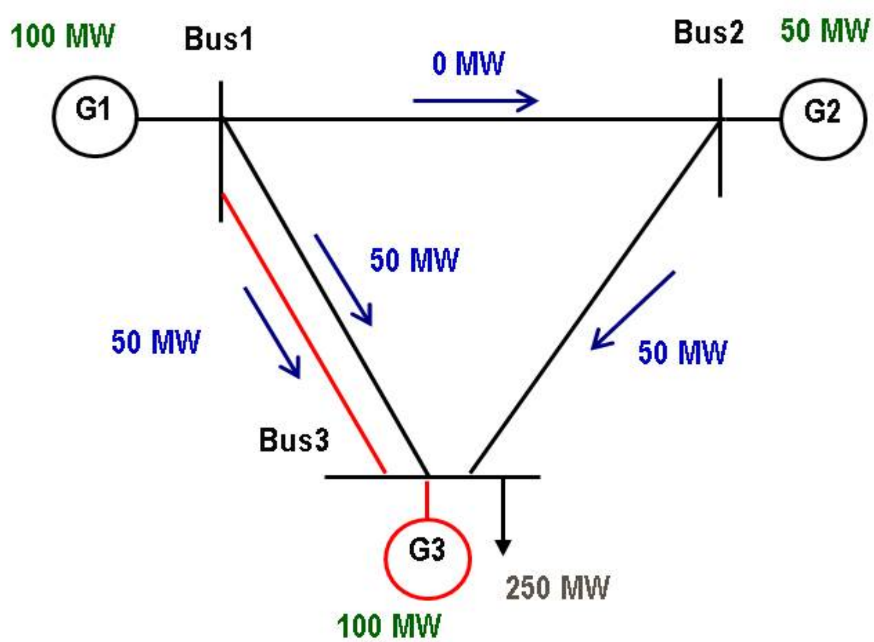

Figure 4-19. Co-optimization solution for benefits category 7 analysis: Resource adequacy

4.3 Benefits and Validation of Co-optimization: Application to a Simplified US Power Sector Network

4.3.1 Introduction

This section identifies ways to validate co-optimization tools. The following three approaches are adopted:

(i) Perform comparative analysis between co-optimization models,

(ii) Perform comparative analysis between a co-optimization model a traditional planning approach whereby generation resources and transmission are planned without co-optimizing, and

(iii) Perform sensitivity analysis where the user makes a change having obvious consequences and then identifies that the program output changes in a predictable fashion.

In the approach (i), three kinds of co-optimization models are identified for the analysis. Each of these models differs in their way of treating transmission network modeling, and their manner in which co-optimization of generation and transmission options are performed. The three models are:

Model 1: Simultaneous optimization of generation and transmission, where transmission is modeled as transportation pipelines. This model is a Linear Program (LP).

Model 2: Iterative optimization of generation and transmission until a co-ordination is achieved. The generation optimization is LP and transmission optimization is Mixed Integer Linear Programming (MILP) with DC power flow model.

Model 3: Simultaneous optimization of generation and transmission, where transmission is modeled with DC power flow model, resulting in a MILP optimization problem.

This section applies all three types of models. Model 1 described above has been solved using both the software NETPLAN and the Johns Hopkins (JHU) model (Appendix II). Based on implementation of Model 1, the validation approaches (ii) and (iii) are presented in later sections. A 13-node U.S. national model has been used to present the benefits of co-optimization approaches under various scenarios. The sensitivities of the results are also studied against expected consequences under different assumptions of transmission costs.

4.3.2 Scenarios

Table 4-27 shows the various scenarios, where scenarios 1-4 are renewable-heavy and scenario 5 is renewable-light, utilizing more conventional forms of generation. Because renewables have investment costs (for geothermal, due to drill depth) or capacity factors (for wind and solar) that are location-dependent, transmission enables renewables to be built in their most economic location, and so it is expected that transmission will have more influence in the renewable-heavy futures.

The different scenarios are characterized by the bounds on their yearly regional (13 NERC regions) investment levels for the various generation technologies. For each number 1-5, Case A represents generation-only optimization, and case B represents co-optimization of generation and transmission. In the various cases labeled A in Table 4-27, the transmission is not allowed to expand and is therefore constrained to the 2010 levels throughout the simulation. In the various cases labeled B in Table 4-27, the capacity of each transmission link is also a decision variable in the optimization, and so transmission capacity is grown as needed in order to minimize the total investment and production cost. Therefore the difference in cost between each Cases A and B provides a valuation of the transmission built. This valuation is made possible via co-optimization.

Table 4-27. Scenarios for validating co-optimization of generation and transmission resources

Scenario	Yearly Generation investment limits in every region	Optimization
A1	Coal, IGCC, IPCC & Hydro - 0 GW, Nuclear, NGCC, OTEC & Tidal - 1 GW, Geothermal (only west) – NWP, RA, CNV - 5 GW; ERCOT, MAPP, SPP - 3GW Wind (Inland and offshore) & Solar (PV and Thermal) - 7 GW Carbon tax - $30/ short ton	Generation resources
B1		Co-optimization
A2	Coal, Nuclear, NGCC, IGCC, IPCC & Hydro - 0 GW, OTEC & Tidal - 1 GW, Geothermal (only west) – NWP, RA, CNV - 5 GW; ERCOT, MAPP, SPP - 3GW Wind (Inland and offshore) & Solar (PV and Thermal) - 7 GW Carbon tax - $30/ short ton	Generation resources
B2		Co-optimization
A3	Coal, Nuclear, NGCC, IGCC, IPCC, Hydro, Geothermal, OTEC & Tidal - 0 Wind (Inland and offshore) & Solar (PV and Thermal) - 10 GW Carbon tax - $30/ short ton	Generation resources
B3		Co-optimization
A4	Coal, Nuclear, NGCC, IGCC, IPCC & Hydro - 0 GW, OTEC & Tidal - 1 GW, Geothermal (entire nation) – 3 GW Wind (Inland and offshore) & Solar (PV and Thermal) - 2 GW Carbon tax - $30/ short ton	Generation resources
B4		Co-optimization
A5	Coal, Nuclear, NGCC, IGCC, IPCC, Hydro, Geothermal, OTEC, Tidal, Wind (Inland and offshore) & Solar (PV and Thermal) - 2 GW No Carbon tax	Generation resources
B5		Co-optimization

Note: Integrated Gasification Combined Cycle (IGCC), Integrated Pyrolysis Combined Cycle (IPCC), Natural Gas Combined Cycle (NGCC), Ocean Thermal Energy Conversion (OTEC)

Inflation and discount rates are assumed to be 2% and 7% respectively. Load growth is modeled at 2%/year. In all cases, a cost of $1B/GW/1000miles (2010 dollars) is placed on interregional transmission (expansion was only considered for adjacent regions). It is assumed that there is no difference between the cost of added AC and DC transmission capacity.

4.3.3 Numerical Results Using NETPLAN

4.3.3.1 Validation approach (i) and (ii): Benefits

Results are summarized in Table 4-28, where net present-worth and the annualized cost, with and without the transmission expansion are provided. When transmission is $1B/GW/1000miles, the differences in net present-worth range from $239B for the "mostly renewable, geothermal-light" case to $492B for the "all-renewable, geothermal-heavy" case.

Table 4-28. Summary of cost results

Cases	Case description	Transmission	Cost (Billion$)	
			Present worth (2010 dollars)	**Annualized over 40 years**
A1	Mostly renewable, geothermal-light	Generation only	5013.12	376.03
B1		Co-optimization	4773.96	358.09
		Difference	**239.16**	**17.94**
A2	All-renewable, geothermal-light	Generation only	5517.83	413.89
B2		Co-optimization	5059.38	379.50
		Difference	**458.45**	**34.39**
A3	All-renewable, no geothermal	Generation only	5328.11	399.66
B3		Co-optimization	5053.70	377.57
		Difference	**274.41**	**20.58**
A4	All-renewable, geothermal-heavy	Generation only	5457.63	409.37
B4		Co-optimization	4965.48	372.47
		Difference	**492.15**	**36.92**
A5	Business as usual	Generation only	4655.70	349.22
B5		Co-optimization	4650.10	348.80
		Difference	**5.60**	**0.42**

Generation investments made for Cases A1 and B1, and for Cases A2 and B2, are illustrated in Figure 4-20. The decreased generation capacity of Case B1 relative to Case A1 shows that the expanded transmission of Case B1 enables use of wind with higher capacity factor relative to Case A1; a similar observation can be made in comparing Cases A2 and B2.

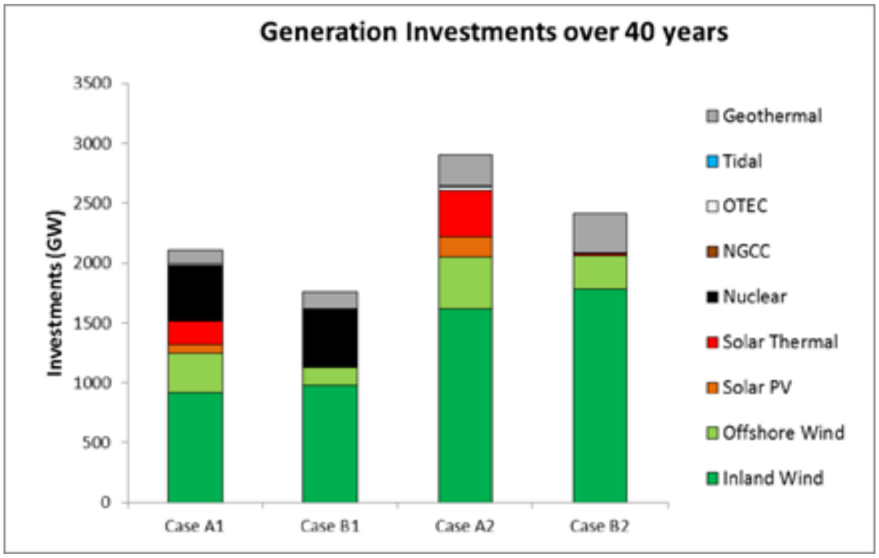

Figure 4-20. Generation investments over 40 years - Cases A1, B1 & Cases A2, B2

Transmission investments made for Cases B1 and B2 are illustrated in Figure 4-21. This chart shows the additional transmission capacity developed over and above the existing transmission capacity, where it is clear that the largest investments are made for MAIN to ECAR, MAIN to MAPP, MAIN to STV, SPP to STV, and RA to SPP, with the investment being about 100 GW in both cases for MAIN to ECAR. (Definitions of region abbreviations are shown in the map in Figure 4-22, below.) Total invested transmission capacity is larger for Case B2 than for B1 because Case B1 was allowed to build some new generation that is not locationally constrained (nuclear) and was therefore built close to the load that it supplied, avoiding some of the transmission needed in Case B2. In contrast, Case B2 was allowed to build only the locationally sensitive renewables; here it was more economical to build the more cost-effective but distant generation and required transmission than to build the less cost-effective generation close to load.

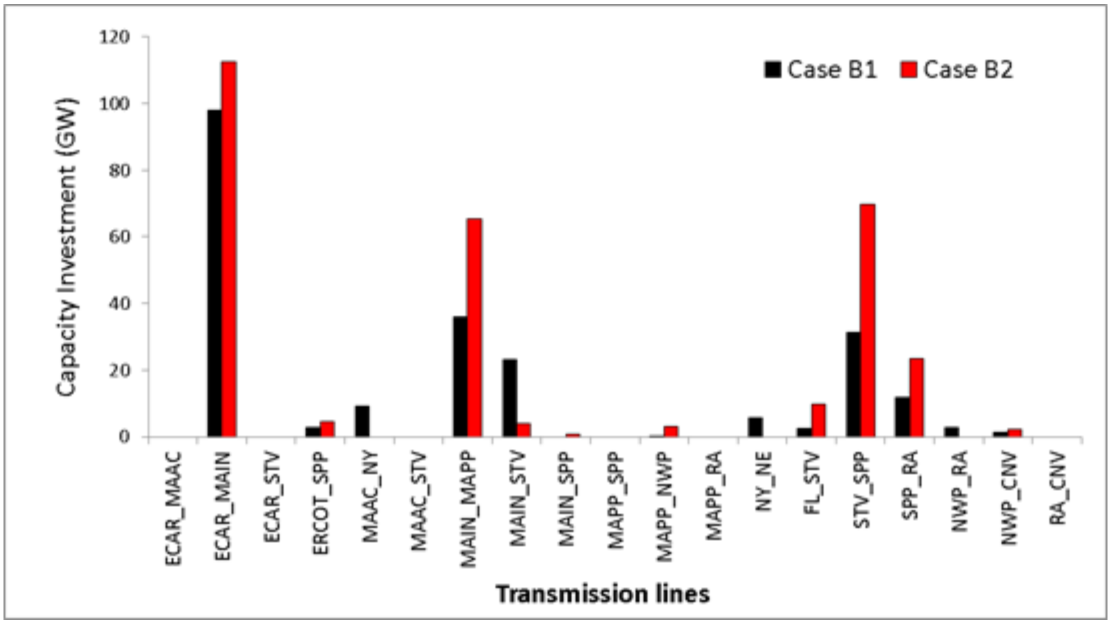

Figure 4-21. Transmission investments over 40 years - Case B1 & Case B2

Figures 4-22 and 4-23 geographically illustrate the additional transmission capacity for Cases B1 and B2 respectively. These figures also provide energy generation and consumption (in Quads). These figures indicate that the energy generally flows west to east, reflecting the facts that the most economical renewables are in the Midwest or West, and a high percentage of the load is in the East, particularly in ECAR and STV.

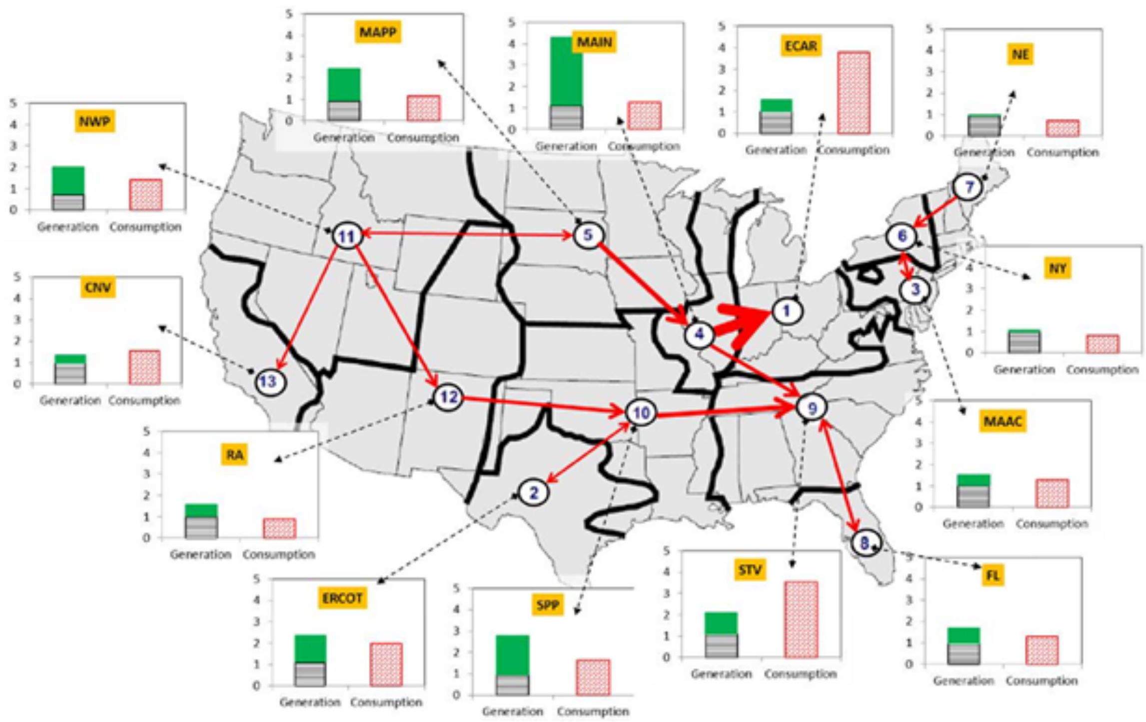

Figure 4-22. Generation mix and transmission investment over 40 years - Case B1

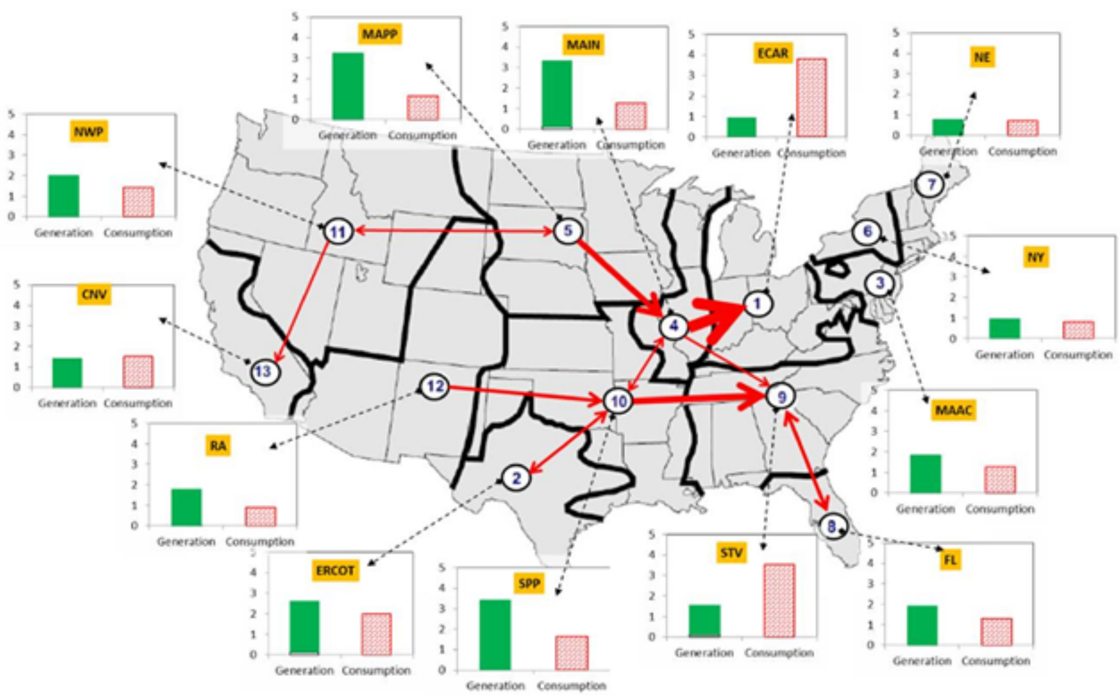

Figure 4-23. Generation mix and transmission investments over 40 years - Case B2

Transmission investments made for Cases B3 and B4 are illustrated in Figure 4-24. The interregional corridors receiving the most transmission investment for Case B3 are generally the same as for Cases B1 and B2, although the amounts are somewhat different for some corridors.

On the other hand, Case B4 invests in some corridors that received little or no investment in other cases, including MAPP to NWP and NY to NE, while most other corridors received significantly less investment (e.g., 40 GW in MAIN to ECAR as opposed to 100 GW or more in other cases). This was because geothermal investment was constrained to be light and only in the West (Cases B1 and B2) or nonexistent (Case B3), whereas Case B4 allowed geothermal investment in both West and East. Also, the total invested transmission is significantly smaller for Case B4 than others due to the presence of the geothermal in the East that relieved part of the need for transmission that was otherwise required to move energy from the West and Midwest to the East. However, the costs for geothermal, being functions of expected drill-depth, are uncertain, and so it is not clear that Eastern geothermal investment can be economically attractive.

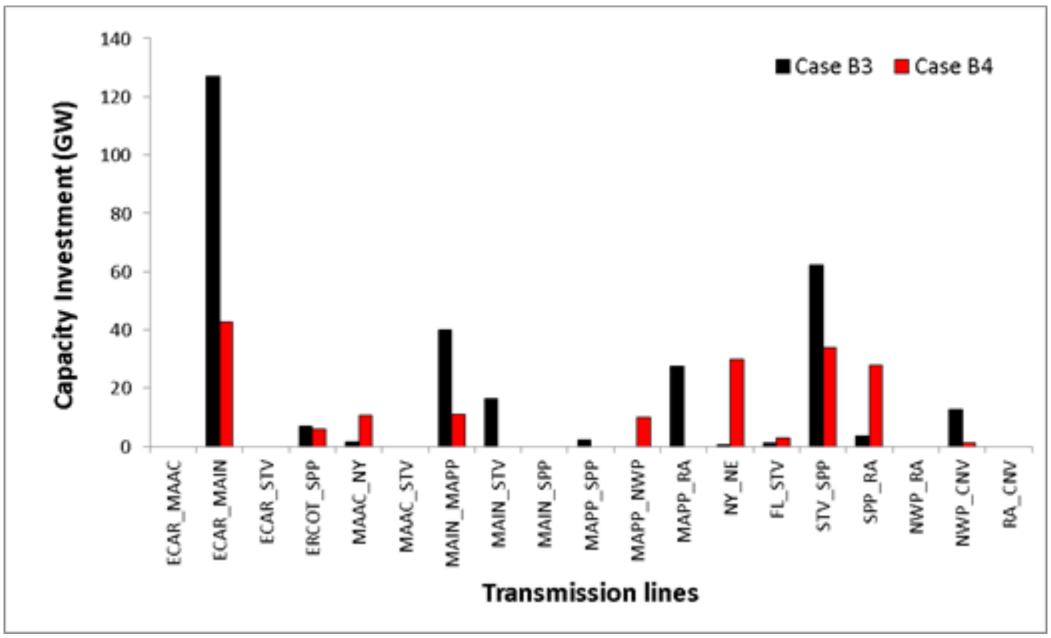

Figure 4-24. Transmission investments over 40 years - Case B3 & Case B4

Figures 4-25 and 4-26 geographically illustrate the additional transmission capacity for Cases B3 and B4 respectively. It is interesting to observe that the flow direction for Cases B1, B2, and B4 (with geothermal) is West to Midwest to East, whereas the flow direction for Case B3 (with no geothermal) is Midwest to West and Midwest to East. This shows that, without geothermal; the Midwestern wind significantly increases its presence in supplying parts of the entire nation.

Figure 4-27 shows the generation production mix for the reference year, Cases B1 and B5 over all the 40 years. The 100% of pie-chart for Cases B1 and B5 represents about 2.2E8 GWh (220 Million GWh) of production over 40 years. The reference year portfolio is dominated by coal generation, followed by nuclear and natural gas. Based on the current cost assumptions, the renewable-light case directed the future portfolio towards nuclear and coal. It is observed from

Figure 4-27 and Table 4-29 that Case B5, dominated by nuclear and coal units, allows for much less investment in transmission overlay (in GW-Miles) compared to Case B1 with higher penetration of wind and geothermal. This is also reflected in Table 4-28, where it shows that the cost benefits of transmission under Case B1 is highly promising compared to Case B5.

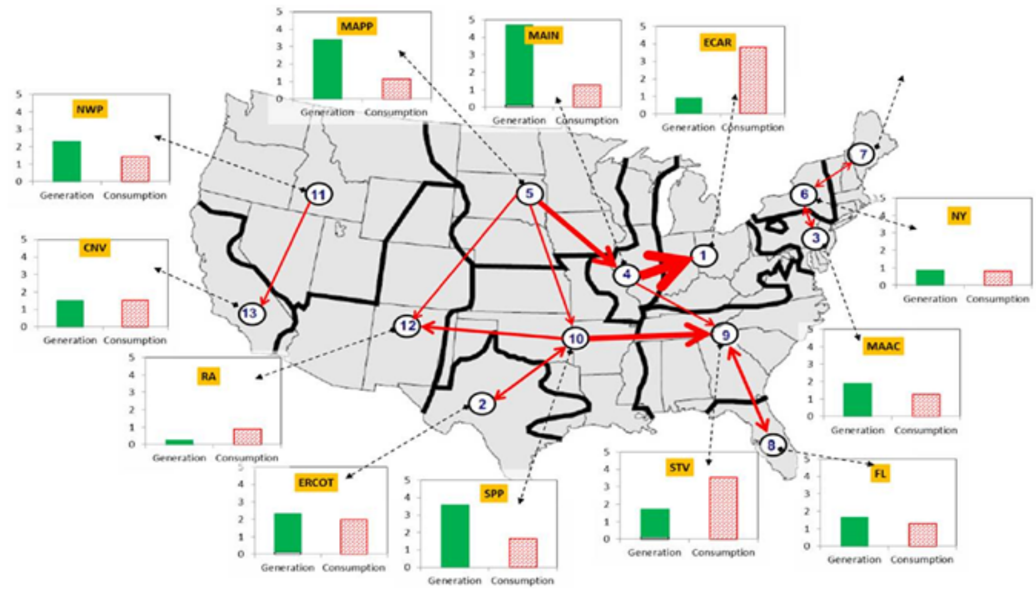

Figure 4-25. Generation mix and transmission investments over 40 years - Case B3

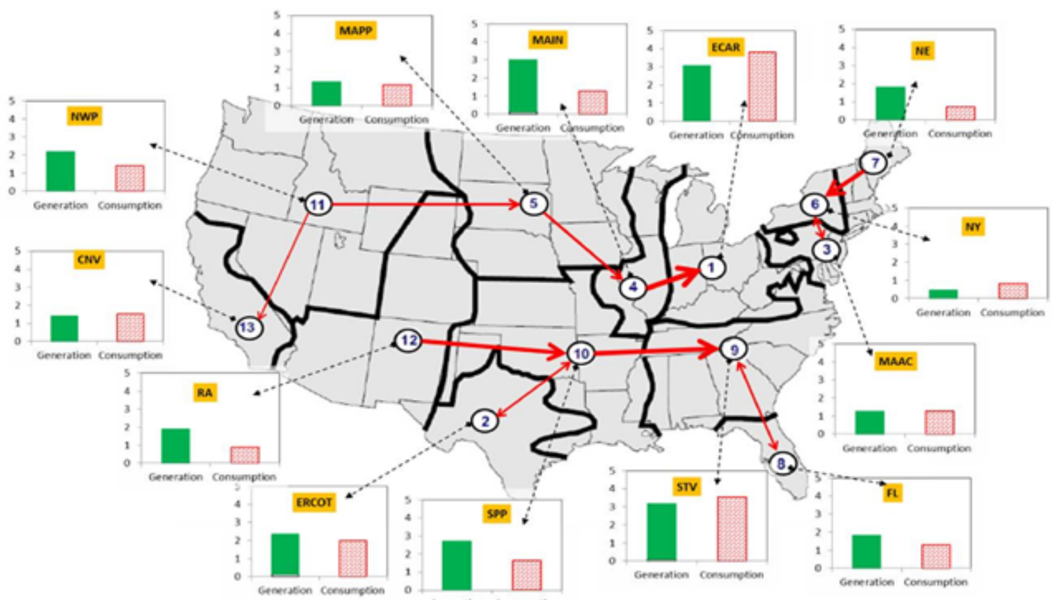

Figure 4-26. Generation mix and transmission investments over 40 years - Case B4

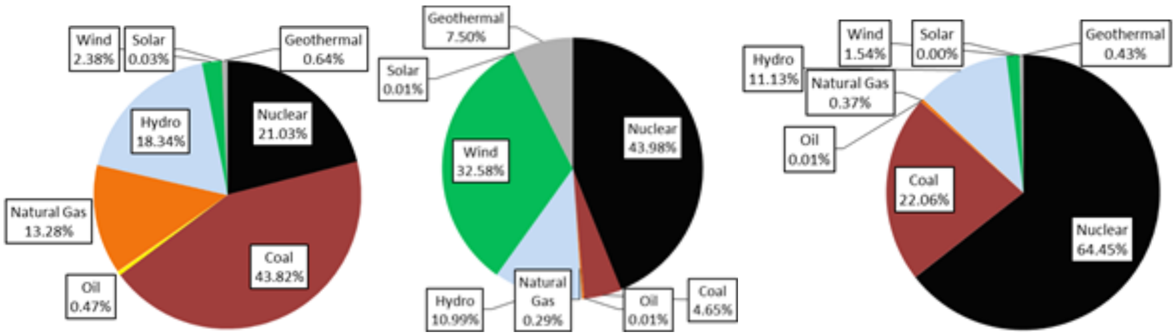

Figure 4-27. Generation production mix – Reference year, Cases B1 and B5 (over 40 years)

Table 4-29 shows that the total cost of Case B5 is about \$123.86B less than Case B1. However, assuming a carbon cost of about \$30/Short ton, Case B1 promises a carbon credit of about \$1245B (~10 times the cost difference between the portfolios) by virtue of its low CO_2 emitting portfolio.

Table 4-29. Summary of results

Cases	**Case description**	**Transmission (2010 Billion \$ (GW-Miles))**	**Cost (2010 Billion \$)**	**CO_2 Emission (Short ton)**
B1	Mostly renewable, geothermal-light	63.09 (126945.9)	4773.96	1.75E+10
B5	Business as usual	5.23 (7167.8)	4650.10	5.90E+10
	Difference	**57.86 (119778.1)**	**123.86**	**-4.15E+10**

4.3.3.2 Validation approach (iii): Sensitivities

To determine the sensitivity of results to transmission cost, Cases B1-1.5T and B1-2T were run, where transmission costs were increased to \$1.5B/GW/1000 miles and \$2B/GW/1000 miles respectively. The transmission topology identified was very similar to that of Case B1 as seen in Figure 4-28, with changes in the capacity investments across various corridors. As the transmission cost increases, there is decreasing investments in North-West to Mid-West (NWP to MAPP and NWP to RA) and Mid-West to East (MAPP to MAIN, MAIN to STV, MAIN to ECAR) corridors, and increase in South-West to East corridors (RA to SPP and SPP to STV). This is because the increase in transmission cost mainly spurred increase in geothermal generation investments in South-West while decreasing wind investments in North-West to achieve an overall cost-effective portfolio. Figure 4-29 indicates an overall increase and decrease in geothermal and wind representations respectively in the portfolios with increasing transmission cost.

Also, 50% and 100% increase in transmission cost only decreases net economic benefit by about 14% and 25% respectively (i.e., from \$239B to \$206B, and \$239B to \$178B respectively). These observations suggest that the long-term benefit obtained from expanded transmission is not very sensitive to the transmission cost. This is a confirmation of the well-known fact that the transmission cost is generally a relatively small percentage of the composite long-term cost of building and operating power systems, as also seen from Table 4-29.

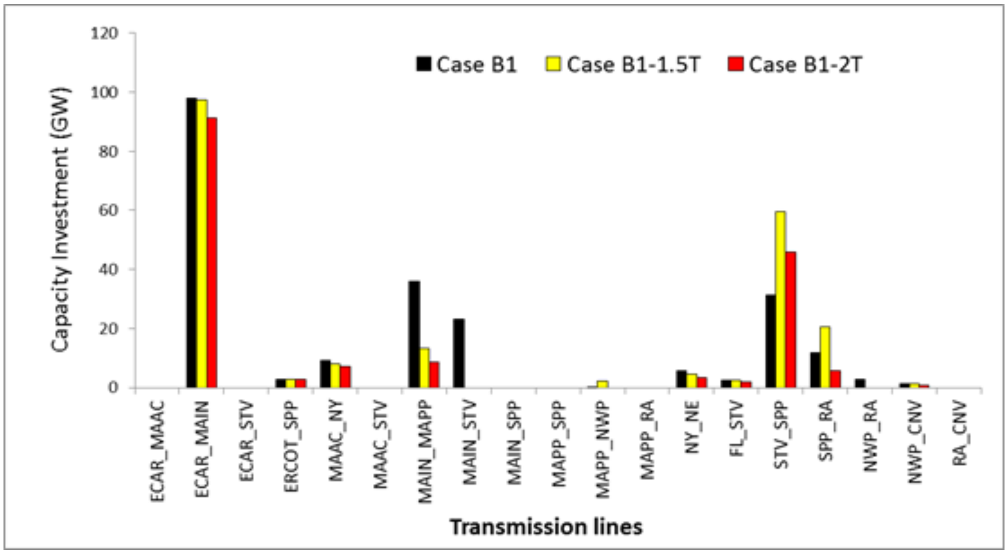

Figure 4-28. Transmission investments over 40 years - Cases B1, B1-1.5T & B1-2T

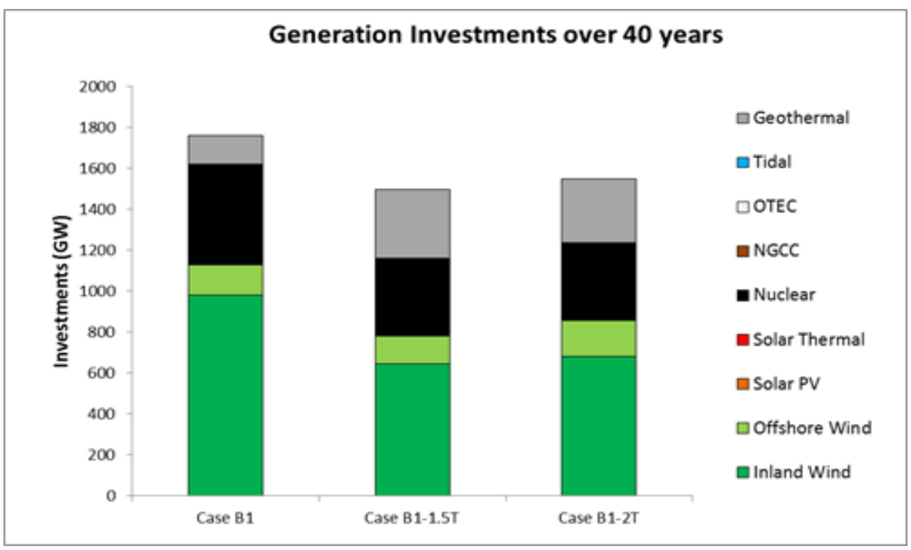

Figure 4-29. Generation investments over 40 years - Cases B1, B1-1.5T & B1-2T

4.3.4 Validation Results Using JHU Software

In the JHU model, new lines within synchronized regions (EI, ERCOT, WECC) are assumed to be AC, so that Kirchhoff's voltage law is enforced within those regions, while lines between any two of those regions are assumed to be DC, so that their flows are controllable. Ten hours per year are considered; wind and load shapes are represented by taking a sample of 10 hours in each year that capture the averages, ranges, and correlations among regions. Details on these and all other assumptions are provided elsewhere.[7]

In adapting the scenarios to the JHU model it was assumed that the annual generation investment applied only over a twenty-year period. In the JHU model, infrastructure investment is modeled as two distinct ten-year periods. The first ten-year period occurs before any operations occur, while the second takes place alongside the first period of operations, followed by a final period with only operations. This time structure is used to account for the time it takes to plan and build new infrastructure before it can be used. The two-stage structure described is compatible with extending the model to a multistage stochastic formulation in which investment commitments have to be made well in advance of operations (here, a ten year lead time is assumed). However, in the deterministic solutions considered in this report, the lag time does not affect the solutions, so the JHU model can be viewed as considering investments and operations for two years: 2020 and 2030, with the 2020 results assumed to apply to each of the years in the range 2020-2029, and the 2030 results applying to 2030-2059.

