



Planning Transmission for Uncertainty:

Applications and Lessons for the Western Interconnection

FINAL REPORT

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Executive Summary

ES-1. Overview

The electricity industry has undergone a series of radical economic, policy, and technology changes over the past several decades. More changes are to come, to be sure, but their nature and magnitude is highly uncertain. Such changes in market fundamentals profoundly impact the economic value of transmission.

This report documents the results of a project whose goal is to carefully evaluate the practicality and potential usefulness of a method for planning transmission under uncertainty. This method, called stochastic programming, quantifies the economic value of simultaneously considering multiple scenarios (or “study cases”) of economic, policy, and technology changes over a multidecadal time horizon in a single model. By considering several possible futures in one model, analysts can identify near-term transmission additions that enhance the adaptability and robustness of the transmission grid in the face of these uncertainties.

In particular, we quantify the economic value of stochastic programming by comparing the performance of near-term (year 10) recommendations from a stochastic model to alternative plans developed using traditional deterministic (single study case) models. The economic value is the difference between the probability-weighted present worth of cost of (1) a stochastic model that chooses first-stage (through 2024) lines to minimize that cost and (2) a stochastic model whose 2024 lines are constrained to be those that were chosen by an alternative process, such as a deterministic model. The analyses show that even considering a small number of scenarios in a stochastic model can significantly improve solutions. Specifically, the probability-weighted cost savings of using stochastic programming rather than single study case models can be as much as or even exceed the cost of the recommended transmission facilities themselves. Furthermore, we provide evidence that the transmission recommendations of stochastic programming models are more robust to scenarios that haven’t been considered than recommendations by deterministic models. That is, stochastic plans appear to make the network more adaptable in the face of all uncertainties, not just those that were included as specific scenarios.

This report also addresses the practicality of implementing stochastic programming, and the sensitivity of the results to assumptions made in the modeling. The assumptions considered include: use of a “pipes-and-bubbles” formulation versus one that recognizes Kirchhoff’s voltage law; whether or not generation unit commitment constraints are included in the operations model; the number of scenarios considered and their probabilities; whether or not lines that are assumed to be built by 2023 in the WECC Common Case Transmission Assumptions (CCTA) are actually completed; and the hydropower scenarios and exact number of operating hours considered in the operations model.

ES-2. Motivation and Goal

Existing long-range transmission system planning methodologies have several shortcomings. Among them are: inadequate treatment of the interaction of renewable variability with generation operational flexibility and transmission additions; a failure to recognize how generation resource investments de-

pend on network investments, and vice versa, and the disregarding of the profound effect of long run technological, economic, and policy uncertainties on transmission economics. Recognizing those limitations, the Western Electricity Coordinating Council (WECC) made several recommendations in its 2013 plan for better inclusion of uncertainty in long range (multidecadal) planning studies. In particular, it identified the following needs:

- to include uncertainty in planning,
- to evaluate hedging options,
- to consider operating flexibility, and
- to acknowledge uncertainty around completion of transmission lines.

This study has been undertaken in response to those recommendations.

In particular, we quantify the benefit of including uncertainty, in the form of multiple scenarios over a multidecadal time horizon, while explicitly representing the information available at different decision points. Two investment decision stages are recognized: “here and now” (first stage decisions that are made without knowing which of the scenarios will turn out to be the case) and “wait-and-see” decisions (later investments that are made after the scenario is known, enabling the planner to adapt the system to the realized conditions). In our modeling framework, these correspond to the year 10 and year 20 phases of the WECC Transmission Expansion Planning Policy Committee (TEPPC) planning process.

This two-stage decision framework (called “stochastic programming” or “mathematical programming with recourse”) is widely used in engineering and business, as the literature survey in the report documents. Applications have included generation investment planning and academic proposals for use in power network planning. Our two-stage stochastic programming model for transmission planning is called JHSFINE (Johns Hopkins Stochastic Multistage Integrated Network Expansion). Compared to stochastic approaches that have been proposed previously, the application here takes place under more realistic conditions with the collaboration of planners and analysts from WECC, using data bases of generation, loads, and networks from the 2013 TEPPC plan.

ES-3. Model Structure

The structure of the decision problem is shown in Figure ES-1. Commitments to investment, both transmission and generation, occur in 2014 (first stage, with an in-service date of 2024) and 2024 (second stage, in service in 2034). Thus, this is a co-optimization model, in which the transmission planner anticipates how the location and types of generation investment respond to network availability. Decisions about system operations (generation dispatch and line flows) are made in 2024 (first stage) and 2034 (second stage), with the second stage operating decisions continuing for additional decades after 2034. The CCTA lines (year 10 lines that the 2013 WECC Plan recommends) are assumed to be built in every solution; our model also recommends additional year 10 lines that appear to be economically attractive by 2024. A focus of our analysis is how those recommendations differ between the stochastic and deterministic models, and what the economic benefits can be of following the stochastic recommendations.

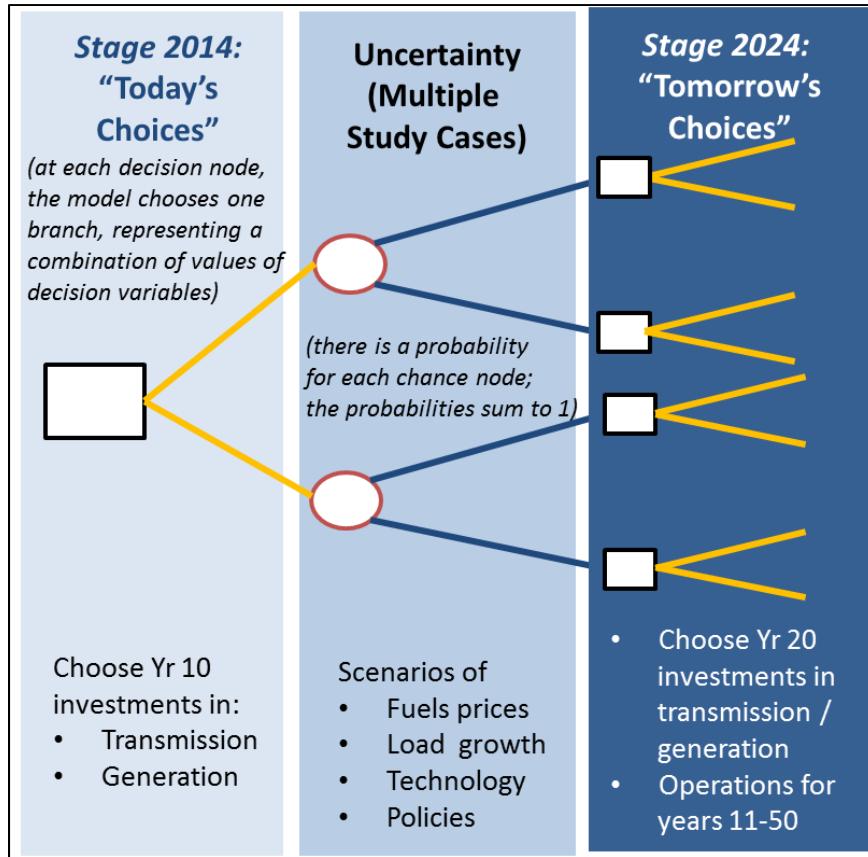


Figure ES.1 Decision tree schematic of the two-stage transmission-generation optimization

The particular mathematical formulation is summarized as follows:

MIN Present worth (PW) of transmission & generation capital + operating costs

subject to:

- Short-run operational constraints (Kirchhoff's laws, capacity limits on plant generation and transmission flow, wind- and solar-output limitations by hour, operating reserve requirements, renewable portfolio standards)
- Long-run expansion constraints (siting limitations on the location and capacity of new lines and generation)

This formulation can be shown to be equivalent to an economic equilibrium in which:

- Short-run generation markets are cleared by competitive generation companies who optimize their generation schedules against locational marginal prices, and there are no barriers to trade among regions aside from physical transmission capacity.

- Long-run generation investment decisions are made by maximizing the probability-weighted present worth of short-run gross margins (based on locational marginal prices) minus investment costs.
- The transmission operator and owner expands the grid to maximize the probability-weighted net social welfare (sum of surpluses in the market), and in the short-run operates the grid to maximize the value to the market provided by transmission (equivalent to maximizing transmission surplus, with price taking assumptions for locational marginal prices).
- All generators are price-takers, and all market parties are risk neutral, have the same interest rate (5%/year real), and have the same expectations concerning the probability distributions of long-run scenarios and short-run load, wind, and solar conditions.

Of course, these assumptions can be viewed as a caricature of actual market conditions. For example, not all markets are competitive, there are significant barriers to trade among control areas in the west, not all markets price on the basis of locational marginal prices, and market parties are likely to be risk averse and to hold different beliefs about the probability distributions of future scenarios. However, adopting the philosophy of “walking before running”, we formulate and solve the computationally tractable model that results from these assumptions, and reserve for future research the formulation of more realistic models that incorporate market shortcomings.

The basic JHSMINE model structure has been varied to create different versions of the model that we apply in this report. These versions include both 21-zone and 300-bus versions of the WECC system (Figure ES.2), which we compare in order to assess the computational effort required for more detailed models and the effects of assuming a more disaggregated network upon the results. The 21-zone model assumes a “pipes-and-bubbles” load flow, as does one version of the 300-bus model. In addition, we apply a 300-bus model that enforces Kirchhoff’s voltage law, thus representing the physics of power flow more accurately. The result is that power flows over all parallel paths between sources and sinks, and congestion is generally greater than in the “pipes-and-bubbles” formulation, which only enforces Kirchhoff’s current law. In all models, we enforce transmission capacity limits corresponding to official WECC paths between the regions of the model. By comparing different power flow formulations, we can assess whether considering Kirchhoff’s voltage law makes an appreciable difference in first stage (year 10) transmission recommendations.

