SAND2015-3669J

Optimizing Your Options: Extracting the Full Economic Value of Transmission When Planning Under Uncertainty

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Public policy objectives and the aging transmission system are today's most important drivers for the development of new transmission infrastructure in the US. Given the anticipated magnitude of the required investments, transmission infrastructure investments must be allocated in a way that maximizes the likelihood of achieving society's goals for power system operation.

I. Introduction

Public policy objectives and the aging transmission system are today's most important drivers for the development of new transmission infrastructure in the US. Chuptka et al. (2008) report that the investments in transmission and distribution assets required to meet forecasted demand, reliability requirements, and environmental and renewable targets by 2030 will cost approximately USD $880B. This quantity is more than seven times the total annual revenues from US electricity sales in 2013 (EIA, 2015). Given the anticipated magnitude of the required investments, transmission infrastructure investments must be allocated in a way that maximizes the likelihood of achieving society's goals for power system operation.

Note that "goals" is plural—it is increasingly recognized that that the ***multiple*** benefits of transmission enhancements—as opposed to just operating cost reductions—must be considered when evaluating alternative network expansions. These extend beyond the ability to meet reliability requirements or to reduce fuel costs. Examples include savings in generation investment through more efficient siting, achievement of public policy goals (e.g., renewable targets and carbon emissions regulations), and minimization of environmental impact of new circuits (Pfeiffenberger & Hou, 2012; Chang et al. 2013). However, a critical part of the planning problem that has received significantly less attention is how to select a portfolio of transmission investments from a potentially very large (even thousands) number of potential combinations and timing of investments that is more cost-effective than any other alternative in simultaneously meeting economic and sustainability goals, while reckoning with long-run uncertainties. We believe that by using state-of-the-art optimization tools we can identify such optimal alternatives, extract more benefits out of transmission expansion investments, and account for the huge economic, technology, and policy risks that the power sector faces over the next several decades.

Our objective here is to outline limitations of current approaches to transmission planning and discuss how advanced optimization-based methodologies and supporting computational tools could be used to systematically achieve a broader range of benefits and decreased costs than tools in use today. We begin in Section II by recounting how advanced computational tools have revolutionized power systems operations, yielding billions of dollars of savings; we argue that analogous improvements are possible in transmission planning. Next, in Section III we analyze three recent, large-scale transmission planning studies conducted for US power system operators. We focus on the methodologies they used to identify and calculate the benefits of transmission investment portfolios. In Section IV we discuss the complexities involved in determining the best mix of transmission investments, and the benefits that can be gained by using optimization-based methodologies to assist with that task. We discuss a variety of difficult transmission planning issues that optimization can help users address, including renewable and load variability and correlations over space and time, long-run uncertainties (e.g., fuel prices), coordination and co-optimization of transmission and generation assets, and the flexibility and option value of alternative decisions, including the possibility of deferred investment. Simultaneous consideration of these issues results in difficult, large-scale optimization models. In Section V, we discuss some exciting and highly promising state-of-the-art solution methods and computational platforms that could be used to solve the resulting models, including decomposition methods and parallel computing. These methods and platforms have been used to solve multi-decadal transmission planning problems considering hundreds of short-run wind/solar output and load scenarios per year and, simultaneously, the flexibility of the system in the face of dozens of long-run scenarios. We argue that such capabilities will soon enable planners to quickly identify cost-effective expansion plans, significantly improving power system economic viability and reliability, while simultaneously achieving sustainability and related policy goals.

II. Optimization and unit commitment

"All models are wrong, some are useful", George E. P. Box.