An important assumption in the JHU model was that transmission capacity additions between regions would be in large (10 GW) increments. This was necessary to obtain quick solution times for the model that includes Kirchhoff's laws; the voltage law is enforced in the JHU model by a set of binary variables, one for each possible amount of transmission between the regions. Because transmission is added in large lumps, differences between some model runs might be obscured if their optimal transmission amounts between regions would be small relative to 10 GW.

4.3.4.1 Economic benefits of co-optimization

Table 4-30 presents the present value and the annualized cost from applying the JHU model to the modeled system under each of the five scenarios without (Model 0) and with co-optimization (Model 3). The present value was discounted back to the very first year simulated in the model (2020). The annualized costs are calculated over a 40-year period of operations starting in 2020 and ending in 2050. This was calculated by computing the present worth in year 2020 and then annualizing this value over 40 years using a 40 year annualization factor and a real interest rate of 4.9%.

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[7] Documentation and databases can be obtained on request from the authors.

Table 4-30. Summary of cost results

Cases	Case description	Transmission	Cost (Billion$)	
			Present value (2011 dollars)	**Annualized over 40 years**
A1	Mostly renewable, geothermal-light	Fixed	1655.59	153.55
B1		Expanded	1614.04	149.69
		Difference	**38.03**	**3.85**
A2	All-renewable, geothermal-light	Fixed	1845.57	171.17
B2		Expanded	1679.40	155.75
		Difference	**166.18**	**15.41**
A3	All-renewable, no geothermal	Fixed	2183.62	202.52
B3		Expanded	1937.73	179.71
		Difference	**245.89**	**22.81**
A4	All-renewable, geothermal-heavy	Fixed	1795.25	166.50
B4		Expanded	1757.22	162.97
		Difference	**38.03**	**3.53**
A5	Business as usual	Fixed	1355.95	125.76
B5		Expanded	1355.95	125.76
		Difference	**0.00**	**0**

Table 4-31 contains the percentage savings realized by co-optimization under each of the five scenarios. The savings realized ranged between 0% and 11.26%. Given that transmission investment costs are well below 10% of the total present worth of generation investment and operations together, this shows that "smart" transmission investment that accounts for the effect of such investments on generation siting and mix can result in savings that equal or exceed the out-of-pocket investment cost of transmission itself.

In the four transmission friendly scenarios a high carbon tax and varying quality of renewable resources drove investments in transmission, which allowed for more cost-effective renewables to be built. Under the business as usual case (Scenario 5), which excluded a carbon tax, near-load conventional generation units along with some renewables were optimal additions under both the generation and co-optimization planning approaches. New transmission additions could not be justified, even in the co-optimization case because fuel and capacity cost differences among regions for conventional generation do not differ enough to justify the cost of the assumed 10 GW minimum transmission addition size.

Table 4-31. Co-optimization cost reductions

Scenario	Case description	Co-optimization cost reduction
1	Mostly renewable, geothermal light	2.51%
2	All renewable, geothermal light	9.00%
3	All renewable, no geothermal	11.26%
4	All-renewable, geothermal heavy	2.12%
5	Business as usual	0.00%

4.3.4.2 Effects of co-optimization upon generation capacity investment

We now consider the effect of co-optimization on the mix of new generation, and in particular upon the economics of new renewables.

First, considering scenarios 1 (mostly renewable, geothermal light) and 2 (all renewable, geothermal light), shown in Figure 4-30, the co-optimization approach increased investment in intermittent resources as better quality renewable resources were made available by expanding transmission. Total GW of installed generation increased, because intermittent resources with low capacity factors in solutions B displace some of the new fossil capacity with higher capacity factors in solutions A.

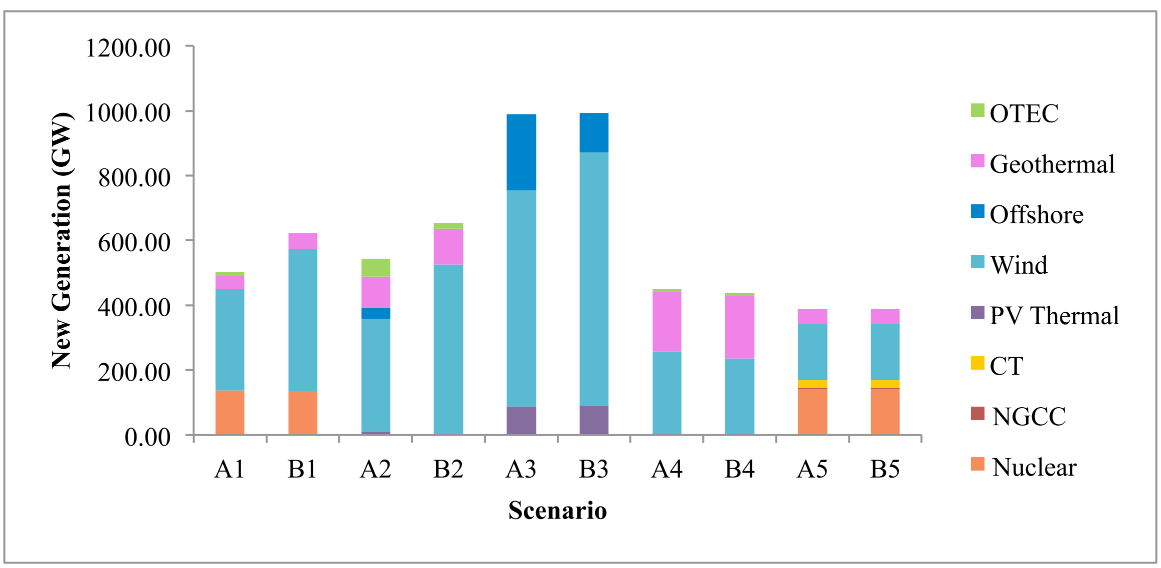

Figure 4-30. Cumulative generation capacity additions in each scenario solved with and without co-optimization (2020 and 2030)

In scenario 3 (all renewable, no geothermal) only intermittent resources were available for construction. With the addition of co-optimization, on-shore wind resources replaced more expensive off-shore resources. The total added capacity did not differ significantly as one intermittent resource was substituted for another as allowed with expanded transmission. This result indicates that off-shore wind is made more attractive if new transmission cannot be built, and that a significant part of the benefit of new interregional transmission is investment cost savings that result from taking advantage of lower cost renewables.

In scenario 4 (all renewable, on-shore wind dominated), geothermal renewables additions were limited to 2 GW/Year, and central solar was also limited. As a result significantly more on-shore wind built. In the co-optimization case, the addition of geothermal resources was shifted west where capital costs of new capacity are cheaper. Finally, in scenario 5 (business as usual case), co-optimization did not change the generation or operation of the system as no additional transmission was added in B5.

Table 4-32 indicates how much the generation investment policies differ between a generation planning approach and a co-optimization approach by quantifying the absolute difference between the two generation investment plans. That is, the absolute value of the difference between the amount of capacity of each type in each region is calculated between solutions A and B, and then summed up over all types and regions. This measure captures not only the differences in total national capacity (as indicated in Figure 4-30), but also changes in the distribution. For instance, if 100 GW total of wind is installed in A, and the same amount in B, but in entirely different regions, the absolute value of the difference is then 100 GW, which reflects the impact that co-optimization had on siting.

Table 4-32. Cumulative deviations in generation additions between co-optimization and generation planning (2020 and 2030)

Scenario	**Case description**	**Sum of absolute value of deviations (GW)**
1	Mostly renewable, geothermal light	187.21
2	All renewable, geothermal light	341.20
3	All renewable, no geothermal	488.50
4	All-renewable, geothermal heavy	262.36
5	Business as usual	0

Table 4-32 indicates that even when the total generation capacity is not changed by co-optimization, the patterns can greatly change. Scenario 3 represents that case. Thus co-optimization not only potentially saves investment costs, it can make a huge difference in the type and location of generation investment.

Figures 4-31 – 4-34 provide additional details on the effects of co-optimization on generation investment patterns. Starting with scenario 1 (mostly renewable, geothermal light), Figure 4-31 shows that wind generation capacity was greatly expanded under co-optimization (B1). This added generation replaced conventional generation units and higher cost intermittent resources that were economic in A1 because of tighter transmission constraints. (Note however that the capacity of new wind is much greater than its energy provision because of its lower capacity factor relative to other new resources. Thus, overall capacity increases under co-optimization as intermittent resources with a lower effective capacity factor replace non-intermittent resources.) Proceeding to scenario B2 (all renewable, geothermal light) in Figure 4-32, co-optimization results in installation of better quality renewables to replace more expensive (off-shore) counterparts installed in A2.

Considering scenario B3 (all renewable, no geothermal), Figure 4-33 shows that the application of co-optimization and expansion of transmission allows for lower quality intermittent resources to be replaced with higher quality resources. The ratio of replacement is nearly 1:1 as the intermittent resources being replaced have similar capacity factors as their replacements. Also, PV and thermal solar are shifted from Florida to the far west. Meanwhile, in scenario B4 (all renewable, geothermal heavy), additional transmission capacity in the co-optimized solution allows a westward shift of geothermal energy production from high capital cost locations in the east to more efficient geothermal locations in the west (Figure 4-34). Slight shifts in the location of OTEC, and a downward shift in wind investment also take place.

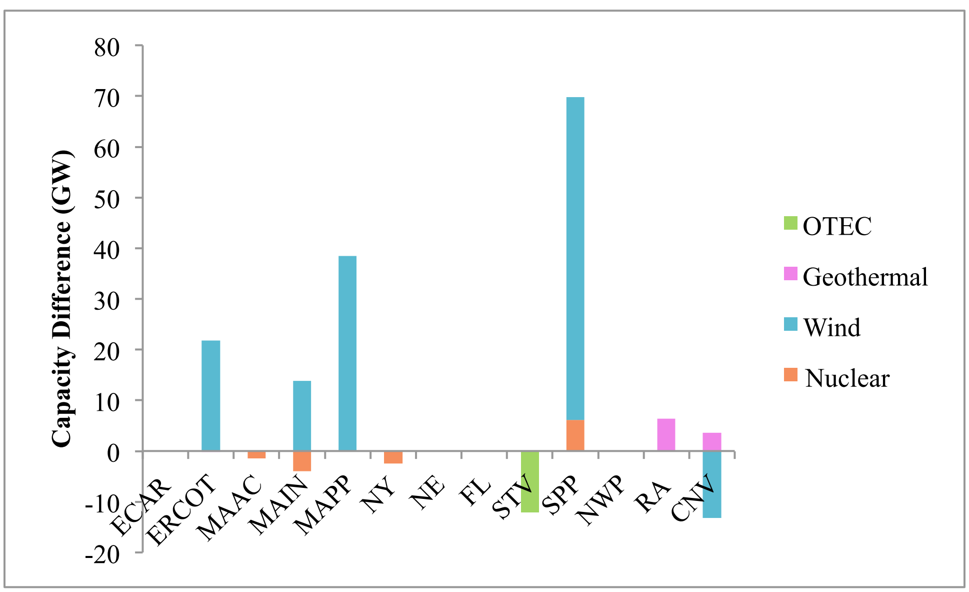

Figure 4-31. Effects of co-optimization on capacity additions: Differences between generation capacity additions in B1 versus A1 as a result of co-optimization

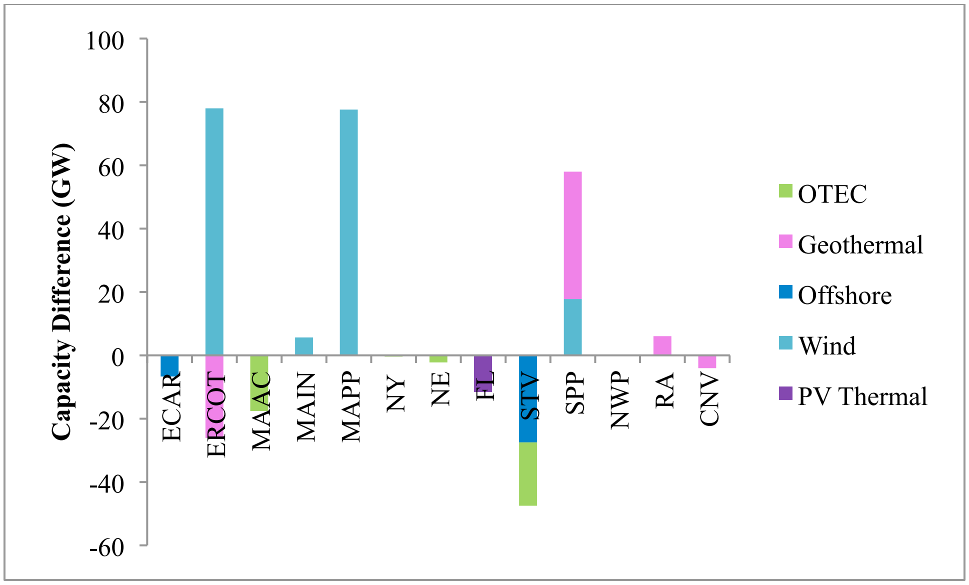

Figure 4-32. Differences between generation capacity additions in B2 versus A2 as a result of co-optimization

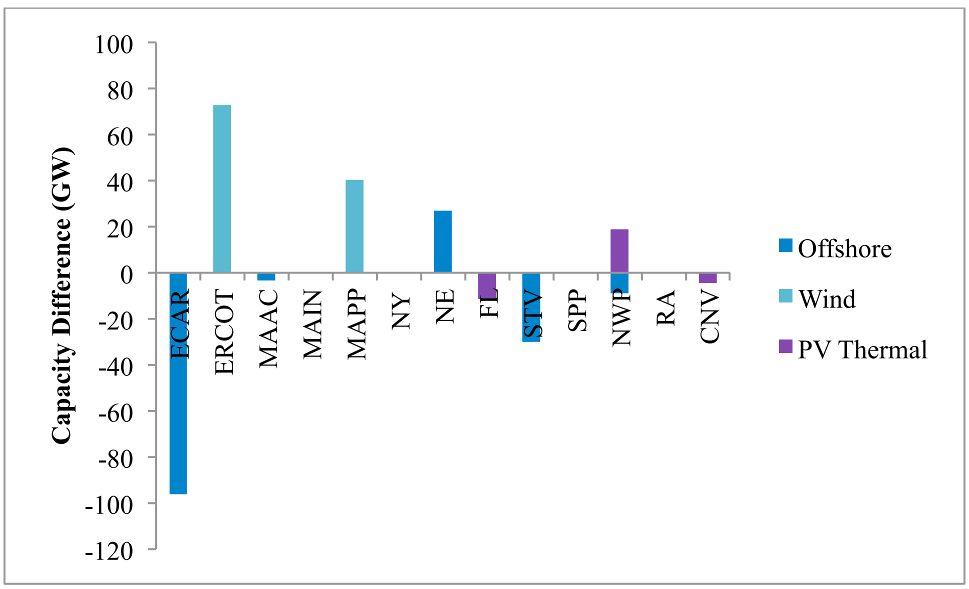

Figure 4-33. Differences between generation capacity additions in B3 versus A3 as a result of co-optimization (cumulative 2020+2030)

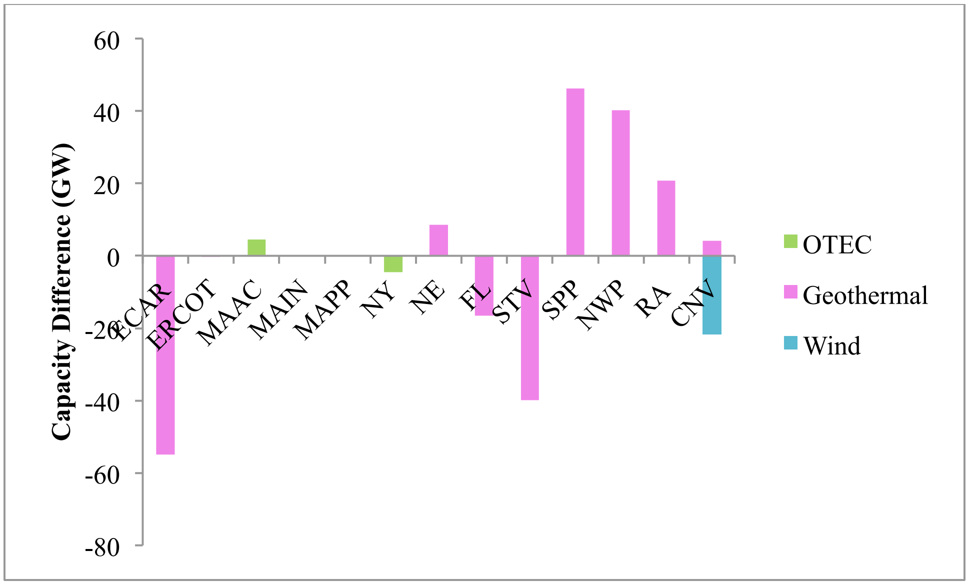

Figure 4-34. Differences between generation capacity additions in B4 versus A4 as a result of co-optimization (cumulative 2020+2030)

In Scenarios A5 and B5 (business as usual), identical generation investment and operation decisions were made, and transmission investments were made in neither. In these scenarios without a carbon tax or significant limits on the construction of non-renewable generation, a generation mix consisting mostly of combustion turbines and nuclear was built. These two generation technologies do not have significant differences in capital or operating costs across regions, and were instead built close to the load centers to meet local needs. As a consequence there are not strong motivations to construct new interregional transmission capacity.

4.3.4.3 Effects of alternative scenarios on transmission and generation additions under co-optimization

In the JHU model runs, co-optimization yields in transmission investments that are justified by regional differences in fuel and capital costs and availability of resources. This section highlights how different assumptions concerning the generation resources can affect decisions concerning transmission additions and generation mix that are recommended by co-optimization.

Transmission capacity additions in the JHU model are motivated by interregional price differences and the quality of intermittent renewable resources. In scenarios B1 and B2, the expansion of transmission capacity appears to have been driven primarily by the resource quality of intermittent generation, since transmission is built radially from regions, such as MAPP and SPP, with high quality wind resources (Figures 4-35 and 4-36). DC lines are also built to link the three interconnections (EI, ERCOT, and WECC). Figure 4-37 directly compares the amounts and locations of transmission additions in those two scenarios.

Both scenarios B1 and B2 expanded transmission along similar corridors. However, less transmission was needed in scenario B1 as low carbon conventional plants (nuclear) could be built in all regions. Differences in fuel and capital costs for conventional thermal plants are not sufficient to motivate large investments in transmission. In scenario B2 (all renewable, geothermal light) transmission capacity was expanded along most of the same corridors as in scenario B1, except at significantly higher capacities. The lack of nuclear power necessitated additional expansion of geothermal as well as additional interconnections with the Western Interconnection.

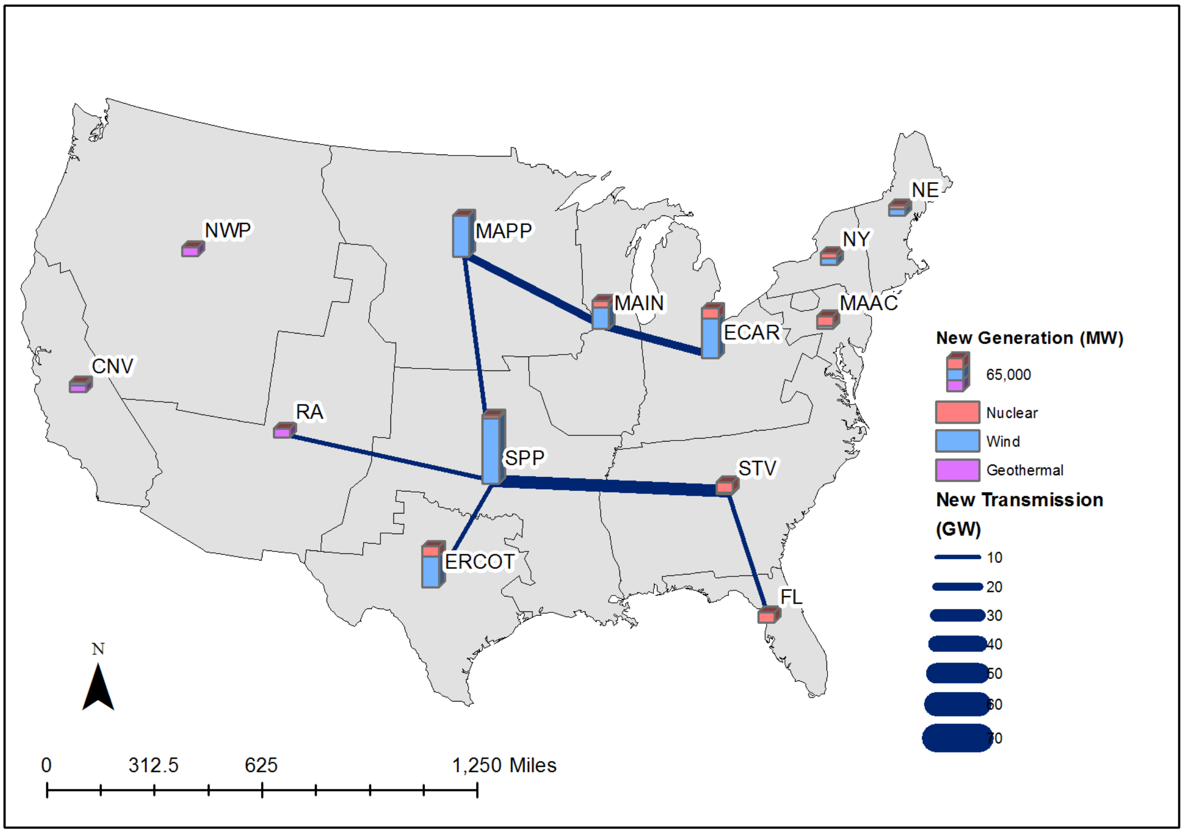

Figure 4-35. Transmission capacity, Scenario B1 (mostly renewable, geothermal light) (Height of the bar in map is proportional to 2020+2030 generation additions; Key shows bar height for 65 GW)

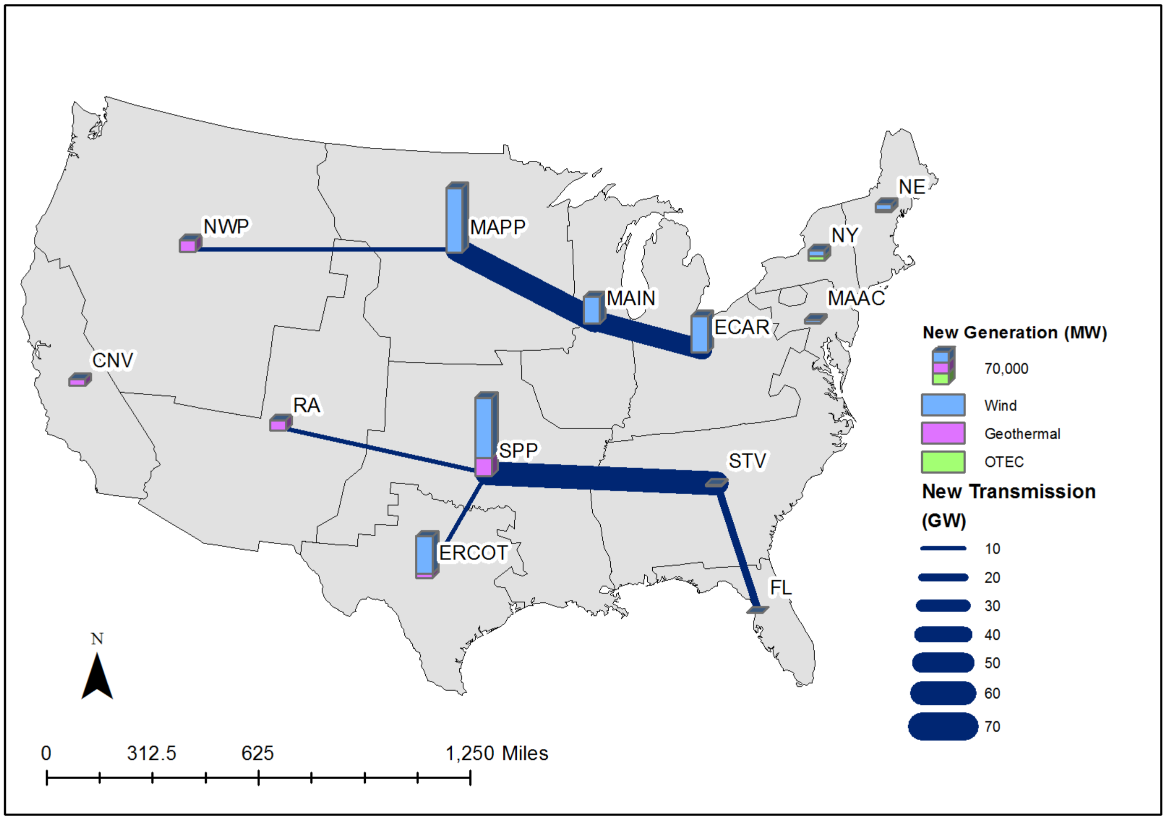

Figure 4-36. Scenario B2 transmission and generation capacity additions (2020+2030)

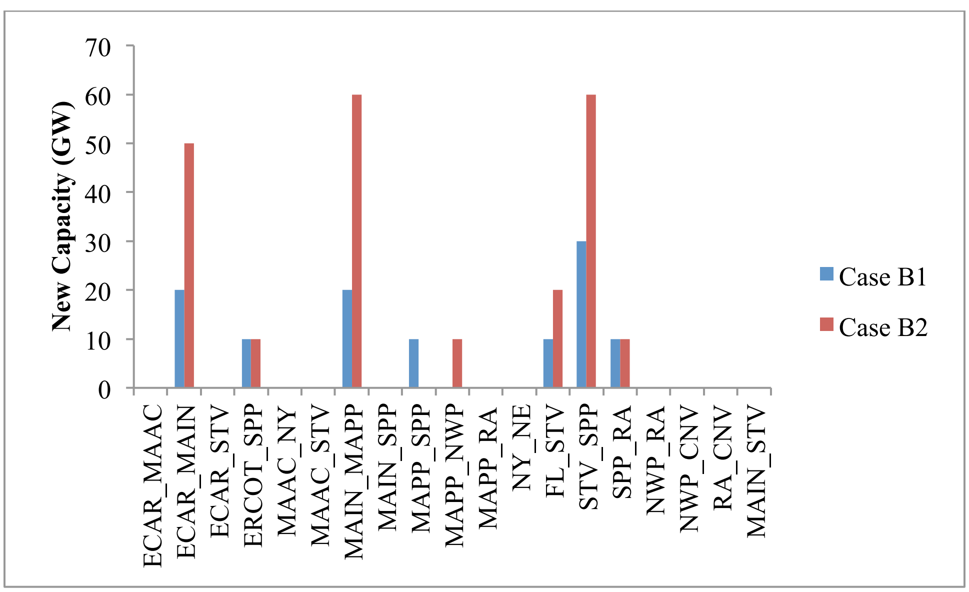

Figure 4-37. Comparison of transmission capacity additions in scenario B1 (mostly renewable co-optimization) and scenario B2 (all renewable co-optimization). (For region abbreviation definitions, see Figure 4-35)

Continuing on to scenarios B3 and B4, the co-optimization model made heavy investment in renewable resources as well as transmission capacity. These scenarios demonstrate strikingly different patterns in transmission expansion (Figures 4-38 – 4-40). Under B3 there is significant expansion along corridors connecting to regions with high quality wind resources (Figure 4-38). In that scenario, the only renewable investment allowed were in intermittent renewable resources (solar and wind), and not geothermal. As a consequence regions with the best quality intermittent resources were heavily invested in. Transmission lines built in this scenario were primarily motivated by interregional differences in renewable resource quality. By contrast, in scenario B4, the expansion of intermittent renewable resources was reduced to 2 GW annually, but geothermal investment was allowed outside of the West. That scenario's transmission expansion (Figure 4-39) was therefore driven by transmission of geothermal energy from the west, where geothermal investment is relatively inexpensive, to the east. That geothermal investment complemented wind investment in regions with high resource quality.

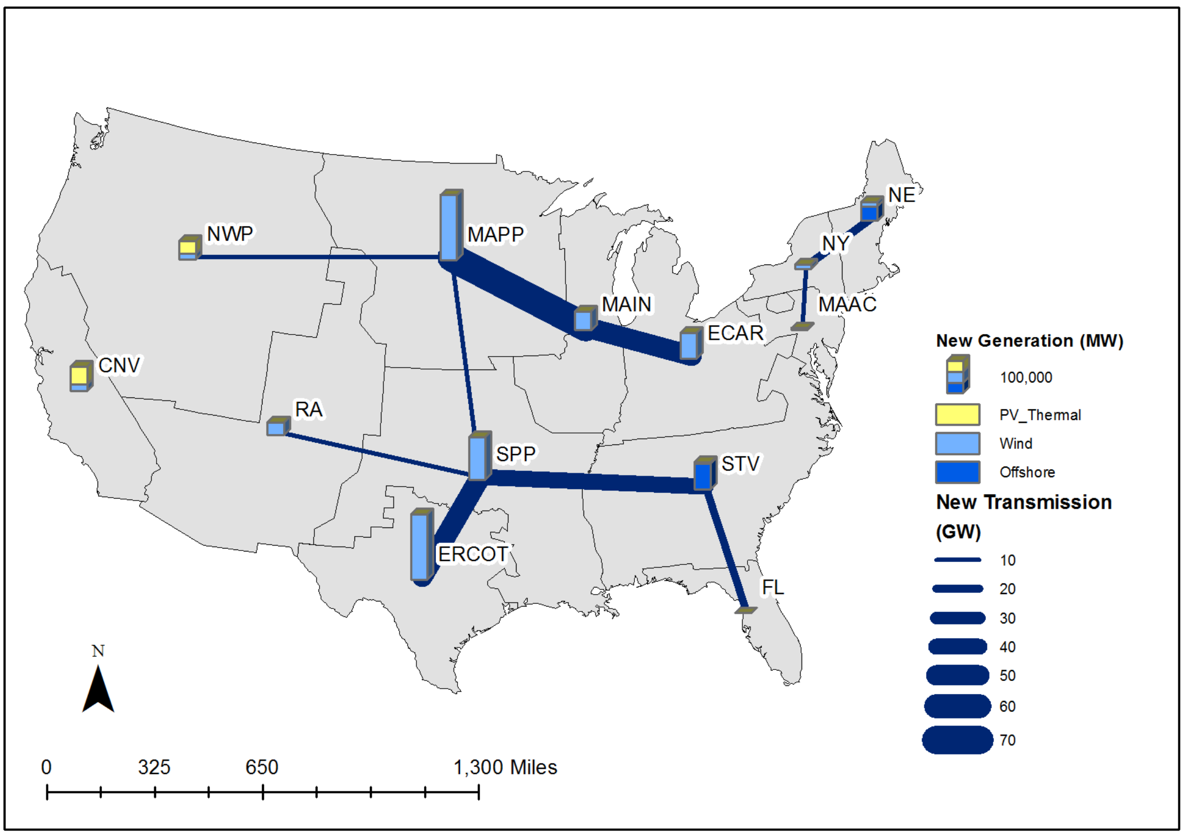

Figure 4-38. Transmission capacity additions (2020+2030), Scenario B3 (all renewable, no geothermal) (Height of the bar in map is proportional to 2020+2030 generation additions; Key shows bar height for 100 GW)

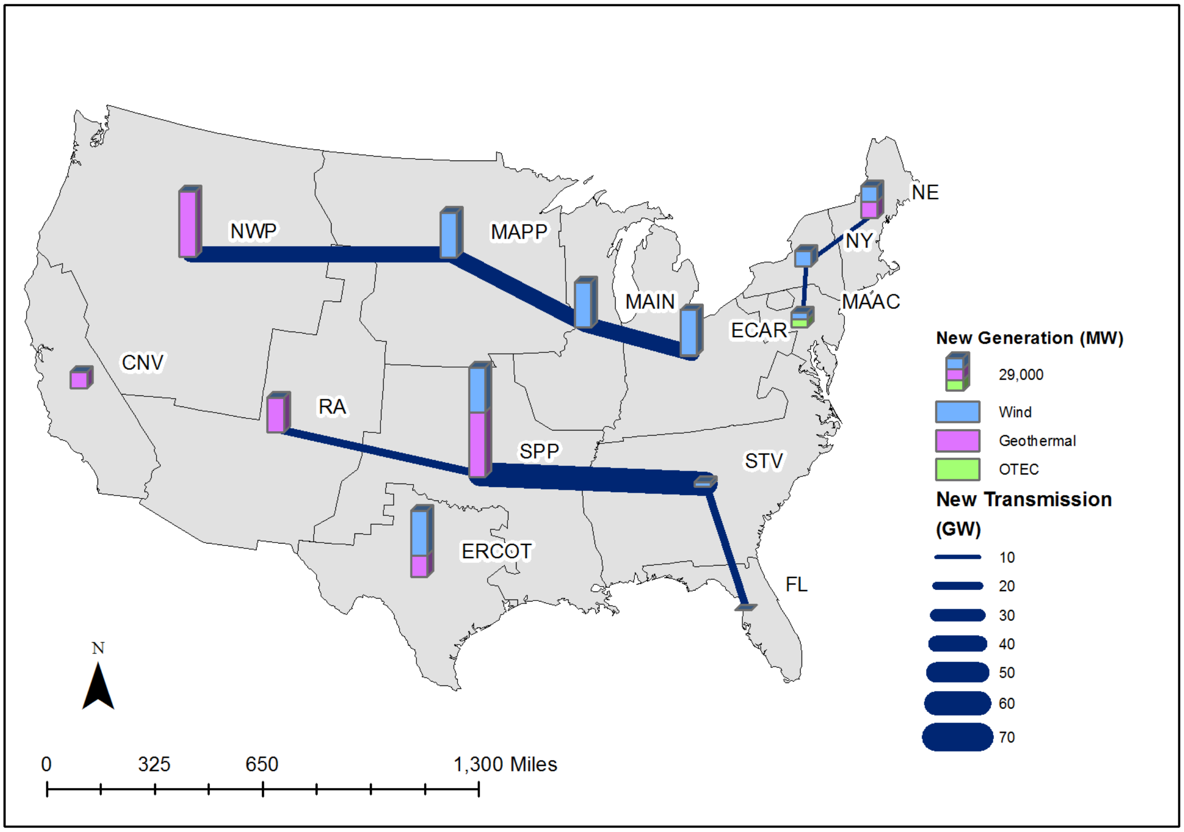

Figure 4-39. Transmission capacity additions (2020+2030), scenario B4 (all renewable, geothermal heavy) (The height of the bar in the key is equivalent to cumulative generation additions of 29 GW)

The differences between scenarios B3 and B4 can be mostly clearly seen by the lack of investment in MAPP-SPP and ERCOT-SPP in scenario B4 (Figure 4-40). Since the expansion of wind is limited in scenario B4, the benefits of connecting wind regions to reduce the effect of intermittency is reduced. Transmission investment in that scenario is redirected by the need to move geothermal energy from west to east. Meanwhile, in B3, transmission expansions between MAPP and SPP or SPP and ERCOT are driven by the need to export wind power, while in case B4 these expansions did not take place.