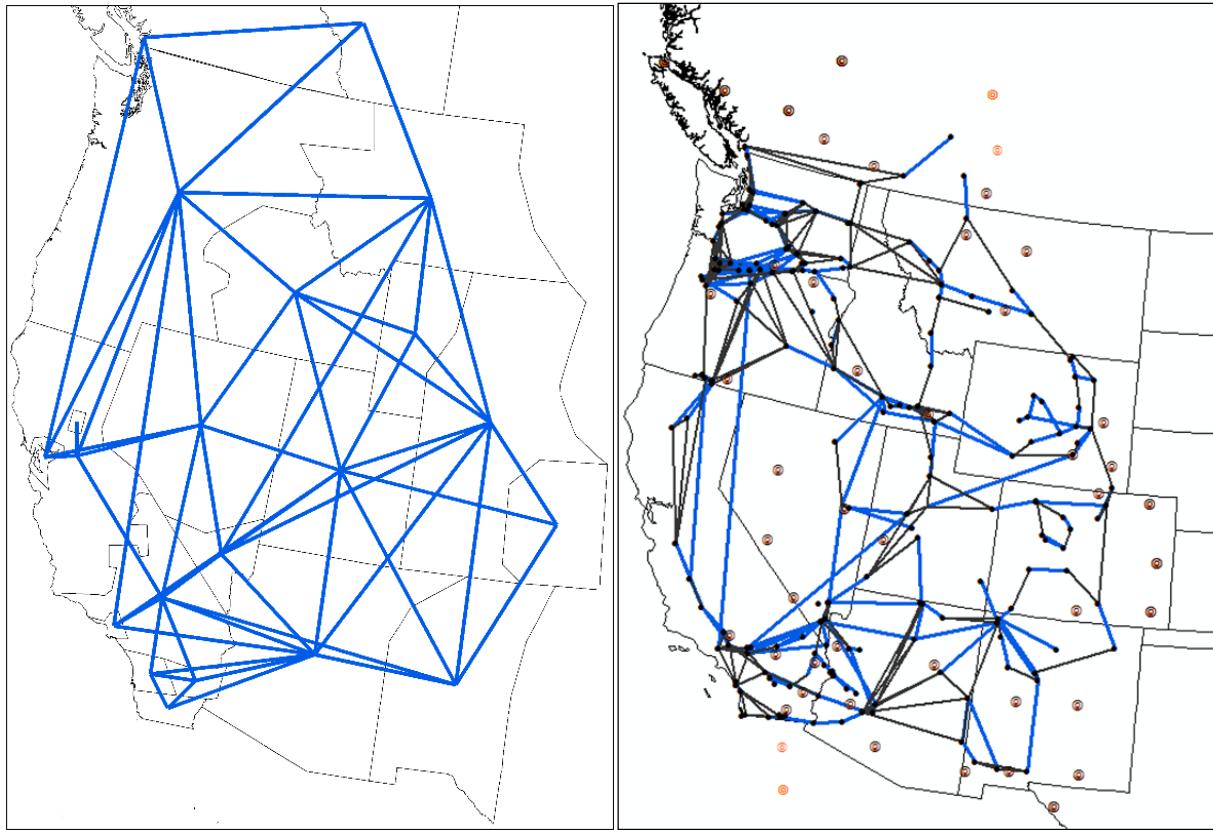


Figure ES.2 Comparison of the 21-zone and 300-bus networks modeled in different versions of the JHS-MINE model

A final variant of JHSMINE implements unit commitment constraints for the 21-zone model. These constraints include definition of start-up and shut-down costs and ramp limitations. This version represents chronologic hourly loads rather than use an annual load duration curve. In theory, additional restrictions on generator flexibility would decrease the economic value of variable renewables and increase the value of flexible gas generation; the focus here is on whether those constraints influence the value of potential year 10 transmission additions and the resulting recommendations. As an example, Figure ES.3 compares the operation of generators in one zone in one day without and with the unit commitment constraints. In the latter case, instead of shutting down a coal plant in the middle of the night, the plant is operating at its “ P_{min} ” level. Also, the ramps for the combined cycle and combustion turbine facilities are less steep. These operating constraints affect market prices and thus the profitability of new generation investments and, potentially, new transmission.

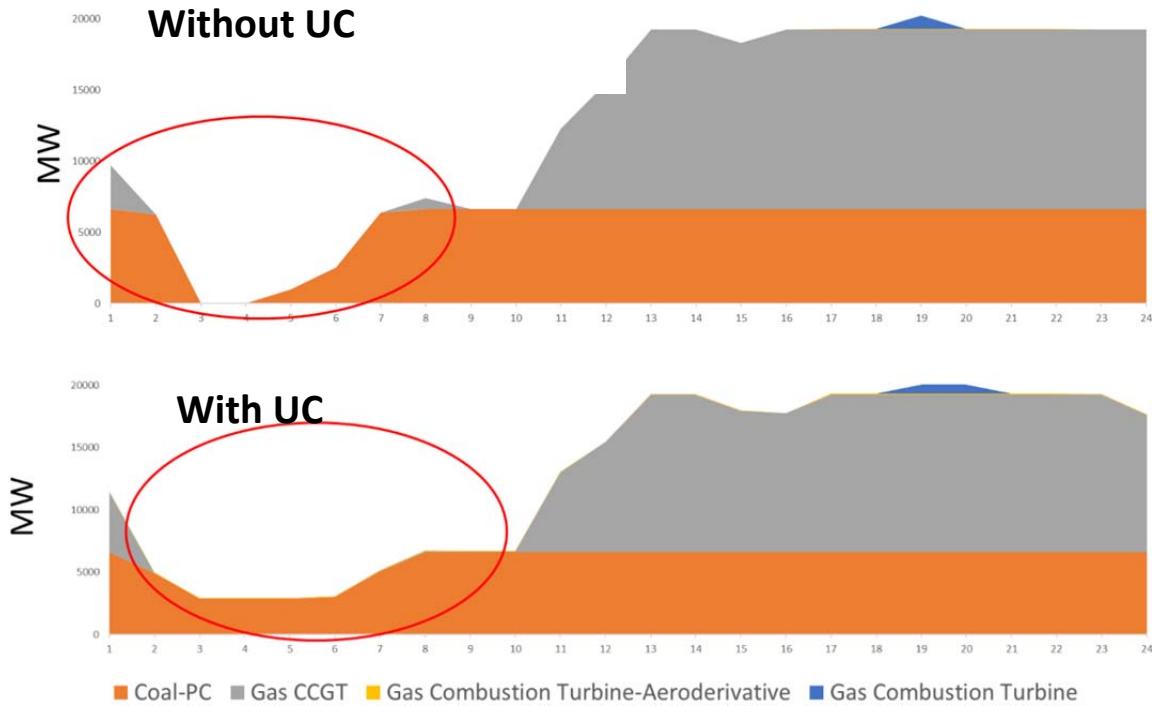


Figure ES.3 One day's operations without UC and with UC constraints in the AZ/NW-NM zone (year 2024, WECC 1 study case, 21-zone model)

ES-3. Scenarios Considered

The basic generation, transmission, and load assumptions are based upon the 2013 WECC TEPPC assumptions. With the collaboration of a project technical advisory committee consisting of WECC stakeholders, we defined 20 scenarios to be considered in the stochastic planning model. These were derived by various combinations of uncertain variables that were identified by the stakeholders as potentially important uncertainties in the 2020's and 2030's. Table 1 shows the assumed values of the variables in 2024, identified by the advisory committee.

Table ES.1 Uncertain 2024 variables used to define scenarios, and their assumed 90% confidence intervals

Variables		Low	High
Fuel & Carbon Prices	Natural Gas (\$/MMBtu)	3.86	14.5
	Carbon (\$/ton)	25.9	87.5
	Coal (\$/MMBtu)	2.24	3.50
Variables		Low	High
Capital Cost	Onshore Wind(\$/kW)	1569	2065
	Offshore Wind (\$/kW)	4639	6106
	Geothermal(\$/kW)	5015	6490
	Solar PV(\$/kW): resid. rooftop	2855	5209
	Solar PV(\$/kW): comm. rooftop:	2320	4233
	Solar PV(\$/kW): Fixed Tilt (1-20 MW)	2048	3736
	Solar Thermal(\$/kW): No Storage	3560	4519
	Solar Ther.(\$/kW): 6 Hr Storage	5178	6572
	IGCC w/CCS(\$/kW)	7600	10000
Variables		Low	High
Net Energy for Load	DG cap as % of Peak Demand (PD) (%)	3.2	20.0
	DR cap as % of PD(%)	2.2	10.0
	Storage cap as % of PD (%)	3.9	10.7
	Total WECC Load Growth (%/yr)	1.0	1.9
	energy reductions (%/yr)	0.3	4.0
	electrification (%/yr)	0.3	1.8

Twenty scenarios based on various combinations of the variables are considered in our analyses, as indicated by the schematic in Figure ES.4. Five of the scenarios are based upon the stakeholder-defined scenarios in the 2013 WECC planning study, although the specific values of the variables assumed are based on stakeholder input. Nine additional scenarios were provided directly by our stakeholder group. Since stakeholders did not evaluate the resulting set of 14 scenarios for completeness, we then defined six additional scenarios to “plug holes”, representing plausible combinations of variables that were not considered in the other 14 scenarios. (In an actual stakeholder-based planning process, the final scenario set would be reviewed and approved by the stakeholder group; however, for the purposes of our methodology demonstration, this was not necessary.)