The electric power industry is a major end-user of optimization algorithms because of the large number of alternative solutions that can be considered, wide availability of data, and—most importantly—the large cost savings that can be realized (Hobbs, 1995). One early, notable application of optimization in power systems operations was the use by Electricite' de France of linear programming for economic dispatch (Turvey and Anderson, 1977). Here, linear programming solvers were used to determine the output levels of generation fleets to meet demand at minimum cost for consumers and, later, to compute nodal electricity prices. An important limitation of early economic dispatch models was that they failed to capture key real-world generator characteristics such as start-up, shut-down, and minimum up/down times. Such "lumpy" characteristics are best captured using discrete (e.g., 0-1) variables, as opposed to the continuous variables used in linear programming. Consequently, early economic dispatch models eventually evolved into what today are known as unit commitment (UC) models, which take into account these additional features—although the former are still used in real-time markets to dispatch units once generator commitment schedules have been determined.

Unfortunately, the introduction of discrete variables makes the optimization of unit commitment models significantly more challenging than that of economic dispatch problems. Optimization models with discrete variables are known as mixed-integer programs. Finding a *provably* optimal solution to a mixed-integer program requires fundamentally different algorithm technologies than those associated with linear programming. At the time economic dispatch applications based on linear programming were first introduced, optimal mixed-integer solver technology was in early stages of development, and only used for research purposes. As an alternative, heuristic solution techniques for solving unit commitment—based on a technique known as Lagrangian relaxation—were introduced in the 1980s (Zhuang & Galiana, 1988; Virmani et al., 1989). Lagrangian relaxation saw widespread use by the late 1990s and early 2000s, after researchers demonstrated the ability of the technique to consistently identify feasible and near-optimal solutions, especially in the absence of "coupling" constraints such as transmission flow limits or emissions caps. However, the growing importance of such constraints, together with power system restructuring and rising fuel costs, combined to provide strong incentives to find commitment schedules of even better quality than the those obtained using Lagrangian relaxation (Hobbs et al., 2001).

Today, most restructured power markets worldwide use advanced mixed-integer programming techniques to solve unit commitment problems to near-optimality and, most importantly, within timeframes compatible with current market designs. However, this transition has proceeded slowly, despite the potential economic benefit. For example, until 2014, the New York ISO used Lagrangian relaxation to solve their day-ahead and real-time unit commitment problems (NYISO, 2014). Reports from the PJM Interconnection, California ISO, and the Southwest Power Pool state that the total aggregate savings resulting from the use of mixed-integer programing instead of Lagrangian relaxation for unit commitment are approximately USD $250M per year (O'Neill et al., 2011). These improvements have been possible largely due to a combination of advances in solution algorithms and computer hardware. In particular, IBM reports cumulative performance improvements on the order of 100,000-fold for their commercial mixed-integer solver CPLEX between 1991 and 2013 (Bixby, 2012; Ashterber, 2013). Such software improvements, coupled with Moore's Law for hardware improvements, enable a unit commitment problem that took 24 hours to solve in 1991 to be solved today in a fraction of a second.

Hence, unit commitment optimization models that were thought to be nearly impossible to solve in the nineties have become trivial, inducing a revolution in power system operations. Operators and energy management system vendors have taken advantage of these capabilities to build in many more capabilities, and to expand the sizes of the systems that are being solved, resulting in the efficiency improvements noted above. We believe that these software and hardware improvements are ripe for exploitation in planning transmission expansion, and can lead to a similar revolution in that context. Specifically, mixed-integer programs have been developed to represent a range of transmission expansion models (Alguacil et al., 2003; van der Weijde & Hobbs, 2012), and researchers have demonstrated that state-of-the-art mixed-integer solvers can identify optimal or near-optimal solutions to these models in practical run-times (Munoz et al., 2015).

III. Current Practices in Transmission Planning

Innovative transmission planning paradigms are being actively investigated or gradually adopted by the power systems industry in response to the challenges of renewable integration, FERC Order 1000, and computational hardware and software improvements. Such new planning paradigms, initially developed by the research community, explicitly address long-run uncertainties, consider detailed representations of short-run operations, acknowledge that power systems must consider multiple societal objectives, and/or consider the effects of transmission planning on generation siting—and vice versa. However, the full implementation of these paradigms, along with full realization of their benefit, requires the use of modern optimization techniques. Existing implementations of these paradigms fall short of what modern optimization techniques can provide, yielding sub-optimal expansion plans (Liu et al., 2013; Munoz et al., 2014a). We argue that these new paradigms, when coupled with state-of-the-art optimization algorithms and computational platforms, will lead to more economic, robust, and sustainable transmission investment plans.