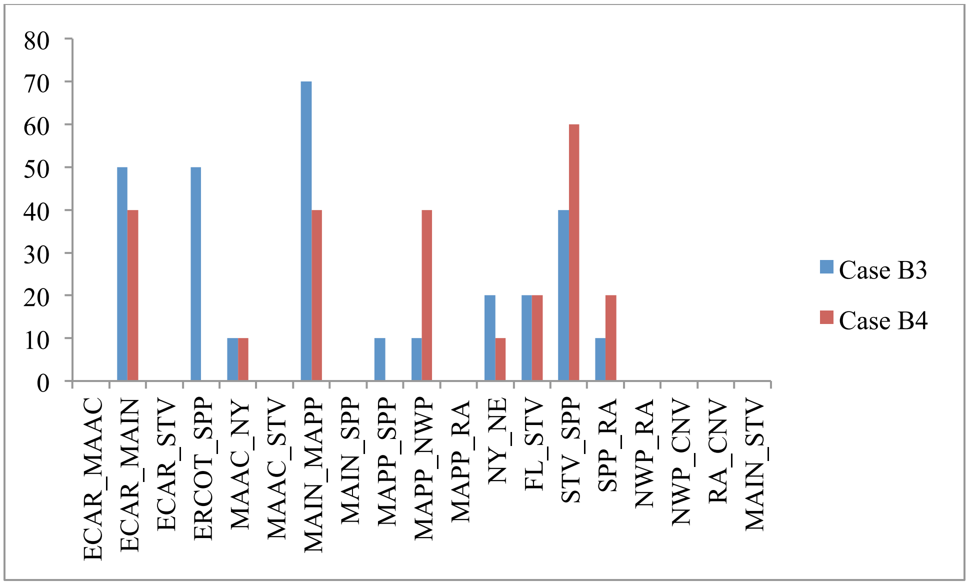

Figure 4-40. Comparison of transmission capacity additions in scenario B3 (all renewable, geothermal light co-optimization) and scenario B4 (all renewable, geothermal heavy co-optimization)

4.3.4.4 Suboptimality of co-optimization via iteration between generation planning and transmission planning: Co-optimization model 2

Because full co-optimization involves a large model with both transmission and generation capacities by location as decision variables, an alternative co-optimization approach has been proposed, which is Co-optimization Model 2. It alternates between optimization of generation investment given a fixed grid configuration, and optimization of the network given a fixed pattern of generation investment. Mathematically, it can be proven that the total cost of the system cannot worsen between iterations, and could improve. However, this iterative approach cannot be guaranteed to yield the same optimal solution or full set of benefits as complete co-optimization (Model 3), and the example below illustrates this fact.

We have tested the iterative approach of Model 2 by executing five iterations as follows for the scenario 2:

1. Optimize generation investment, given the 2010 grid. Thus, there are no transmission investment decision variables in this iteration. (This is the same as Model 0, scenario A2.)
2. Given the optimal pattern of generation investment from Iteration 1, optimize the network additions. Generation operation in all years is optimized, but capacity is fixed at the Iteration 1 values.
3. Given the expanded transmission network from Iteration 2, re-optimize generation investment.

4. Given the optimal pattern of generation investments from Iteration 3, re-optimize network additions.
5. Given the expanded transmission network from Iteration 4, re-optimize generation investment.

A full implementation of Model 2 would continue the iterations until the solutions no longer change. Here, we quit iterating after Iteration 5 (the third generation capacity optimization).

This iterative approach (Model 2) as well as the simultaneous co-optimization model (Model 3) was applied to scenario 2 (all-renewable, geothermal light), resulting in the following costs:

Iteration	**Cost ($ Billion)**
Model 2: Iteration 1. Optimize Generation (A2, Table 4-27)	1845.57
Model 2: Iteration 2. Optimize Transmission	1765.83
Model 2: Iteration 3. Re-Optimize Generation	1723.83
Model 2: Iteration 4. Re-Optimize Transmission	1715.91
Model 2: Iteration 5: Re-Optimize Generation	1711.37
Model 3: Full Co-Optimization (B2, Table 4-27)	1679.40

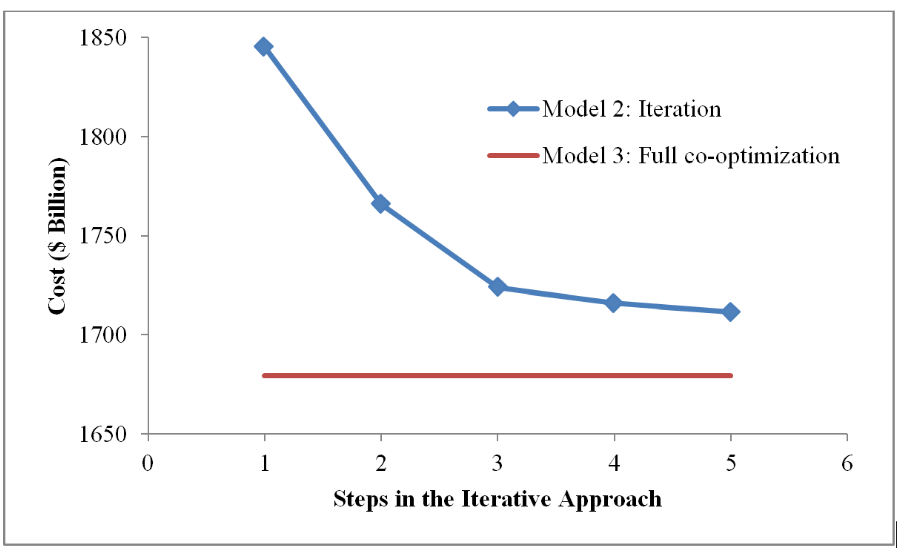

Figure 4-41. Comparison of the cost convergence of the Model 2 iterative co-optimization model with the lower bound set by the Model 3 full co-optimization approach.

These results show that Model 2 has nearly, but not fully converged after five iterations. The results illustrate how applying this iterative approach can reduce the total cost of the system. As expected, the cost improves with each iteration (as we explained, it cannot get worse), but at a diminishing rate. Most importantly, iterative solution of Model 2 was unable to achieve the same level of cost reductions as the fully co-optimized approach. The cost reduction relative to generation planning subject to a fixed grid ($134B) is just over 80% of the $166B cost reduction that full co-optimization can achieve.

In addition to subsequent iterations of Model 2 not fully achieving the full cost reduction benefits of co-optimization (Model 3), the transmission plans between the two models also differ spatially. Spatially the transmission plans found by the second (Figure 4-43) and fourth (Figure 4-44) iterations of Model 2 bear some similarity to the full co-optimization case (Figure 4-45), but also differ in important ways. With subsequent iterations, the corridors SPP-STV as well as MAPP-MAIN-ECAR are further enforced, although by iteration 4 they still have less capacity added than in Model 3. Subsequent iterations of Model 2 did not produce the same network of reinforcements as full co-optimization; for instance, in iteration 4 a line is added MAPP-SPP that does not appear in the full-optimization (Model 3, Figure 4-44). Furthermore the line ERCOT-SPP appearing in Model 3 (Figure 4-45) never appears in the iterated transmission investment solution.

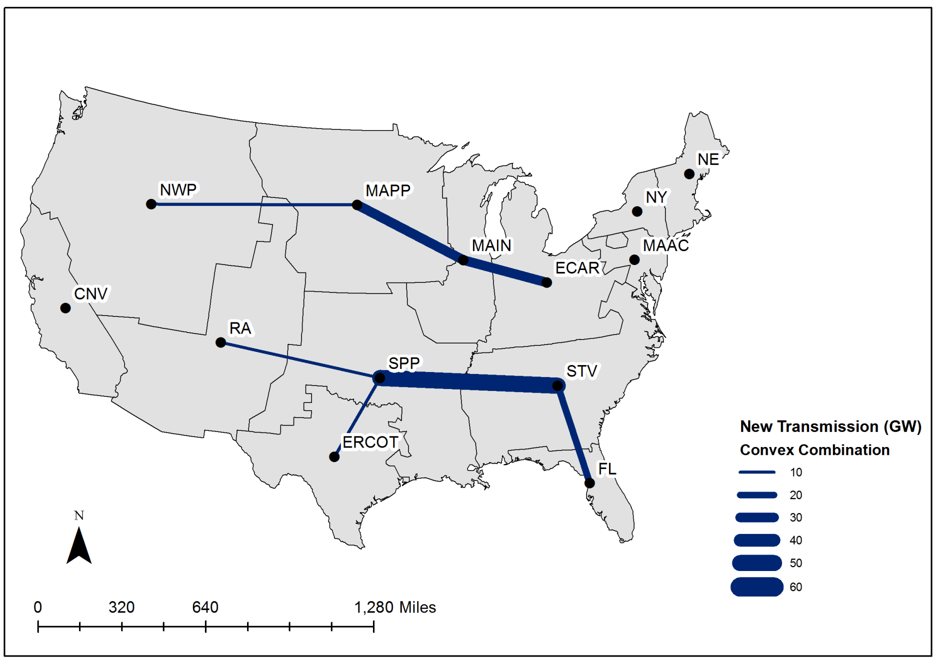

Figure 4-42. Cumulative transmission additions optimized in response to a generation plan that is an average of generation planning and full co-optimization. The thicknesses of the lines are proportional to GW transmission additions between 2010-2030.

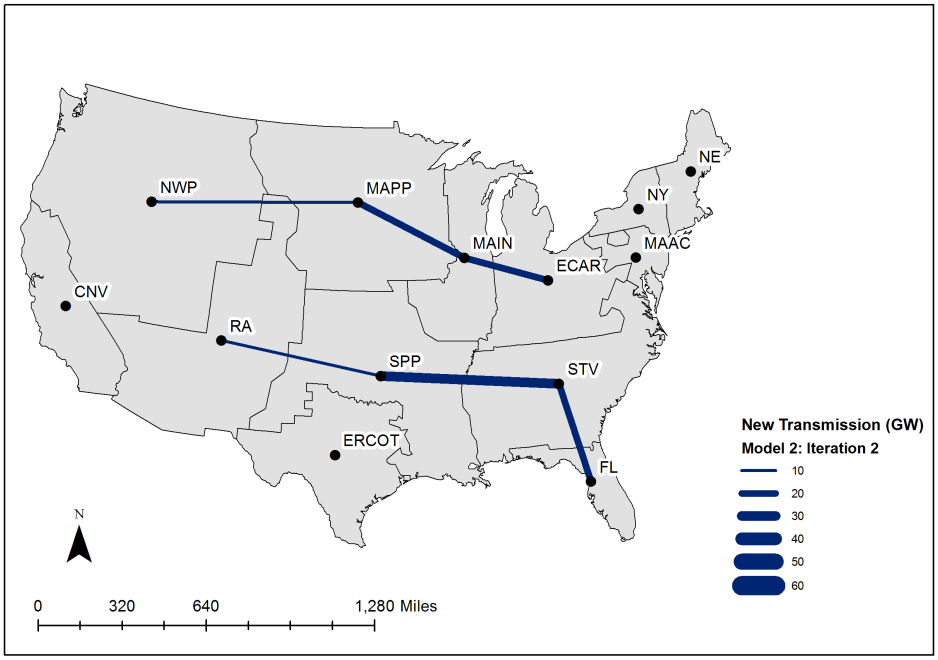

Figure 4-43. Cumulative transmission additions made in the second iteration of Model 2. The thicknesses of the lines are proportional to GW transmission additions between 2010-2030

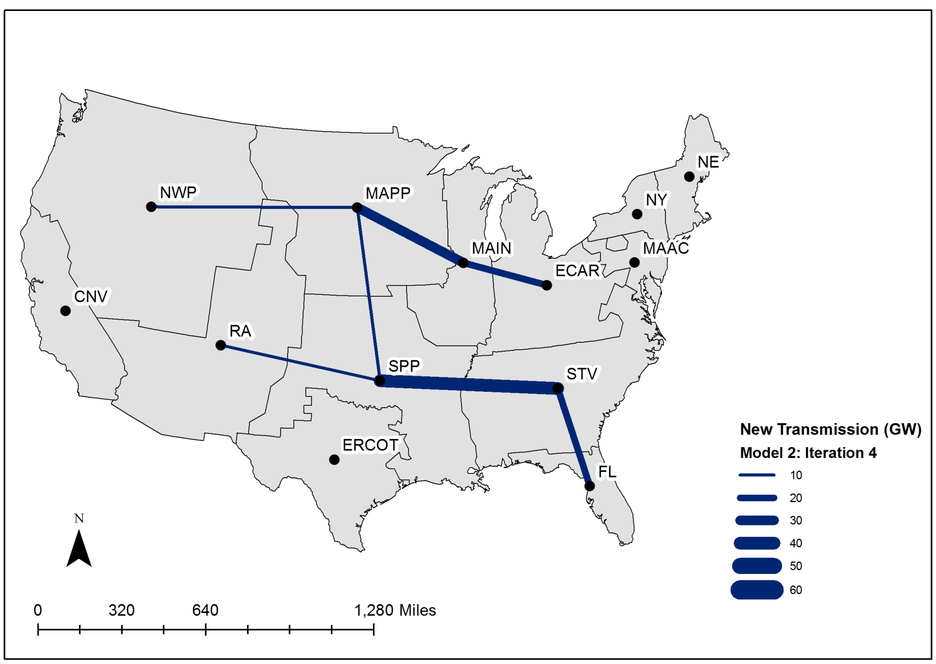

Figure 4-44. Cumulative transmission additions made in the fourth iteration of Model 2. The thicknesses of the lines are proportional to GW transmission additions between 2010-2030

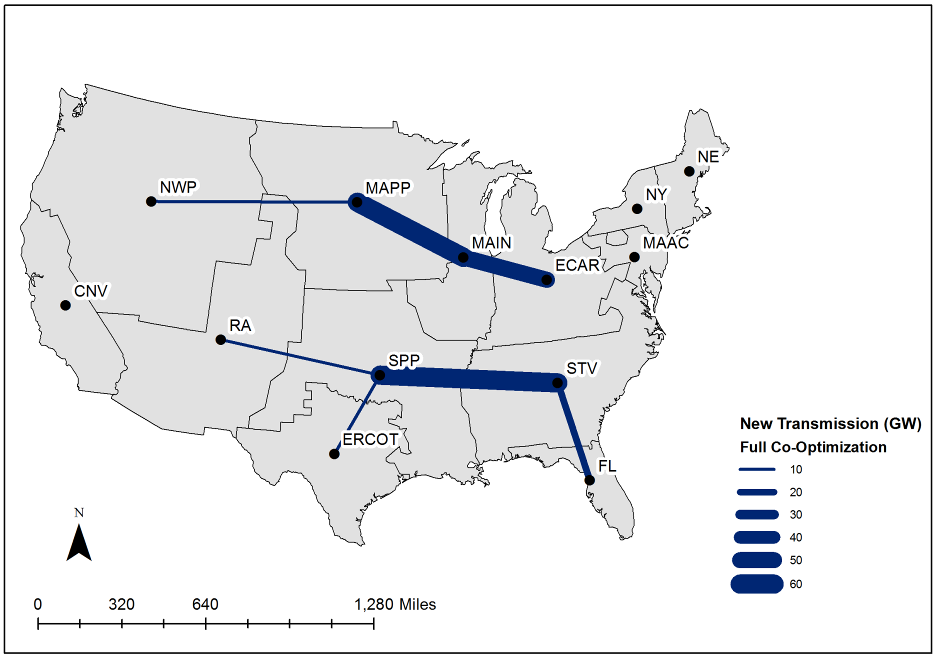

Figure 4-45. Cumulative transmission additions made under Model 3: Full Co-optimization. The thicknesses of the lines are proportional to GW transmission additions between 2010-2030

These differences in transmission plans between the two models appear because each iteration lacks information about the response one planner has to the other's decisions. For instance, Model 3 builds a ERCOT-SPP line to enable more wind generation and less baseload generation to be built in ERCOT, so that excess wind can be exported, while imports to ERCOT can replace wind when it isn't blowing. To arrive at this solution requires that both generation and transmission be considered at the same time in a model, which the iterative (Model 2) approach does not do. This confirms that Model 2 does not achieve full co-optimization, but rather should be viewed as a heuristic that can gain a significant portion but not all of the benefits of co-optimization.

Also of interest are the differences among the amounts invested in transmission within these solutions. In particular, the three transmission planning models (Model 2 Iteration 2 (transmission-only), Model 2 Iteration 4 (transmission-only), and Model 3 (full co-optimization)) had \$54.3B, \$70.9B, and \$116.46B respectively, of transmission investment (present worth) over the planning time horizon (Table 4-33). Particularly striking are the differences in the first period (2010-2020), when the fully co-optimized model invests in roughly three times as much transmission as the transmission-only models. For instance, the ERCOT-SPP line is built in Model 3, but not in the iterative Model 2, again because when Model 2 considers transmission it does not recognize that generation investment would shift (saving gen investment and operations costs) at the same time.

As a sensitivity analysis to assess whether this result just depends on the initial generation scenario, Table 4-33 shows another transmission-only run based upon a generation investment scenario that is an average of the co-optimized generation investment (Model 3) and Model 2, Iteration 1 (Generation-only). Again, the investment is well below the co-optimized model level. This does not imply that full (simultaneous) co-optimization always yields more transmission investment—indeed, it is possible to contrive situations where it would not—but there appears to be a tendency for this to be the case.

Table 4-33. Transmission and generation addition expenditures with operations

Modeled Case	Present Worth ($ Billion)					
	Decisions 2010-2020[b]		Decisions 2020-2030			Decisions 2030-2060[c]
	Transmission Investment	Generation Investment	Transmission Investment	Generation Investment	Generation Operations	Generation Operations
Transmission First, using average gen scenario[a]	49.60	534.47	35.75	426.91	237.31	450.05
Iteration 2 of Model 2	19.46	521.99	34.87	470.17	265.99	453.35
Iteration 4 of Model 2	25.88	531.56	45.05	410.93	252.78	485.70
Model 3 Co-optimized Model	72.90	546.96	43.56	383.65	213.85	418.48

a. Generation investment scenario defined as average of gen investments from Model 2 (Iteration 1, equivalent to generation-only) and Model 3
b. Operations in 2010-2020 not simulated because they are assumed to be unchanged by 2010-2020 investment, which is in place in 2020.
c. Investments in 2030-2060 not simulated. Investments from 2010-2030 are assumed to be in place (except for retirements) for 2030-2060 retirements.

Since the optimal co-optimization case (Model 3) has the highest total transmission cost, all improvement over the suboptimal iterated Model 2 must come from more efficient investment and operation of generation. Comparing the individual cost components of iteration 2 of Model 2 to Model 3 (Table 4-33) shows that Model 3 yields a $150 billion reduction in generation costs, of which $88 billion is from reduced operations costs and $62 billion from reduced investment. Thus, 40% of the generation cost savings would be completely missed by the transmission-only iterations of Model 2. This demonstrates that transmission-only models that consider only fuel cost savings and not generation capacity cost savings can miss a large portion of the benefits of transmission, and as a result yield suboptimal investment plans.

These differences in transmission investment show that the treatment of generation investment and siting has a dramatic effect on transmission plans. In particular, the traditional practice of transmission expansion under a fixed scenario of generation investments (transmission-only; Model 2, Iteration 2) has given very different levels of investment than full co-optimization (Model3). Thus, these results indicate that anticipating how generation investment might react to transmission network plans is a highly important feedback that can drastically change the recommendations for transmission investment, and result in important cost savings.

5 UNCERTAINTIES IN MODELING

Long-term planning in any sector usually is subject to significant risks and uncertainties, which are particularly important for the power sector because of the long lives of transmission and generation assets. On the supply side, short-term risks, such as the intermittent nature of wind and solar energy, pose considerable challenges to system operation as electricity supply and demand must be balanced at all times to ensure system reliability. As an example of a long-run uncertainty, the pressing concerns of global warming, coupled with the lack of federal policy on greenhouse gas (GHG) emissions, create huge risks to any capital-intensive investments in energy industry. Such risks are intensified by highly volatile fuel prices.

On the demand side, on top of constantly varying consumption, the increasing penetration of demand response and distributed generation resources, plus the potentially widespread adoption of plug-in vehicles (PEVs), will make future demand more unpredictable. As a result, long-term planning models (or processes) that do not consider uncertainties may provide misleading results that could be far from socially optimal solutions once the uncertainties unfold, and such models cannot be used to assess system reliability.

There are two main purposes for considering uncertainties in the modeling/planning process: (a) to study the impacts of uncertainties of inputs on system outcomes (such as investments, electricity prices, reliability, etc.), as illustrated in Figure 5-1; and (b) to find robust solutions that can produce reasonably good outcomes regarding all possible realizations of future uncertainties.

Figure 5-1. Effects of input uncertainties on outputs[8]

To achieve the two purposes stated above, we need to understand the sources of uncertainties in the power sector and their characteristics, which are summarized in Section 5.1. The section will also discuss techniques for representing the different types of uncertainties in optimization models. Section 5.2 describes methods for solving the resulting stochastic optimization problems, and their applications to the co-optimization models discussed in earlier sections. A case study

[8] Figure source: "Uncertainty Analysis and Optimization: Opportunities and Challenges," by Gianluca Iaccarino, presentation at the Optimization Day Workshop, 2/1/2011, Stanford, CA.

will be shown in Section 5.3 to illustrate the impacts of uncertainties on the solutions of co-optimization models.

5.1 Uncertainty Categorization and Modeling

5.1.1 Uncertainty categorization

Each of the many sources of uncertainties present in the power sector have vastly different impacts on individual market participants. We focus on the uncertainties that may significantly impact long-term resource planning. While there is no single method to categorize uncertainties, our approach groups them by their characteristics, such as by the causes of the uncertainties (e.g., market versus nature). Our categorization is summarized in Table 5-1 below.

Table 5-1. Uncertainties in the power sector

Types of Uncertainties	Examples	Characteristics
Market uncertainties	Capital costs Fuel costs Fuel availability Emissions permits costs	Fundamentals-driven (supply-demand dynamics) Have historical data – can be used to derive probability distributions
Nature-related uncertainties	Water availability (or hydro plants' outputs) Wind speed (or wind plants' outputs) Solar irradiation (or solar plants' outputs)	Have extensive historical data Can have probability distributions
Consumption uncertainties	Load DR/DGs/Microgrids PHEV charging	Probability distributions of load can be obtained through historical data Probability distributions of other demand resources need to rely on simulation
Individual-asset uncertainties	Forced outage (units; transmission lines) Firm-builds' availability at the scheduled online time New built/ Retirements/ Retrofits/ Uprates	Asset owners have better knowledge than system operators For new builds, no known probability distribution for system operators
Regulatory uncertainties	New reliability standards Environmental policies	Low frequency No historical data No known distributions
Other uncertainties	Technology breakthrough New discovered resources Catastrophic events	Low frequency No historical data No known distributions

5.1.2 Uncertainty modeling

Uncertainty modeling is the process of using mathematical approaches to represent the random variation in data that are observed in real world. The method used to represent an uncertainty should be specific to its type, largely depending on their nature and the availability of data. In the following we review techniques for modeling each of the categories of uncertainties identified in Table 5-1.

Market uncertainties are mainly caused by fluctuations in the overall economy and varying influences on supply and demand, such as fuel costs and capital costs. Generally, there are two approaches to model fluctuating variables related to market conditions. The first approach is simply to assume a probability distribution of an uncertain variable, such as fuel costs or capital costs. The specific distribution might be selected as that which best fits a sample of historical data. Once a distribution is chosen, Monte Carlo simulation[9] can be employed to generate random data to be used as input parameters in an optimization model, for instance to define a set of load or wind production realizations to be considered in the operations part of the model.

While this approach is simple to implement, it is limited as it cannot be used for forecasting. Forecasting using this approach would be inappropriate since it would be assuming that "the future is in the past," and the probability distribution selected would not reflect fundamental changes in markets that would make the future deviate from past trends. Also, extreme, but rare, events not observed in the historical data are not likely to be captured using this approach.

In addition, such an approach ignores temporal linkages among random variables. For example, even though historical data may suggest a variation (standard deviation) of natural gas price to be 80%, the variation *conditional* on what we know today would be much less – e.g., given that today's natural gas price is \$4/MMBTU, the variation of tomorrow's price would be much smaller than 80%. A more sophisticated simulation-based approach is to model the evolution of a random variable over time (such as fuel prices) as a stochastic process.[10] One particularly useful stochastic method is the mean-reverting process, as given below.

$$P_{t+1} - P_t = \alpha(P^* - P_t) + \sigma\, \varepsilon_{t,}$$

Here, P_t and P_{t+1} represent the price of a commodity at time period t and $t+1$, respectively. P^* is an input representing a long-run equilibrium of the commodity price. α is the mean-reverting factor, indicating how quickly the random process will return to its mean; σ is the volatility (standard deviation) of the commodity price (P), and ε_t is a random variable (such as a normal random variable with mean 0 and standard deviation 1).

The idea behind such a model is simple. Suppose that crude oil price has jumped from \$50/barrel (P_t) to \$150/barrel (P_{t+1}) in a short period of time, due to either an unexpected events or speculation. It might be expected that the price would eventually revert to its long-run equilibrium level (P^*), reflecting the marginal production costs of crude oil. Figure 5-2 shows a comparison between a stochastic process (left figure) where the intertemporal linkage of the

[9] Monte Carlo simulation, in non-technical language, can be understood as a black box with the assumed probability distribution's parameters as the input, and with a series of random numbers following the specified distribution as the outputs for each simulation run.

[10] Simply put, a stochastic process is a mathematical model to depict the changes of a random variable over time.

random variable is ignored (more specifically and technically, a geometric Brownian motion process), and a mean-reverting process (right figure). Since fuel prices are fundamentally determined by the supply-demand dynamics and marginal production costs, any short-term extreme variations tend to dissipate quickly. Hence it is generally believed that mean-reverting processes are good models to capture the randomness of commodity prices and so they have been widely used in the energy sector for asset valuation and risk management [15,28,38].

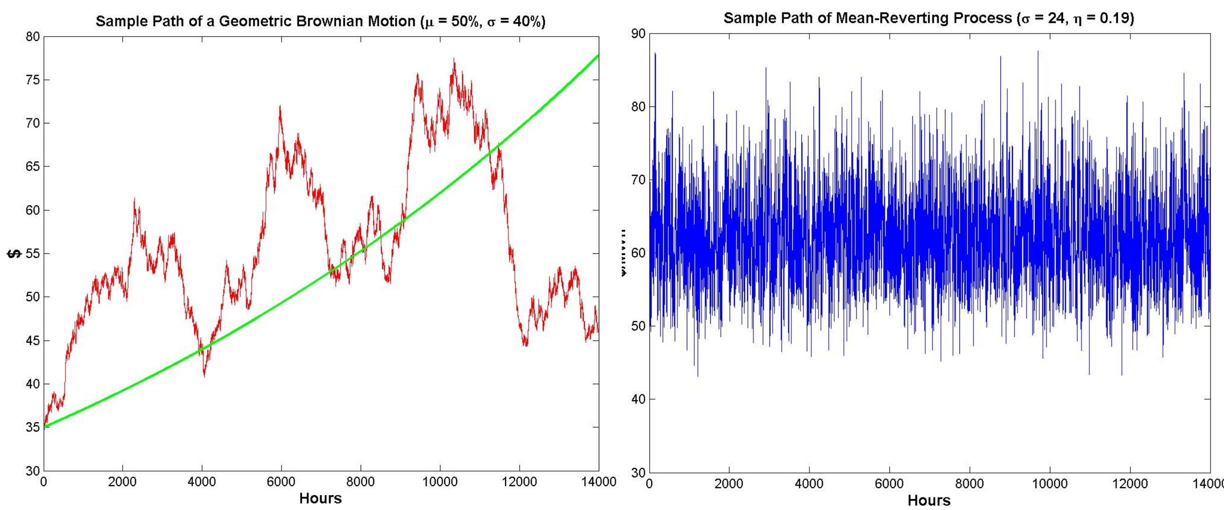

Figure 5-2. Comparison between a geometric Brownian motion (left) and a mean-reverting process (right)

The second approach for modeling random variables is the econometric method. With this approach, there are two categories of models: time series models and structural models. Both of are forecasting models, but are based upon different forecasting philosophy. To forecast future realizations of a random variable changing over time, time series models only rely on historical data. A simple form of a time series model is as follows.

$$P_t = \beta_1 P_{t-1} + \ldots + \beta_p P_{t-p} + \varepsilon_t,$$

Again, P_t represents the value of the random variable of interest at time t. The β's are coefficients estimated from historical data, and ε_t is a random error term. Such a model indicates that the random variable P_t (e.g., natural gas or crude oil price at time t) can be inferred from the information contained in the observed data up to p periods back. Such a model is called an autoregressive process with order p, or AR(p). Another type of model explores the relationship between the random shocks (ε_t, $\varepsilon_{t-1}, \ldots \varepsilon_{t-q}$) with the random variable P_t, is the moving average model (or MA(q)). The AR and MA models can be combined into more sophisticated time-series models that may produce more accurate forecasts.

A general limitation of time-series models is that they are often only good for making short-term projections. Structural models, the other category of econometric models, are better suited for long-term forecasts. Structural models link the random quantity of interests with a set of fundamental variables that are believed to have impacts to the random variable. For example, to forecast future crude oil prices, the fundamental variables selected could be a (quantifiable) variable that describes the role played by OPEC in the oil market, as well as variables that represent the current and future physical oil availability [33]. For forecasting peak electricity demand, the fundamental variables may include overall economic conditions, weather, electricity and natural gas prices, and population growth. The parameters associated with the fundamental variables can be estimated with historical data. Once the parameters are obtained, the structural model can then be used to forecast future values (or to generate random samples to be fed into an optimization model).

While this approach is easy to understand and implement (given data availability), it requires significant experience with modeling and data processing to produce useful models. This is because selecting the right fundamental variables requires sound knowledge of the underlying drivers of the quantities of interests, and the observed data are usually noisy and it may not be possible to use them directly to estimate parameters.

For forecasting electricity demand (or generating random samples), all of the previously-described approaches are applicable. For example, a time-series model is used for projecting hourly load in an electric utility's portfolio optimization problem [117]. A structural model is the basis for ISO-New England's forecasting of future peak demand [61]. While methodologies for demand forecasting (and random demand sampling) are well-established, emerging resources on the customer side of the meter, including demand response, distributed generation (DG), microgrids, and plug-in electric vehicles (PEVs), pose new challenges to the traditional approaches.

The key challenge is that the information about the new resources is not contained in historical data. If DG and microgrids are dispatchable by the grid operators, this challenge could be overcome by treating them as generation resources. Although this could become a reality in a smart-grid world, existing technological and institutional barriers prevent most distributed resources from being dispatchable. Another method to address the challenge of incorporating emergent technologies is to rely on agent-based simulation. Under this approach, computer programs are trained to behave like PEV owners or entities that manage DG or microgrids. The net electricity demand directly related to an individual agent's PEVs. and distributed resources can be obtained through a simulation model and then aggregated. Such an approach has been employed in [58] to study the impacts California's retail rate structure on PEV adoptions and in [145] to study the effects of PEV charging on wholesale electricity prices.

For weather-related uncertainties, such as wind speed and solar irradiance, there are three approaches for uncertainty modeling; Monte Carlo simulation, time series analysis, and numerical weather prediction models. The Monte Carlo approach simply samples from an assumed or fitted distribution for the variables of interest (such as wind speed, or more directly, the energy output from a wind power plant). As mentioned previously, it is not a forecasting tool, and the distribution is likely to be obtained through analysis of historical data. The time series approach is similar to the modeling and forecasting of fuel costs and load uncertainty described above. It is suited for more aggregate and long-term forecasts of weather-related quantities, such as the monthly average wind speed over a multiple-year horizon. Finally, numerical weather prediction (NWP) models combine mathematical models of the atmosphere and oceans, with the current weather conditions used as "boundary conditions" to predict future weather. Due to the complexity of the underlying methods and the high computational burden, NWP is best suited for short-term (e.g., less than a week) forecasts. While such approach may not be suitable for long-term planning models, it is very useful for short-term unit commitment or dispatch modeling involving a large amount of variable energy resources. For co-optimization models that can handle more detailed production modeling of a power grid, both the time series and the NWP approach can be useful for understanding weather-related uncertainty and informing the choice of loads and wind conditions to include in the model.

From power system planners' perspective, there are risks associated with the unknown status of individual assets, such as forced outages of existing assets, and delays in the construction of new power plants. All power system operators account for the potential impacts of unavailability of certain important generation or transmission assets through N-k contingency analysis. This approach ensures that a system remains operable after losing all possible combinations of k of the selected generation units and transmission lines. However, minimizing operation costs of a power system subject to system reliability requirements (such as the requirement to withstand a N-k contingency) is computationally intensive even for short-term analysis, and it has yet to be extended to long-term power system planning. The best practical approach may be to first generate an initial investment plan using a co-optimization model followed by an N-k contingency analysis on the planned system that can inform adjustments of the plan. For other individual asset-related uncertainties for which historical data is lacking, such as future project uncertainties (delayed or canceled construction), it can be best to handle these through stochastic optimization (to be introduced in the next section) rather than sampling the uncertainties through an assumed probability distribution (like the Monte Carlo approach).