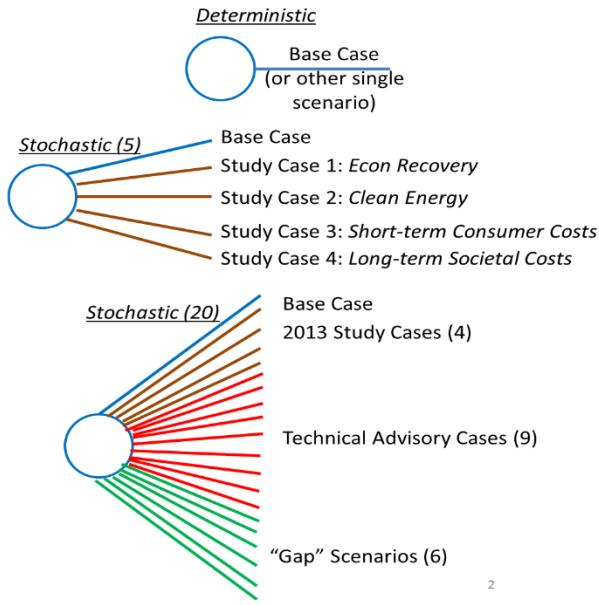


Figure ES.4 Schematic of chance node of stochastic program under one, five, or twenty scenarios

ES-4. Quantifying the Value of Stochastic Programming

We quantify the economic value of identifying near-term transmission investments by stochastic planning by comparing the cost performance of the first stage (year 10) investments derived with versions of JHSMINE that consider 1, 5 or 20 scenarios (Figure ES.4), as follows:

- “Deterministic Planning” (20 plans examined). A single scenario (either a base case scenario, or one of four alternative “study cases” considered in the 2013 WECC planning study, or one of the other 15 scenarios we consider in Figure ES.4).
- “Deterministic Heuristics” (3 approaches). The first stage decisions here are identified by comparing the deterministic solutions. “DH: Build All” assumes a 1st stage line is built if it appears in any of the 20 deterministic model solutions. “DH: Majority Vote” chooses lines that appear in a majority of the 20 deterministic solutions. “DH: Unanimous” builds only those lines that appear in all 20 deterministic solutions. These heuristics simulate how the California and Mid-Continent ISOs have identified robust transmission recommendations in their planning studies.
- “Stochastic (5)” (1 approach). This solution is obtained by considering only the first five scenarios (those from the 2013 Plan) in JHSMINE. Two variants are considered: one with a 20% probability for each scenario and the other considering differentiated probabilities that are chosen so that the probability-weighted values of the uncertain variables are close to their base case values.
- “Stochastic (20)” (1 approach). This solution is based upon including all 20 scenarios in the stochastic version of JHSMINE. In one variant, each scenario is assigned a 5% probability, while in the other, probabilities are assigned to the scenarios so that each has a probability of at least 2%, and the expected values of the variables are close the values assumed in the base case.

We then compare these plans in terms of their expected performance. This is done by inserting the values of the first stage (year 10) decisions that represent values of the transmission investments installed by 2024 into the 20 scenario stochastic model. All other variables (including the 2024 and 2034 generation investments, and the 2034 transmission investments) are allowed to take on their optimal values. This means that, first, generators invest anticipating the “actual” distribution of 20 scenarios, and, second, the transmission owner makes optimal decisions in the 2nd stage when it knows what scenario is realized.

The economic benefit of using stochastic programming to make near-term transmission investments is then obtained by comparing the present worth of expected costs of (a) the naïve solution in which the 20 scenario stochastic program is solved while imposing the first stage transmission decisions from one of the suboptimal models (Deterministic, Heuristic, or Stochastic(5)) with (b) the present worth of expected costs of the unconstrained 20 scenario model, which can be no worse than the value in (a). This difference is called the “value of the stochastic solution” in stochastic programming, and also has been called the “cost of ignoring uncertainty.”

By comparing the values of (a) for different solutions, we can see how well, for example, the heuristic strategies do. We also compare the Stochastic (5) solution performance with the other solutions to determine if a model that includes multiple scenarios, but only a small subset of them, does almost as well as the fully optimal Stochastic (20) solution. We find that this is indeed the case.

ES-5. Quantifying the Value of Stochastic Programming

The results discussed here are based on our 300-bus model. The 21-zone model shows a lower (but still significant) value of stochastic programming because, by its nature, that model considers fewer candidate transmission options and has less congestion. Full details on the results of all models are presented in the report.

Comparison of first stage (2024) lines: does stochastic transmission result in different recommendations? Here we consider whether investment plans developed by stochastic planning differ from deterministic plans.

- On one hand, we might guess that stochastic plans would delay investments until more is known about future load growth, prices, etc.
- On the other hand, we might instead anticipate that more near-term investment in a diverse set of network investments would be justified so that the system in 10 years is positioned to respond to whatever load, price, technology, and policy scenario occurs.

What JHSMINE shows is that under the 2013 TEPPC assumptions a greater number of transmission investments are economically justified compared to a deterministic base case. Figures ES.5 and ES.6 show the additions made in the first (2024) stage. The additional investments made with the stochastic planning model provide additional flexibility to adapt to future conditions. The stochastic model with the most scenarios (20) made approximately 20% to 50% more line additions (measured in terms of investment cost) in year 10 as the base case deterministic model.

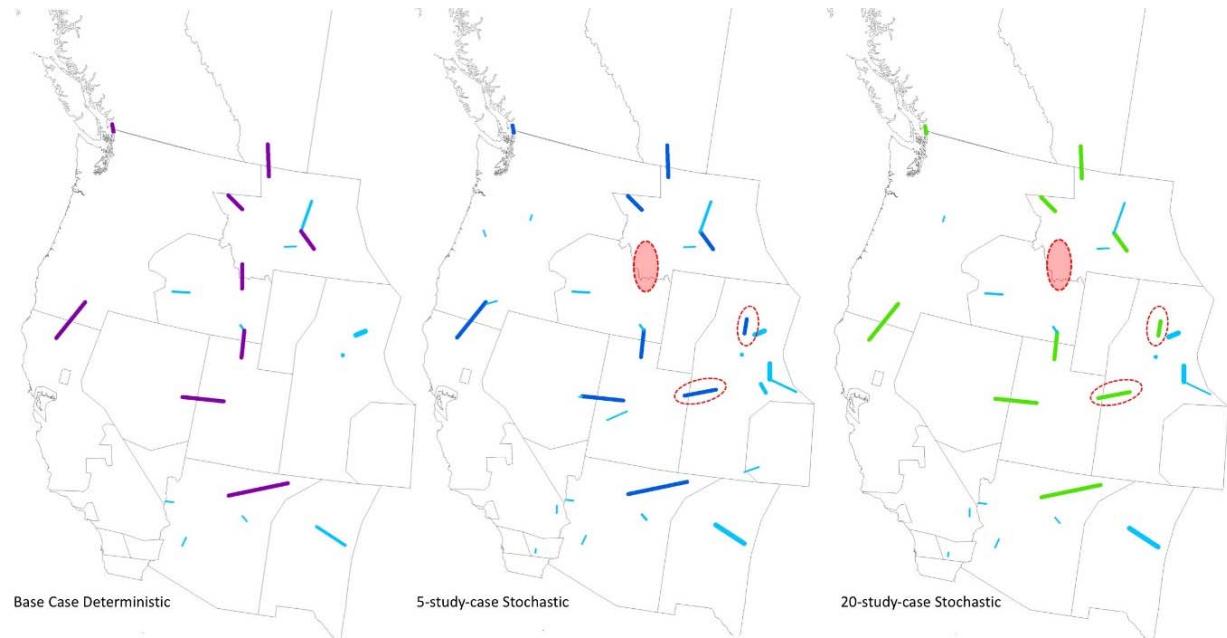


Figure ES.5 Comparison of year 10 transmission recommendations for the deterministic (base case scenario), stochastic (5, equal probability), and stochastic (20, differentiated probability) solutions, 300-bus version of JHSFINE (differentiated probabilities)