To motivate these paradigms and survey the existing state-of-the-practice, we now examine three large-scale transmission planning studies, focusing on the increasingly sophisticated analytical tools used to identify candidate transmission portfolios and the criteria used to select among them. These studies are associated with major US power systems operators: the California ISO (CAISO), the Midcontinent ISO (MISO), and the Western Electricity Coordinating Council (WECC). We highlight how recent computational advances could be exploited in such studies to address features present in newly proposed transmission expansion paradigms.

The CAISO 2013-2014 Study: Production Costing as a Classic Application of Optimization

The 2013-2014 CAISO transmission planning study aims to select new transmission projects (CAISO, 2014). The objectives of the new projects are to (1) enable the state to meet a 33% renewables penetration target by 2020, (2) enhance the economic efficiency of the system (e.g., via reduced production costs), and (3) maintain reliability standards in the region under the increased penetration of renewables. CAISO used the WECC's Transmission Expansion Planning Policy Committee (TEPCC) dataset as a baseline for projected generation resources in the region and in neighboring states. The development of transmission portfolios is based on information obtained from detailed ABB GridView production cost simulations and AC power flow analyses performed using GE PSLF for stressful system conditions (e.g., a summer peak hour). Production cost simulations are a type of optimization—of operations—that are frequently used for simulating how a predefined investment plan performs in terms of operational cost and compliance with renewable targets and emissions limits (Kahn, 1995); they represent the widest (albeit indirect) use of optimization in transmission planning studies.

CAISO used the results from production cost simulations to identify congested transmission paths and to rank them by severity (quantified as event magnitude and duration). In conjunction with stakeholder input, this information was subsequently used to propose a set of alternatives for transmission upgrades to mitigate congestion. CAISO then selected the most cost-effective investment portfolio by comparing gross operating benefits and investment costs among all selected alternatives. This planning process was repeated for three different plausible scenarios of generation developments for meeting the 33% state renewable target by 2020, resulting in three diverging transmission investment portfolios. Subsequently, CAISO developed a single investment recommendation based on these three distinct scenario-specific portfolios following an engineering rule known as the "least regrets" principle, which seeks approval of *"…those transmission elements that have a high likelihood of being needed and well-utilized under multiple scenarios"* (p. 19). We will comment on the effectiveness of this heuristic decision rule in Section IV.

MISO Transmission Expansion Plan 2013: Using Optimization Models for both Production Simulations and to Define Generation Investment Scenarios

MISO performs annual transmission planning studies to identify those projects needed for their reliability, economic, and policy purposes over the next 10 years (MISO, 2013). MISO first identifies a least-cost generation investment portfolio that meets forecasted demand, renewables targets, and reliability requirements using EPRI's Electric Generation Expansion Analysis System (EGEAS). The EGEAS is an optimization-based capacity planning tool—the capacity of generators are variables in the optimization model—that finds a generation investment portfolio that minimizes the present worth of capital and operating cost subject to a reliability constraint (e.g., Loss of Load Probability or Expected Unserved Energy). This approach is more sophisticated than CAISO's, mainly because MISO relies on a formal optimization tool that *automatically* analyzes millions of possible combinations of generation portfolios and selects the most cost effective one. The EGEAS tool has, however, a crucial limitation: it does not take into account transmission constraints when selecting an optimal portfolio of generation investments. For this reason, MISO optimizes generation capacity for sub-regions of the system, independently.