Different categories of longer-run uncertainties such as regulations or technological breakthroughs, despite having different origins, can be treated in a similar manner. These uncertainties cannot be predicted using historical data, and are not daily or even yearly events. In addition, such uncertainties usually have only a few possible realizations. For example, for federal greenhouse-gas regulation, there may be three basic possible regulatory outcomes over the next several decades – no regulation, carbon tax, or cap-and-trade. For such uncertainties, the widely used scenario-based analysis approach (namely, the "what-if" type of analysis) is an option for analyzing the potential impacts of low-frequency events on the power sector. However, representing the actual timing of future events related to policy or technological breakthrough remains a challenge in long-term planning models, and requires expert judgment. More sophisticated approaches to handle such uncertainties, including stochastic programming and robust optimization, are introduced in the following section.

5.2 Optimization under Uncertainties and Applications to Co-Optimization

The previous section discusses how to model uncertainties that are commonly faced in a long-term planning process. Such representations need to be incorporated into an optimization model in order to create useful decision-making tools. There exist several approaches for performing optimization under uncertainty, ranging from the intuitive and simple scenario-based analysis, to more complex mathematical modeling and solution methods. This section will provide an overview of such approaches.

In a deterministic optimization model, all input data are known to the modeler for the model to be solved to optimality. When the input data exhibit significant uncertainty (such as forecasted data), a deterministic optimization model with a fixed set of input data (such as using the expected value of the forecasts) is likely to recommend a solution that is actually suboptimal or even infeasible when the uncertainty unfolds. This would pose significant challenges particularly to power system planning as infeasible resource planning solutions could jeopardize system reliability. Hence, it is important for resource planners to explicitly consider the impacts of uncertainties on the quality and robustness of the solutions produced by an optimization-based planning model.

The research field of optimization under uncertainty has advanced significantly in both theory and computational capability over the past two decades. The main approaches include scenario-based analysis, stochastic programming, robust optimization, and dynamic programming.

5.2.1 Scenario analysis

Scenario-based analysis, also known as what-if analysis or the wait-and-see approach, has been widely used in practice. In this approach, inputs that are unknown at the time of preforming the analysis, such as future fuel and capital costs, renewable resource outputs, forced outages, are generated by using Monte Carlo simulation (or even simpler, based on expert judgment). Each series of simulated (or manually selected) input data consists of a scenario, and for each scenario a deterministic optimization model is solved. The particular model will then be re-solved multiple times, once for each of the scenarios simulated (or provided). Such an approach can be easily implemented in the co-optimization models discussed in the earlier sections. While the biggest advantage of a scenario-based analysis is its simplicity, both conceptually and computationally, a major drawback is that it does not provide a single set of implementable investment recommendations for decision-makers. Instead, there is a deterministically optimal solution for each scenario, and solutions for different scenarios are likely to contradict each other. For example, the optimal near-term resource expansion corresponding to a high-fuel-cost, high-demand growth scenario is likely to be very different than that from a low-fuel-cost, low-demand-growth scenario.

Scenario analysis does not provide an obvious mechanism to reconcile such disparate solutions. Heuristics, which are approximate "rules-of-thumb", can be used – for instance, build any line that is recommended for near-term construction in a majority of the scenarios. However, such heuristics will not minimize average cost over the scenarios, and may in fact perform worse than single-scenario solutions. For instance, this occurred in a hypothetical co-optimization problem under uncertainty for the WECC region [90], in which the very best lines (in terms of average cost) were not chosen by any scenario, and furthermore the heuristic had even higher average costs than any of the scenario solutions. That being said, scenario analysis remains a viable approach to gain insights on the impacts of those low-frequency/no-historical-data events on system cost and reliability, as discussed in the previous subsection.

To overcome this drawback of scenario-based analysis, while maintaining its simplicity, one option is to create a number of scenarios and develop plans that perform acceptably in all scenarios. Recent research has formalized this approach in order to explicitly design for planning flexibility, whereby core costs (investment only) and adaptation costs (investment and production costs of adapting from the core to each scenario) are simultaneously minimized, as illustrated in Figure 5-2.

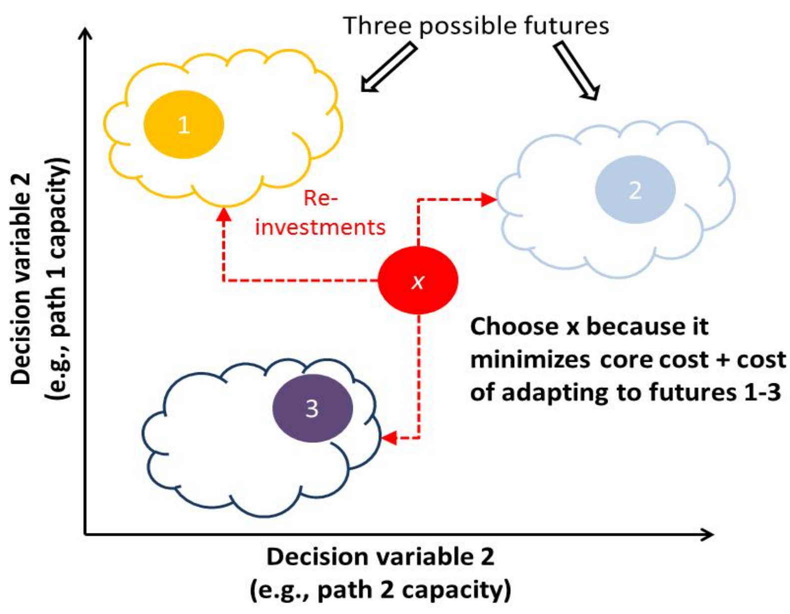

Figure 5-2. Illustration of flexibility design [87]

A simplified problem statement that implements this flexibility-based design process is

Minimize: CoreCosts($\underline{x}^f$) + β[Σ_i AdaptationCost($\Delta\underline{x}_i$)]

Subject to: Constraints for scenario $i = 1,\ldots N$: $g_i(\underline{x}^f + \Delta\underline{x}_i) \leq \underline{b}_i$

where

- $\underline{x}^f$ are the core investments, to be used by all scenarios i,
- $\Delta\underline{x}_i$ are the additional investments needed to adapt to scenario i, and
- β weights the solution towards core investments (large β) or towards adaptation (small β).

This approach was implemented for a 40-year multi-period generation planning problem to identify generation investment in a five-region representation of the US for a number of selected futures. Results, shown in Figure 5-3, indicate that in year 2049 (a) wind, nuclear, and natural gas are the technologies of choice when designing for planning flexibility; and (b) the core investment cost increases while adaptation cost decreases as β increases from 0.2 to 1.0. The investment schedule over the 40-year period is shown in Figure 5-4 for a choice of β = 0.6. Although this example focused only on generation expansion, application of this approach within a co-optimization framework is possible and currently under development.

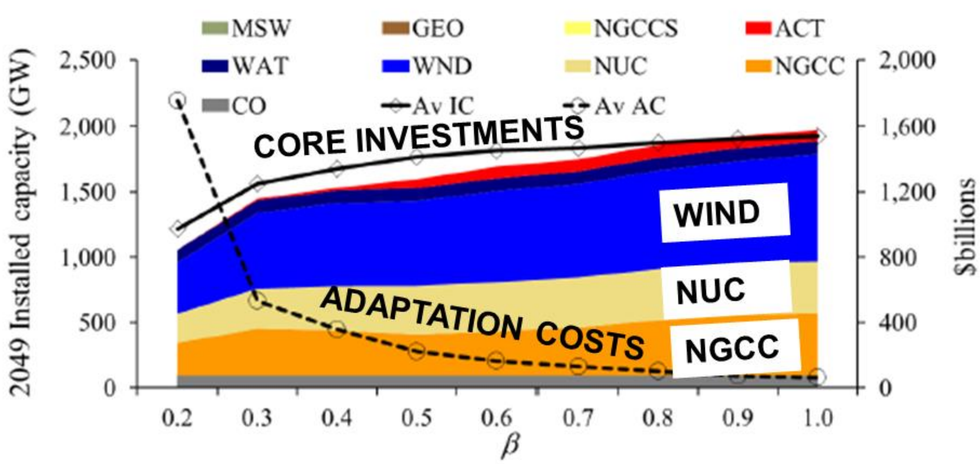

Figure 5-3. Effect of β upon core investment, adaptation costs, and generation capacity portfolio

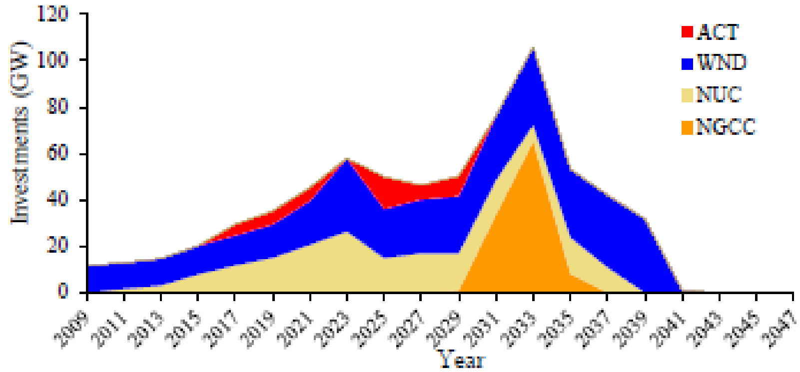

Figure 5-4. Capacity investments for $\beta = 0.6$

5.2.2 Stochastic programming

To further enhance the usefulness of optimization models with input uncertainties, along with the quality of their solutions, stochastic programming models (or more specifically, here-and-now type of models) and algorithms have been developed. The simplest form of such models is the two-stage stochastic problem with recourse, in which decisions are separated into two groups – those that need to be made before uncertainty unfolds (such as investment decisions), and those that can be adjusted once uncertainty is realized (such as unit commitment and dispatch decisions to be made after capital and fuel costs become certain). The first group of decisions are made in the first stage in the two-stage model, while the second group of decisions, also known as recourse decisions, are made in the second stage. The general formulation of the two-stage model in a power system's resource-planning context is as follows.

Minimize the discounted sum of {future investment costs + sum of probability of each scenario of the future uncertainty × operating costs under each scenario}

Subject to:

First-stage constraints:

e.g., Resource adequacy constraints: sum of unforced capacities ≥ peak demand × (1 + reserve margin requirement)

Linkage between first-stage and second-stage constraints:

e.g., Capacity constraints: Unit energy production (*s*) ≤ Unit capacity for each generating unit, for all scenarios *s*

Second-stage constraints (for all scenarios *s*):

e.g., Supply-demand balancing constraints: Total energy production of all units (s) = Demand (s)

By solving such a model, the (first-stage) solutions will provide decision-makers a uniform set of actions to implement (such as generation and transmission expansion decisions). In addition, when the model makes first-stage decisions, it will ensure the feasibility of first-stage solutions under the second-stage constraints for each and every scenario. For example, consider the supply-demand balancing constraint in an economic dispatch problem (the second-stage problem) in which the generation and transmission capacity expansion decisions are already made (in the first stage). While future demand and the output of renewable resources are uncertain, the first stage decisions will ensure that there is sufficient generation and network capacity (new built plus existing) to meet the demand and need for network flexibility under all possible scenarios. This is fundamentally different than the scenario-based analysis (the wait-and-see approach) where a set of capacity expansion solutions will only be guaranteed to be feasible for the corresponding scenario (e.g., high gas price, high demand growth) and may not be feasible under other scenarios.

A natural extension of the two-stage stochastic programming approach is to multi-stage stochastic programming, which can be understood as a repetition of the two-stage models with multiple decision stages or "epochs." Since resource planning in the power sector usually covers a long time horizon, with investment and retirement decisions made at multiple time periods, a multi-stage stochastic programming model would appear to be a more fitting approach than a two-stage model. However, it has been shown that in general, a power sector resource-planning model formulated as a multi-stage stochastic programming model is equivalent to a two-stage stochastic programming model [123]. Taking advantage of this result drastically reduces the computational burden of solving stochastic resource-planning models because a large-scale, multi-stage stochastic model is computationally prohibitive to solve.

Two-stage stochastic programming techniques have been used in co-optimization models, as documented in [90,142]. While this approach provides better decision-support than scenario-based approaches, it faces two major challenges. First, even though two-stage stochastic problems are computationally simpler than multi-stage problems, and have been extensively studied over several decades, they remain computationally intensive for large-scale problems coupled with a large number of scenarios. [11] To overcome computational difficulties, sophisticated algorithms have been developed, including scenario reduction methods [29], decomposition-based approaches [112], and stochastic sampling [67]. Some algorithms have been developed into commercial-grade solvers and are linked to a modeling interface package,

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[11] For example, consider a two-stage stochastic resource-planning model with the second-stage problem being the economic dispatch problem. Assume that without considering uncertainty, the dispatch problem has 1,000 variables (such as dispatching from 1,000 generation units). Further assume that there are only two sources of uncertainty, demand and wind output, each with 10 possible realizations. Then there are combined 10 x 10 = 100 scenarios, and the total number of second-stage variables will be 1,000 x 100 = 100,000. In this example we only consider the demand and wind output at a single location. When a transmission network is considered, the number of scenarios (and hence the number of second-stage variables) can quickly become too large for even the most advanced computers to solve the resulting two-stage problem directly.

such as GAMS, AIMMS, or AMPL. Through the interface package, users can provide input data (including the scenarios generated by Monte Carlos simulation or other uncertainty modeling methods), and the interface converts the inputs into a mathematical programming problem. Despite the continuing development in modeling systems and solvers, the sizes of stochastic programming problems that can be solved are unsatisfactory relative the sizes that result from considering a realistic (say, several dozen) number of scenarios for a large region over multiple decision stages. In addition, users of stochastic programming modelers need to be more sophisticated than users of deterministic models. As a result, there are relatively few real-world resource planning models that utilize stochastic programming. However, as software and computational capabilities improve, we anticipate that this will change.

The second challenge associated with a stochastic programming approach is that it may yield overly conservative solutions. As discussed above, in the context of resource planning, to ensure feasibility of second-stage constraints (such as supply-demand balancing constraints in an economic dispatch problem) under all scenarios, redundant capacities of generation and transmission assets may need to be built. However, certain extreme scenarios, such as extreme weather conditions coupled with the forced outage of several large generation units, might only occur with extremely small probabilities. The added investment costs to maintain system reliability under such rare events may not be justifiable.

There are several approaches to deal with such issues. One is to make sure that the probabilities of such extreme events are not overstated; smaller probabilities effectively discount the cost of extreme cases. However, this can be dangerous, because it is well known from the behavioral decision making literature that decision makers tend to underestimate the probability of extreme events.

Another approach is to relax some constraints to the point that they are only required to be satisfied with a given probability. Such constraints are called chance constraints. An example would be instead of requiring that the supply and demand of electricity are balanced under all scenarios, the constraint may be relaxed so that supply has a 99% probability of equaling or exceeding load, allowing for a 1% possibility of unserved energy. Such small relaxations may significantly reduce overall investment costs since it is often the peak demand that requires large incremental capital investments. While chance constraints are intuitively easy to understand, and can be integrated with system reliability rules (such as the one-day-in-ten-years resource adequacy rule), they nonetheless pose significant mathematical challenges. This is so because not all random variables have explicit mathematical expressions of their probability distributions. Even if explicit probability distribution functions exist, the resulting stochastic programming problem often does not possess the required mathematical properties (convexity, in mathematical terms) to be easily solved. To overcome the computational difficulty, recently stochastic resource-planning models using the concept of Conditional-Value-at-Risk (CVaR) have been proposed [150].

CVaR was originally developed in the finance literature as a measure of risk. In the context of power sector planning, it can be interpreted as the expected value of loss given that a contingency event occurs. For instance, considering just the 1% worst outcomes, their expected loss might be $1,000,000. The loss may be measured in monetary value (such as value of lost load) or in terms of energy units (such as unserved energy). Then a chance constraint in a stochastic programming model can be replaced by a constraint requiring the CVaR to be less than a pre-specified value (referred to as the risk tolerance level). The benefit of such reformulation can be traced to the seminal work by Rockafellar and Uryasev [109], where they show that the CVaR constraint can be equivalently replaced by a set of linear constraints. As a result, a stochastic resource-planning model with CVaR constraints should be applicable to much larger-scale planning models than the chance-constrained formulation. At the same time, the CVaR formulation gives the modeler flexibility to adjust the trade-off between investment costs and system reliability by changing the specified risk tolerance level (similar to adjusting the probability requirement in a chance constraint). The application of such a modeling and computational framework to real-world-sized co-optimization problems is an active area of research.

5.2.3 Robust optimization

In addition to the above-mentioned challenges faced by stochastic programming, that framework may have further limitations from a decision-making perspective. Since that method mainly focuses on optimizing the expected value (i.e., the probability-weighted average) of the objective function (such as minimizing the expected investment cost over a certain period), it ignores the effect of decision-maker's attitude towards taking risks. Stakeholders and managers may be very averse to large negative outcomes, implicitly giving them more weight than they would in a expected value calculation. For example, the probability distribution of lost load or financial costs associated with catastrophic events, such as hurricanes, earthquakes, terrorist attacks, is usually very asymmetric (compared to a symmetric, bell-shaped distribution curve), reflecting the fact that such events are possible even if they happen with very low probability.[12] In the resource-planning context, decision-makers may want to limit the damages in a catastrophic event, as well as lowering the average investment cost over all possible future scenarios. This leads to a multi-objective optimization problem, and its objective function can be written as follows.

Minimize (over a finite period of time)

w_1 × Expected value of cost + w_2 × Deviation from the expected value (e.g., variance) + w_3 × penalty of infeasibility under all scenarios

[12] Such probability distributions are referred to as fat-tailed distributions.

The w_i's (i = 1, 2, 3) represent the weights that a decision maker puts on the three quantities that he or she wishes to minimize – the expected cost, the variance from the expected value and the infeasibility that may occur under certain scenarios. The last item in the objective function is to accommodate situations where ensuring that the system remains feasible is either impossible or prohibitively expensive. For example, guaranteeing that an electrical grid is able to serve all customers even under the extreme events such as Hurricane Katrina or Sandy is simply unachievable. Hence, we can relax the problem and allow infeasibility to happen under some scenarios, but will assign a penalty factor (w_3) to infeasibility in such cases.

This is sometimes called robust optimization (RO), and has been implemented for the resource planning in the electricity sector [84]. (RO is a term also applied to a related method, described below, which can lead to confusion.) While the solutions of the RO approach may be shown to be more robust[13] than the scenario-based analysis or the stochastic programming approach, there are limitations with such an approach as well. First and foremost is the selection of the weights on the different objectives, which can be somewhat arbitrary. Different weights may produce drastically different solutions, and it may be difficult for the decision-maker to justify one particular set of weights over another. As a remedy, the RO approach may be used to plot the trade-off curves between costs and reliability of a system (as measured by the total infeasibility of the system) by gradually shifting the weight from cost to reliability. While this approach may not provide specific strategies for a decision maker to execute, it can provide insights on the best level of reliability that the system could achieve with a certain level of system cost.

The second limitation of the RO approach is that with the added terms in the objective function, the variance term and the infeasibility measurement, the resulting function is in general not linear (or not even convex, which is a key property for efficient computing of solutions). As a result, the RO approach faces significant computational challenges with real-world-sized problems.

There are recent developments in the general area of robust optimization that focus on optimization under uncertainties with only the ranges of the uncertainties (as opposed to their probability distributions) specified. We refer to these developments as the general RO approach (as opposed to the more specific RO approach described above), and it can find a set of solutions that will remain optimal as long as the realizations of uncertainties fall within the specified range. No probabilities need to be specified for scenarios within the range, which is seen by some users as an advantage. This approach has been applied to short-term unit commitment in power system operations [63]. This approach is attractive from the decision-maker's perspective, as it can provide a solution that performs well under all scenarios, even in the worst cases (given that the correct bounds on uncertain parameters are given, which are often arbitrary but easier for

[13] Robustness here means that a solution is near optimal regardless the actual realizations of the uncertainties. Stochastic programming minimizes expected cost over all the scenarios, but the solution may still perform poorly under some low probability scenarios. RO can sometimes avoid that outcome.

decision makers than specifying probability distributions). However, the robustness of the solutions usually comes with the added cost of maintaining additional capacity redundancy in the system. In addition, the general RO approach is computationally intensive as well and is not amenable for large-scale computation.

5.2.4 Dynamic programming

Dynamic programming (DP) is a mathematical tool to aid sequential decision-making over multiple time periods. It attempts to break a complex, multi-stage decision-making problem into a sequential of simpler problems, and solve them step-by-step, moving backwards from the last time period to the beginning. This process (known as the backward induction approach) in theory ensures optimality of the solutions over all stages. DP models have state variables to represent the current status of a system, such as the current demand level, weather conditions, capacity mix and level, the current unit commitment status, or the energy stored in a storage resource.

Uncertainties can be readily incorporated into a DP model through the transitioning of state variables. For example, the transition of the current system's demand level to the next decision stage (e.g., next hour, next day, next year, etc.) may follow a probability distribution. Such models are referred to as stochastic dynamic programming.

Although DP is a classic decision-making tool, it is usually best suited for the situations with only a few decision choices to make and a few sources of uncertainties, but with many time steps. The computational burden of the backward induction method for solving a DP increases exponentially with more decision variables and states variables being added. As a result, the DP framework in general is not suitable for long-term resource-planning problems, as such problems typically have a large number of decision variables and multiple sources of uncertainties.

Nonetheless, recent developments in designing approximation-based algorithms to solve DP problems (termed as Approximate Dynamic Programming, or ADP) have significantly expanded the problem sizes that the original DP framework can handle, and such approaches have been applied to power systems' resource planning [145, 105]. While the ADP approach is designed to incorporate multiple sources of uncertainties and is amenable to large-scale computation, the transmission networks in those papers are still represented as transshipment ("pipe-and-bubble") networks, and the modeled power plants are highly aggregated (by types and locations). Whether this approach could be applied to co-optimization with the needed level of disaggregation and detailed modeling on both transmission networks and power plants is currently under active research.

5.3 Co-optimization under Uncertainties – A Case Study using GENTEP

In this section, we provide a case study to compare the modeling results without and with explicit consideration of uncertainties, in this case outages of generation and transmission equipment. GENTEP, which is described elsewhere in this report, is used for the long-term co-optimization of generation and transmission planning by explicitly addressing demand growth uncertainties and random outages of generating units and transmission lines. The resource-planning problem considers multiple decades and numerous variables, and so requires a proper reduction in the number of scenarios in order to keep the problem manageable. Monte Carlo simulation and an approach called scenario reduction are applied to represent the uncertainties in long-term resource planning.[14] The range of energy and perhaps capacity price signals calculated in the various scenarios reflect the modeling of uncertainties and provide investment signals for planning decisions. The GENTEP iterative scheme between the ISO and participants may not converge in every case. Accordingly, the user may stop the coordination process and make a final decision based on pre-specified rules or judgment.

5.3.1 GENTEP Planning Algorithm

This section presents details on the algorithm used by GENTEP to solve the planning problem. Unless the reader is interested in these details, she or he can skip to the next subsection where the case study and results are described.

The GENTEP planning process is decomposed into three problems as shown in Figure 5-5 including the planning problem of GENCOs and TRANSCOs, the ISO's transmission reliability check problem, and the ISO's optimal operation problem. The capacity signal loop provides capacity signals to participants and the price signal loop provides price signals based on the market clearing process. The proposed formulation also considers uncertainties in the ISO's reliability check problem and optimal operation problem.

The solution steps according to Figure 5-5 for the proposed planning problem are given as follows:

Step 1: Monte Carlo simulation generates a set of scenarios assuming uncertainties of generation units, transmission lines and future load growth. Scenarios are assumed to have equal probabilities, and here are sampled from a set of independent and identically distributed random variables. Alternatively, users can enter specific probabilities for the given scenarios. Then scenario reduction is executed. It is assumed that the outage characteristics and capacity of all candidate units and lines are identified by the ISO.

Step 2: Individual GENCOs' generation resource planning problems and TRANSCOs' merchant transmission resource planning problem are solved based on initially forecasted LMPs and FMPs. LMP is the shadow price or Lagrangian multiplier associated with delivering a marginal unit of energy at a bus. FMP is the shadow price associated with a flowgate. FMP is equivalent

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[14] Scenario reduction involves generating many scenarios (e.g., load growth over the next 20 years), and then selecting a small subset that preserve the range of variation of the original set of scenarios so that the resulting solution is not appreciably distorted by omitting most of the scenarios [129].

to the change in the social benefit or social cost of transactions settled through the spot market when the transmission constraint is relaxed by an increment. Each GENCO and TRANSCO maximizes its profit according to the expected LMPs and FMPs.

Step 3: Benders Loop – The Benders master problem is represented by profit maximization problems for GENCOs and TRANSCOs. The ISO's reliability check problem is the Benders subproblem. The ISO calculates the nodal power balance mismatch at each scenario. Then, the expected nodal power balance mismatch is calculated and compared with the given reliability criterion. Once a reliability constraint violation is detected, a corresponding Benders cut is generated. The Lagrangian relaxation will relax complicated and linking constraints into the objective function of planning problem and obtain locational capacity signals.

Step 4: Capacity Signal (LR) Loop – A method called Lagrangian relaxation is applied to relax Benders cuts (coupling constraints) when solving the individual planning problem. Depending on the proposed Benders cuts, the Lagrangian multipliers are updated and capacity signals are formed by the ISO and fed back to individual GENCOs and TRANSCOs. Capacity signals provide incentives for generation and transmission capacity expansion. Among iterative planning solutions, the one with the minimum capacity signal is selected by the ISO as the best solution. The resource planning problem will be declared infeasible if no feasible solution is found.

Step 5: Price Signal Loop– The ISO solves the optimal operation problem and calculates LMPs and FMPs for each scenarios deterministically. The optimal operation is a linear programming problem with the objective of maximizing the social surplus. After completing the calculation of LMPs and FMPs for every scenario, the average or expected LMPs and FMPs are calculated and fed back to GENCOs and TRANSCOs iteratively until the convergence criterion is met. The ISO would compensate GENCOs and TRANSCOs based on capacity signals for maintaining the system reliability. GENCOs obtain their revenues from capacity and energy payments and TRANSCOs obtain their revenues from capacity and flowgate payments. The energy payments for GENCOs are simulated by LMPs, which are calculated by the ISO and introduced into GENCOs' capacity investment decisions. The FMP is also calculated and provided by the ISO to facilitate TRANSCOs' capacity investment decisions.

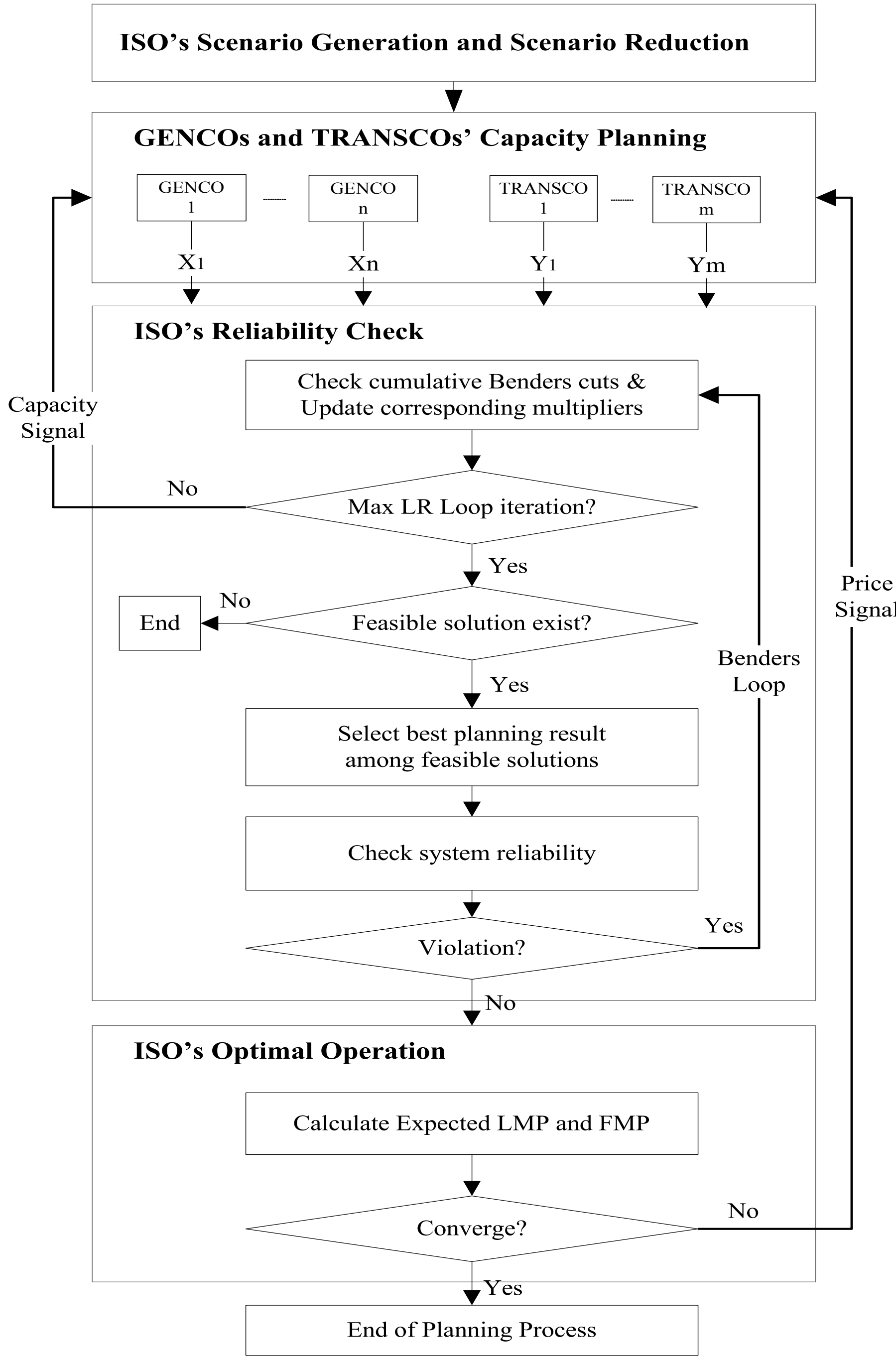

Figure 5-5. GENTEP for the Stochastic Co-Optimization of Generation and Transmission Planning

5.3.3 Case Studies

Here we examine how explicit consideration of random load growth as well as forced outages of generation and transmission equipment can affect the solutions of a co-optimization model. We compare deterministic solutions (no outages) with stochastic ones in which we assume that outages of different components of the system are statistically independent with each occurring with a stated probability ("forced outage rate").

A six-bus system shown in Figure 5-6 is used to analyze the effectiveness of the GENTEP model for solving the stochastic planning problem. The six-bus case study is applied to a 10-year planning horizon to show the effectiveness of the proposed model. The load forecasts over the planning horizon, generators data, and transmission lines data and are shown in Tables 5-2 – 5-6. Although the forced outage rates are small (at most, a handful of percent) as is the random component of load growth, our calculations show that they are large enough to affect the optimal plans.

The tables show that GENCO A has three existing units and five candidate units, and GENCO B has one existing units and eight candidate units. Candidate generating units differ in locations, operation costs, investment costs and forced outage rates. Hence, these factors would be anticipated to affect the planning decisions concerning where and when to install new capacity. There are seven candidate transmission lines listed in Table 5-6. The loads are located at buses 3, 4 and 5. The average peak load and energy demand growth rate is 5% per year. The random component in peak load and energy demand growth rate has a normal distribution with zero mean and 0.01 standard deviation. Generating units submit their cost of operation as bids and the flowgate bid is the levelized investment cost with a 10% capacity factor. The discount rate is 5%, which is used in the calculation of net present value and capacity payment for new generating units and transmission lines. The stopping criterion for the iterative procedure (called ε) is 5%. A planning year is divided into 4 load blocks by grouping similar loads. The target unserved energy (LOEP) is 5% for all load blocks.

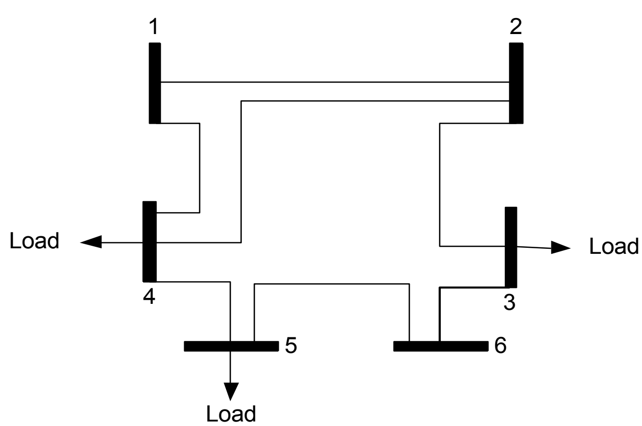

Figure 5-6. One-line diagram of six-bus system

Table 5-2. Yearly peak load and energy demand

Year	**1**	**2**	**3**	**4**	**5**
Peak Load (MW)	25.00	26.25	27.56	28.94	30.39
Energy(GWh)	179.8	188.7	198.2	208.1	218.5
Year	**6**	**7**	**8**	**9**	**10**
Peak Load (MW)	31.91	33.50	35.18	36.94	38.78
Energy(GWh)	229.4	240.9	252.9	265.6	278.9

Table 5-3. Load distribution by bus

Bus	**1**	**2**	**3**	**4**	**5**	**6**
Distribution	0.0	0.0	0.4	0.3	0.3	0.0

Table 5-4. Load blocks in base year

Subperiod	**1**	**2**	**3**	**4**
Duration (%)	1	29	50	20
Load (MW)	25	23	20	18

Table 5-5. Generation unit data

Unit	**Bus**	**Capacity (MW)**	**Forced Outage Rate (FOR) (%)**	**Operating cost ($/MWh)**	**Investment Cost ($/kW/year)**
AE1	2	10	3	25	Existing unit
AE2	3	5	3	35	Existing unit
AE3	6	5	3	37	Existing unit
A1	1	10	3	22	100
A2	1	7	3	30	80
A3	2	5	5	35	60
A4	2	3	3	40	30
A5	4	3	5	40	40
BE1	1	10	3	25	Existing unit
B1	3	3	2	40	45
B2	3	2	1	55	20
B3	5	5	5	35	70
B4	5	3	3	40	35
B5	6	10	3	22	110
B6	6	8	3	29	85
B7	6	5	5	35	50
B8	6	2	1	55	15

Table 5-6. Transmission line data

Line	From	To	Capacity (MW)	Forced Outage Rate (FOR) (%)	X (p.u)	Investment Cost ($/kW/year)
TE1	1	2	10	0.1	0.170	Existing line
TE2	2	3	7	1.0	0.037	Existing line
TE3	1	4	7	1.0	0.258	Existing line
TE4	2	4	7	1.0	0.197	Existing line
TE5	4	5	7	1.0	0.037	Existing line
TE6	5	6	7	1.0	0.140	Existing line
TE7	3	6	7	1.0	0.018	Existing line
T1	1	2	10	0.5	0.170	5
T2	2	3	7	0.5	0.037	8
T3	1	4	7	0.5	0.258	12
T4	2	4	7	0.5	0.197	10
T5	4	5	7	0.5	0.037	7
T6	5	6	7	0.5	0.140	5
T7	3	6	7	0.5	0.018	6

We consider four test cases that are categorized into two deterministic cases (Cases 1 and 3) and stochastic cases (Cases 2 and 4). In Cases 1 and 2, generation only planning is considered, so no new lines are allowed. Cases 3 and 4 deal with the coordinated transmission and generation planning (co-optimization).