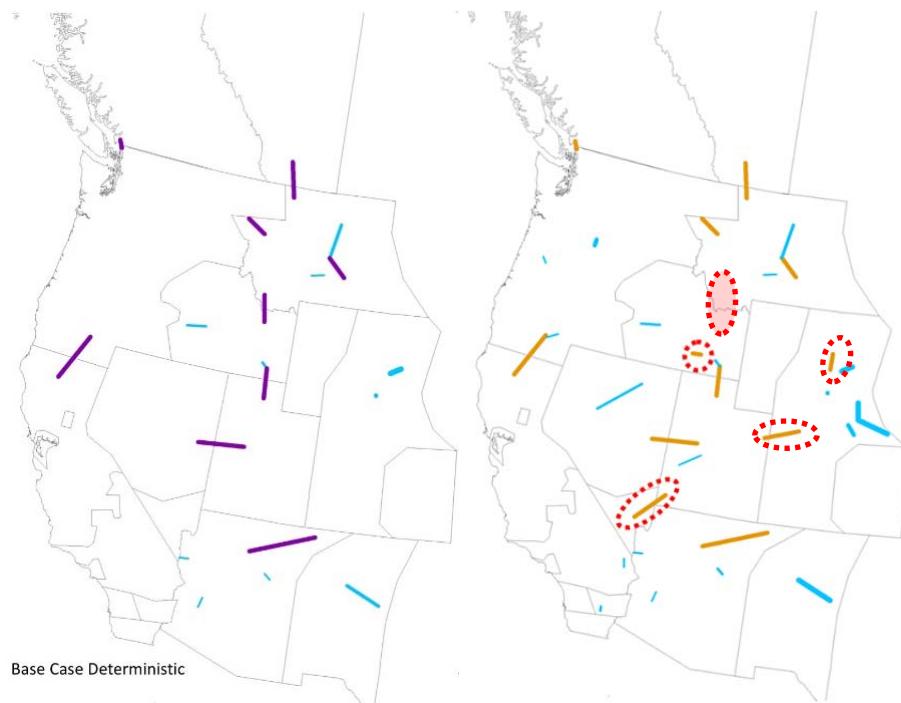


Figure ES.6 Comparison of year 10 transmission recommendations for the deterministic (base case scenario), and stochastic (20, differentiated probability) solutions, 300-bus version of JHSFINE (equal probabilities)

Are stochastic first stage recommendations actually better? Of course, just because the stochastic solution differs from deterministic planning doesn't mean that these differences are important economically. Therefore, we quantified the (probability-weighted) cost savings resulting from implementing the near-term (10 year plan) recommendations of the stochastic model rather than recommendations from any of the deterministic, scenario-based models. In particular, what are the consequences of building the "wrong" lines (from the deterministic model) now, assuming (optimistically) that generation investments adapt as best they can to what is built, and the transmission system is still optimally planned in the second decade once it is known which scenario occurs? For instance, different sets of year 10 recommendations may have similar net benefits, or the system may readily adapt to a misconfigured network by adjusting generation sites or later line additions.

For the 300-bus model, the stochastic solutions perform \$1B to \$12B better than the base case deterministic solution, in terms of the present worth of probability-weighted costs of transmission and generation construction and operations over the 50 year time horizon. For instance, the base case solution (based on the middle values of all the variables), which yields the solution on the left side of Figures ES.5 and ES.6, results in expected costs that are \$11.66 billion higher than the Stochastic (20) solution based on equal probabilities. On the other hand, planning for the 2013 Plan's WECC 3 scenario (which is the low growth, low fuel cost scenario) leaves the system vulnerable to the high growth rates, high renewable installation, or high fuel costs of other scenarios (e.g., the 2013 Plan's WECC 1, 2, or 4 scenarios). Consequently, operating costs in stage 1 (2024) are much higher in those scenarios than they would be otherwise, and there is a relatively large expected penalty (\$28.28 billion) for planning based on the WECC 3 scenario, if it is assumed that the 20 scenarios are equiprobable. This penalty falls to \$6.89 billion if instead the differentiated set of probabilities for the scenarios is used.

The differences in expected costs may appear relatively small at first glance (the \$28.28 billion in present worth terms is still less than 5% of the present worth of generation investment and operating costs in WECC, which over 50 years at a 5% interest rate amount to about one trillion dollars). However, the cost penalties of inefficient planning turn out to be of the same order of magnitude as the construction cost of the 10 year plan lines. In particular, the penalties are comparable in magnitude to the size of the year 10 transmission investments, which are \$3.58B and \$3.75B, respectively, in the base case and WECC 3 deterministic models, and \$4.25B and \$5.43B in the two stochastic (20 scenario) cases (differentiated and equal probabilities, respectively).¹ This shows that the economic losses from suboptimal (deterministic) planning can be highly significant relative to the cost of transmission.

Are stochastic plans more robust against scenarios not considered than deterministic plans? We compared how the stochastic (5 scenario) solutions fared against 15 scenarios that weren't considered in the model, relative to how the base case fared. The stochastic solution did better in a large majority of those scenarios, by a significant margin. Thus, it appears that the transmission investments recommended by

¹ These cost figures count only the additional year 10 lines added by the model, and not the CCTA year 10 lines that are assumed to be included in all solutions.

stochastic programming are inherently robust against future uncertainties compared to deterministic solutions, even if they were not explicitly modeled.

Do heuristics based on identifying lines common to several deterministic plans perform as well as stochastic programming? The California ISO and Mid-Continent ISO have promoted planning processes similar to our Heuristic solutions. They have identified “robust” solutions as ones that include lines that appear in several or all deterministic solutions. This planning approach is represented by our Heuristic models. Of the three possible heuristics we defined, the best is to build lines now that are built in a majority of the 20 individual deterministic models (one model for each of the 20 scenarios). The resulting penalty relative to the stochastic (20) solution is \$1.3B. Thus, although such a heuristic sometimes (but not always) does better than planning for a single scenario, the stochastic solution does better.

What does better than these heuristics, however, is stochastic planning based on a subset of scenarios. We have optimized transmission additions considering only five of the 20 scenarios, and the resulting solutions do nearly as well as the stochastic (20) case if differentiated probabilities are used. Under equal probabilities, the stochastic (5 scenario) solution does much better than the base case solution and as well as any of the heuristics. Meanwhile, the stochastic (5) solution has the distinct advantage of investing less in transmission than does the stochastic (20) solution, which will be attractive to regulators and environmentalists alike.

ES-6. Sensitivity of Transmission Recommendations to Assumptions

Six groups of sensitivity analyses were undertaken, and their conclusions are summarized here.

1. *Which sets of scenarios (what WECC calls “study cases”) are considered and what probabilities are used to weight them.* We consider a series of single scenarios (the five TEPPC base and alternative cases), as well as sets of 5 and 20 scenarios, some with equal probabilities, and some with differentiated probabilities chosen so that the average values of uncertain variables match the base case. As pointed out above, the stochastic solutions, whether based on 5 or 20 scenarios, differ appreciably from deterministic solutions. Compared to the base case, more lines are added; however, some other individual deterministic scenarios (characterized by high load growth) invest in more transmission than the stochastic solution. It turns out that the specific number of scenarios considered by the stochastic plan is less important than the fact that multiple scenarios are considered. The key is to consider a range of possible futures in the first place. This can be observed in our comparisons of the stochastic solutions for the 5 and 20 scenario cases, as well in comparisons of stochastic solutions with different probabilities.
2. *Whether the transmission lines in the TEPPC “common case” year 10 plan are actually completed.* Although common case (CCTA) lines are designated by the TEPPC process as highly probable for completion, in reality there are regulatory and economic hurdles that might not be successfully overcome by every such proposal. In addition, our model identifies additional lines that are economically attractive and merit construction in the first decade. We ask whether having a significant probability of “failure to launch” for the “common case” lines increases the attractiveness of other, non-common case lines in the first ten years, or has a material impact on year 20 (second decade) recommendations. We addressed this with the 21-zone model by

assigning a 20% probability to non-completion of selected subsets of CCTA lines. We found that this risk did not change the year 10 recommendations for line. Consequently, there is no “insurance effect” in which extra lines are recommended in the first stage in case other lines are not completed. Nor is there a “weak link in the chain” effect in which the chance of non-completion of one line lessens the value of another line that is in series with the first line. However, second stage (year 20) transmission additions did change if CCTA lines fail to materialize as planned, with additional lines sometimes built in compensation for the loss of the CCTA lines.

3. *Whether unit commitment constraints that limit thermal generator flexibility are modeled, including start-ups, minimum output levels, and ramp rate limits.* Such constraints make the production costing (operations) part of JHSMINE more realistic, and in other studies it has been shown to significantly influence the optimal mix of thermal and renewable investment by increasing the attractiveness of flexible gas generation, and penalizing slower thermal units and inflexible renewables. Whether near-term transmission recommendations would be affected is the question here. It turns out that the key factor is whether a large amount of slow capacity is being cycled, in particular coal plants. Under an intermediate carbon price, this can happen, and in this circumstance unit commitment constraints can change energy prices, for instance as coal capacity is maintained at its “P_{min}” capacity, causing energy prices to fall during such times. However, under most scenarios and carbon price assumptions, the year 10 transmission expansion recommendations did not change.
4. *Which WECC network representation is adopted (21-zone vs. 300-bus; “pipes and bubbles” vs linearized DC load flow that accounts for Kirchhoff’s voltage law).* Smaller models that omit the voltage law are much easier to solve, and allow more detail to be included in, for example, short-term scenarios of renewable output or long-term planning scenarios. However, geographic aggregation and simplification of the grid may distort the net benefits of particular transmission investments and the resulting model recommendations. The 21-zone model added much less transmission capacity than the 300-bus model in the first stage, and the lines it added were sometimes in different places because of the differing sets of candidate line additions considered in each case. However, both models agreed on the desirability of stronger Pacific Northwest-BC connections. We examined the importance of path constraints in the 300 bus model and found that they made crucial differences in line recommendations compared to the case where only line thermal limits are included. Finally, we examined the effect of including Kirchhoff’s voltage law in form of a linearized DC load flow in the 300 bus model. Compared to a pipes-and-bubbles representation, 50% more lines are added in the first stage (12 vs. 8 lines, incurring 30% more capital cost). However, all the lines recommended in the pipes-and-bubbles version were also chosen by the linearized DC load flow model, suggesting that the pipes-and-bubbles model might be useful for identifying candidate lines for expansion.
5. *The number of distinct hours that are used to represent load, wind, and solar variability in each year.* More hours result in a more textured representation of the distribution of renewable generation and loads over time. Furthermore, representing diversity of output and loads between the WECC sub-regions can, in theory, significantly affect the value of transmission. This turned out to be the case. We compared models with samples of 24 and 72 hours and found

that although six of the lines included in their year 10 recommendations were the same, each model chose two lines not considered by the other.