As in the CAISO study, MISO utilizes the portfolio of generation resources identified in the first step as a *fixed* input for production cost simulations performed using PROMOD and PLEXOS, which are then used to identify the most congested paths in the network. One difference compared to CAISO's approach in this step of the planning process is that MISO additionally performs production cost simulations *without* transmission constraints. This additional step is used to estimate what MISO calls the "maximum allowed budget for new transmission investments," which is measured as the difference of production costs between the transmission-constrained and unconstrained cases. All of this information is then used to perform a *holistic* transmission portfolio analysis that relies on both congestion data and stakeholder input. The study also considers five different future scenarios of varying economic, policy, and technology conditions for which MISO develops generation and transmission investment portfolios. After identifying the investment needs for each scenario, MISO produces a single investment recommendation according to a rule that is similar to the one used by the CAISO: *"If the same group of projects is the preferred solution for multiple scenarios, it is a good indication that a given portfolio is robust and would result in a less future regrets than a portfolio that does not"* (p. 62).

Thus, both the CAISO and MISO processes rely on *manual* identification of transmission investment, which is an extremely laborious task given the scale of the power systems considered and the astronomical number of possible investment portfolios. We argue that modern optimization methods can be used to systematically evaluate extremely large numbers of transmission and generation portfolios and to select the most cost-effective alternative. In addition, both studies emphasize the definition of robust transmission plans by identifying individual investments that appear attractive in a number of scenarios. This is an important change in paradigm relative to traditional approaches of planning for a single scenario of demand growth, fuel prices, etc. But, as we point out below, this approach to robustness may miss alternatives that "put the system on its toes"… that is, increase the flexibility of a transmission system to respond to uncertain developments ten years out and beyond. Optimization can provide a rigorous assessment of the adaptability of a transmission plan, and the resulting "option value".

2013 WECC Interconnection-wide Transmission Plan: Adding Transmission Investment Variables to the Optimization

The WECC planning approach is, to our best knowledge, the most sophisticated in the US. For 20-year planning studies, the WECC utilizes an optimization-based long-term planning tool (LTPT) that explicitly considers transmission and generation investments as *decision variables* (WECC, 2013). Consequently, in the WECC study, the investment portfolio is selected *automatically* instead of *manually*, as is done for transmission and generation in CAISO, or for transmission in MISO. The LTPT operates by iterating between a Scenario Case Development Tool (SCDT) and a Network Expansion Tool (NXT) until a feasible investment portfolio is found. The SCDT selects generation capacity based on levelized energy costs (i.e., it relies on expected capacity factors for renewables). SCDT is therefore a simpler tool than the EGEAS module used by MISO, which considers instead the full distribution of loads, wind, and solar parameters as well as generator outages. This generation investment portfolio is then fed into the NXT module, which *automatically* selects a transmission portfolio that results in no branch violations for one study hour—the summer peak condition—and that minimizes investment cost. The results from NXT are then used to calculate and assign transmission costs for all generation resources, which modify the levelized cost of energy assumed in the previous run of SCDT. The LTPT iterates between the SCDT and NXT until the generation and transmission investment portfolio does not change between iterations.

The WECC study recognizes the mutual dependence of generation and transmission investments. Where new lines are placed will affect the attractiveness of different locations for siting generation, and will influence where plants are built and how they are operated. Similarly, generation siting affects the benefits of transmission investments. In some parts of the US, these investments can be coordinated—or "co-optimized"—through integrated resource planning processes. In other parts, where transmission and generation decision-making is unbundled, transmission owners need to anticipate how network expansions will affect incentives to site generation. In our analyses (e.g., Liu et al. 2013), we have found that a large fraction—up to half—of the benefits of transmission investments arise from the more efficient siting and construction of generation that results. Models that simultaneously optimize transmission and generation investments can be used to quantify these benefits by simulating how generation locations are affected by grid investments. The WECC-like iterative approach of optimizing generation investments then transmission and then back to generation, and so forth, can capture some but not all of the benefits of co-optimization. This limitation has been demonstrated both in general and in case studies (Liu et al., 2013; Johnson, 2015) in which such iteration converged to joint investment plans with higher costs than truly co-optimized solutions.