Tables 5-7 and 5-8 show the installation year of candidate generating units and transmission lines respectively. First, we consider the generation-only models. In Case 1 (the deterministic gen-only case), B2 and B8 with small capacity and low investment costs are installed in earlier years and the 3 MW units, A5, B1, and B4, are installed in later years. The installation of low investment units could minimize the social cost. When uncertainties are considered in Case 2, the increase in system capacity resulting from a change in the installation schedule will make it possible to cope with possible outages, i.e., to satisfy the reliability target. As expected in Case 2, generating units B2 and B8 are installed earlier compared to Case 1. Also in Case 2, unit B7, which has a larger capacity than A5 and has the cheapest investment cost among 5 MW candidate units, replaces A5 in year 10.

Turning to the co-optimization cases, in Case 3 (deterministic co-optimization), transmission lines T2 and T6 are installed to relieve the load balance mismatch in year 6. Accordingly, fewer generating units are installed in Case 3 as compared with Case 1 (gen-only). Also the installation of A5 and B1 is cancelled. Unit A4, which is located far from load, is installed in year 10 when the transmission line expansion is considered.

In the stochastic co-optimization model (Case 4), small and low investment cost units B2 and B8 are installed in year 1 to prevent possible supply shortages caused by the random outages of units and lines. A5 is added in Case 4 when compared with Case 3. In Case 4, the added generation capacity is smaller than that of Case 2 when T2 is installed in year 8. Table 5-9 shows that a considerable savings in social cost is achieved by the coordinated planning. The social costs in the deterministic cases (Cases 1 and 3, where there is no load growth uncertainty or forced outages) are lower than those of Cases 2 and 4 (with load growth and outages). Comparing the social costs of cases with and without uncertainties, we learn that social costs increase when additional generating units and transmission lines are installed to cope with uncertainty.

Table 5-7. Candidate Generation Unit Installation Year

Case	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	B6	B7	B8
Case 1 (Deterministic, Generation Only)	0	0	0	0	10	9	6	0	7	0	0	0	4
Case 2 (Stochastic, Generation Only)	0	0	0	0	0	9	1	0	8	0	0	10	1
Case 3 (Deterministic, Co-optimization)	0	0	0	10	0	0	7	0	8	0	0	0	4
Case 4 (Stochastic, Co-optimization)	0	0	0	10	9	0	1	0	8	0	0	0	1

Table 5-8. Candidate Line Installation Year (Co-optimization Cases Only)

Case	T1	T2	T3	T4	T5	T6	T7
Case 3	0	6	0	0	0	6	0
Case 4	0	8	0	0	0	0	0

Table 5-9. Social Costs in the 6-Bus System (Million$)

	Case 1	Case 2	Case 3	Case 4
Social Cost	51.67	51.75	50.83	51.45

But this is not to say that deterministic planning is better. If we naively planned for certainty and implemented the deterministic plans, but in fact had outages and uncertain load growth, the costs of Cases 1 and 3 would instead be higher than 2 and 4. That is, we would pay a penalty for naïve decision making, and a stochastic approach would result in lower expected costs. This penalty, which has been demonstrated in other generation and transmission planning problems [57,142], is sometimes called the "value of the stochastic solution" or the "cost of ignoring uncertainty."

This stochastic market-based approach could provide signals to investors on the location of new generation and transmission facilities and help system planners, regulators, and local authorities concur on transmission planning. Numerical results illustrate the ability of the GENTEP model to account for uncertainty and to coordinate generation and transmission investment. The results above show the effects of system component outages and demand uncertainties on the co-optimization of generation and transmission capacity expansion schedules and social costs. The merit of the stochastic approach is that it can provide more realistic and reliable energy and capacity price signals to participants on the long-term capacity expansion.

6 INSTITUTIONAL ISSUES

This section addresses several groups of institutional issues, including confidentiality (Section 6.1), the pros and cons of having co-optimization models in the public domain (Section 6.2), and potential roles of the states (Section 6.3).

6.1 Confidentiality Concerns

The electric power system for generating, transferring and delivering electricity is considered a critical infrastructure, as it is vital for supporting the economy's normal operation and people's common life. Generally speaking, any information that could potentially make the infrastructure vulnerable is deemed confidential from national security's perspective. The development of co-optimization models, while aimed at improving the efficiency of power system planning, should not jeopardize the energy system's security by inadvertently releasing confidential information. On the other hand, the success of any model development shall not hinge upon the availability of confidential information. This section discusses the existence of confidentiality concerns regarding all aspects of co-optimization models, including model formulae, modeling assumptions, data and model outputs.

For what is considered as confidential information in the power sector, North American Electric Reliability Corporation (NERC) has a clear set of definitions as follows [98]:

> "*Confidential Information means (i) Confidential Business and Market Information; (ii) Critical Energy Infrastructure Information; (iii) personnel information that identifies or could be used to identify a specific individual, or reveals personnel, financial, medical, or other personal information; (iv) work papers, including any records produced for or created in the course of an evaluation or audit; (v) investigative files, including any records produced for or created in the course of an investigation; or (vi) Cyber Security Incident Information; provided, that public information developed or acquired by an entity shall be excluded from this definition.*"

Based on the above definitions, formulae and assumptions of a co-optimization model are not likely to be considered confidential. Such information is indeed widely available in the public domain (see, for example, the documentation for NREL's ReEDS model [124], PIK's LIMES model [45], UC Berkeley's SWITCH model [34]). The outputs of co-optimization models, as long as they do not reveal the system's vulnerability to the unavailability of certain assets (such as a power plant or a transmission line), should not be considered as confidential either. The results of all the co-optimization models surveyed in Section 2.3.2 and Appendix II are publicly available (see the corresponding citations therein).

Instead, the potential concerns for confidentiality lie in the data required for developing and running co-optimization models. Before discussing such concerns, it is important to distinguish between proprietary and confidential information. Proprietary information refers to the information that is exclusively owned by its owner. Such information may or may not be confidential in terms of critical infrastructure security. For example, fuel costs projected by data vendors, based on their data collection and in-house forecast, are proprietary. However, they are not confidential based on NERC's definition. Based on the data summary provided in Section 3.3 (Table 3-3), detailed transmission network data are considered as Critical Energy Infrastructure Information (CEII). Power plant availability data, as available through NERC's GADS database, are also treated as confidential.

Confidential data are not unobtainable, as long as the receiving parties are qualified for obtaining the data and agree to certain confidentiality agreements. For example, transmission network information can be obtained for FERC through filling out the CEII Request Form. Hence, the development of co-optimization models should not been hindered by requiring confidential data. However, such data cannot be made available in the public domain, raising potential difficulties for the public to assess the validity and quality of the model outputs. Such issues are discussed in the following subsection.

6.2 The Pros and Cons of Having Co-Optimization Models in the Public Domain

The potential benefits of having the co-optimization models in the public domain include, but are not limited to the following:

- increased transparency in resource planning,
- broader involvement by non-industry stakeholders,
- assisting investors to make more economically sound decisions,
- assisting policy makers to design the best public policies,
- receipt of feedback from model users to support improvement of the models, and
- contributing to informed discussions and debates among model builders and users.

However, in addition to the apparent concern of confidentiality, which is addressed above, there are other disadvantages of having the co-optimization models in the public domain. Disputes concerning modeling inputs and assumptions would almost surely arise; this would ideally lead to healthy debate and more transparency, but it could also slow down decision processes and obscure—rather than illuminate—the important issues [64]. Misuse of models by third parties could also erode confidence in using such models for decision-making (for examples, see [91]). In the following, we will provide a detailed assessment of the advantages and disadvantages to have the co-optimization models in the public domain based on discussions with practitioners and studies of different models.

In order to better understand the viewpoints and thoughts of academicians and practitioners/Planning Coordinators towards having co-optimization models in the public domain, we have held informal discussions with experts in both academia and power industry, including coordinators in several utilities and system operators in the Eastern Interconnection. Based on these discussions, we have obtained some understanding of the viewpoints of the practitioners and the gap between academic modeling and real practice. Pros and cons are largely dependent on the standpoint of the viewer. What is viewed as a "pro" by academicians might be a "con" for some Planning Coordinators. Below, we review the pros and cons based on the standpoints of a number observers, including academicians, independent systems operators, generation companies, transmission companies, and public policy makers.

6.2.1 Discussion and assessment of pros of having co-optimization models in public domain

The first benefit of having co-optimization models in public domain is that it will increase transparency for resource planning from the public side. This is almost unanimously viewed as am advantage. When the co-optimization models are from governmental agencies or public policy makers, it is very clear that academicians, Planning Coordinators and stakeholders can benefit by understanding what and how the government or policy-makers conduct their resource planning studies. In addition, people will know the intents and assumptions of the studies. This is especially important to Planning Coordinators and market participants such as ISOs/RTOs, generation companies, transmission companies, and distribution companies.

When the co-optimization models are from academicians, the policy makers and Planning Coordinators can know what kind of state-of-the-art modeling tools, techniques and computational methods are used, and can assess how they might benefit policy making and industry planning. Finally, when co-optimization models are from practitioners such as ISO/RTO, generation companies, and transmission companies, public information can give the policy makers and academicians better understanding of the industry's assumptions, concerns and objectives. This could lead to healthy collaboration among different companies, which would, for instance, support the goals of FERC Order 1000.

Public information and public domain models will certainly lead to broader involvement by non-industry stakeholders. By non-industry stakeholders, we mainly refer to consumers (the demand/load side), environmental groups, and governmental entities (e.g., both state and federal governments). Models and results from the policy makers and power industry practitioners will certainly interest the consumer groups, who take a keen interest in industry costs and often take part in regulatory proceedings on cost recovery. Having co-optimization models in the public domain creates an environment that can foster healthy discussion between power industry stakeholders and non-industry stakeholders. However, in the short run, better informed consumer groups may delay important capacity expansion by the power industry, since the goals of non-industry stakeholders might not be aligned with the long-term goals of the co-optimization process. For governmental entities, having access to co-optimization models used in power industry will enable them to understand the industry more, and improved understanding can (but do not necessarily) lead to better policies that are good for the long-run future of the industry and society.

Having co-optimization models in the public domain will also help investors to make more financially sound decisions. For example, models and results published by policy makers or their consultants are likely to contain many details on policy and its impact on the power industry. To practitioners or the investor, these are very important to make decisions that take due account of public policies. For instance, many models assume renewable energy (due to increasingly stringent environmental regulations or policies) will grow rapidly. Investors clearly received this message and hence investments have been much heavier in these areas than those related to traditional energy resources such as coal.

Models and results from Planning Coordinators carry information about the status of the market and anticipated trends. However, this information may appear more authoritative than it should, if based on expert judgment and not hedged by appropriate acknowledgement of uncertainties. This could deliver misleading messages to the market, the implications of which we will discuss in the next subsection. In addition to help investors make better decisions, publicly available co-optimization models and their data could also improve regulatory decisions, such as certificates of convenience and necessity, and assist researchers. Models and results from academicians can, in theory, assist planning, regulatory, and public policy processes by giving groups access to state of the art modeling tools. However, "research grade" tools are particularly difficult for non-specialists to master.

Model builders in turn will receive feedback from model users which will support improvement of their models. Model users feedback generally will include concerns, suggestions and questions regarding input data, assumptions, modeling techniques, mathematical formulations, computational methods, and results. For example, model users might suggest relaxation of some restrictive assumptions, or more realistic representations of certain aspects of power systems. For instance, some models only take into account static and deterministic information, and then the model's developers are likely to be asked to make the model dynamic and stochastic. Models with simplified and aggregated input data will certainly receive comments expressing concerns over the model simplification. Feedback received by model builders could make models more realistic and robust, and their solutions more decision-relevant and understandable.

The feedback given to developers of public domain models can help create healthy debate among users and builders. Input data, model assumptions and considerations will be in the center of the debates because these are key factors that will drive the results. Such discussions could lead to enhancing co-optimization models by including more appropriate features and better data. For example, it was such debates that lead to the use of mixed integer programming in power systems' unit commitment and the abandonment of the previously popular Lagrangian relaxation method [55]. These MIP models are estimated to save hundreds of millions of dollars in dispatch costs [99]. We believe that similar debates will likely lead to healthy improvements in the co-optimization models and help improve the efficiency of transmission infrastructure planning. Interaction between the model builders and users could be enhanced by using the sort of web appliances that are used, for example, by evacuation planning researchers to broaden impacts [25, 89]. In these web appliances, the user can upload their own data and see the results. But this might lead to confidentiality issues that are discussed in Section 6.1, and briefly in the next section.

6.2.2 Discussion and assessment of cons of having co-optimization models in public domain

As just discussed, there are many potential benefits to having co-optimization models in the public domain. However, public domain models would also have disadvantages, which we detail in this subsection.

Confidentiality is the first concern with public domain models. During our discussions with practitioners, especially transmission coordinators, this was a highly salient concern because reliability and security is their first priority. To most power industry practitioners, the data inputs are under non-disclosure protection. In order to access power system infrastructure data, a FERC Critical Energy Infrastructure Information (CEII) agreement needs to be signed. Showing the mathematical models and their corresponding results poses less of a concern to industry practitioners. These confidentiality issues are explained in more detail in Section 6.1. We now turn to issues other than confidentiality.

While debate could be able to help improve co-optimization models, it could also potentially delay the decision process and obscure important issues. The history of integrated resource planning (IRP), which in some jurisdictions like California fell into disfavor because of protracted "battle of the models" in adversarial regulatory proceedings, is cautionary in this regard [64]. When transmission investments are needed to maintain reliability or to interconnect new renewable facilities, delays could pose a big problem. Arguments concerning model assumptions could be difficult to resolve quickly since different players in the power market could have different concerns, interests, and understandings of the future. For example, traditional generation companies may be disinclined to go "the extra mile" on environmental protection or renewable investments; they might, for instance, discount the possibility of significant federal greenhouse gas legislation. However, environmental groups might favor the opposite assumption.

Whether such disputes are more or less likely to happen in deregulated markets is unclear. It might be argued that such disagreements would be more likely to happen in a restructured market such as the PJM market because decision making is diffuse, with no single utility or regulator in charge. However, precisely because vertically integrated utility systems are highly regulated, contention among opposing interests could stretch out regulatory proceedings—again, the lessons of the IRP era are relevant.

Co-optimization models usually involve many types of decision variables and constraints, which make them complicated and difficult for stakeholders and even users to understand. For this reason, misinterpretation and misuse is a danger, and results could be misleading or essentially wrong. Their implementation could hurt the public and the industry. If models are shown to misunderstood and misapplied, public and regulatory confidence in co-optimization modeling could be sabotaged. In order to prevent this from happening, it would be best to provide transparent, comprehensive, and accessible documentation of models and assumptions. Customer and user assistance is essential. Incorrect or inappropriate data inputs should be avoided, and transparency can help internal and external parties uncover errors.

Murphy and Shaw [91] have shown how energy modeling in the federal government has been evolving since the 1970s and interacting with politics, public policies, and opinions. The reactions toward federal models and results ranged "from extreme gratitude to rage." The electrical power system has always been a critical portion of the national energy system and economy. With environmental concerns, renewable energy mandates, and increasing electrification of the economy, the role of electricity in the economy can only increase, as will the scrutiny it will get from policy makers, investors, and the public. This scrutiny may slow down planning for transmission infrastructure, or it may increase pressures for concrete results. Public disclosure of information and public domain software may be intentionally misused for political reasons, unintentionally misused out of misunderstanding, or (hopefully) support more informed public debates and ultimately better decisions. As indicated in [91], models have sometimes served to cloud issues but have frequently provided important insights that have significantly affected policy outcomes in positive ways.

6.3 Potential Roles of the States

Strong cooperation between Planning Coordinators and the corresponding states is critical. In its National Transmission Grid Study [134], the DOE concluded that regional transmission constraints increase electricity costs and decrease electric system reliability to consumers in many states. The study concluded that regional planning processes must consider co-optimization of regional transmission and local non-transmission alternatives when trying to eliminate system bottlenecks. A regional co-optimization planning process that involves the states would be essential because most transmission investments are recovered under regulated cost-of-service rates, and because these investments often have local environmental and economic impacts. The DOE study identifies a number of policies that could promote investments in new transmission facilities, but also notes that local generation and demand-side options at the state level can play an equally important role in delaying or avoiding the need for those investments. State-level options such as enabling local customers to reduce load on the transmission system through voluntary load reduction, targeted energy efficiency, and reliance on distributed generation are important but presently underutilized approaches that could do much to address regional transmission bottlenecks today and delay the need for new transmission facilities.

Often, transmission planning is viewed mainly as a technical activity and is not necessarily structured to reflect state policies and priorities in resource deployment. A robust co-optimization planning, reflecting the interests of states and the region, could address regional transmission congestion relief and long-term resource adequacy. On the other hand, state and local interests could also block transmission reinforcements that increase energy trade and national economic activity, which is part of the motivation for FERC Order 1000. Formal co-optimization could help make state and local involvement constructive and contribute to more reliable and economic power systems. Such a planning process should involve the following elements:

- It should provide a formal role for state governments, and thus ensure more active participation by state official, including utility regulators, energy offices, consumer advocates, and environmental regulators, as appropriate to each state; and
- It should actively involve consumer, environmental, and other stakeholder interests in the planning process, in addition to traditional market players.

A well-designed co-optimization planning process for generation and transmission can identify the needs of state governments and Planning Coordinators, balance competing public interests (e.g., cost, reliability, environmental impact), and help allocate scarce resources more efficiently among potential investment choices. The participation of the region's state governments in regional transmission planning could accomplish the following:

- Avoid duplication of effort;
- Add efficiency to regulatory decision-making and certainty to the marketplace; and
- Enhance the ability of state PUCs to conduct independent reviews of siting proposals within their jurisdiction, while appropriately accounting for regional economic benefits of transmission construction.

Appendices

Appendix I. Mathematical Model Statements

A.I.1 Generation Planning Model

The mathematical statement of the generation planning model from Section 2.2.1 is as follows:

Minimize Present Worth Total Cost =

$$\sum_y \sum_j \frac{InvestmentCost_{jy} + \sum_t OperatingCost_{jyt}}{(1+i)^y}$$

subject to $\sum_j EnergyProduction_{jyt} = Demand_{yt}$ for all time periods t and years y,

$EnergyProduction_{jyt} \leq Capacity_{jy}$ for all generation technologies $\_j$, periods t, years y,

$LossOfLoadProbability_y \leq LOLPR$ for all years y,

where i is the interest rate, and $LOLPR$ is the Loss of Load Probability requirement or threshold, and $\sum_k(\cdot)$ reads as "sum over all values of index k."

A.I.2 AC Optimal Power Flow based Generation-Transmission Expansion Planning Model

Full ACOPF-GTEP model

This appendix gives a detailed description of the typical ACOPF based multi-period Generation-Transmission Expansion Problem (ACOPF-GTEP), which is a minimization problem defined by the following equations (1) – (12). The objective function is the total operation and investment cost. The objective function may also include a transmission loss component. There can be several versions of such co-optimization formulations which may include minimization of network losses, emission, maintenance costs and so on. Constraints (2) – (3) model the nodal real and reactive power balance, which are subject to integer transmission expansion variables of candidate corridors. Constraints (4) – (5) model non-linear AC power flow relations across line ij. Constraints (6) – (8) model the network security limits for voltage magnitude, voltage angle and apparent line power flow. Constraints (9) – (10) model the generation power bounds, which are subject to the generation expansion variable. Constraints (11) and (12) model the investment bounds on the number of transmission lines and generation size respectively, in a time period.

Minimize $$T_t \sum_t \sum_{(i,j)} C_i(t)\, P_{gi}(t) + \sum_t \sum_i I_i(t)\, PI_{gi}(t) + \sum_t \sum_{(i,j)} I_{(i,j)}(t)\, z_{(i,j)}(t) \quad (1)$$

subject to

$$P_{gi}(t) - P_{di}(t) = P_{(i,j)}(V,\theta,t)\left(z_{(i,j)}(0) + \sum_{start \to t} z_{(i,j)}(t) \right) \quad (2)$$

$$Q_{gi}(t) - Q_{di}(t) = Q_{(i,j)}(V,\theta,t)\left(z_{(i,j)}(0) + \sum_{start \to t} z_{(i,j)}(t) \right) \quad (3)$$

$$P_{(i,j)}(V,\theta,t) = V_i^2(t) G_{(i,i)} + \sum_{j=1, j\neq i}^{N} |V_i(t)||V_j(t)| \left(G_{(i,j)} cos\theta_{ij} + B_{(i,j)} sin\theta_{ij} \right) \quad (4)$$

$$Q_{(i,j)}(V,\theta,t) = -V_i^2(t) B_{(i,i)} + \sum_{j=1, j\neq i}^{N} |V_i(t)||V_j(t)| \left(G_{(i,j)} sin\theta_{ij} - B_{(i,j)} cos\theta_{ij} \right) \quad (5)$$

$$V_i^{min} \le V_i(t) \le V_i^{max} \quad (6)$$

$$-\pi \le \theta_i(t) \le +\pi \quad (7)$$

$$0 \le P^2_{(i,j)}(t) + Q^2_{(i,j)}(t) \le S^2_{(i,j)}{}^{max} \left(z_{(i,j)}(0) + \sum_{start \to t} z_{(i,j)}(t) \right) \quad (8)$$

$$P_{gi}^{min} \le P_{gi}(t) \le P_{gi}^{max} + \sum_{start \to t} PI_{gi}(t) \quad (9)$$

$$Q_{gi}^{min} \le Q_{gi}(t) \le Q_{gi}^{max} + \beta \sum_{start \to t} PI_{gi}(t) \quad (10)$$

$$0 \le z_{(i,j)}(t) \le n_{(i,j)}^{max} \quad (11)$$

$$0 \le PI_{gi}(t) \le PI_{gi}^{max} \quad (12)$$

where, t is the time period, T_t is the number of hours in a time period, C_i is the operational cost of generation in \$/MWh, I_i is the investment cost of generation in \$/MW, $I_{(i,j)}$ is the investment cost of transmission line in \$/MW, P_{gi} is the real power generation in MW (decision variable), Q_{gi} is the reactive power generation in MVar (decision variable), P_{gi}^{min} & P_{gi}^{max} are the minimum and maximum real power generation in MW, Q_{gi}^{min} & Q_{gi}^{max} are the minimum and maximum reactive power generation in MVar, PI_{gi} is the generation capacity investment (decision variable), PI_{gi}^{max} is the maximum allowable generation capacity investment, $z_{(i,j)}(0)$ is the existing transmission lines, $z_{(i,j)}$ is the transmission investment (integer decision variable), $n_{(i,j)}^{max}$ is the maximum allowable transmission lines across a corridor, $P_{(i,j)}$ is the real power flow across line ij, $Q_{(i,j)}$ is the reactive power flow across line ij, $S_{(i,j)}^{max}$ is the maximum apparent power flow across line ij, P_{di} is the real power demand, Q_{di} is the reactive power demand, V_i is the bus voltage magnitude (decision variable), V_i^{max} is the maximum limit on bus voltage magnitude, θ_i is the bus voltage angle (decision variable), θ_{ij} is the bus voltage angle difference, $G_{(i,j)}$ is the line conductance (Y-bus element), $B_{(i,j)}$ is the line susceptance (Y-bus element), and β is the maximum real to reactive power conversion constant at rated voltage based on generator capability curve.

Relaxed ACOPF-GTEP model using Binary variables

Instead of the integer decision variable in (11) for optimizing the total number of lines to be built across a transmission corridor, a binary decision variable can be used to decide if a certain candidate line across a corridor should be built at any time ($s_b(t)$) or not? This replaces the integer variable with multi-stage to a variable with two stages (0 or 1), thereby reducing the problem complexity. In such a case, the existing arc and candidate arc are represented individually in the network, and equations (13-18) are used in the model instead of equations (2, 3, 8, 11). The ability to consider investing in multiple lines across a corridor can be modeled by designing many candidate arcs across that corridor, each having its own binary decision variable. Though this MINLP formulation will have a larger number of constraints and variables due to inclusion of many candidate arcs, it will have reduced problem solving complexity due to removal of multi-stage integer variables.

$$P_{gi}(t) - P_{di}(t) = P_{(i,j)}(V,\theta,t)\, z_{(i,j)}(0) + \sum_{k \to i} P_{(i,k)}(V,\theta,t) s_{b(i,k)}(t) \tag{13}$$

$$Q_{gi}(t) - Q_{di}(t) = Q_{(i,j)}(V,\theta,t)\, z_{(i,j)}(0) + \sum_{k \to i} Q_{(i,k)}(V,\theta,t) s_{b(i,k)}(t) \tag{14}$$

$$0 \le P^2{}_{(i,j)}(t) + Q^2{}_{(i,j)}(t) \le z_{(i,j)}(0)\, S^2{}_{(i,j)}{}^{max} \rightarrow Existing\ branch \tag{15}$$

$$0 \le P^2{}_{(i,j)}(t) + Q^2{}_{(i,j)}(t) \le s_{b(i,j)}(t)\, S^2{}_{(i,j)}{}^{max} \rightarrow Candidate\ branch \tag{16}$$

$$0 \le z_{(i,j)}(t) \le 1 \tag{17}$$

$$0 \le s_{b(i,j)}(t) = \sum_{start \to t} z_{(i,j)}(t) \le 1 \tag{18}$$

In the above model, equations (13) and (14), which have binary variables multiplying non-linear power flow equations, can be further relaxed by considering a disjunctive formulation of MINLP problem using the big "M" method [148].

The MINLP or MILP formulation can be further relaxed to NLP or LP problem by assuming the transmission investment variable as continuous, instead of binary. The continuous variable can be constrained close to discrete 0 or 1 value by using a binding constraint relaxed using ε, as shown in (19).

$$z_{(i,j)}(t)\left(1 - z_{(i,j)}(t)\right) \le \varepsilon \tag{19}$$

The AC formulation also allows to include shunt devices such as MSCs (Mechanically switched capacitors) and SVCs (Static Var Compensators) as investment options. Their influence can be accounted within equation (5), which has bus shunt susceptance $b_i(t)$ as shown in (20).

$$B_{(i,i)}(t) = \sum_j b_{(i,j)}(t) + b_i(t) \tag{20}$$

where $b_{(i,j)}$ is the line susceptance and b_i is the bus shunt susceptance.

A.I.3 DC Optimal Power Flow based Generation-Transmission Expansion Planning Model

The DCOPF formulation is based on the following simplifications to ACOPF model:

1. R<<<X: The resistance of transmission circuits is significantly less than the reactance.
2. Voltage angle differences very small: For typical operating conditions, the difference in voltage angles for two buses is very low (about 10-15 degrees). For smaller angle differences, the cosine function approaches 1.0 and the sine function is the angle itself (expressed in radians).
3. Voltage magnitudes are assumed 1.0: In the per-unit system[15], the numerical values of voltage magnitudes are very close to 1.0, and little error occurs with this assumption wherever two voltages are multiplied.

The resulting power flow model has two equations, a real power flow equation (21) which is directly proportional to angle difference (in radians) and reactive power flow equation (22) which is directly proportional to bus voltage difference.

$$P_{(i,j)}(\theta,t) = B_{(i,j)}\left(\theta_i(t) - \theta_j(t)\right) \tag{21}$$

$$Q_{(i,j)}(V,t) = -b_i + \sum_{j=1, j\neq i}^{N} \left|b_{(i,j)}\right|\left(\left|V_i(t)\right| - \left|V_j(t)\right|\right) \tag{22}$$

[15] A typical power system with several transformers and machines consists of many different voltage levels. The per-unit (p.u.) system simplifies the analysis of complex power systems by choosing a common set of base parameters in terms of which, all systems quantities are defined. The different voltage levels are normalized to scalar values between 0-1.0 (usually values for various components lie in a narrow range), and the p.u. system provides many advantages for modeling, computation and assessment.

The DCOPF-GTEP problem has the following constraints as shown in equations (23-29) and equations (7, 9, and 12) in Appendix I.2. It should be noted that in the formulation of (23-29), binary transmission investment decision variable is used instead of integers, and hence the network expansion problem is formulated using arcs representing existing and candidate lines individually, so that the decision taken is if a certain candidate line across a corridor should be built at any time ($s_b(t)$)? The described problem is according to co-optimization definition-A in Section 2.3.1. If the co-optimization definition-B is adopted, then the problems can be broken into LP model for generation expansion and MINLP of reduced size for transmission expansion.

$$\sum_i P_{gi}(t) = \sum_i P_{di}(t) \tag{23}$$

$$P_{(i,j)}(t) = B_{(i,j)}\big(\theta_i(t) - \theta_j(t)\big) z_{(i,j)}(0) \rightarrow Existing\ branch \tag{24}$$

$$-z_{(i,j)}(0)\, P_{(i,j)}{}^{max} \leq P_{(i,j)}(t) \leq P_{(i,j)}{}^{max}\ z_{(i,j)}(0) \rightarrow Existing branch \tag{25}$$

$$P_{(i,j)}(t) = B_{(i,j)}\big(\theta_i(t) - \theta_j(t)\big) s_{b(i,j)}(t) \rightarrow Candidate\ branch \tag{26}$$

$$-s_{b(i,j)}(t)\, P_{(i,j)}{}^{max} \leq P_{(i,j)}(t) \leq P_{(i,j)}{}^{max}\ s_{b(i,j)}(t) \rightarrow Candiate\ \ branch \tag{27}$$

$$0 \leq z_{(i,j)}(t) \leq 1 \tag{28}$$

$$0 \leq s_{b(i,j)}(t) = \sum_{start \rightarrow t} z_{(i,j)}(t) \leq 1 \tag{29}$$

The above MINLP model can be relaxed to a MILP using a disjunctive formulation using big "M" for candidate branches as shown in (30-32), instead of (26).

$$P_{(i,j)}(t) = B_{(i,j)}\big(\theta_i(t) - \theta_j(t)\big) + (S_b(t) - 1)\ M + U_b(t) \tag{30}$$

$$U_b(t) \leq 2\ (1 - S_b(t))\, M \tag{31}$$

$$U_b(t) > 0 \tag{32}$$

A.I.4 Network Flow based Generation-Transmission Expansion Planning Model

The network flow model based linear programming cost minimization formulation is shown in equations (33-36), where the operational arc flows and investments are minimized in (33). Since, both generation and transmission arcs are considered as transportation pipelines (with different properties), the only equation that governs this model is (34), the nodal power flow balance equation. Equation (35) represents the capacity constraint for both generation and transmission arcs.

Minimize $$\sum_{t}\sum_{(i,j)} C_{(i,j)}(t)\, P_{(i,j)}(t) + \sum_{t}\sum_{(i,j)} I_{(i,j)}(t)\, PI_{(i,j)}(t) \tag{33}$$

subject to $$\sum_{i} \eta_{(i,j)}(t)\, P_{(i,j)}(t) - \sum_{j} P_{(j,k)}(t) = d_j(t) \tag{34}$$

$$P_{(i,j)}{}^{min} \le P_{(i,j)}(t) \le P_{(i,j)}{}^{max} + \sum_{start \to t} PI_{(i,j)}(t) \tag{35}$$

$$0 \le PI_{(i,j)}(t) \le PI_{(i,j)}{}^{max} \tag{36}$$

DC lines are modeled as real power injections (positive and negative) at both the ends of the lines, which effectively translate to modeling it as a transportation pipeline. Equation (37) shows the inclusion of power injection from a DC line into nodal real power balance equation. To consider DC lines among the transmission investment options, candidate arcs for DC lines are created separately from AC lines with appropriate cost and operational characteristics. The cost may also include the power electronics component costs at both the terminals.

$$P_{gi}(t) - P_{di}(t) = P_{(i,j)}(V,\theta,t)\, z_{(i,j)}(0) + \sum_{k \to i} P_{(i,k)}(V,\theta,t) s_{b(i,k)}(t) + P_{(i,j)}{}^{HVDC}(t) \tag{37}$$

Appendix II. Review of Selected State-of-the-Art Co-optimization Models

This appendix presents a review of some existing co-optimization tools that were summarized briefly in Section 2.3.2. Many of the tools are in-house research grade software that are being developed by the research teams that worked on this whitepaper, which have been tested using real-scale test systems and results have been published. The review covered the following aspects of the tool, namely, the different infrastructure sectors modeled, the different types of infrastructure investment decisions made, the computational model, the associated optimizer and solvers, and other planning attributes such as network modeling, optimization time steps, handling uncertainties, and modeling demand side options. The reviews also presented the development status of each tool, along with their limitations and possible improvements.