6. *The effect of considering climate changes in which less or more hydropower production is available.* The WECC system's dependence on hydro output means that production costs vary greatly between years with drought and hydro surplus conditions. If climate change occurs such that the amount of hydropower available is consistently different than under today's conditions, this possibility could significantly affect the value of transmission between hydro rich regions and the rest of WECC. However, in our runs, including scenarios of possible climate change did not alter first stage decisions.

ES-6. Conclusions

Our experience running stochastic planning models indicates that they are practical to do so for 21-zone or 300-bus models of the WECC system under multiple scenarios, and that considering more than one scenario simultaneously in a planning model results in distinctly different plans. The reduction in probability weighted cost that would result from implementing the stochastic model's recommendations is on the same order of magnitude as the size of the first stage (year 10) investment.

The analyses show that some compromises are required to keep solution times within reasonable bounds (minutes, rather than hours). If multiple scenarios are to be considered, then running the full 300-bus model with Kirchhoff's voltage law together with just 6 sample hours within a year for the multiyear problem is not yet practical. Executing the voltage law model with that number of sample hours was successful only for a model with one study case as a scenario. The voltage law model selects more lines as economic because of the greater amount of congestion, but in our test case, the lines it selected also included all the lines that the simpler pipes-and-bubbles model chose, as long as both models represent path constraints.

We conclude that appreciably different recommendations are made by the 300-bus model relative to the 21-zone model, so that the larger network is preferred if the effort can be made to build the larger data base it requires. We also find that selection of operating hours to simulate within a given year can make an important difference, and so should be done carefully in order to capture the variations as well as correlations of loads, wind output, and solar output over the region. On the other hand, incorporating unit commitment constraints in the production costing part of the model is less important, making no difference in year 10 line recommendations in most cases tested.

We recommend that WECC consider implementation of a stochastic model as part of its next planning cycle in order to build confidence that near term (year 10) transmission reinforcements will contribute to an adaptable and robust network. Adaptability and robustness is best assessed with a model that recognizes that some line additions will be more effective in poising the system to accommodate future changes in fuel costs, loads, technologies, and policies. Such a model must consider multiple possible futures at once and how a system can adapt to them over multiple decades. Finally, because the generation siting responds to transmission availability, a co-optimization formulation, such as used here, should be adopted. This is essential for capturing the savings in generation capital costs as well as production expenses that can be realized from transmission additions.

1 Introduction

1.1 Motivation

The electricity industry has undergone a series of radical changes over the past several decades. Over this period there have been sudden shifts in fuel costs, adoption of new environmental policies, declines in load growth, and expansion of clean energy technologies, all of which affect the value of transmission [1, 2]. More changes are certain to come, but their nature and magnitude is highly uncertain. Such changes in market fundamentals profoundly impact the economic value of transmission for accessing inexpensive resources, diversifying supply sources, and enhancing competition. Depending on what happens in the future, transmission facilities added today may provide far more value than planners anticipate, or may turn out to be costly stranded assets. But it is unrealistic to just wait to see what happens before committing to build, because delays in realizing the benefits of stronger interconnections can also be costly.²

Balancing these risks requires that we not only consider a wide range of possible study cases (or “scenarios”) for the 2015-2035 timeframe, but also how transmission investments we make now either enhance or undermine the system’s ability to adapt to future conditions. Placing a value on potential additions to the network therefore requires that a transmission planning method recognize three key considerations: system-level interactions among transmission and generation; variation in generation and load conditions and uncertainty concerning long-run drivers of supply and demand conditions; and system adaptability as conditions change in unexpected ways.

- To recognize *system-level interactions* is to address two questions: how do transmission reinforcements interact with each other and with generation? In particular: (1) How do proposed transmission facilities interact with each other, resources, and the rest of the network to determine overall system economic and environmental performance? And: (2) How might siting and operating decisions by investors in generation and other resources be affected by the availability of transmission resources? Because our modeling anticipates how generation investments might shift in response to transmission investment, our modeling approach represents a “proactive” or “anticipative” transmission planning paradigm, which is simulated by co-optimizing transmission and generation investment.³
- Risk is a fact of life for planners, who must make commitments without knowing the future. Thus, planning methods should consider *many scenarios of both short-term variations and long-run uncertainties*: In the short-run, how does a proposed investment enhance a system’s ability to take advantage of short-run resource and load diversity? In the long-run, how does the in-

² For instance, stronger interconnections between California, the rest of the WECC, and other interconnections would have enabled imports of additional highly valuable power during the 2000-2001 California crisis.

³ For a review of co-optimization methods and applications, including a documentation of the benefits of anticipative planning, see [7] and [14]. Under assumptions of a competitive generation market and efficient pricing of transmission, a joint optimization of transmission and generation is equivalent to a transmission planner maximizing total net benefits to the market considering the reactions of a competitive generation market [18].

vestment contribute to the system's robustness in the face of the profound long-run policy, technology, and economic changes that might occur over the assets' 40 or more-year lifetime? Given the uncertainties, what investments can be made now with confidence, and which ones should be deferred?

- The ability of a system to cope with long-run uncertainties depends in large measure on its *adaptability*. There are several dimensions to adaptability. First, would a particular proposed transmission addition open up alternative operational and planning responses to future developments, or does it foreclose them? Second, is flexibility in timing of investments; it is important to consider how uncertainty could affect the optimal timing of a proposed transmission addition. For instance, in the face of uncertainty, postponing commitments to obtain more information or resolve uncertainties about, e.g., the future of climate policy could be optimal. Is the best response to long-run uncertainties to delay transmission investments in order to avoid the risk of stranded assets by waiting until uncertainties are resolved? A third dimension is portfolio diversification: might the best response to uncertainty be to build a larger portfolio of transmission. Extra lines might then act as "insurance" against the uncertainties, for instance by ensuring access to a wider range of possible developable renewable resources.

The goal of this study is to demonstrate the usefulness of a method that includes these three considerations, the Johns Hopkins Stochastic Multi-Stage Integrated Network Expansion (JHSFINE). This demonstration addresses three questions.

- *First, what can be learned* from applying a multi-scenario and adaptive ("stochastic") method for transmission system planning to the WECC region? The answer is: the method can identify individual lines or combinations of lines that enhance network flexibility that can be overlooked in deterministic planning, and the method can quantify the economic value of that flexibility.
- *Second, is it practical* to use stochastic planning for large regions, such as the Western Interconnection? The answer to that question is: yes, although compromises must be made in terms of modeling Kirchhoff's voltage law,⁴ the number of long-run scenarios that are considered, and the number of short-run load and renewable energy instances that are represented.
- *Third, what are the impacts* upon recommendations of the 10 and 20 year WECC planning process of uncertainties and generator flexibility? In particular, we consider the assumptions and recommendations of the 2013 TEPPC (Transmission Expansion Planning Policy Committee) process [3], which considers near-term (next decade or "year 10") and long-term (second decade, or "year 20") transmission investments in the WECC region. The answer is: the impacts depend on which particular assumptions concerning those uncertainties and flexibility are considered. Some assumptions matter strongly; others make little difference.

⁴ Kirchhoff's voltage law states that the sum of voltage drops around any loop in a network is zero. It implies that power will flow along all parallel paths between the point of injection and the point of withdrawal. In the case of a linearized DC load flow approximation, which is used in one version of JHSFINE applied here, it further implies that the split of flows among possible paths occurs according to fixed proportions that are called "power transfer distribution factors."

We elaborate on these answers in this report. From these results, we have developed a concise set of lessons that are directly relevant to WECC transmission planning processes.

1.2 Scope

The report begins with a brief review of the current state of transmission expansion planning models both in development and currently implemented (section 2.1). This is followed by an overview of the two-stage stochastic planning methodology for transmission planning (section 2.2). Section 3 provides detail on the methodology used and the specific implementations of JHSMINE, a multistage stochastic co-optimization planning model. JHSMINE makes recommendations for line construction both in the first and second decades in a single model run (years 10 and 20), considering their performance over 50 years, including a 30 year “extension” period. Year 10 lines include both “common case” transmission lines that are pre-specified by the TEPPC process, based on TEPPC’s assessment that they are highly likely to be constructed, plus additional lines that the model may find economic to build in the near term. The model must commit to year 10 decisions before it is known which scenario (what WECC calls “study case”) will actually happen, while year 20 lines are chosen by the model depending on which scenario occurs, which is assumed to be revealed at the end of year 10. Thus, year 20 lines represent adaptation by the grid to the policy, economic, and technology developments, while year 10 decisions must reckon with the risk of becoming stranded assets. On the other hand, year 10 additions will realize ten more years of benefits than additions that are deferred until the second decade. This is a fundamental tradeoff in uncertainty-based planning.

The next section (section 4) documents the extensive data development process and assumptions. This includes the construction of scenarios, two network representations (21-zone and 300-bus), operations, and regulatory conditions needed to represent the WECC system in JHSMINE.