IV. Optimal Transmission Planning

"While we realize no such comprehensive structure exists in transmission planning to date, we believe that analytical tools based upon developments in advanced computing and optimization such as have seen in other segments of the industry (e.g., operations/market dispatch) could help inform the design of improved analytical and decision frameworks for transmission planning." (Chang et al., 2013)

Several research articles have proposed advanced optimization-based planning tools for *automatic* generation of cost-effective network expansions in the last two decades (Latorre et al., 2003). However, as we just discussed, these tools are seldom used in practice. We now describe the core components of a generic optimization-based transmission planning tool. In addition, we enumerate a series of optional model features found in advanced transmission planning paradigms, including the co-optimization of transmission and generation resources, capturing the key features of detailed production cost simulations, explicit modeling of uncertainty, and the option of delaying investments. A comprehensive description of these elements is provided by Donohoo & Milligan (2014).

The basic components of an optimization model are a set of decision variables, a set of constraints, and an objective function. In the context of transmission planning, the main ***decision variables*** correspond to investment options in different corridors (e.g., new transmission capacity between Devers-Palo Verde or between Tehachapi and Big Creek in California) and of different types (e.g., a 345-kV double-circuit line versus a 500-kV single-circuit line). In transmission planning, there is an additional set of decision variables that are not directly related to investment decisions, but are included in the optimization model to capture operational details, e.g., as found in a production cost simulation. Examples of such "auxiliary" variables include generator dispatch levels, line power flows, and bus voltage angles. The set of ***constraints*** includes transmission build limits (e.g., transmission right-of-way restrictions), power flow limits, generation dispatch limits, a power balance at every bus in every time interval considered, and compliance with renewable targets and/or emissions limits. The ***objective function*** in transmission planning is often defined as the sum of capital cost of transmission investments plus the net present costs of operations for the planning horizon; cost is minimized in such a formulation.

Features found in more advanced transmission planning paradigms can be included by augmenting the basic model described above in order to obtain a transmission planning model more representative of the how the system is likely to be operated in the future and of how investment decisions are made in reality. We summarize some specific examples below.

a) Co-optimization of generation and other resources: In Liu et al. (2013)(p. 3) we define co-optimization as the *"…simultaneous identification of two or more classes of investment decisions within one optimization strategy."* In a vertically integrated environment, co-optimization can be achieved by augmenting the core transmission planning model described above, specifically by introducing decision variables and constraints to represent non-transmission investment alternatives, including generation capacity and/or energy storage devices. The objective function would also be modified to account for the capital cost of these alternatives. In restructured power systems these additional decision variables represent a *market response* to transmission investments, as generation assets are not centrally planned. Consequently, this approach is often referred to *anticipatory* or *proactive* transmission planning.[i]

b) Time granularity: One the main limitations of the planning tool used by the WECC to select a transmission portfolio is that it only optimizes investments for the most stressful hour of the year, i.e., the summer peak load. This approach is mainly an artifact of a now-dated planning paradigm, which emphasized the feasibility or security of the system at any cost. Unfortunately, under such planning criteria it is not possible to capture the broader economic benefits of new transmission lines under operating conditions other than the peak load. An important benefit of new transmission capacity for the overall system is the possibility of reducing congestion costs across a large fraction of hours of the year. This is particularly important for newer systems with large shares of variable generation from renewable energy technologies—in general, a single representative time slice is insufficient to capture all of the individual and complementary (e.g., correlated) properties of these resources (Joskow, 2011).[ii] In an ideal planning model one would compare and select an investment portfolio by performing a detailed production cost simulation for all hours in a year, and for all years in the planning horizon. However, the number of additional decision variables and constraints needed to model production costs at such a fine resolution often yields optimization models of unmanageable size.

c) Long-run uncertainty: The three planning studies we describe in Section III account for the possibility of varying economic conditions, fuel prices, demand growth rates, and environmental regulation through a series of *scenarios* that are constructed using stakeholder input. Consequently, those studies *do* account for uncertainty in the form of sensitivity analysis. However, they do not *explicitly* account for uncertainty when developing investment alternatives. The approach of identifying the optimal investment strategy for each scenario independently—as done in the CAISO and MISO studies—is known as *scenario analysis.* This procedure allows decision makers to analyze the effect of different scenarios on investment plans, though it is a weak strategy for finding a *single* investment portfolio that will perform best *across all scenarios, simultaneously*. As discussed by Wallace (2000), the main issue with a scenario analysis framework is that the flexibility of a transmission plan to adapt to a set of scenarios as they unfold over time is not modeled or economically valued at the time of plan development.