A.II.1 NETPLAN

The National long term Energy and Transportation Planning (NETPLAN) model is a software tool developed at Iowa State University that models the transportation and energy sectors, as well as their operational interdependencies, in order to perform national-level, long-term (i.e., 40 years), and multi-sector infrastructure planning. NETPLAN accounts for electric generation and transmission, production and transportation of fuel (coal, gas, and petroleum), and freight and passenger transportation systems (highway, rail, air). The co-optimization framework identifies investment portfolio (which technology, where, which year, what capacity) based on minimizing long term investment and operational costs in both the sectors, using time steps appropriate to each sector.

A.II.1.1 Types of investment decisions made

Depending upon the type and scope of investigation, the investment decision variables can include generation technologies, transmission, natural gas pipeline, transportation fleet and their corresponding static infrastructure.

- Generation technologies and attributes: Currently, 15 generation technologies have been modeled that include pulverized coal, nuclear, oil, integrated gasification combined cycle, integrated pyrolysis combined cycle, natural gas combined cycle, combustion turbine, hydro, inland wind, offshore wind, solar PV, solar thermal, geothermal, tidal, and ocean thermal energy conversion. Each of these technologies' operational and planning attributes include existing capacity, future retirements, operational and maintenance cost, emission (CO2, NOx, SOx, particulate matter, ash, and nuclear waste) metrics, capacity factor, capacity value, ramp rates, investment cost, and lifespan.

- Transportation fleet and attributes: The transportation sector comprises of intra- and inter-state freight and passenger transportation needs. Freight demand constitutes transportation requirements for energy (coal) and non-energy commodities such as cereal grains, foodstuffs, chemicals, gravel and wood. The inter-state freight needs are served by diesel train and diesel trucks. The inter-state passenger demand is served by airways, roadways (gasoline and hybrid cars) and railways (high speed rail (HSR)). NETPLAN also models intra-state personal vehicle transportation, comprising of gasoline, compressed natural gas (CNGs), fuel-cell (FCVs) and hybrid (HEVs. and PHEVs) vehicles. The operational and planning attributes include existing capacity, investment cost and lifespan of vehicles and their corresponding commuting infrastructure (roads, rail tracks), vehicle occupancy factor, operating and maintenance cost, emission (CO2) metrics, and energy consumption (gallons or MWh per vehicle-mile).

In cases, where the focus needs to be only on the energy network, the model can be simplified by screening out the data related to the transportation network, and the transportation related energy demand can be represented by a constant demand at the energy node.

A.II.1.2 Features and computational methods of model optimizer

Optimization in NETPLAN occurs at two levels:

- A lower-level linear programming-based cost minimization program that produces a minimum cost portfolio of energy and transportation investment, with associated resilience and sustainability metrics; and

- A higher level Non-dominated Sorting Genetic Algorithm-II (NSGA-II) multi-objective evolutionary algorithm that identifies Pareto optimal solutions[16] in the space of cost, resilience, and sustainability metrics.

Sustainability metrics include annual CO_2, SO_2, and NO_x emissions. The resilience of long-term planning solutions is evaluated in terms of the system's ability to minimize the impact and recover from extreme events such as Katrina/Rita hurricanes, loss of petroleum supply from the Middle-east, or say, shutdown of 70% of nuclear plants.

A.II.1.3 Summary of additional planning tool attributes

Load duration curve or chronologically ordered load curves: The optimization can be performed at any time step, viz. hourly, monthly, and yearly, and accordingly electric and non-electric loads (natural gas, freight and passenger transportation) can be represented either by chronological data or duration curves. If the electric sector is not represented at an hourly time step, then the electric load is represented by slices of load duration curves in the chosen time period. For instance, at a yearly time step, the electric load is represented in terms of sets of average load for a particular slice of load duration curve and the number of hours in the year that slice spans.

Network representation and transmission options: Transmission lines can be modeled as transportation pipelines or with DC power flow equations. The line attributes include existing transmission capacity between nodes, losses, investment cost, lifespan, and line impedances. Inter-state gas pipelines are modeled with a transportation model, i.e., nodal balance. However, currently the transmission options are not differentiated based on KV levels or DC/AC lines. The transmission line capacities can be made a function of pre-determined line lengths between any two existing nodes (St. Clair curves (refer footnote 3)); however this feature is currently not modeled.

Depreciation and end-period effects: A discount and inflation rate is applied to the objective function of the optimization to represent the future year costs in present values. Yearly retirements are input exogenously to the program, and they are not decision variables. A salvage value approach is used to avoid the end effects in the final years of the long-term optimization. This is accomplished by prorating the investment cost of the infrastructure at a particular year to the available life within the optimization horizon, assuming a typical operational lifespan for each infrastructure.

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[16] In a multi-objective decision making, there is rarely a single solution that is best in all the objectives. Pareto optimal solution is a popular way to handle this tradeoff associated with multi-objective problems, where a set of solution (depicting a frontier in the multi-dimensional plane defined with individual objectives as the axes) is identified. In this set there is no solution that is dominated by some other solution in all the objectives, and a solution is the best compared to the rest in atleast one of the objectives.

Modeling of operational and maintenance costs: The operational and maintenance cost is one of the parameters of the various network arcs in NETPLAN (i.e., generator arc, transmission arc, fuel arcs (coal, petroleum, gas supply), transportation arcs (pipeline, freight and passenger vehicles)), based on which minimum cost energy flow optimization is performed. The arcs that connect the fuel network to the electric network have an efficiency parameter which is a function of the respective generator's heat rate (a flat heat rate is assumed for all ranges of power output). Fuel cost characterization is based on geography: the cost and capacities of four varieties of coal supply across various regions in the country are modeled. The natural gas production cost and capacities, gas imports, pipeline capacities and storage capacities are also characterized based on geography.

Optimization interval: Currently studies are done for the full 40-year period with inter-temporal relationships, where operations are optimized for each sector at user defined time intervals (hourly, monthly, yearly), and investments are optimized for all sectors at yearly time intervals.

Application of reserve constraints: The operational reserve (regulation and spinning reserves) and ramping requirements are modeled as a function of net-load variability (i.e., load – variable generation output), and consequently is a function of investment decisions in variable generation. The ability of each generation technology to provide these ancillary services is subject to its ramp rate at the respective time interval (i.e., 1-minute for regulation services and 10-minute for spinning reserve services).

Provision for demand-side option: Currently, demand side and electric energy storage options are not modeled, but it can be done. Section 3.2.3.1 discusses about modeling these resources in long-term planning.

Methods of handling uncertainty: The uncertainties can be classified into local (such as yearly fuel prices, variable generation output, generation availabilities) and global (futures governed by policies or public reactions such as no more coal generation, natural gas dominated electric sector, high renewables). The local uncertainties can be handled by many solves of the LP cost minimization for different input data, and producing a final robust and economic plan subject to the probabilities of considered scenarios. The global uncertainties are handled via a "flexibility design" optimization problem whereby two costs are minimized: (1) a cost of a core investment that is made independent of the scenario; and (2) the cost of adapting the core investment to the needs of a particular scenario should it occur. A detailed description of this approach concept is given in (Diego, 2013), where it is applied to national long-term generation expansion planning.

A.II.1.4 Development status, previous applications and associated typical run times

A complete dataset of the national energy and commodity and passenger transportation system has been developed for U.S. using DOE-EIA, NHTS and industry sources. The data and NETPLAN software has been validated, and interesting analyses have been performed including:

(a) National level electric (13 electric regions) and transportation (freight and personal vehicles in 48 states) portfolio planning [59]

(b) Nation-wide transmission overlay design and benefit assessment (13 electric regions, no transportation) [71]

- Run time: ~10 minutes (636,201 variables, 495,920 constraints)

(c) National level electric (13 electric regions) and transportation (freight and inter-state passenger transportation including HSR, Air and roadways) portfolio planning (Krishnan et al. [70])

- Run time: ~15 minutes (889,160 variables, 748,680 constraints)

(d) National level electric (13 electric regions, no transportation) portfolio planning with operational effects [69]

- Run time: ~1 hour (823,921 variables, 850,560 constraints)

(e) National level electric (62 electric regions) and transportation (freight and personal vehicle in 48 states) portfolio planning

- Run time: ~10-17 hours (3,444,800 variables, 2,664,640 constraints)

A.II.1.5 Limitations and challenges

The co-optimization of transmission and generation resources is currently performed simultaneously with the transportation model of transmission lines, which renders the optimization linear. However, in the future if transmission expansion has to be modeled using DC power flow, then the resulting non-linear optimization model has to be formulated as mixed integer linear program using disjunctive format. Advancements in computational efficiencies will be one of the future developments. This will enable expanding the model's spatial (electric regions) and temporal granularity (optimization time steps and horizon). Decomposing the LP problem using Bender's decomposition methods and parallelization have been and are being studied. NSGA-II based multi-objective optimization is parallelizable, and has been tested by running parallel LP codes within each generation of NSGA-II on multiple clusters.

A.II.2 An iterative approach to generation/transmission co-optimization

Iowa State University has developed a comprehensive tool to design inter-regional transmission overlays using an iterative approach for co-optimizing generation and transmission resources, where NETPLAN is an integral part.

A.II.2.1 Types of investment decisions made

Generation and transmission planning is done sequentially, but coordinated by an iterative approach as shown in Figure A.II-1.

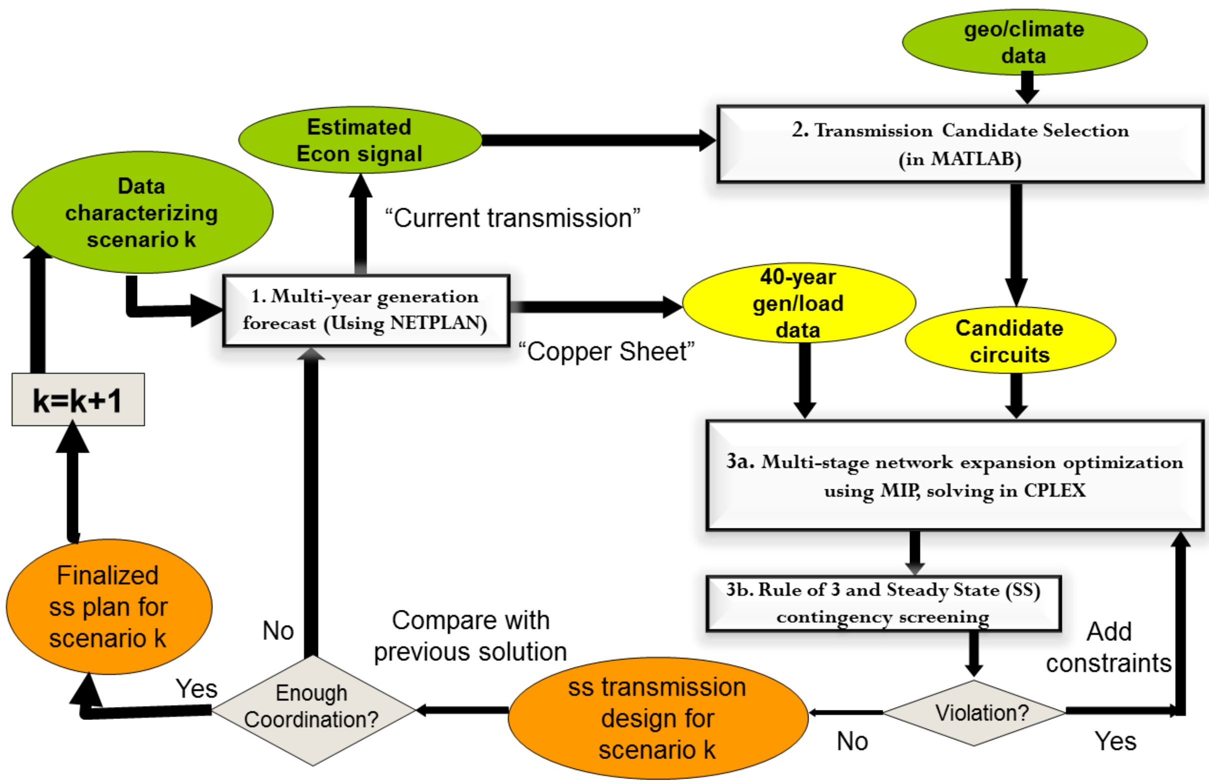

Figure A.II-1. Iterative approach to generation/transmission co-optimization

A.II.2.2 Features and computational methods of model optimizer

Generation Planning: This step determines the amount, type, location, and timing of future generation capacity investment using NETPLAN software. The objective of the linear optimization is to minimize the total cost, which comprises of generation investment and operation cost that include cost incurred from natural gas and coal production and transportation.

Transmission Candidate Selection: This stage selects proper transmission candidates between node pairs based on a series of factors which may influence transmission investment decisions, including right of way availability, economic value, restricted land, land type, population density, forest, lightning density, wind, ice-loading and others. This is accomplished using a "minimum spanning tree" algorithm that weighs the cost of all possible transmission arcs based on the factors mentioned above.

Network expansion optimization: In this step, based on the generation portfolios and transmission candidate set above, a Mixed Integer Linear Programming (MILP) model is utilized to optimize transmission investments for 40 years. The objective is to find the transmission investment plan with minimum total investment and production cost subject to power balance, DC power flow, generation capacity, and transmission loadability constraints. Existing and future generation capacities are assumed to be fixed. Only the transmission network is expanded. For each generation expansion scenario, a particular transmission design is obtained. The problem statement is summarized below:

Minimize (over 40 years)

Transmission investment cost + Generation production cost + Levelized transmission loss cost

Subject to:

Power balance in each node

DC power flow constraints (in disjunctive format)

Generation capacity constraints

Binary Investment decision variables

A.II.2.3 Summary of additional planning tool attributes

Load duration curve or chronologically ordered load curves: The optimization can be performed at any time step, viz. hourly, monthly, and yearly, and accordingly loads can be represented by chronological data or load duration curves.

Network representation and transmission options: The transmission network optimizer models the network using DC power flow. Non-linear constraints in the DC flow investment model are eliminated by using disjunctive formatted inequality constraints. Consideration is given to 500kV EHVAC, 765kV EHVAC, 600kV HVDC and 800kV HVDC, which are today's most popular and technically mature transmission technologies for bulk power transfer. Investments can be made in multiple lines across a single corridor. The AC transmission line capacities are made a function of pre-determined line lengths between any two existing nodes (St. Clair curves (refer footnote 3)).

Depreciation and end-period effects: All costs have been discounted to the reference year (2010 dollars). Yearly retirements are modeled exogenously. A salvage value approach is used to avoid the end effects in the final years of the long-term optimization. This is accomplished by prorating the investment cost of the infrastructure at a particular year to the available life within the optimization horizon, assuming a typical operational lifespan for the infrastructure.

Modeling of operational and maintenance costs: The transmission candidate selection based on "minimum spanning tree" algorithm chooses cost for every possible arcs between all node pairs as a function of many factors which may influence transmission investment decisions, including right of way availability, economic value, restricted land, land type, population density, forest, lightning density, wind, ice-loading and others.

Optimization interval: The MILP is performed for the full 40-year period, where investments are optimized at yearly time intervals and operations are optimized at user defined intervals (hourly, monthly or yearly).

A.II.2.4 Development status, previous applications and associated typical run times

The electric network is built up by reducing the Ventyx national production cost model, and therefore represents the U.S. with 62 nodes, 142 existing transmission paths, and 15 different generation technologies. Several studies have been done to expand transmission economically for various generation expansion scenarios (i.e., high wind, high solar and high geothermal) (Villegas et al.).

- Run time: ~ 25-46 hours (1,855,612 variables, 3,244 Binaries, 1,918,260 constraints)

A.II.2.5 Limitations and challenges

The computational challenge is serious, and hence two methods have been investigated. The first is to implement a parallel computing algorithm on a high performance computing platform at ISU, which has 3200CPUs, 44TB memory and a peak performance of 15.7 TF. The second is to enhance traditional Benders' decomposition algorithm to speed up its convergence rate.

A.II.3 META•Net modeling system

The Market Equilibrium and Technology Assessment Network (META•Net) Modeling System developed at Lawrence Livermore National Laboratory [73] could be used for building and solving multi-period equilibrium energy economic models to analyze the energy system.

A.II.3.1 Types of investment decisions made

The energy system model is comprised of market dynamics within and across sectors such as major consumers (industrial, residential, commercial), electric (generation and transmission), transportation, and fuel sources (petroleum, coal and gas). The model optimizes the component capacities within each sector, which includes generation and transmission in the electric sector.

A.II.3.2 Features and computational methods of model optimizer

META•Net is a market equilibrium model that optimizes the yearly operations and dispatch of supplies to meet the demand within each sector at hourly time steps. The component capacities are adjusted each iteration, but once they are set, they are constant for the entire year's optimization of operations. Essentially, the capacities are adjusted until the marginal value of capacity is equal to the marginal cost of additional capacity (i.e., investment cost). The decision variables are continuous, and there is no linearity assumption. Functions do have to be convex.

Description of the model: META•Net models a market economy as a network of nodes representing resources (coal, gas, petroleum), conversion processes (generation, transmission), markets, and end-use demands (industrial, residential, commercial). Commodities flow through this network from resources, through conversion processes and markets, to the end-users. META•Net then finds the multi-period equilibrium prices and quantities. This economic equilibrium solution is equivalent to a cost minimization solution (proof by Hogan and Weyant [56]). The solution includes the prices and quantities demanded for each commodity along with the capacity for each conversion process (which includes infrastructure investment decisions). A simple schematic of algorithm is illustrated in Figure A.II-2 [12, 74].

- *Optimizing operations:* The markets represent the points in the system where a total demand (e.g., for electricity) will be allocated among a set of suppliers. META•Net finds a set of allocations for each hour that is an economic equilibrium—all the demands are met and each market is in equilibrium. The demand nodes send down a quantity demanded. The market nodes allocate total demand among the generators based on prices provided by the generators (generators with lower prices receive higher allocations). When a generator's allocation is less than its capacity, it sends a price equal to its operating cost. Such a low cost can elicit a demand that exceeds the capacity of the generator. In that case, over a series of iterations the generator increases its price. As the price increases, the market allocates less demand to the generator until a price is found such that demand sent to the generator is equal to its capacity. Congestion occurs when the transmission node's capacity is reached. The transmission node responds by sending a higher price for its "product" (i.e., transmitted electricity). This will force the market node to shift load away from that transmission line to another supplier. If the market nodes are highly price sensitive, the price in a particular hour is approximately equal to the system marginal cost at that hour.

- *Optimizing generation investments*: Based on the above, the generator can make an accurate estimate of the system marginal cost or price. From this, it can estimate the shadow value on the constraint that generation cannot exceed capacity, and, through a series of iterations, adjust its capacity until the condition all the demands are met. This can be interpreted as a perfect market in which each supplier to a market (i.e., each generator) receives as payment the marginal cost in the market. It then can make the financial calculation as to whether or not additional increments of capacity would earn an acceptable rate of return and increase or decrease its capacity accordingly.

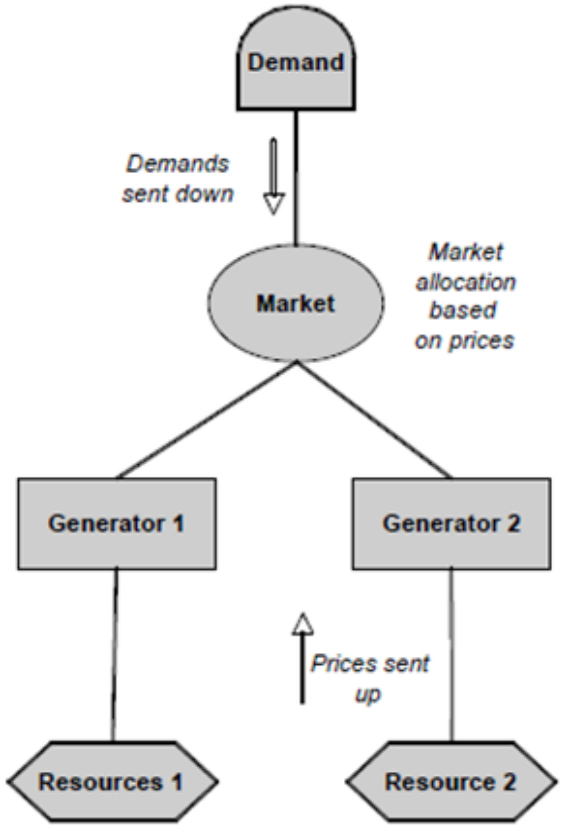

Figure A.II-2. META•Net schematic

A.II.3.3 Summary of additional planning tool attributes

Load duration curve or chronologically ordered load curves: Multi-year analysis uses a load duration curve, where the total energy for each load factor is allocated among the generators. For a single year capacity planning analysis, chronological hourly load of specific year is used.

Network representation: Transmission lines are modeled as transportation pipelines, which move a commodity from one place to another at a cost and an efficiency loss.

Modeling of operational and maintenance costs: The market equilibrium algorithm works based on the offers and bids submitted by generator companies and load entities within the electric sector.

Optimization interval: Investments are optimized at yearly time intervals and operations are optimized at user defined intervals (hourly, weekly, monthly or yearly).

Provision for demand-side option: META•Net allows for price sensitive demands.

A.II.4 COMPETES

The planning model formulation of COMPETES [19] (COmpetition and Market Power in Electric Transmission and Energy Simulator) from Energy Research Centre of the Netherlands (ECN) is built upon the short-run competitive and oligopolistic market simulation models described in [79] and [54]. The COMPETES website provides information on recent applications and the dynamic (capacity expansion) formulation.

A.II.4.1 Types of investment decisions made

Investment decisions include EHV AC and DC transmission line additions and new generation capacity (thermal dispatchable and renewable intermittent), both represented as continuous decision variables denominated in MW.

A.II.4.2 Features and computational methods of model optimizer

The basic model is a linear program that is solved iteratively. Between iterations, there are two updates: one of the linearizations of the bilinear Kirchhoff's voltage law relationships between impedance and flows, and the other of load levels based on the locational marginal prices calculated by the linear programming. The model is run until convergence is achieved. In general, multiple starting points for the iterative process are required because of discontinuities in cost as a function of a corridor's transmission capacity at zero capacity; as a result of that discontinuity, the iterative process may not converge to the global optimum. If multiple years are considered, a series of static (one year) models are solved, with one year's solution constraining the next's. Oligopoly versions of the model (based on Cournot or conjectural variation game representations) are solved with a complementarity solver (PATH) available from the AIMMS modeling software http://business.aimms.com/.

A.II.4.3 Summary of additional planning tool attributes

Load duration curve or chronologically ordered load curves: The dispatch sub-problems are presently represented as a sample of hours (equivalent to a load duration curve). Sufficient hours need to be chosen in order to adequately capture the joint distributions of loads and intermittent renewable generation over the study region.

Network representation & transmission options: A linearized DC load flow is used, with voltage law equations that force the sum of the products of impedance and flow around any loop of the network to be zero. Quadratic loss terms are included as in [52]. As far as the transmission options are concerned, a single transmission technology is predetermined by the analyst for each corridor, although different corridors can use different technologies. The present version represents DC links between non-synchronized areas. The flow limits are made a function of investment capacity, while the corridor lengths are fixed.

Depreciation and end-period effects: End effects are not considered; optimizations are for one planning year at a time, with one year's decisions constraining investment choices in the next planning year.

Modeling of operational and maintenance costs: System operational and maintenance costs are modeled as a cost coefficient on generation dispatch variables, and as an adder to the investment cost of transmission lines (representing the present worth of future O&M).

Optimization interval: In the present applications, investment decisions are made for a single year, and then constrain decision in the next planning year (typically 5 years in the future)

Application of reserve constraints: Installed capacity reserve margins are imposed on collections of buses (subregions), alternatively, more sophisticated representations that allow for capacity trading among subregions are possible. Operating reserve constraints are not presently considered.

Provision for demand-side option: Demand response (to dynamic prices) is represented by adjusting load between iterations of the linear program in response to the latest set of prices (dual multipliers to the energy balances).

Methods of handling uncertainty: Short-run load and renewable generation output variability is handled by considering a large enough sample of hours to adequately represent their joint distribution. Generator outages are approximated by deterministic derating of capacity. Long-run uncertainties only considered by sensitivity analyses.

A.II.4.4 Development status, previous applications and associated typical run times

The model has been applied in a number of policy studies concerning the short-run and long-run development of the north-western Europe and European Union markets [79]. The applications consider each of 27 countries in the EU as a node/bus, except for Denmark which is split between two synchronous areas. An application to the design of the EU grid in 2015 has demonstrated that consideration of demand response can make a significant difference in the optimal transmission reinforcement solutions, especially in the heavily congested Western European area.

A.II.4.5 Limitations of the model

- All investments are continuous; lumpiness is not considered. Voltages and technology (AC or DC) need to be preset by the user.
- Energy efficiency programs have to be chosen exogenously, but demand response is modeled as elastic demand curves.

- The coarse scale of the model (countries or subregions as nodes) means that this is most useful for assessing the economic benefits of interconnection expansion at a rough scale, rather than individual circuit evaluations.

A.II.5 Stochastic transmission planning model

This model has been developed at Johns Hopkins University, in collaboration with ECN and Cambridge University researchers [52, 90, 142].

A.II.5.1 Types of investment decisions made

Investment decisions include EHV transmission line additions (represented as binary decision variables) and new generation capacity (thermal dispatchable and renewable intermittent, represented as continuous decision variables denominated in MW).

A.II.5.2 Features and computational methods of model optimizer

The basic model is a mixed integer linear program that is solved non-iteratively. Larger versions of this model are solvable by a Benders decomposition method, which iterates between a master problem (investment) and set of subproblems (dispatch).

A.II.5.3 Summary of additional planning tool attributes

This section is included to identify additional features of software applications for planning which are important to power system design but germane to any planning software and not necessarily unique to those which perform co-optimization.

Load duration curve or chronologically ordered load curves: The dispatch sub-problems can represent load as either a sample of hours or as a sample of days, each with 24 chronological hours. Sufficient hours are chosen in order to adequately capture the correlations, as well as means and standard deviations, of loads and intermittent renewable generation over the study region.

Network representation & transmission options: For general networks, a linearized DC load flow is used based with explicit phase angles for each bus. To linearize the bilinear (product) relations between corridor impedance and flows in the Kirchhoff's voltage law equations of the linearized DC load flow, the disjunctive approach from Ref. [5] is used. This allows modeling of the simultaneous effect of a new line upon both corridor thermal capacity and impedance. Both individual corridor capacity (based on thermal or St. Clair curve-based limits) and interface capacity (covering several lines and considering limits resulting from off-line n-1 analyses) can be represented. The formulation is considerably simplified for radial networks, requiring neither the angle variables nor representation of the voltage law. Appropriate choice of cost, flow limit, and per unit impedances for each transmission reinforcement alternative is considered within a corridor.

Depreciation and end-period effects: Retirement of generation can be done exogenously (by a fixed depreciation amount in each year) or using decision variables whose costs considers the going forward cost of maintaining generation capacity. End-period effects are avoided by assuming that the last year considered repeats infinitely. For instance, if year 2030 is the last year dispatched, then that year's cost is multiplied by a factor that is equivalent to the same cost occurring in 2031, 2032, etc.

Modeling of operational and maintenance costs: As a cost coefficient on generation dispatch variables, and an added to the investment cost of transmission lines (representing the present worth of future O&M).

Optimization interval: In the present applications, investment decisions are made in years 0 and 10, and investments are assumed to be in place 10 years after the decision is made; the dispatch in years 10 and 20, constrained by those investments, is optimized.

Application of reserve constraints: Installed capacity reserve margins are imposed on collections of buses (subregions), alternatively, more sophisticated representations that allow for capacity trading among subregions are possible. Operating reserve constraints are modeled by defining operating reserve variables for each generation type at each location in each period, and constraining the total amount provided by subregion.

Provision for demand-side option: Only through exogenous load adjustments prior to running the model; the linear programs assumed that load in each hour is fixed.

Methods of handling uncertainty: Short-run load and renewable generation output variability is handled by considering a large enough sample of hours to adequately represent their joint distribution. Generator outages are approximated by deterministic derating of capacity. A notable feature of this model is its ability to consider multiple scenarios of future economic, technological, and regulatory conditions. This is done through stochastic (two stage) programming in which the first stage investments ("here and now" decisions) must be made without knowing which scenario will occur, and the second stage investments ("wait and see" decisions) are made after the scenario is known. This allows for calculation of indices of the economic significance of uncertainty, such as the value of perfect information[17] and the cost of

[17] The expected value of perfect information (EVPI) provides an upper bound on the value of better forecasts for uncertain parameters and scenarios, and is calculated as the difference between two estimates of the present worth of the net benefits of transmission expansion: the probability-weighted ("expected") net benefits if better forecasts are available (so that transmission investments can be tuned to the scenario that is most likely to occur), and the expected benefits in the absence of better forecasts (so that investments made now have a greater risk of being stranded, while potentially beneficial investments might not be made because of high risks of their costs exceeding their benefits). Reducing uncertainty through better forecasts and scenarios has value (a positive EVPI) only if better forecasts might change investment decisions; if decisions are not changed, then the economic value of better forecasts is zero. We have quantified the value of better forecasts of gas prices, demand, and government siting and renewables policy as approximately 100M to 3.7B U.K. pounds (over 30 years) for the U.K. [142]. For the WECC, we estimated an EVPI of $45.4B under policy uncertainties concerning climate and renewable policy [90].

ignoring uncertainty.[18] The latter quantifies the consequences of using deterministic planning rather than stochastic planning; the result is, in general, lower net benefits for the transmission plan, averaged over all the scenarios. For instance, we have found in our analyses of WECC that the best transmission plan under uncertainty includes such flexible transmission backbone additions that keep later options open, even though some of those particular additions would not be chosen by a deterministic plan for any of the individual scenarios (see the highlighted circuits in Table 1 of [90]).

A.II.5.4 Development status, previous applications and associated typical run times

The model has been applied to a radial system (the United Kingdom) and a 240-bus representation of the WECC. Each has on the order of 10E5 to 10E6 decision variables for a two-stage decision problem with three to seven scenarios, and is solved within minutes on a desktop computer.

A.II.5.5 Limitations of the model

- Does not include n-1 constraints endogenously
- Demand management or response not included endogenously
- The expected benefits in the absence of better forecasts (so that investments made now have a greater risk of being stranded, while potentially beneficial investments might not be made because of high risks of their costs exceeding their benefits).
- For systems larger than ~250 (aggregated buses), ~5 scenarios, ~2 planning stages, and ~300 hours/yr, decomposition is needed, given the capabilities of typical new desktop computers.
- More than two investment decision stages are desirable to ensure that the assumption of known scenarios in the last stage does not bias the immediate (first stage) investment decisions.

[18] We have quantified this cost (also known as the value of the stochastic solution or the value of planning uncertainty) for high-voltage transmission planning in the U.K. and western U.S. (WECC). In the U.K., better forecasts of gas prices, demand, and government policy concerning siting of renewables and nuclear power in the U.K. would be worth about 100M U.K. pounds (over 30 years) in the case of backbone transmission planning [142]. Meanwhile, ECIU was estimated to be $46.7 billion in the case of backbone and major interconnection planning in the Western U.S. (WECC) under uncertainties concerning climate and renewable policy [90]. The latter value is greater than the anticipated cost of transmission investments over this time because better transmission investments can have an amplifying effect on generation cost savings. The optimal plan under uncertainty also has much less exposure to risk of stranded assets than deterministic plans developed under some scenarios.

A.II.6 ReEDS

The Regional Energy Deployment System (ReEDS) is a long-term capacity-expansion model for the deployment of electric power generation technologies and transmission infrastructure in the contiguous United States. Developed at the National Renewable Energy Laboratory's (NREL) with support from the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy, ReEDS is designed to analyze critical issues in the electric sector, especially those relating to renewable energy resources, potential, and integration.

A.II.6.1 Types of investment decisions made

A linear transmission and generation co-optimization model, ReEDS selects generation and transmission investments and dispatches units to meet load and reliability requirements at least system cost. ReEDS includes a full suite of electricity generating technologies: several distinct coal technologies, natural gas turbines and combined-cycle units, nuclear, geothermal, biopower, hydropower, onshore and offshore wind, solar photovoltaic and thermal. Electricity storage systems are also available: pumped hydropower, compressed air (CAES), and batteries. Limited demand-side options include ice storage and interruptible loads. Electric and hybrid-electric vehicles are not included in the investment decisions, but charging of exogenously defined electric vehicle adoption can affect electric loads.

Plant operation is characterized by fuel type, heat rate; emissions levels for CO_2, SO_2, NO_x, and Hg; outage rates; ramping cost; and ability to provide ancillary services. Variable resource renewable energy units are also characterized by resource characteristics—annual and time-slice average capacity factor and probability distribution of likely output. Storage units are also characterized by round trip efficiency. Investment decisions consider assumptions of capital cost, construction schedule, availability of financing and tax incentives, and fixed and variable operations and maintenance costs.

Transmission lines are built as MW of new carrying capacity over a known-length corridor, at a capital cost defined in $/MW-mi. While transmission is built continuously rather than in increments of conductors at voltage level, transmission costs reflect an assumption that dense areas of the country are likely to build 765-kV lines while other areas build 500-kV lines.

A.II.6.2 Reduced-form dispatch

The dispatch representation in the model is across 17 annual time-slices, where 16 time-slices are based on one representative day from four seasons, with each day comprising four diurnal slices. The seventeenth time-slice is a super peak representing the 40 highest-load hours of the summer. Model linearity necessitates certain approximations: aggregate units, flat heat rates, linear power flow.

ReEDS is required to serve load and meet adequacy and operational reserve requirements in each time-slice through construction and operation of generating units and sufficient transmission capacity.

A.II.6.3 Features and computational methods of the model optimizer

ReEDS is a linear optimization model written in GAMS, solved with CPLEX. ReEDS operates from the year 2010 to 2050 in sequential fashion: 21 successive solves, one for each two year period, with limited knowledge of future behavior. Each solve makes simultaneous investment and dispatch decisions: one round of investment with a 20-year evaluation period for operation. The primary purpose of the sequential structure is to allow non-linear updating of system infrastructure parameters (e.g., transmission line susceptances) between individual linear optimizations.

A.II.6.4 Summary of additional planning tool attributes

Load duration curve or chronologically ordered load curves: The 17 time-slices in ReEDS are organized by season and time-of day: summer afternoons, spring mornings, etc. Each representative day is considered to be experienced chronologically, but there is limited information transfer across seasons.