Following the methodology and data sections, we present an overview of the results from our analysis (section 5). Within that section, we address key questions central to our results. These include whether stochastic programming is practical (section 5.1), and whether stochastic transmission plans differ from, and perform better, than the results of traditional planning approaches (section 5.2). The traditional planning approaches include deterministic (single scenario planning) against the 2013 TEPPC base case and the creation of transmission plans by identifying transmission investments that are recommended in some or all of a set of deterministic runs under a set of five 2013 TEPPC scenarios. The latter approach has been used by MISO [4] and CAISO [5] to identify “most value” or “robust” transmission investment lines, respectively.

We then devote section 5.3 to a series of sensitivity studies that examine how the recommended year 10 additions and other results change if key assumptions are altered. The year 10 recommendations are arguably the most important results of the TEPPC process because their implementation would require action now to begin the detailed planning studies and permitting processes that are prerequisites to building a line within the next decade. The section analyzes the sensitivities of the model’s construction recommendations and costs to the following six sets of assumptions:

7. Which sets of scenarios (what WECC calls “study cases”) are considered and what probabilities are used to weight them (section 5.3.1). We consider a series of single scenarios (the five TEPPC base and alternative cases), as well as sets of 5 and 20 scenarios, some with equal probabilities, and some with differentiated probabilities chosen so that the average values of uncertain variables match the base case.
8. Whether the transmission lines in the TEPPC “common case” year 10 plan are actually completed (section 5.3.2). Although common case lines are designated by the TEPPC process as highly probable for completion, in reality there are regulatory and economic hurdles that might not be successfully overcome by every such proposal. In addition, our model identifies additional lines that are economically attractive and merit construction in the first decade. We ask whether having a significant probability of “failure to launch” for the “common case” lines increases the attractiveness of other, non-common case lines in the first ten years, or has a material impact on year 20 (second decade) recommendations.
9. Whether unit commitment constraints that limit thermal generator flexibility are modeled, including start-ups, minimum output levels, and ramp rate limits (section 5.3.3). Such constraints make the production costing (operations) part of JHSMINE more realistic, and in other studies it has been shown to significantly influence the optimal mix of thermal and renewable investment by increasing the attractiveness of flexible gas generation, and penalizing slower thermal units and inflexible renewables (e.g., [6]). Whether near-term transmission recommendations would be affected is the question here.
10. Which WECC network representation is adopted (21-zone vs. 300-bus; “pipes and bubbles” vs linearized DC load flow that accounts for Kirchhoff’s voltage law) (section 5.3.4). Smaller models that omit the voltage law are easier to solve, and allow more detail to be included in, for example, short-term scenarios of renewable output or long-term planning scenarios. However, geographic aggregation and simplification of the grid may distort the net benefits of particular transmission investments and the resulting model recommendations.
11. The number of distinct hours that are used to represent load, wind, and solar variability in each year (section 5.3.5). More hours result in a more textured representation of the distribution of renewable generation and loads over time. Furthermore, representing diversity of output and loads between the WECC sub-regions can, in theory, significantly affect the value of transmission.
12. The effect of considering climate changes in which less or more hydropower production is available (section 5.3.6). The WECC system’s dependence on hydro output means that production costs vary greatly between years with drought and hydro surplus conditions. If climate change occurs such that the amount of hydropower available is consistently different than under today’s conditions, this possibility could significantly affect the value of transmission between hydro rich regions and the rest of WECC.

Following those sensitivity analyses, we present conclusions in section 6, including recommendations for additional research and applications that could enhance the practicality and usefulness of stochastic programming for long-term transmission planning.

Finally, in Appendices A-C, we document in detail the process we followed to define the scenarios, the differences among the scenarios in terms of the values of the uncertain variables assumed, and their probabilities. Appendix D presents the mathematical formulation of the generator unit commitment version of JHSMINE, which has not previously been documented in the literature.

2 A Brief Review of Economic Methods for Long-Run Transmission Planning

2.1 Methods Used in Practice and Their Limitations

Computational planning tools commonly used for transmission planning studies have a number of widely acknowledged limitations. Three key limits are: 1) supply resources and transmission are optimized independently; 2) the effect of long run technological, economic, and policy uncertainties on transmission economics is either ignored or assessed through sensitivity analyses that cannot identify the mix of transmission investments that optimize probability-weighted costs and benefits; and 3) the impact of variable generation on the need for operational flexibility is greatly simplified or is not represented at all. In this section, we briefly summarize available software and their limitations; the interested reader is referred to the detailed reviews provided by Liu et al. [7] and Krishnan et al. [8].

The most common approach that planners use is detailed production cost modeling tools to assess the economic performance of pre-defined transmission and generation configurations. Examples of such tools include PSS-E [9], GridView [10], and PROMOD IV [11]. These commercial modeling packages are not capable of topology optimization and will not suggest potentially better transmission investments [12, 13]. A very few commercial models have topology optimization capabilities, like NETPLAN, but they assume a fixed scenario of generation build-out (i.e., they are unable to represent how generator siting and investment mix responds to transmission investment) and, furthermore, they do not consider the uncertainties in market and regulatory conditions. A notable exception to this is WECC's Long-term Planning Tool, which provides insights on the interactions of generation and transmission investments in the second decade of the TEPPC planning process [3]. It does this by iterating between new generation capacity evaluation (using a leveled cost methodology) and transmission investment optimization. Another exception is Energy Exemplar's PLEXOS (www.plexos.com), which performs simultaneous generation and transmission co-optimization but does not consider long-run uncertainties except through sensitivity analyses [14].

Current transmission planning methods are limited in their ability to represent uncertainty. Under scenario planning, a range of scenarios are defined, each of which represent one possible combination of future variables, such as load growth, fuel prices, or environmental policies. For each of these scenarios a separate transmission plan is developed using either deterministic optimization (as in NETPLAN) or, more often, by testing various pre-defined plans using production costing models. In some studies, investments that are selected in all or most of the scenario plans are identified as "robust" decisions. Examples of this type of planning approach include the "Multi-Value Projects" by MISO [4], and the "least-regret investments" by the California ISO [5]. The central assumption of these approaches is that investments selected in all or most scenarios provide a hedge against uncertainty and should therefore be developed. However, it has been proven theoretically that optimal stochastic investment strategies (i.e., ones that minimize probability-weighted costs across scenarios) cannot be constructed through such heuristics. Indeed, a heuristic, like the examples provided above, can perform considerably worse than a deterministic plan due to building too few lines [15]. Plans that are optimal under uncertainty are rarely

optimal for any given deterministic scenario. For example, a particular transmission investment might perform well in many scenarios because it gives the system flexibility to, for instance, develop any of several renewable energy zones. But that investment might never be the very best choice in any particular scenario of renewable development. However, when considered stochastically, such a line would provide a hedge against uncertainty and could be optimal overall. For this reason, scenario planning and heuristics are unable to consider the full value of alternatives that increase the flexibility of transmission plans.

The future need to integrate renewable resources will be a major driver of inter-regional transmission investments. Transmission expansion can be justified both by the need to access high quality resources as well as the need to take advantage of resource diversity. Many evaluations of transmission expansion consider only a small set of years or hours, such as the California ISO Transmission Economic Assessment Methodology [16], or do not incorporate ramping and unit commitment constraints which can greatly impact the ability of generation, storage, and demand resources to respond to renewable variability. Some transmission analyses have incorporated approximations for ramping constraints but detailed representations of the variability of renewable resources have made other simplifications necessary (such as considering highly aggregated networks with few zones, or disregarding or simplifying how Kirchhoff's laws affect the flow impacts of new additions, e.g., NREL ReEDS. Elsewhere, it has been shown that including renewable variability together with more realistic representation of generation ramping and unit commitment constraints can make large differences in optimal resource portfolios, for example the split between baseload, cycling, and peaking capacity [6].

Thus our review of the literature confirms that there is a need for co-optimizing investments in transmission and generation while considering long-run uncertainties, as well as for addressing renewable variability in long-term expansion planning applications. There is a particular need for developing and applying methods for realistic networks such as the Western Interconnection.

2.2 What is Stochastic Transmission Planning?

Traditional deterministic or scenario-based planning methods identify transmission investments that are beneficial under one set of assumptions, and then consider whether those recommendations would be altered if the assumptions are changed. For instance, if natural gas prices go up, investment *plan A* may be the best, but if prices stay low, then *plan B* might instead be preferred. As noted above, sophisticated versions of scenario-based planning might attempt to identify transmission investments that are recommended under each of a wide range of possible scenarios. However, such a plan developed in this way may have much higher costs than a plan that is developed considering all scenarios--and their relative likelihoods--at once.

Stochastic planning is an approach that allows a decision maker to ask: what network investments should be made now, and what investments should be deferred and made later, considering multiple possibilities of what might happen and how those investments affect the ability of a system to adapt to later changes. This decision structure is shown in Figure 2.1 as a decision tree, in which time proceeds from left to right. Three steps of the decision process are shown, consisting of two decision stages sepa-

rated by uncertain scenarios, although stochastic programming models can include more than three such steps. The steps are:

1. “Here and now” decisions--that are made before it is known how longer-run uncertainties will be resolved--are shown as the first square node on the left. A particular decision (one set of transmission investments, for instance) might be represented as one of the arcs leaving that node to the right.
2. Then proceeding to the right, the decision maker will next encounter chance nodes (round nodes). These represent the range of possible scenarios (one per arc leaving the node to the right) of what could happen to long-run demand growth, prices, policies, etc. Each of the scenarios has a probability.
3. Finally, for each scenario, there is a decision node (square node) representing a set of “wait and see” or “recourse” decisions that are made after it is known which scenario has occurred, represented as a second set of square decision nodes. What choice is made in this second stage is conditioned on the scenario; as a result, the decisions made if, say, wind development costs fall dramatically can differ if instead a scenario occurs in which wind costs are unchanged as time progresses. Thus, recourse decisions allow the system to adapt to technology, economic, and policy changes embodied in the scenarios.