A more sophisticated tool that explicitly accounts for uncertainty within an optimization-based planning model is stochastic programming. In a stochastic planning model, the optimization objective is to minimize the *expected* net present cost—the probability weighted sum of costs going forward across all scenarios—using a unique investment portfolio for all scenarios, instead of one per scenario as is the case in scenario analysis. Consequently, a stochastic plan is not necessarily optimal for any individual scenario, but it is likely to be better in an expected value sense, assuming that a representative range of scenarios have been modeled. In Munoz et al. (2014a) we compared the performance of a stochastic planning model to investment strategies developed using scenario analysis. In that study, we found average cost savings of approximately 8% of the total system cost, which was nearly three times the cost of the transmission lines themselves.

d) Option value: Most transmission planning studies are performed every year using the latest available information about near-term system needs. In some cases, a change in projected system conditions on a given year (such as the enactment of a new environmental policy) could turn transmission and generation projects that were not identified as necessary during previous planning studies into *optimal* investment decisions for the future, given the new information. Planning models that disregard this option to delay investment decisions are likely to provide investment recommendations that are overly conservative; because all decisions have to be made today, there is no opportunity for learning about the future and then determining investment decisions. In order to capture the *option value* of delaying an investment, it is necessary to explicitly consider uncertainty—through a set of scenarios, for instance—and to incorporate additional investment decision variables to represent future actions, after uncertainty is revealed. These additional variables are often referred to as *recourse* or *wait-and-see* decisions and do not necessarily correspond to investments that will be ultimately realized in the future. This contrasts with *here-and-now* investment recommendations. By including recourse decisions as a modeling feature, we can represent the possibility of delaying or modifying an investment and the effect of these extra degrees of freedom on decisions that we have to make today.

V. Leveraging Advanced Computing Tools for Transmission Expansion

Accounting for all of the advanced model features we just introduced above will require sophisticated computing to solve the resulting planning models. Recent advances in computer hardware and commercial mixed-integer solvers such as CPLEX, Gurobi, and Xpress-MP—de facto industry standards for solving unit commitment and production cost models—may suffice for identifying high-quality investment strategies for small and perhaps medium-sized systems. However, more sophisticated solution strategies will be needed for large-scale applications (e.g., the entire WECC or Eastern Interconnection), with thousands of transmission elements, dozens to hundreds of scenarios, and multi-year modeling of investment alternatives.

One alternative to reduce solution times for large stochastic planning models is to employ decomposition; well-known exemplars are Benders decomposition and Lagrangian relaxation (Conejo et al., 2006). Benders decomposition for stochastic transmission expansion executes a “divide and conquer” strategy in which the algorithm iterates between an approximation of the investment problem (e.g., to determine which transmission corridors are selected) and a (typically) large set of production cost models representing operational conditions under consideration (e.g., to quantify operational costs and reliability under various scenarios, and for various days or hours). The production cost models are evaluated using the fixed solution from the investment problem approximation, while the investment problem is solved using best available approximations of the generator operating costs obtained from the production cost models. Both the investment problem and the production cost models are substantially smaller that the monolithic problem, and are consequently much easier to solve. In contrast to some iterative strategies presently used in transmission planning, there is a guarantee under certain circumstances that Benders and related decomposition strategies can identify optimal solutions, or provide a bound on solution quality if optimality cannot be established. A bound is a metric that quantifies how much additional improvement, typically quantified as cost reduction, could be achieved by continuing the iterative process. Further, many decomposition strategies allow for early termination, e.g., subject to a pre-specified time bound. In general, it may be sufficient for practitioners to consider sub-optimal solutions in preliminary and/or exploratory stages of a planning study, and gradually increase target bounds on solution quality in final study stage