Geographic resolution and transmission characteristics: For a national model, ReEDS has a highly resolved regional structure. Roughly 300 transmission lines connect the 134 balancing areas. Load and generation are balanced, and reserves required, at each balancing area; and a linear DC power flow algorithm governs transmission flows among them. Transmission lines are characterized by carrying capacity (MW) and susceptance. While the rest of the network is subject to Kirchoff's laws, interconnect interties and the major high voltage DC lines are granted flow control. Linearity dictates aggregate transmission lines and precludes representation of explicit voltage levels.

Integration of variable resource renewable energy technologies: ReEDS has been designed to focus on a variety of issues related to renewable energy technologies, including accessibility and cost of transmission, regional quality of renewable resources, seasonal and diurnal load and generation profiles, variability and uncertainty of wind and solar power, and the influence of variability on the reliability of electric power provision. In addition to the regional structure, ReEDS accomplishes this through explicit statistical treatment of the variability in wind and solar output over time, and consideration of ancillary service requirements and costs.

In each time-slice, wind and solar resources are characterized by long-term-average time-slice capacity factor and the probability distribution of output across the time-slice. Based on that distribution as well as the performance characteristics of the balance-of-system, including the topology of the transmission network, renewable generators are assigned capacity values that reflect their effective load-carrying capacity, induced operating reserve requirements, and expectation of potential output curtailed due to generation in excess of load. These characteristics maintain statistical reliability of the electric system through planning and operating reserve requirements and, along with resource depletion, steadily reduce the value of wind and solar to the electric system as their contribution grows.

Demand-side options: ReEDS has limited demand-side options including a supply curve of interruptible loads, allowed investment in ice-storage for time-shifting of cooling loads, and external projections from other NREL models for adoption of rooftop PV and electric vehicles.

A.II.6.5 Development status, previous applications, and associated typical run times

ReEDS is a fairly mature modeling framework, having been used for numerous policy or technology analysis projects over the past several years. Among the analyses for which ReEDS has been used are the 20% Wind Energy by 2030 report [135]; the Renewable Electricity Futures Study [95], an analysis of how the United States might provide 80% of its electricity from renewable sources; and the Sunshot Vision Study [128], which explores how solar technologies might deploy if cost and performance continue to improve. Most analyses consist of an ensemble of scenarios with a range of input assumptions—technology and fuel prices, policy options, resource scenarios—to provide a set of potential futures or a range of impacts of a policy, technological advancement (e.g., R&D), or shift in economic conditions. Individual ReEDS scenarios (2010-2050) solve in 4-6 hours.

A.II.7 Prism 2.0 model

Prism is an Electrical Power Research Institute (EPRI) project to conduct the U.S. Energy and Environmental Analysis. This project aims to understand the greenhouse-gas-reduction potential of the electric sector in the U.S. EPRI released its first Prism analysis in 2007, together with the findings based on Model for Estimating the Regional and Global Effects of Greenhouse Gas Reductions (MERGE). In 2009 EPRI released the updated Prism and MERGE analysis [31]. In the EPRI report, Prism analysis provided an assessment of the CO2-reduction potentials of eight key technology areas in the electricity sector, including end-use energy efficiency (6.5%), transmission and distribution (0.9%), renewable energy resources (13%), nuclear power (11%), fossil efficiency (3.7%), carbon capture and storage (11%), electric transportation (9.3%), and electro-technologies (6.5%). On the other side, the MERGE analysis helped find out the most economic combination of different technologies while meeting a specified CO2 emission constraint. It made projections of the U.S. electricity generations and costs from different technologies, the CO2 prices, and overall costs of carbon emission reductions.

In late 2010, EPRI initiated the Prism 2.0 [32] collaborative project to conduct analyses to assist U.S. generating companies to understand various technology options and cost scenarios to better cope with their generation fleet asset management. This is because new regulations from U.S. Environmental Protection Agency (EPA) concerning various pollution sources will be implemented in the upcoming decades. This will become a critical issue for the U.S. coal-based generation fleet. The Prism 2.0 analysis projects the generation mix in the next decades based on different scenarios of the implementation of the environmental regulations. Details of the Prism 2.0 model will be discussed in the following five parts, including types of investment decisions, model features and computational methods, additional planning tool attributes and model and input assumptions, development status and analysis results, and model limitations.

A.II.7.1 Types of investment decisions made

As described in [97], the goal of the Prism project is to help understand the potential of electric sector CO2 reduction. Prism 2.0 project provides a bottom-up (including multiple energy technology areas) estimate of greenhouse gas (GHG) reduction potentials, but not a rigorous unit-by-unit assessment, not a detailed economic analysis, and not a climate policy recommendation. The U.S. Regional Economy, Greenhouse Gas, and Energy (US-REGEN) model is the analytical platform or tool EPRI uses in the Prism 2.0 project. At the same time the Prism 2.0 project was initiated to accelerate the development of US-REGEN model and then study and analyze the expansion planning issues in the electric sector and problems in the broader U.S. energy sector. As is stated in EPRI Prism 2.0 report, "At times people use the term 'Prism 2.0 model' for the ease of communication." In the electric sector part of the US-REGEN model, or the generation planning model, it follows "the standard approach of aggregating electric power units with similar attributes at the regional level". The electric sector of the model makes decisions on generation capacities (on multiple generation technologies across 15 geographical regions), additional inter-regional transmission, and dispatch to meet energy demand for both generation and inter-region transmission. The generation portfolio includes new coal generators, existing coal generators, retrofitted coal generators, natural gas generators, both existing and new nuclear power, hydro power, wind power, and other renewable generation. For the generator asset owners, the model assumes that, starting from 2015, the decision for each existing coal generator is either to retire or to retrofit to meet the current and environmental regulations expected to be in force between 2015 and 2020.

A.II.7.2 Features and computational methods

US-REGEN model is a combination of two models, a dispatch and capacity expansion model of the electric sector and a dynamic computable general equilibrium model of the U.S. economy including sector details across 15 geographical regions. Power units (with similar attributes) are aggregated at the regional level and intra-annual load segments are used. Although studies of this model based on three cases have been run to have multiple analyses, the US-REGEN model is a deterministic model.

The macroeconomic model of US-REGEN uses the classical Arrow-Debreu general equilibrium framework (one of the most general economy models whose existence was proven in [3]) incorporating the whole economy over the planning horizon. This also takes into account the observed U.S. economy data covering all transactions among firms and households and forecasted economic growth in the future. As is discussed in the 2012 Prism 2.0 report, "Production in each sector is described by a constant elasticity of substitution (CES) production function. Firms are assumed to maximize profits, and households maximize utility, the latter assumed to be a function of consumption across the time span of the model." Models coupling equilibriums usually are hard-to-solve optimization problems. In their approach, the two models are solved iteratively to convergence.

A.II.7.3 Summary of additional planning tool attributes

Load duration curve or chronologically ordered load curves: Power units (with similar attributes) are aggregated at the regional level and intra-annual load segments are used.

Network representation and transmission options: The power grid representation in Prism 2.0 model is similar to a transportation network. It does not consider power flow analysis using Kirchhoff's current and voltage laws.

Optimization interval: This model assumes only one-time investment decisions will be made. The decisions are used evaluate the environmental controls on power systems and U.S. economy out to 2035.

Application of reserve constraints: Based on available publication, no reserve constraints are considered in this model.

Provision for demand-side option: Based on available publication, no demand-side options/management is considered in this model.

Methods of handling uncertainty: Prism 2.0 model is a deterministic, mixed-integer linear programming model, and does not handle uncertainty endogenously. Although studies of this model based on three cases have been run to have multiple analyses, the US-REGEN model is a deterministic model.

Incorporating Environmental Regulations of Different Cases: The Prism 2.0 project is to understand the GHG reduction potentials and also the policy impacts on economic activities. Hence the US-REGEN model "aggregates electric power units with similar attributes at the regional level" and "use the bottom-up representation of power generation capacity and dispatch across a range of intra-annual load segments." The key inputs and assumptions for the US-REGEN model include the data regarding economic growth and energy demand and supply from EIA's Annual Energy Outlook 2011, economic data from IMPLAN and electric power unit data from Ventyx (2009 and 2010 datasets), electric sector policies, including state renewable portfolio standards (December 2011), the Cross-State Air Pollution Rule (CSAPR), and that new coal plants only include the units currently under construction. In order to understand different situations, three different cases concerning investment costs and regulation implementation details are used as the inputs to the US-REGEN model. The three cases are Reference Case, Flex

Case, and High Case. Reference case provides a central estimate of the costs and regulation details. Flex case is with lower costs and more flexible on the timing for retrofitting SO_2, NO_x and mercury controls. High case is an upper bound estimate, where higher costs and more stringent regulations are used.

For all of three cases, the Prism 2.0 project used EPRI's IECCOST model to estimate the investment and operating costs for retrofitting coal plants which require controls of SO2, NOx and Hg. Mercury (Hg) control assumes compliance by 2015 for both High and Reference cases and by 2017 for the Flex case. For SO2 control, all three cases assume the generator owner will make decisions based on a SO2 limit of 0.15lb/MMBtu. Both Reference and High cases assume compliance by 2015, and Flex case by 2017. For NO_x control, all three cases assume the generator owner will make decisions based on a NO_x limit of 0.10/MMBtu. Both Reference and High cases assume compliance by 2018, and Flex case by 2020. For cooling water control, all three cases assume compliance with the Clear Water Act Section 316(b) by 2018. With the additional required expenditure in the power sector, GHG will be effectively reduced, but on the other hand this also "leads to higher price for electricity and natural gas, which correspondingly reduce economic output."

A.II.7.4 Development status and analysis results

As in the EPRI Prism 2.0 report, the US-REGEN model has been developed and produced results to analyze the road map of U.S. GHG reduction. Key results from the Reference Case include significant retrofit of the existing coal plants, addition of new nuclear power plants, and steady increase of wind generation, and generation expansions are different for different areas and inter-regional transmissions are built as well. "The projected composition in 2035 is as follows: coal at 28%, natural gas at 25%, nuclear at 21%, renewables 26%." East and south see many retirements of coal units, an increase of natural gas generation, and new renewables in the east and nuclear in the south. Midwest sees a great growth of wind generation. West shows lesser changes. The results also show that there are 50% and 70% reductions for NOx and SO2 respectively. CO2 emission continues to decline. The economy-wide impacts of the solutions will be between \$175 and \$275 billion. In addition, the results also shows that solutions of generation mix are very sensitive to the volatile natural gas price.

A.II.7.5 Limitations of the model

The Prism 2.0 analyses provide a great view of the road map of GHG reduction in the next 20 or so years. Although the US-REGEN model is a bottom-up model, it has not included many important engineering details of the electrical power systems, such as generator scheduling, power flow equations (Kirchhoff's current and voltage laws), etc. The intra-annual electricity demands are not able to model the variations and uncertainty of renewable resources. Energy storage and demand side management have not been included to balance the heterogeneous variations between renewable availability and demands. However, the costs and availability of technologies are constantly changing over time with high uncertainties. Hence dynamic and stochastic models are more appropriate in this respect.

A.II.8 REMix

German Aerospace Center DLR has used a geographic information system to assess the potentials of renewable energy generation in Europe with high spatial and temporal resolution. The results have been used in a model to balance renewable generation and demand, and interregional energy flows []. The model, which is used to analyze the new generation mix and regional and interregional electricity balance and flows, is the REMix model (Renewable Energy Mix for sustainable energy supply in Europe) [115]. This model is in accordance with the Europe Energy Policy to have sustainable, secure and competitive energy supplies to help combat climate change and reduce reliance on foreign fossil fuel. Because of the existence of fluctuations in both renewable energy availability and demand at times, it is necessary to have a model to evaluate the potentials to sustain the whole energy system using more renewable resources. In the following, details of the REMix model will be discussed and compared, including types of investment decisions, model features and computational methods, additional planning tool attributes and input assumptions, development status and findings, and model limitations.

A.II.8.1 Types of investment decisions made

Because of the variation of renewable energy among times and locations, and the fluctuation of demands, the decentralized generation mix including both fossil fuel and renewable sources, transmission and energy storage are all required to fulfill all criteria aimed by European Union Energy Policy. In order to have them done in a cost-efficient way, the questions to ask are: what types of generation capacity need to be installed and where; how much storage and transmission capacity are needed and where to cover fluctuating demands by fluctuating renewable resources at low costs?

The REMix model includes investment decisions on the generation portfolio (both fossil fuel and renewable generators), power transmission between regions and energy storage. Renewable resources include solar energy (both photovoltaic and concentrating solar thermal power), wind power, hydro power, biomass and geothermal power. Transmission includes both traditional high voltage AC and high voltage DC technologies. Energy storage includes pumped-storage hydro power, adiabatic compressed air energy storage, and hydrogen energy storage. As this model is a static model in terms of capacity expansion, the investment decisions are only associated with spatial information but not with temporal information. This means that the investments are made only once at the beginning. Once invested (given the new capacities), the remaining part of the model is how to perform efficient operations in terms of total cost.

A.II.8.2 Model features and computational methods

The REMix model is a pure linear programming (LP) model with only continuous variables, "in order to keep the running time as low as possible." Its objective is to minimize the total energy system cost, including both investment costs and systems' operating and maintenance costs. The model is coded in GAMS and solved by popular LP solvers such as CPLEX. In terms of expansion planning, this is a static model. But the operational level problem is capturing multiple-year features of the energy systems in terms of the electricity and heat demands. In this level, the constraints are standard capacity and demand satisfaction constraints. However, the operational decisions across years are not directly related to each other except all coupling with the investment decisions.

Although this model is an LP, which can be solved efficiently by commercial solvers such as CPLEX, EXPRESS, etc., the problem instances of REMix are still very challenging. This is because it includes large-scale temporal and spatial information. Hourly demands for multiple years in 36 European and North African regions/countries are considered in the runs of the model. To this end, aggregations and reductions of regions and times are used to reduce the computational burden of the large-scale instances. As stated in [115], "depending on the number of regions and time steps regarded, the model running times are several hours up to several weeks on a server with a 64 bit operating system, 2.8 GHz processor and 32 GB main memory."

A.II.8.3 Additional planning tool attributes and model assumptions

Load duration curve or chronologically ordered load curves: Hourly electricity and heat demands from 2010 to 2050 across 36 European and North African regions/countries are used in this model. The regions are further divided into 10km by 10km blocks, some of which are the conservation or protected areas and then are excluded in its current analyses. Policy goals are incorporated in the model by additional constraints. For example, a renewable energy share can be set up; for regions, a domestic supply share can be set up. In addition, some variables can be preset or bounded by upper and lower limits to ensure the share of renewables and domestic supply. Interregional transmission is modeled by the simple transportation constraints instead of using the DC or AC current flow representations. This is because the aim of the study is to understand the energy flows among the 36 regions, and thus technical details of power transmission are not included.

Network representation and transmission options: The power grid representation is similar to a transportation network. It does not consider power flow analysis using Kirchhoff's current and voltage laws.

Optimization interval: This model is to understand the total amount of installed capacity for each generation technologies within the given region. Hence it is a static model. Its operational problem is a one-year demand and supply problem by using the transportation model.

Application of reserve constraints: Based on the available publication, no reserve constraints are considered in this model.

Provision for demand-side option: Based on the available publication, no demand-side options/management is considered in this model.

Methods of handling uncertainty: This is a deterministic linear programming model, which does not include uncertainty.

A.II.8.4 Development status and findings

This model has been fully developed before 2012, and details are discussed in Dr. Scholz's PhD dissertation. As this model is capturing the features of multiple-region energy system and there exist high variations among different renewable resources and heterogeneous electricity and heat demands among regions, transmission expansion or build-up is a crucial element of a low-cost and renewable-energy-based energy supply and demand system. Although the results show that it is very important and necessary to have international/interregional cooperation to reach the cost-minimal energy system, it might not be directly applicable due to political or other reasons. Hence, the REMix model also considers this aspect by limiting the transmission. Both whole-networked and island-constrained instances have been run to obtain some insights. It is certain the total cost is lower in the whole-networked system. Depending on the regions' locations, certain region island-constrained electricity costs can be much higher than, or a little higher than, or even lower than the whole-networked case. In addition, [115] reported that the model results are very sensitive to the parameter changes.

A.II.8.5 Limitations of the Model

As is stated in **Error! Reference source not found.**, a stochastic model is more realistic for this study since the renewable energy availability is very uncertain. However, due to computational reasons, the model only captures the deterministic features. A stochastic model along with more advanced computational techniques is expected to obtain more robust and realistic optimal solutions. The REMix model in essence is a static model in terms of expansion investments. However, the costs and availability of technologies are constantly changing over time with high uncertainties. Hence dynamic and stochastic models are more appropriate in this respect. Again, it has to come with strong computational tools capable of solving instances with realistic sizes. Another limitation of this model is that expansions are considered as continuous variables. In reality, some of the investment decisions are discrete, which denote whether some investment are made and cannot be continuous. Hence multistage stochastic mixed integer programming models are more appropriate.

A.II.9 LIMES

LIMES is a long-term power system model developed by researchers at Potsdam Institute for Climate Impact Research (PIK). It is built from a social planners' perspective to minimize overall power system costs, including the costs of power generation and transmission investments, fuel, and O&M. It is formulated as a linear program (without uncertainties) through GAMS and is solved by the CPLEX solver [45, 46, 96].

A.II.9.1 Types of investment decisions made

The LIMES model is a power-sector-only model. It endogenously determines the capacity expansions of generation, transmission and energy storage resources, as well as short-term electricity dispatch level. The generation resources include renewable energy. Based on the publicly available documents, LIMES does not include investment decisions on demand-side resources.

A.II.9.2 Features and computational methods of model optimizer

The salient feature of the LIMES model is its usage of time slices to realize the multiscale modeling of both long-term planning and short-term dispatch operations of power systems. The model is a multi-period, deterministic, linear programming model.

A.II.9.3 Summary of additional planning tool attributes

Load duration curve or chronologically ordered load curves: The LIMES model uses the concept of time slices (a variation of the load duration curve). Within each calendar year, four seasons are modeled. In each season, three representative days are chosen to respectively represent three renewable supply regimes: low, medium and high. Within each of such days, 4 time slices are modeled, with each slice being the average load of a period of six hours. In addition to the 48 time slices (4 slices/day × 3 days/season × 4 seasons/year) in a year, one more slice is included in the model to represent a super-peak period. Hence, total of 49 time slices (and correspondingly, 49 supply-demand balancing constraints) are modeled in each year within the planning horizon.

Network representation and transmission options: The grid representation in LIMES model is similar to a transportation network. It does not consider power flow distribution effects.

Depreciation and end-period effects: A salvage value approach is used to avoid the end effects in the model. Salvage values are calculated as a percentage of the investment costs, with the investment time of new capacities explicitly considered in the calculation; namely, the later capacity is built, the higher salvage value it has.

Modeling of operational and maintenance costs: Both fixed and variable O&M costs of each technology are considered in the model. Fixed O&M costs of a particular technology are given as a percentage of its investment costs per year. Marginal costs are assumed to be constants and are given through input data.

Optimization interval: The optimization model builds upon a multi-scale structure, in while investment intervals are years, while short-term operational decisions are made by time slices.

Application of reserve constraints: Based on publicly available documents of LIMES, there are no reserve constraints in the model.

Provision for demand-side option: Currently there are no demand-side options available in LIMES.

Methods of handling uncertainty: Since the LIMES model is a deterministic linear programming model, uncertainties are not endogenously considered in the model when investment or operational decisions are made. However, in preparing input data to the deterministic model, the time-slice concept is used to simulate the fluctuation of renewable resources' outputs and demand. For wind (on-shore and off-shore) and solar plants (PV and CSP), the fluctuation of the resources' outputs is reflected in their capacity factors, which are input data, but have different values at different time slices.

Historical meteorological data are collected and the conversion from such data to capacity factors of the corresponding renewable power plants are through established mathematical formula in literature, as documented in [45]. Load variations across time slices are calculated through historical load data, but scaled to match the projected load growth rate.

A.II.9.4 Development status, previous applications and associated typical run times

The LIMES model has been utilized to analyze the power systems in Europe and Middle East/North Africa (MENA) regions [45]. The model, together with the regional database, is referred to as the LIMES-EU+ model. This model includes EU-27 member countries, Norway, Switzerland, and the Middle Eastern and North American countries surrounding the Mediterranean Sea. They are represented as 20 geographical regions in the model, and are connected by 32 transmission corridors. Nine generation technologies are included in the model: coal, natural gas, nuclear, biomass, IGCC, hydro, wind (onshore/offshore), photovoltaic (PV) and concentrating solar power (CSP). The planning horizon is from 2010 to 2050. No information is publicly available about the solving time of the resulting LIMES-EU+ model.

A.II.9.5 Limitations and challenges

The main limitation of the model lies in its time representation in the finer time scale, which only uses aggregate hours in representative days. Such a structure cannot capture extreme events or finer time scale fluctuations of renewables and demand. In addition, the model cannot handle uncertainties explicitly, and hence is only useful for scenario-based analyses.

A.II.10 SWITCH

The SWITCH model – a loose acronym for Solar, Wind, Hydro, and Conventional generation and Transmission Investment – is a long-term power system capacity expansion model developed at University of California, Berkeley.

A.II.10.1 Types of investment decisions made

Investment decisions in the SWITCH model include new generation (including distributed generation), storage, and high-voltage transmission lines.

A.II.10.2 Features and computational methods of model optimizer

The SWITCH model is a mixed-integer linear programming model (MILP). The integer variables are of binary form only, and arise from the decisions of whether existing units in a particular planning period should be operated or not. The model is coded through the modeling language AMPL, and uses CPLEX as the optimization solver. For the study of the WECC power system, the SWITCH model results in a MILP of approximately 800,000 constraints, 800,000 linear decision variables, and 2000 binary variables.

A.II.10.3 Summary of additional planning tool attributes

Load duration curve or chronologically ordered load curves: The SWITCH model uses a similar approach to model short-term system operation as in PIK's LIMES model. Within an investment period (that may be of one or multiple years), two days are selected for each month for a total of 12 months. Within each day, 6 hours are selected, which result in a total of 144 sampled hours (6 hours/day × 2 days/month × 12 months) per investment period.

Network representation and transmission options: The SWITCH model represents the electric grid as a transportation model. It does not consider Kirchhoff's Laws and does not include power flow analysis.

Depreciation and end-period effects: The SWITCH model amortizes the capital costs of new investment over its specified book life, instead of the modeled planning horizon, to avoid the end-period effect.

Modeling of operational and maintenance costs: Both fixed and variable O&M costs are considered in SWITCH model.

Optimization interval: The SWITCH model considers two different time scales. On the planning level, the optimization interval is by years, or by planning periods (with a planning period possibly contains multiple years). On the operation level (i.e., the economic dispatch level), the optimization interval is by hours. But only the selected hours within each planning period are considered, as described above.

Application of reserve constraints: The SWITCH model contains a reserve margin constraint to ensure long-term resource adequacy. Modeling of short-term ancillary services is not done currently in SWITCH, but is under development.

Provision for demand-side option: Based on publicly available documents, no demand-side options are available in the SWITCH model.

Methods of handling uncertainty: SWITCH is a deterministic, mixed-integer linear programming model, and does not handle uncertainty endogenously.

A.II.10.4 Development status, previous applications and associated typical run times

SWITCH model has been used to analyze the power system of western North America (WECC). The analysis is done for years 2014 to 2029. A total of 124 existing and new transmission corridors are modeled in the study. Total of 5 different cases are constructed for scenario-based analysis. The study results are documented in [96].

A.II.10.5 Limitations and challenges

As the SWITCH model shares similarities with the PIK's LIMES model in several key modeling approaches, including its deterministic nature, network and load representation and short-term operation modeling, all the limitations and challenges faced by the LIMES model are also shared by the SWITCH model.

A.II.11 GENTEP

The Illinois Institute of Technology's (IIT) software tool for the stochastic co-optimization of generation and transmission expansion planning (referred to as GENTEP) in electric power systems explores various alternatives for enhancing the power system economics and reliability while accommodating the inherently random characteristics of the future power grid, especially those caused by the large-scale penetration of renewable energy, widespread implementation of microgrids, and the additional utilization of capacity-based demand response [65]. GENTEP represents a unique and innovative power system expansion planning tool for several reasons. GENTEP considers:

1. a large-scale market-based co-optimization of generation and transmission planning rather than the traditional decoupled (staged, transmission-only, generation-only, etc.) planning.
2. a stochastic mixed-integer linear programming approach in which the uncertainties in load and renewable energy as well as forced outage rates of system components are considered.

3. a microgrid-based regional planning in congested and less accessible transmission zones as an alternative to the large-scale generation and transmission expansion planning.
4. a capacity-based demand response of aggregated loads as a coordinated planning alternative for deferring the large-scale expansion of generation and transmission systems.

GENTEP applications will address such critical questions as: How much transmission capacity would be needed to economically and reliably deliver the energy produced by a wind farm with a typical installed capacity of 1,000MW? How much backup generation capacity would need to be planned to reliably operate a power system with a 60% renewable energy penetration? How much of co-optimized generation and transmission capacity would need to be planned to support a microgrid with a 30MW peak demand, 20MW of gas turbine generation, 10MW of wind energy turbines, and storage capacity of 5MW? How much of generation and transmission capacity could be saved at the planning stage when considering a load aggregator with a 100MW peak demand and a potential for 20% demand response? Is it more economical/ reliable to invest in remotely located large-scale generating stations and additional long distance HVDC/AC transmission for delivery or is it more justifiable to invest in locally distributed generation and multiple microgrids with small generators?

Figure A.II-3 shows the inputs, the engine, and the outputs of GENTEP. On the input side, loads with or without demand response options could be aggregated. Microgrids equipped with local generation (renewable and/or non-renewable) and large-scale storage would act as loads in most cases. However, they could also provide energy to the grid under certain conditions. To supply the increase in aggregated loads or those of microgrids, the RTO/ISO should plan a proper mix of generation and transmission technologies. Renewable energy could contribute to the generation mix depending on their locations and profiles. When renewable energy constitutes a significant percentage of the total generation supply, it has to be backed up by a certain amount of conventional and controllable generation technologies such as gas turbines. To connect the generation supply to the load requested by aggregators and microgrids, the RTO/ISO should also plan a proper mix of transmission capabilities including HVDC/AC transmission.

GENTEP will also consider other inputs including the minimum reliability criteria, demand and fuel price forecasts, and regulatory policies. The GENTEP algorithm will execute a stochastic co-optimization of generation and transmission planning, microgrid planning, and capacity-based demand response for calculating the minimum total of investment cost, operation cost, and unserved energy cost, as shown in Figure A.II-4. The stochastic optimization will rely on scenario analyses for representing the demand, capacity-based demand response, and generation and transmission.

The input/output of GENTEP uses the Oracle database, and GENTEP solves the mixed integer linear programming problem by using CPLEX.

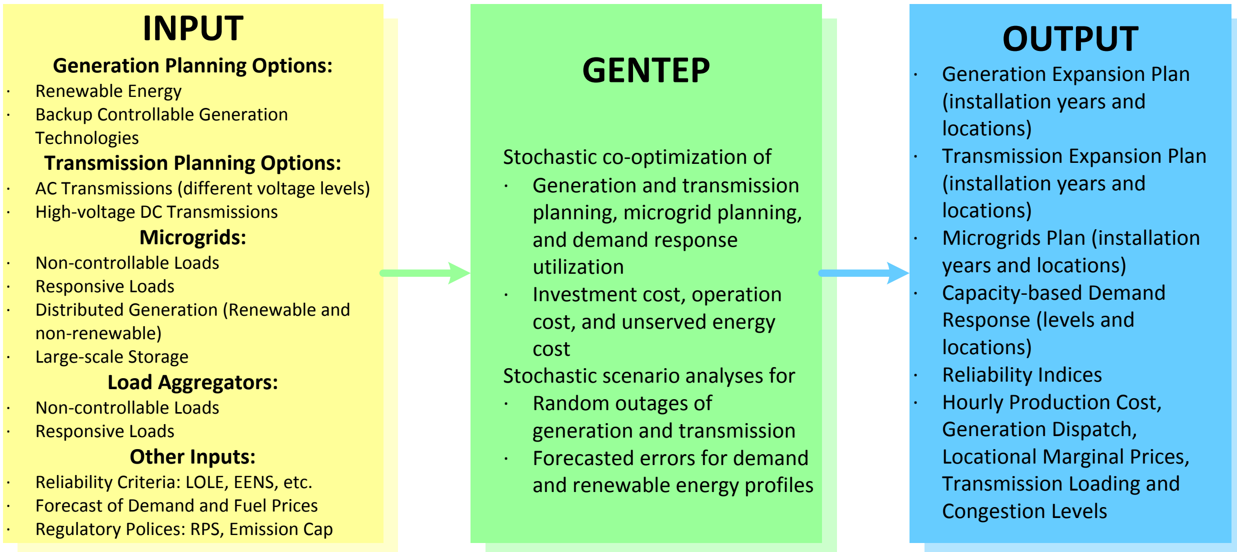

Figure A.II-3. GENTEP input, engine and output

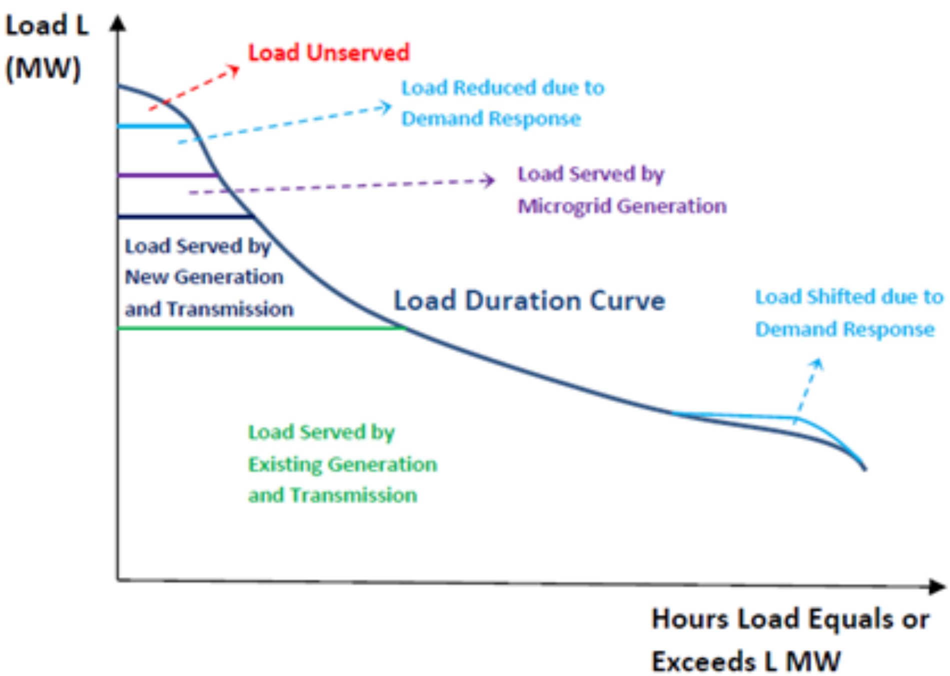

Figure A.II-4. Resource planning alternatives for serving the annual load

A graphical illustration of the GENTEP planning problem is shown in Figure A.II-5. The entire planning problem is solved by decomposing it into a master planning problem, a reliability subproblem, and an operation subproblem. The most unique feature of GENTEP is that it provides a proactive optimization-based solution, rather than a heuristic or experience-based approach on selecting potential generation, transmission, microgrid, and capacity-based demand response alternatives, that optimizes investment strategies along with operation and reliability constraints. The input information are categorized into various types of generating units, various transmission elements including HVDC transmission, and demand response, and output information include commitment and dispatch of generating units, transmission flows and controls.

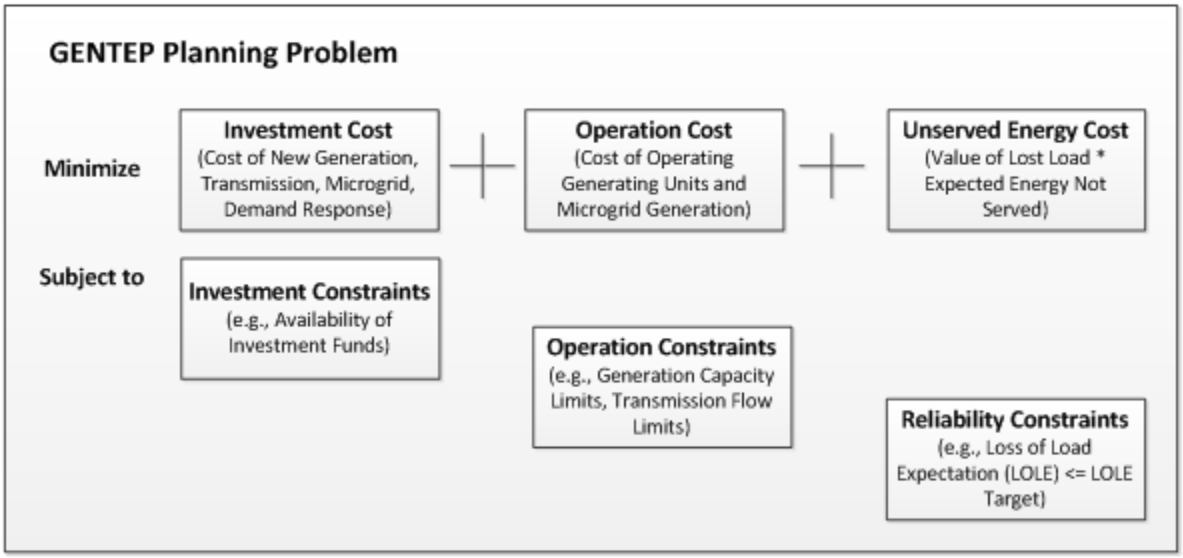

Figure A.II-5. Co-optimization planning model of GENTEP

Appendix III. Computational Algorithms for Large-scale Co-optimization Models

A.III.1 Benders Decomposition

This appendix gives an introduction to Benders decomposition, whose potentials, benefits, limits and applications in large-scale co-optimization models are discussed in Section 2.3. Given the following problem [P],

$$
\begin{aligned}
\text{[P]:}\quad \textbf{Minimize}\quad & c^T x + d^T y \\
\textbf{subject to}\quad & x \in X \\
& Ax + By \geq b \\
& y \geq 0
\end{aligned}
$$

When solving [P] is much harder than solving problem involving only x or y individually, we can choose to break down the problem to two problems: the restricted master problem [RMP] and subproblem [SP], which are both shown as follows,

[RMP]: **Minimize** $c^T x + \pi$

subject to $x \in X$

$\pi \geq \hat{\mu}_k^T (b - Ax)$

[SP]: **Minimize** $c^T \hat{x} + d^T y$

subject to $By \geq b - A\hat{x}$

$y \geq 0$

where $\hat{x}$ is a solution of [RMP] and $\hat{\mu}_k^T$ is an optimal dual solution corresponding to the first constraint of [SP]. In the above we assume [SP] is always feasible since we always can add artificial variables with huge penalties to make it happen. Benders decomposition solves these two problems iteratively until the upper bound (optimal objective value of [RMP]) meets or gets very close to lower bound (optimal objective value of [SP]) [121]. The steps of the algorithm is shown as follows,

Step 1: Initialization of a feasible $\hat{x} \in X$;

Step 2: Solve [SP], obtain the optimal primal and dual solutions $(\hat{y}, \hat{\mu})$;

Update upper bound if $c^T \hat{x} + d^T \hat{y}$ is smaller than the incumbent;

Step 3: Add a Benders' cut as in [RMP] by using $\hat{\mu}$;

Solve [RMP], and update lower bound by the new optimal objective value;

Step 4: Compare upper bound and lower bound if convergence criterion is met;

If so, stop; otherwise, go back to Step 2.