An optimal solution, or “decision strategy”, for this problem is a single set of choices in the first decision stage (shown in Figure 2.2 as a red line from the first decision node) plus a set of choices for each of the scenarios that are considered in the second decision stage (shown as the red lines from the second set of decision nodes that are reached, given the first stage’s decisions).

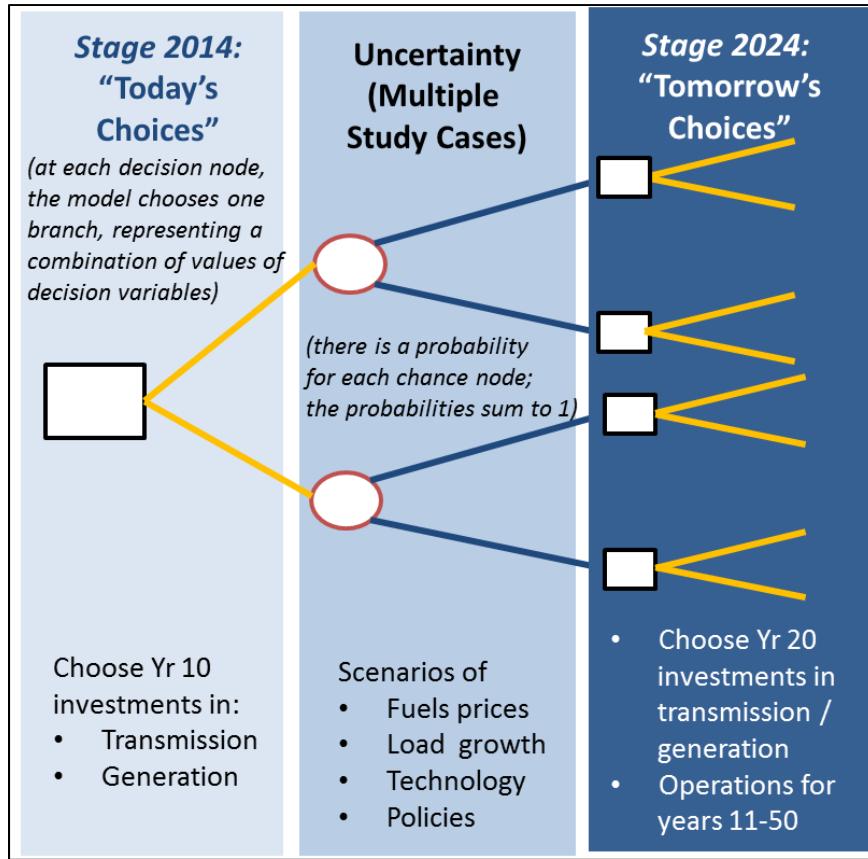


Figure 2.1 Decision tree schematic of the two-stage transmission-generation optimization

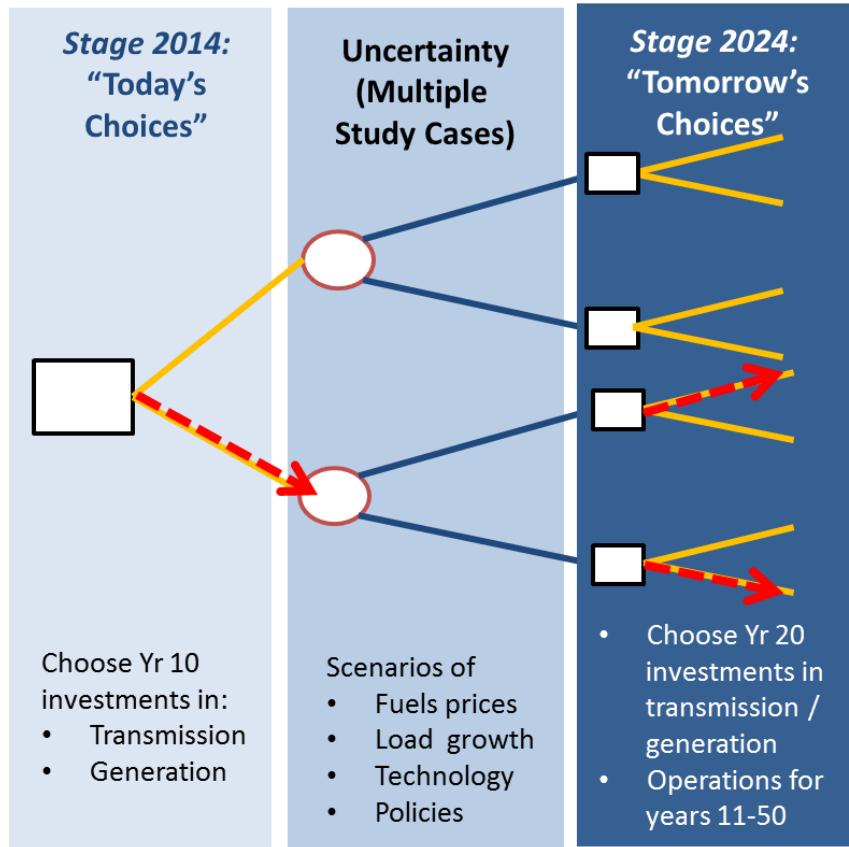


Figure 2.2 A solved decision tree, indicating which decisions are made in the first stage and, for each scenario, in the second stage

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

Figure 2.3 shows the relationship of these variables to the decision trees of Figures 2.1 and 2.2; the first set of variables (shown as a vector \mathbf{X}_1) are chosen in the first stage’s decision node, while there is a separate set of second stage variables (shown as a vector $\mathbf{X}_{2,S}$) for each of the scenarios S in the second stage. The second stage variables include both the year 20 investments and all operations after year 11. The mathematical statement is a standard “two stage” linear stochastic optimization model with a linear

objective function (*Minimize the present worth of probability-weighted costs*) that is to be optimized [17]. The model limits the feasible values of the variables using two sets of linear constraints: one set limits the possible values of first-stage decisions, while the second set represents the relationships between first- and second-stage decisions. For instance, if a transmission corridor is developed in stage 1, a constraint might state that it cannot also be built again in stage 2. In the model, input data include the matrix \mathbf{A} and vectors \mathbf{B} , which define the constraints, and the objective function parameters \mathbf{C} (vectors representing costs associated with the decisions \mathbf{X}). Costs incurred in the second stage under a given scenario S are weighted by the assumed probability of that scenario P_S .

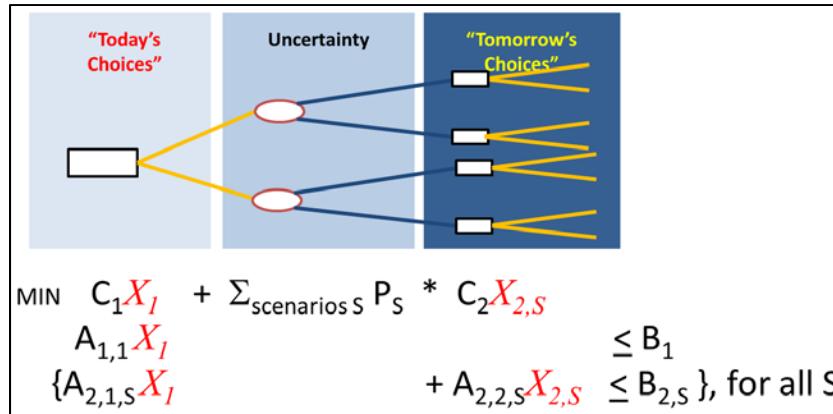


Figure 2.3 A two-stage stochastic program written in abstract mathematical form, showing the relationship of the first and second stage decision variables to the decision nodes of the decision tree

The network reinforcements recommended by a stochastic planning method may be very different from those of scenario-based planning deterministic methods. Because deterministic methods cannot quantify flexibility in the face of long run uncertainties, the stochastic model's solution may have much lower probability-weighted costs. In particular, in our analyses described in section 5, we find that the cost savings from stochastic planning, in terms of decreased investment and production costs, can be of the same order of magnitude as the transmission investment itself. Such general advantages of stochastic planning have been understood for many decades, but only recently have advances in computer hardware and software made their use in transmission planning practical. In this project, we test a transmission planning implementation of stochastic programming—JHSMINE—using the 2013 WECC TEPPC assumptions [3] in order to assess what can be learned and what benefits might result from considering multiple scenarios simultaneously in a single stochastic model. In the next section, we provide an overview of the JHSMINE model.

3 Methodology

First we begin with an overview of the Johns Hopkins Stochastic Multi-stage Integrated Network Expansion model (JHSMINE) utilized in our analysis (section 3.2). This includes examining the unique features of this particular planning model. Then section 3.2 documents the three versions of JHSMINE that were used in this analysis to address specific needs related to the WECC project; these versions include ones with 21 zones as well as versions of the 300-bus model based on a “pipes-and-bubbles” and Kirchhoff’s voltage law representations. Later, in section 4, we summarize the data assumptions used in the model.