While the application of decomposition strategies to large-scale power systems problems has been largely restricted to the academic research community, there are cases where such methods have been used by industry to solve planning problems that otherwise proved intractable. For instance, the Electric Generation Expansion Analysis System (EGEAS) has used Benders decomposition since the 1980s to identify optimal generation investment strategies by iterating between an investment planning model and a probabilistic production cost model. Similarly, the SDDP tool developed by PSR (PSR, 2015) for multi-stage hydrothermal system operations under stream flow uncertainty uses a variant of Benders decomposition. These examples illustrate that the complexity of decomposition strategies—relative to more straightforward, black-box use of commercial solvers—has not been a barrier to their adoption in power systems applications ranging from long-term investment planning to short-term scheduling. However, to our best knowledge, there are currently no commercial implementations of decomposition methods for transmission planning.[iii]

Another rapidly emerging aspect of the commercial computing landscape that could have a significant impact on our ability to overcome the challenges associated with solving large-scale planning problems is parallel computing. Software vendors have recently introduced products that take advantage of parallel compute resources, driven by cost reductions in large compute servers and online services such as the Amazon EC2 compute cloud. For example, the Brattle Group uses the pCloudAnalytics module to parallelize large production cost simulations (NEG, 2015). The New York ISO is now using high-performance computing to perform reliability and economic studies using the GE MARS tool, reducing simulation times from 16 hours to 30 minutes (Chao, 2012). However, such applications have an “embarrassingly parallel” structure, and do not require the use of iterative decomposition strategies. Unlike investment planning problems, an 8760-hour production cost simulation can be approximated via a collection of smaller (e.g., month-long) independent production cost problems that can be solved simultaneously and independently. In contrast, decomposition strategies collect information from the solutions to each sub-problem, modify the sub-problems based on the aggregate, and iterate. This more complex communication structure still lends itself to parallelization, specifically because the sub-problems can be solved independently. Indeed, such parallelization is often required in order to obtain tractable solution times for decomposition strategies.

While there are still no commercial tools available for transmission planning that use decomposition algorithms to leverage parallel computer systems, there exist some promising research implementations that show that it is possible to solve medium to large-scale problems using current software and hardware technology. For instance, Munoz et al. (2014b) use a 240-bus network reduction of the WECC to illustrate an application of decomposition algorithms to transmission and generation investment planning. The resulting optimization model has 31 million decision variables and 56 million constraints and it is currently not solvable using off-the-shelf commercial solvers; however, the model can be solved using Benders decomposition in a medium-sized computer workstation in nearly 80 hours. A more recent implementation of a variation of the same network used in Munoz et al. (2014b) is in Munoz & Watson (2015). Here the authors find a near optimal solution using the Progressive Hedging decomposition algorithm on a high-performance computer available at a national laboratory. Running the decomposition algorithm in parallel instead of serially reduced solution times from 40 days to 1.9 hours.

Therefore, we conclude that both sophisticated solution algorithms and parallel computing technology are promising alternatives to tackle large-scale planning problems in practical solution times for real-world planning studies and not just research applications. The challenge is to make these models truly useful to planners by implementing algorithms and developing interfaces that would enable planners to solve such models on their own computers.

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[i] A much more sophisticated approach to model the effect of transmission investments on generation capacity additions is the use of game theory (Sauma & Oren, 2006); however, most existing applications of that approach are restricted to small systems with a focus on academic research.

[ii] In Munoz et al. (2014b) and Munoz & Watson (2015) we studied the effect of using a sample of representative hours to simulate production costs for a year and to select optimal transmission and generation investments for a large-scale system. We found that at least 500 representative hours are needed to approximate an 8760-production cost simulation with an error of less than 3% in total system cost.

[iii] Promising implementations of decomposition algorithms to solve large-scale transmission planning problems using parallel computing are described in Munoz et al. (2014b) and in Munoz & Watson (2015).