A.III.2 Column Generation Algorithm

This appendix gives an introduction to column generation algorithm, whose potentials, benefits, limits and applications in large-scale co-optimization models are discussed in Section 2.3. Column Generation (CG) algorithm is based on a convex analysis theorem that any point in a convex set can be represented by a convex combination of some extreme points of the convex set. For example, instead of using the constraints defining the whole convex set *X*, we only use some of its extreme points. The restricted master problem then uses the convexity variables (λ^j) instead of the original variable x. Still considering the original problem [P] in Benders decomposition, the restricted master problem is shown as follows,

$$\text{[CG-RMP]: } \textbf{Minimize} \quad \sum_j (c^T x^j)\lambda^j + d^T y$$

$$\textbf{subject to} \quad \sum_j (Ax^j)\lambda^j + By \geq b$$

$$\sum_j \lambda^j = 1$$

$$y \geq 0$$

When x are binary or discrete variables, λ's need to be restricted as binary variables as well. The restricted master problem keeps adding the most promising (with the most reduced cost) columns, which are obtained by solving the subproblems. When the same structure is experienced as in Figure A.III-1, there are many convex sets, $X^1, X^2, \ldots, X^n$. These convex sets are not related to each other, and then the subproblems can be solved individually when the dual solutions of the restricted master problem are known. Each of them is a much easier problem to solve. The master problem with multiple subproblems is shown as the following figure,

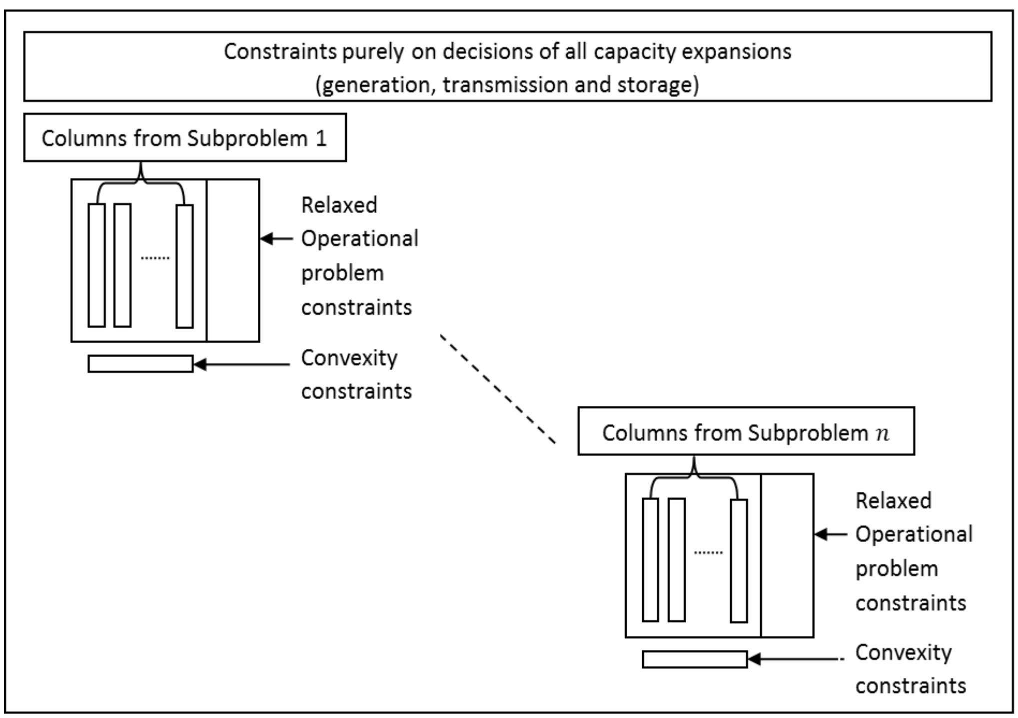

Figure A.III-1. Restricted master problem with multiple subproblems in parallel

REFERENCES

[1] S. Ahmed, A. J. King, and G. Parija, "A multi-stage stochastic integer programming approach for capacity expansion under uncertainty," Journal of Global Optimization, Vol. 26, 3–24, 2003.

[2] B. Alizadeh and S. Jadid, "Reliability constrained coordination of generation and transmission expansion planning in power systems using mixed integer programming," IET Generation, Transmission & Distribution, Vol. 5(9), 948–960, 2011.

[3] K. J. Arrow and G. Debreu, "Existence of an equilibrium for a competitive economy," Econometrica, 22: 265–290, 1954.

[4] M. Awad, K. E Casey, A. S. Geevarghese, J. C. Miller, A. F. Rahimi, A. Y. Sheffrin, M. Zhang, E. Toolson, G. Drayton, B. F. Hobbs, and F. A. Wolak, "Economic assessment of transmission upgrades: application of the California ISO approach," Ch. 7, in X. Zhang, Restructured Electric Power Systems: Analysis of Electricity Markets with Equilibrium Models, Power Engineering Series, J. Wiley & Sons/IEEE Press, 241-270, July 2010.

[5] L. Bahiense, G. Oliveira, M. Pereira, and S. Granville, "A mixed integer disjunctive model for transmission network expansion," IEEE Transactions on Power Systems, Vol. 16, no. 3, 560–565, Aug. 2001.

[6] N. J. Balu, R. Adapa, G. Cauley, M. Lauby, and D. J. Maratukulam, "Review of expert systems in bulk power system planning and operation," Proceedings of the IEEE, Vol. 80, No. 5, May 1992.

[7] L. Baringo and A. J. Conejo, "Transmission and Wind Power Investment," IEEE Transactions on Power Systems, Vol. 27 (2): 885-893, 2012.

[8] C. Barnhart, C. A. Hane and P. H. Vance, "Using branch-and-price-and-cut to solve origin-destination integer multicommodity flow problems," Operations Research, Vol. 48(2), 318-326, 2000.

[9] J. Barquín, E. Centeno and J. Reneses, "Stochastic market equilibrium model for generation planning," Probability in the Engineering and Informational Sciences, Vol. 19, 533-546, 2005.

[10] J. Bastian, J. Zhu, V. Banunarayanan, and R. Mukerji, "Forecasting Energy Prices in a Competitive Market," IEEE Computer Applications in Power Magazine, Vol. 12, no. 3, 40-45, July 1999.

[11] J. F. Benders, "Partitioning procedures for solving mixed-variables programming problems," Numerische Mathematik, Vol. 4, 238–252, 1962.

[12] G. D. Berry, and A. D. Lamont, "Carbonless Transportation and Energy Storage in Future Energy Systems," UCRL-ID-142084, January 17, 2001.

[13] D.P. Bertsekas, L.C. Polymenakos, and P. Tseng, "Epsilon-Relaxation Method for Separable Convex Cost Network Flow Problems", SIAM Journal on Optimization, Vol. 7 (1997), 853-870.

[14] C. Blair and R. Jeroslow, "The value function of an integer program," Mathematical Programming, Vol. 23, 237–273, 1982.

[15] C. Blanco and D. Soronow, "Mean reverting processes – energy price processes used for derivatives pricing & risk management," Commodities Now, June 2001, 68-72.

[16] J. A. Bloom, "Solving an electricity generating capacity expansion planning problem by generalized Benders' decomposition," Operations Research, Vol. 31(1), 84–100, 1983.

[17] A. Castillo and R. P O'Neill, "Computational performance of solution techniques applied to the ACOPF," Optimal power flow paper-5, FERC staff paper, March 2013.

[18] J. W. Chang, J. P. Pfeifenberger, and J. M. Hagerty, A WIRES Report on the Benefits of Electric Transmission: Identifying and Analyzing the Value of Investments, The Brattle Group, www.WIRESgroup.com, July 2013.

[19] COMPETES website: www.ecn.nl/units/ps/models-and-tools/competes/

[20] D. Connolly, H. Lund, B. V. Mathiesen, M. Leahy, "A review of computer tools for analysing the integration of renewable energy into various energy systems," Applied Energy, Vol. 87(4), 1059–1082, April 2010.

[21] J. Contreras and F. F. Wu, "A kernel-oriented algorithm for transmission expansion planning," IEEE Transactions on Power Systems, Vol. 15, 1434–1440, Nov. 2000.

[22] G. B. Dantzig and P. Wolfe, "Decomposition principle for linear programs," Operations Research, Vol. 8, 101–111, 1960.

[23] T. Das, V. Krishnan, and J. McCalley, "High-fidelity dispatch model of storage technologies for production costing studies," under review in IEEE Transactions on Power Systems, 2013

[24] T. Das, "Performance and Economic Evaluation of Storage Technologies," Ph.D. Dissertation, Iowa State University, May 2013

[25] J. R. Davis, Q. P. Zheng, V. A. Paramygin, B. Tutak, C. Vogiatzis, Y. P. Sheng, P. M. Pardalos, and R. J. Figueiredo, "Development of a Multimodal Transportation Educational Virtual Appliance (MTEVA) to study congestion during extreme tropical

events," Proceedings of the Transportation Research Board (TRB) 91st Annual Meeting, Paper No. 12-1119, Washington, D. C., January, 2012.

[26] C. De Jonghe, B. F. Hobbs, and R. Belmans, "Optimal generation mix with short-term demand response and wind penetration," IEEE Transactions on Power Systems, Vol. 27, No. 2, 830-839, May 2012.

[27] J. Ding and A. Somani, "Parallel computing solution for capacity expansion network flow optimization problems," Journal of Computing, Vol. 4(7), July 2012

[28] S. Deng, "Stochastic models of energy commodity prices and their applications: mean-reversion with jumps and spikes," working paper PWP-073, University of California Energy Institute, 2000. Vol.

[29] Dupačová, N. Gröwe-Kuska, and W. Römisch. "Scenario reduction in stochastic programming," Mathematical Programming, Series A, Vol. 95, Issue 3, 493-511, 2003.

[30] Y. P. Dusonchet, and A. El-Abiad, "Transmission planning under discrete dynamic optimization," IEEE Trans. On Power Apparatus and Systems, Vol. PAS-92, Jan. 2007.

[31] EPRI Prism/MERGE Analyses – 2009 update (EPRI Report 1019563). August 2009. www.epri.com/abstracts/Pages/ProductAbstract.aspx?ProductId=000000000001019563

[32] EPRI Prism 2.0: The Value of Innovation in Environmental Controls (EPRI Report 1026743), October 2012. www.epri.com/abstracts/Pages/ProductAbstract.aspx?ProductId=000000000001026743

[33] G. Frey, M. Manera, A. Markandya and E. Scarpa, "Econometric models for oil price forecasting: a critical survey," CESifo Forum, 2009, 29-44.

[34] M. Fripp, "Optimal Investment in Wind and Solar Power in California," PhD Dissertation, University of California, Berkeley, 2003.

[35] Y. Fukuyama, and H. Chiang, "A parallel genetic algorithm for generation expansion planning," IEEE Transactions on Power System, Vol. 11, May 1996.

[36] S. A. Gabriel, A. J. Conejo, J. D. Fuller, B. F. Hobbs, and C. Ruiz, Complementarity Modeling in Energy Markets, Springer-Verlag, International Series in Operations Research and Management Science, Heidelberg/Dordrecht/London, 2012.

[37] GenTrader website: www.powercosts.com/products/gentrader.asp

[38] H. Geman, "Mean reversion versus random walk in oil and natural gas prices," in Advances in Mathematical Finance, Birkhäuser Boston, edited by M. C. Fu, R. A. Jarrow, J-Y. J. Yen, and R. J. Elliott, 219-228, 2007.

[39] M. Geoffrion, “Generalized Benders decomposition,” Journal of Optimization Theory and Applications, Vol. 10(4), 237–260, 1972.

[40] R. C. Grinold, “Model Building Techniques for the Correction of End Effects in Multistage Convex Programs,” Operations Research, Vol. 31, No. 3, 407-431, May-Jun., 1983

[41] Y. Gu and J. McCalley, “Market-based transmission expansion planning with uncertainty,” in Proceedings of North American Power Symposium, Arlington, Texas, September 2010.

[42] Y. Gu and J. McCalley, “Market-based transmission planning considering large-scale wind power,” in Proc. The International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants, Québec, Canada, October 2010.

[43] Y. Gu and J. McCalley, “Market-based transmission expansion planning,” in Proc. IEEE PES Power Systems Conference & Exhibition (PSCE), Phoenix, Arizona, March 2011.

[44] Y. Gu, J. McCalley, and M. Ni, “Coordinating large-scale wind integration and transmission planning,” submitted to IEEE Transactions on Renewable Energy, 2011.

[45] M. Haller, S. Ludig, N. Bauer, “Decarbonization scenarios for the EU and MENA power system: Considering spatial distribution and short-term dynamics of renewable generation: Supplementary material,” 2011.

[46] M. Haller, S. Ludig, and N. Bauer, “Decarbonization scenarios for the EU and MENA power system: Considering spatial distribution and short-term dynamics of renewable generation,” Energy Policy, Vol. 47, 282 – 290, 2012.

[47] E. Handschin, M. Heine, D. König, T. Nikodem, T. Seibt, and R. Palma, “Object-oriented software engineering for transmission planning in open access schemes,” IEEE Transactions on Power Systems, Vol. 13, 94–100, Feb. 1998.

[48] W. Head, H. Nguyen, et al “The procedure used to assess the long range generation and transmission resources in the Mid-Continent Area Power Pool,” IEEE Transactions on Power Systems, Vol. 5, Nov. 1990.

[49] K. W. Hedman, S. S. Oren, and R. P. O’Neill, “A review of transmission switching and network topology optimization,” in IEEE Power and Energy Society General Meeting, 2011

[50] B. F. Hobbs, “Regional energy facility location models for power system planning and policy analysis,” in Analytic Techniques for Energy Planning, B. Lev, F. Murphy, J. Bloom, and A. Gleit, eds., North-Holland Press, Amsterdam, 1984, 53-66.

[51] B. F. Hobbs, “Optimization methods for electric utility resource planning,” European Journal of Operational Research, Vol. 83(1), 1-20, 1995.

[52] B. F. Hobbs, G. Drayton, E.B. Fisher, and W. Lise, “Improved transmission representations in oligopolistic market models: Quadratic losses, phase shifters, and DC lines,” IEEE Transactions on Power Systems, Vol. 23(3), 1018-1029, July 2008.

[53] B. F. Hobbs, M. Hu, Y. Chen, J. H. Ellis, A. Paul, D. Burtraw, and K. L. Palmer, “From regions to stacks: Spatial and temporal downscaling of future pollution scenarios for the power sector,” IEEE Transactions on Power Systems, Vol. 25(2), 1179-1189, May 2010.

[54] B. F. Hobbs and F. A. M. Rijkers, “Modeling strategic generator behavior with conjectured transmission price responses in a mixed transmission pricing system I: Formulation, II: Application,” IEEE Trans. Power Systems, Vol. 19(2), 707-717, 872-879, May 2004.

[55] B. F. Hobbs, M. H. Rothkopf, R. P. O'Neill, and H.-P. Chao, eds., The Next Generation of Electric Power Unit Commitment Models, International Series in Operations Research & Management Science, Kluwer Academic Publishers, Boston/Dordrecht/ London, 2001.

[56] W. W. Hogan and J. P. Weyant, “Combined energy models,” Advances in the Economics of Energy and Resources, Vol. 4, 117-150, 1982.

[57] M.-C. Hu and B.F. Hobbs, "Analysis of multipollutant policies for the U.S. power sector under technology and policy uncertainty using MARKAL", Energy: The International Journal, Vol. 35, 5430-5442, 2010.

[58] S. Huang, B-M. S. Hodge, F. Taheripour, J. F. Pekny, G. V. Reklaitis and W. E. Tyner. “The effects of electricity pricing on phev competitiveness,” Energy Policy, Vol. 39, 1552-1561, 2011.

[59] E. Ibanez, “A Multi-objective Optimization Approach to the Operation and Investment of the National Energy and Transportation Systems,” Ph.D. dissertation, Iowa State University, 2011, http://lib.dr.iastate.edu/etd/11948

[60] ICF, Inc., Integrated Planning Model, http://www.icfi.com/insights/products-and-tools/ipm, Fairfax, VA, 2013.

[61] ISO New England, CELT Forecasting Details, http://www.iso-ne.com/trans/celt/fsct_detail/

[62] International Atomic Energy Agency, Enhanced Electricity System Analysis for Decision Making, 2000.

[63] R. Jiang, J. Wang and Y. Guan. “Robust unit commitment with wind power and pumped storage hydro,” IEEE Transactions on Power Systems, Vol. 27, No. 2, 800-801, 2012.

[64] E. Kahn, “Regulation by simulation: the role of production cost models in electricity planning and pricing”, Operations Research, Vol. 43 no. 3, 388-398, 1995.

[65] A. Khodaei and M. Shahidehpour, “Microgrid-based co-optimization of generation and transmission planning in power systems,” IEEE Transactions on Power Systems, Vol. 28, no. 2, 1582–1590, 2013.

[66] A. Khodaei, M. Shahidehpour, L. Wu, Z. Li, “Coordination of short-term operation constraints in multi-Area expansion planning,” IEEE Transactions on Power Systems, Vol. 27, no. 4, 2242–2250, 2012.

[67] A. J. Kleywegt, A. Shapiro, and T. Homem-de-Mello. “The Sample Average Approximation Method for Stochastic Discrete Optimization,” SIAM Journal on Optimization, Vol. 12(2), 479-502, 2002.

[68] V. Koritanov, T. Veselka, “Modeling the regional electricity network in Southeast Europe,” Power Engineering Society General Meeting, Vol. 1, July 2003.

[69] V. Krishnan, T. Das, E. Ibanez, C. Lopez, and J. McCalley, “Modeling operational effects of wind generation within national long-term infrastructure planning software,” IEEE Transactions on Power Systems, 2012.

[70] V. Krishnan, E. Kastrouni, D. Pyrialakou, K. Gkritza, and J. McCalley, “An optimization model of national energy and transportation systems: Application on assessing the impact of high-speed rail on US passenger transportation investment portfolio,” working paper available at www.ece.iastate.edu/research/netscore-21

[71] V. Krishnan, J. McCalley, S. Lemos, and J. Bushnell, “Nation-wide transmission overlay design and benefits assessment for the US,” Energy Policy, 2013, http://dx.doi.org/10.1016/j.enpol.2012.12.051

[72] V. Krishnan, H. Liu, and J. D. McCalley, “Coordinated reactive power planning against power system voltage instability,” in Proceedings of IEEE/PES Power Systems Conference and Expo., Mar. 2009

[73] A. Lamont, “User's guide to the META-Net economic modeling system; version 1.2,” Lawrence Livermore National Laboratory, UCRL-ID-122511, 1994.

[74] A. Lamont, “Assessing the economic value and optimal structure of large-scale electricity storage,” to appear in IEEE Transactions on Power Systems, 2013.

[75] G. Laporte and F. V. Louveaux, “The integer L-shaped methods for stochastic integer programs with complete recourse,” Operations Research Letters, Vol. 13, 133–142, 1993.

[76] G. Latorre-Bayona and I. J. Pérez-Arriaga, “Chopin, a heuristic model for long term transmission expansion planning,” IEEE Transactions on Power Systems, Vol. 9, 1886–1894, Nov. 1994.

[77] W. Li. and R. Billinton, “A minimum cost assessment method for composite generation and transmission system expansion planning,” IEEE Transactions on Power Systems, Vol. 8(2): 628–635, 1993.

[78] Y. Li, H. Villegas, J. D. McCalley, and D. Aliprantis, “National transmission overlay design,” working paper, Iowa State University.

[79] W. Lise, B. F. Hobbs, and S. Hers, “Market power in the European electricity market - The impacts of dry weather and additional transmission capacity,” Energy Policy, Vol. 36(4), 1331-1343, April 2008.

[80] J. A. López, K. Ponnambalam, and V. H. Quintana, “Generation and transmission expansion under risk using stochastic programming,” IEEE Transactions on Power Systems, Vol. 22(3), 1369–1378, Aug. 2007.

[81] M. Lu, Z. Dong, T. Saha, “A framework for transmission planning in a competitive electricity market,” Proc. of the Transmission and Distribution Conference and Exhibition: Asia and Pacific, 2005 IEEE/PES, 1-6, 2005.

[82] G. Lulli and S. Sen, “A branch-and-price algorithm for multistage stochastic integer programming with application to stochastic bath-sizing problems,” Management Science, Vol. 50(6), 786–796, 2004.

[83] M. Madrigal and S. Stoft, Transmission Expansion for Renewable Energy Scale-Up: Emerging Lessons and Recommendations, World Bank, Washington, DC, 2012.

[84] S. A. Malcolm and S. A. Zenios, “Robust optimization for power systems capacity expansion under uncertainty,” The Journal of the Operational Research Society, Vol. 45, No. 9, 1040-1049, 1994.

[85] MARS, 2013, website: www.gepower.com/prod_serv/products/utility_software/software/en/ge_mars.htm.

[86] J. McCalley, J. Bushnell, V. Krishnan, and S. Cano, “Transmission design at the national level: Benefits, risks and possible paths forward,” White Paper to PSERC, The Future Grid to Enable Sustainable Energy Systems, Jan 2012, www.pserc.wisc.edu/research/FutureGrid/broadanalysis.aspx.

[87] D. Mejia-Giraldo, “Robust and Flexible Planning of Power System Generation Capacity,” PhD Dissertation, Iowa State University, Ames, Iowa, 2013.

[88] A. Motamedi, H. Zareipour, M. O. Buygi, and W. D. Rosehart, “A transmission planning framework considering future generation expansions in electricity markets,” IEEE Transactions on Power Systems, Vol. 25(4), 1987–1995, Nov. 2010.

[89] Multimodal Transportation Educational Virtual Appliance (MTEVA), 2011. www.grid-appliance.org/wiki/index.php/MTEVA:Index.

[90] F. D. Munoz, B. F. Hobbs, J. Ho, and S. Kasina, “An engineering-economic approach to transmission planning under market and regulatory uncertainties: WECC case study,” IEEE Transactions on Power Systems, in press, 2013.

[91] F. H. Murphy and S. H. Shaw, “The evolution of energy modeling at the Federal Energy Administration and the Energy Information Administration,” Interfaces, Vol. 25(5), 173-193, 1995.

[92] P. Murugan, S. Kannan, and S. Baskar, “Application of NSGA-II algorithm to single objective transmission constrained generation expansion planning,” IEEE Transactions on Power Systems, Vol. 24(4), 1790–1797, 2009.

[93] N. Nabona, “Multicommodity network flow model for long-term hydro-generation optimization,” IEEE Transactions on Power Systems, Vol. 8(2), May 1993.

[94] F. E. N. Nasser, A. P. A. Silva, and L. A. P. Araujo, “Development of an expert system for long-term planning of power transmission networks,” in Proceedings of the 2nd Symposium of Experts Systems and Applications in Power Systems, 237–242, Jul. 1989.

[95] National Renewable Energy Laboratory, Golden, CO, Renewable Electricity Futures Study, NREL Report No. TP-6A20-52409, 2012.

[96] J. Nelson, J. Johnston, A. Mileva, M. Fripp, I. Hoffman, A. Petros-Good, C. Blanco, D. M. Kammen, “High-resolution modeling of the Western North American power system demonstrates low-cost and low-carbon futures,” Energy Policy, Vol. 43, 436–447, 2012.

[97] V. Niemeyer, “Prism 2.0: Preliminary insights from EPRI’s regional model,” Presentation to South Carolina PURCEAC Meeting, Feb. 2011.

[98] North American Electric Reliability Corporation (NERC), “Rules of procedure,” 2013. www.nerc.com/files/NERC_ROP_Effective_20130305.pdf.

[99] A. L. Otta, “Evolution of computing requirements in the PJM market: Past and future,” Proceedings of IEEE Power and Energy Society General Meeting, 1-4, 2010.

[100] C. K. Pang, G. B. Sheble, and F. Albuyeh, “Evaluation of dynamic programming based methods and multiple area representation for thermal unit commitments,” IEEE Transactions on Power Apparatus and Systems, March 1981.

[101] M. Pereira and L. Pinto, “Multi-stage stochastic optimization applied to energy planning,” Mathematical Programming, Vol. 52, 359-375, 1991.

[102] M. Pereira, L. Pinto, S. Cunha, and G. Oliveira, “A decomposition approach to automated generation/transmission expansion planning,” IEEE Transactions on Power Apparatus and Systems, Vol. 104(11), 3074–3083, 1985.

[103] J. P. Pfeifenberger and D. Hou, “Transmission’s true value: Adding up the benefits of infrastructure investments,” Public Utilities Fortnightly, February 2012, 44-50.

[104] PLEXOS, 2013, website: www.energyexemplar.com

[105] W. B. Powell, A. George, H. Simão, W. Scott, A. Lamont, J. Stewart. “SMART: A Stochastic Multiscale Model for the Analysis of Energy Resources, Technology, and Policy,” INFORMS Journal on Computing, Vol. 24, No. 4, 665-682, 2012.

[106] Power System Planning and Investment, NEDRI Report, March 2003.

[107] Promod, 2013, website: www1.ventyx.com/analytics/promod.asp

[108] ProSym, 2013, website: www.ventyx.com/analytics/market-analytics.asp

[109] R. T. Rockafellar and S. Uryasev, “Conditional value-at-risk for general loss distributions,” Journal of Banking & Finance, Vol. 26, 1443–1471, 2002.

[110] J. H. Roh, M. Shahidehpour, and Y. Fu, “Market-based coordination of transmission and generation capacity planning,” IEEE Transactions on Power Systems, Vol. 22(4), 1406–1419, Nov. 2007.

[111] J. H. Roh, M. Shahidehpour, and L. Wu, “Market-based generation and transmission planning with uncertainties,” IEEE Transactions on Power Systems, Vol. 24(3), 1587–1598, Aug. 2009.

[112] A. Ruszczyński. “Decomposition methods in stochastic programming,” Mathematical Programming, Vol. 79(1-3), 333-353, 1997.

[113] E. E. Sauma and S. S. Oren, “Proactive planning and valuation of transmission investments in restructured electricity markets,” Journal of Regulatory Economics, Vol. 30(3), 261-290, 358-387, 2006.

[114] R. Sawey and C. Zinn, “A mathematical model for long range expansion of generation and transmission in electric utility systems,” IEEE Transactions on Power Apparatus and Systems, Vol. 96(2), 657–666, 1977.

[115] Y. Scholz, Renewable Energy Based Electricity Supply At Low Costs – Development Of The Remix Model And Application For Europe, PhD Dissertation, German Aerospace Center (DLR), Institute of Technical Thermodynamics, 2012, http://elib.dlr.de/77976/1/REMix_Thesis_YS.pdf.

[116] Y. Scholz, C. Hoyer-Click, C. Schillinga, J. Gehrung and W. Krewitt, “High resolution inventory of renewable electricity generation potentials in Europe,” In 2nd International Conference on Integration of Renewable and Distributed Energy Resources, 2006. http://elib.dlr.de/56864/.

[117] S. Sen, L. Yu, and T. Genc, “A stochastic programming approach to power portfolio optimization,” Operations Research, Vol. 54, 55–72, 2006.

[118] M. Sepasian, H. Seifi, A. Foroud, and A. Hatami, “A multiyear security constrained hybrid generation-transmission expansion planning algorithm including fuel supply costs,” IEEE Transactions on Power Systems, Vol. 24(3), 1609–1618, 2009.

[119] M. Shahidehpour, “Investing in expansion: The many issues that cloud electricity planning,” IEEE Power and Energy Magazine, 14-18, Jan 2004.

[120] M. Shahidehpour, “Global broadcast - transmission planning in restructured systems,” IEEE Power and Energy Magazine., Vol. 5(5), 18-20, Sep./Oct. 2007.

[121] M. Shahidehpour and Y. Fu, “Benders decomposition,” IEEE Power and Energy Magazine, Vol. 3(2), 20-21, March 2005.

[122] M. Shahidehpour, W. Tinney, and Y. Fu, “Impact of security on power system operation,” IEEE Proceedings, Vol. 93(11), 2013 – 2025, Nov. 2005.

[123] T. Shiina and J. R. Birge, “Multistage stochastic programming model for electric power capacity expansion problem,” Japan Journal of Industrial and Applied Mathematics, Vol. 20(3), 379-397, 2003.

[124] W. Short, P. Sullivan, T. Mai, M. Mowers, C. Uriarte, N. Blair, “Regional energy deployment system (ReEDS),” NREL Technical Report NREL/TP-6A20-46534, November 2011. www.nrel.gov/analysis/reeds/pdfs/reeds_documentation.pdf.

[125] K. J. Singh, A. B. Philpott, and K. R. Wood. “Dantzig-Wolfe decomposition for solving multistage stochastic capacity-planning problems,” Operations Research, Vol. 57, 1271–1286, 2009.

[126] H. Stoll, Least-Cost Electric Utility Planning, 1989, John Wiley, New York.

[127] H. Sun and D. C. Yu, “A multiple-objective optimization model of transmission enhancement planning for independent transmission company (ITC),” Proceedings of IEEE Power and Energy Society Summer Meeting 2000, Vol. 4, 2033–2038, 2000.

[128] SunShot Vision Study: February 2012 (Book), SunShot, Energy Efficiency & Renewable Energy (EERE), NREL Report No. BK-5200-47927; DOE/GO-102012-3037, 2012.

[129] O. Tor, A. Guven, and M. Shahidehpour, “Congestion-driven transmission planning considering the impact of generator expansion,” IEEE Transactions on Power Systems, Vol. 23, No. 2, 781-790-137, May 2008.

[130] O. Tor, A. Guven, and M. Shahidehpour, “Promoting the investment on IPPs for optimal grid planning,” IEEE Transactions on Power Systems, Vol. 25, No. 3, 1743-1750, Aug. 2010.

[131] TPLAN website: www.pti-us.com/pti/software/tplan/index.cfm.

[132] T. Tran, J. Kwon, J. Choi, D. Jeon and K. Han, “Sensitivity analysis of probabilistic reliability evaluation of KEPCO system using TRELSS,” International Conference on Probabilistic Methods Applied to Power Systems, 2006.

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

[134] U.S. Department of Energy, National Transmission Grid Study, May 2002.

[135] U.S. Department of Energy, “20% wind energy by 2030: Increasing wind energy's contribution to U.S. electricity supply,” DOE Report No. DOE/GO-102008-2567, 2008.

[136] R. Van Slyke, R. Wets, “L-shaped linear programs with application to optimal control and stochastic programming,” SIAM J. Appl. Math., Vol. 17, 638-563, 1969.

[137] P. H. Vance, C. Barnhart, E. L. Johnson and G. L. Nemhauser, “Airline crew scheduling: A new formulation and decomposition algorithm,” Operations Research, Vol. 45(2), 188-200, 1997.

[138] M. Ventosa, Á. Baíllo, A. Ramos, M. Rivier, "Electricity markets modeling trends", Energy Policy, Vol. 33, No. 7, 897-913, May 2005.

[139] R. Walawalkar, J. Apt, and R. Mancini, “Economics of electric energy storage for energy arbitrage and regulation in New York,” Energy Policy, Vol. 35, No. 4, 2558-2568, 2007.

[140] X. F. Wang and J. McDonald, Modern Power System Planning, McGraw-Hill Publishing, 1994.

[141] WASP, 2013, WASP-IV model documentation: www.adica.com/wasp_iv.html.

[142] A. H. van der Weijde and B. F. Hobbs, “The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty,” Energy Economics, Vol. 34(5), 2089-2101, Sept. 2012.

[143] K. P. Wong. “Artificial intelligence and neural network applications in power systems,” IEE Second International Conference on Advances in Power System Control, Operation and Management, Hong Kong, December 1993.

[144] F. F. Wu, F. L. Zheng, and F. S. Wen, “Transmission investment and expansion planning in a restructured electricity market,” Energy, Vol. 31, 954 – 966. 2006.

[145] J. Xiao, “Grid integration and smart grid implementation of emerging technologies in electric power systems through approximate dynamic programming,” Ph.D. Dissertation, School of Industrial Engineering, Purdue University, July 2013.

[146] H. Yamin, J. Finney, W. Rutz and H. Holly, “GENCOs portfolio management using “STRATEGIST” in deregulated power markets,” Large Engineering Systems Conference on Power Engineering, July 2001.

[147] H. K. Youssef and R. Hackam, “New transmission planning model,” IEEE Transactions on Power Systems, Vol. 4, 9–18, Feb. 1989.

[148] H. Zhang, G. T. Heydt, V. Vittal, and H. D. Mittelman, “Transmission Expansion Planning Using an AC Model: Formulations and Possible Relaxations” IEEE PES General Meeting, 2012

[149] Q. P. Zheng and A. L. Liu, “Transmission and generation capacity expansion with unit commitment – A multiscale stochastic model,” Presentation at the INFORMS Annual Meeting, Nov. 2011.

[150] Q. P. Zheng and P. M. Pardalos, “Stochastic and risk management models and solution algorithm for natural gas transmission network expansion and LNG terminal location planning,” Journal of Optimization Theory and Applications, Vol. 147(2), 337-357, 2010.

[151] Q. P. Zheng, J. Wang, P. M. Pardalos, and Y. Guan. "A decomposition approach to the two-stage stochastic unit commitment problem," To appear in Annals of Operations Research, 2013.