3.1 JHSMINE Transmission Planning Tool

For our study we utilize JHSMINE, a stochastic two-stage co-optimization model, which captures timing and uncertainty considerations involved in transmission expansion planning. Originally developed in 2010, this model has been applied to a range of networks including Great Britain [18], the California ISO [19], a 13 node representation of the U.S. grid [7], the Eastern Interconnection [14], and a 240 bus representation of WECC [15]. JHSMINE performs a simultaneous optimization of generation, transmission, and operations across the scenarios considered by the model. Operations are simulated using a bottom-up (engineering economic) approach considers the types and capacity generators in each region, and represents their dispatch and flow of power along the network.

Here, we use JHSMINE to quantify the possible benefits of stochastic programming for three different representations of the WECC system: a 21-zone “pipes and bubbles” network and a 300 aggregated bus network that can be solved either as a pipes-and-bubbles network, or as a linearized “DC load flow” network. The network aggregation was accomplished with Arizona State University software developed by Dr. Daniel Tylavsky and Yujia Zhu [20]. We considered a fifty-year time horizon in which investments can be made over the next decade in new lines that would be available in the year 2024 (modeling the 10 year TEPPC transmission process), and additional transmission investments can be made subsequently (representing the 20 year TEPPC plan). The lines in place by 2024 are constrained to include, at a minimum, all the TEPPC “common case” lines. These are lines that the 2013 TEPPC 10-year process has identified as likely and desirable lines for implementation by 2023 [3]. Generation investments are also made by the model. Therefore, the model is a “co-optimization” model that anticipates how generation siting and fuel mix responds to where transmission investments are made, and so can quantify both the production cost and generation capital cost savings resulting from transmission investments [7, 8]. Our application of JHSMINE considered up to 25 future scenarios at once, with probabilities of each determined by the user.

The structure of the decision problem is shown in Figure 2.1 (Section 2). Commitments to investment, both transmission and generation, occur in 2014 (first stage, with an in-service date of 2024) and 2024 (second stage, in service in 2034). Those 2014 decisions occur before it is known which of the several scenarios will occur, and so the model must identify a single set of investment decisions at that time that will then be in place in 2024 for all scenarios. The consideration of generation investments as well as transmission means that this is a co-optimization model, in which a “pro-active” transmission planner anticipates how the location and types of generation investment respond to network availability [7, 21].

Decisions about system operations (generation dispatch and line flows) are made in 2024 (first stage, representing operations from 2024-2033) and 2034 (second stage, modeling operations from 2034-2063), with the second stage operating decisions including both the decade after the second stage investments are in place (2034-2043) and an “extension period” accounting for production cost impacts of the investments in subsequent years (2044-2063). The extension period is necessary so that there is not an “end effects” bias against capital-intensive investments whose benefits are in form of later fuel savings. The production costs for each year in the 2024-2033 decade are assumed to be the same as 2024; i.e., that year is repeated ten times. Similarly, 2034’s costs are used for each year in 2034-2043, and 2044 is used for each year in 2044-2063.

The model optimizes under uncertainty by minimizing the expected (probability-weighted) total present worth cost of investments and operations. We assume a real interest rate of 5% in calculating present worth, consistent with what the U.S. Energy Information Agency assumes in its National Energy Modeling System. Probability weights assign a relative likelihood to each scenario and allow the model to determine a plan accordingly. As the model makes its investments, it is able to simultaneously evaluate their benefits considering how those investments affect system operations under a range of short-run load and renewable output conditions as well as several future scenarios. For a full mathematic documentation of the model please refer to Munoz et al. [15]. Table 3.1 summarizes, in descriptive form, the objective function, variables, and constraints of the model.

Table 3.1 Summary of the structure of JHSMINE

Optimize the objective:

Minimize (probability-weighted, present worth) of cost over
50 yrs

By choosing values of decision variables:

- Transmission investment (0-1)
 - 10 yr “portal” (optional) lines (in addition to Common Case lines)
 - 20 yr lines
- Generation investment & dispatch (*co-optimized*)

Respecting constraints:

- Kirchhoff’s laws (linear OPF)
 - Load by hour
- Generator operating constraints
 - Variable renewable availability by hour
- Renewable Portfolio Standards
- Siting restrictions

Accounting for uncertainties:

- Short-term load/renewable conditions (hourly variability)
- In stochastic model: long-run scenarios (study cases)

JHSMINE is a flexible modeling tool and the exact implementation can be varied depending on the specific needs of the user. For example, versions have been implemented for this project that are based on three different network types (21-zone and 300-bus pipes-and-bubbles networks and a 300-bus linearized DC load flow formulation) and two different generation production costing methods (representations based on a discretized load duration curve and a linearized unit commitment with chronologic hours). Despite this variety, there are many core features that are common among all versions of the model. A common structure of decision stages is adopted in all models, divided into 2014-2023 (first stage investments, assumed to be in place in 2024), 2024-2033 (second stage investments to be in place by 2034, and operations for 2024-2033), and 2034-2063 (an extension period representing post second-stage operations). Future costs are discounted in the same way in all model formulations. Costs are calculated using standard approaches including capital costs for investments as well as fixed and variable O&M for generation (fuel and non-fuel), as well as CO₂ taxes. All models include Kirchhoff's current law (zonal or bus energy balances) and thermal limits on transmission lines. Regulatory issues such as CO₂ taxes and renewable portfolio standards (RPSs), both for individual states and provinces as well as for defined sets of states and provinces, are handled by the model. Trading of renewable energy credits (RECs) between states and provinces where trading is allowed by law is also modeled.⁵

3.2 Specific WECC Implementations of JHSMINE

There are four specific network implementations of JHSMINE that we used in this project's WECC analyses. One implementation uses a 21-zone model which has a smaller network but a more detailed representation of variations of load and renewables across the year. A load duration curve approximation with discrete hours was used for that representation. Here we also included additional requirements on operating reserves and modelled the reserve sharing groups [3]. We also included the option of a national RPS which must be satisfied in addition to state RPS requirements. For each pair of regions directly connected by the transmission lines, the pipes-and-bubbles representation defined a single transmission link with an equivalent thermal capacity, based upon both thermal and path limits.

For the second and third implementations, we use a 300-bus model, which has a more detailed representation of the WECC network, while necessarily including fewer hours in the load duration curve approximation to accommodate the limitations of the optimization software that we used (AIMMS/CPLEX on either a 6 core desktop or a 32 core server). We included additional details about the network that were not explicitly represented in the 21-zone model. This included explicit transmission path limits as well line impedances. The included path constraints limit flow on all transmission lines which are part of a path. Investing in a line that was part of a path was assumed to increase the path limit by a proportional amount. As a necessary byproduct of the network reduction, a number of unmonitored lines were included network. Such lines have impedances but lack thermal limits. In the 300-bus model, generation investments take place at a fictional hub located within a specified region. All buses within that region are connected to this investment hub but power can only flow outward along these fictional lines.

⁵ For an analysis using JHSMINE of the economic benefits and environmental consequences of wider trading of RECs in the WECC region, see [40].

The 300-bus model was solved in two different versions, a transportation (pipes-and-bubbles) model and a KVL (linearized DC load flow) model. The transportation model was capable of being solved under a greater number of scenarios and/or hours. The KVL model requires use of a reduced set of hours and scenarios in order to solve within a regional time.

Section 5.3.4 analyzes the impact upon the solutions of using the 21-zone versus 300-bus representation, and the effect of using a Kirchhoff's voltage law representation in the 300-bus model.

The fourth implementation has the goal of assessing the impact of including unit commitment into our model and therefore contains additional constraints upon the chronological operations of generators, while adopting the 21-zone network representation of the first implementation. Analyzing the effect of unit commitment on transmission investment requires chronological data so that inter-temporal operational constraints such as ramp limits and generator start-ups can be accurately represented. To construct a chronologic sequence of demand, wind, and solar data, we sampled three days in a year (one typical day, one summer peak, and one winter peak day with appropriate weights) with the 24th hour of each day looping back onto the 1st hour of the same day, to avoid end effect distortions. In that model, we use a unit commitment approximation that is a linear programming relaxation of a full unit commitment MIP, with additional constraints that capture ramp limits more realistically.⁶ As an example of these additional constraints, ramping capability - which determines the maximum energy a unit can provide from one hour to the next – is a function of the capacity that has been started up in the previous hour. We also account for minimum run constraints that mandate the minimum capacity a unit should be producing if it is running. To be more specific, here are the changes made to the operations model to accommodate unit commitment costs and restrictions:

1. Constraints on hour-to-hour ramps of each generation type are defined, as are variables that represent start-ups and the Pmin capacity on line. Generation is constrained to be between the on-line Pmin and Pmax capacity for each type of generator. Other constraints force start-ups to occur when the Pmin capacity on-line increases.
2. The binary (0-1) variables are allowed to take on any value between 0 and 1. This elimination of binary variables is crucial to attain reasonable solution times for a planning model.
3. The ramp constraints are modified to account for how unit start-ups and shut-downs affect the change in generation that can occur.

Mathematical details are provided in Appendix D. The impact of including these unit commitment constraints is considered in Section 5.3.3.

3.3 Experimental design

In Sections 5.1 and 5.2, we quantify the value of stochastic transmission planning by comparing the cost performance of the first stage investments derived with versions of JHSMINE that consider 1, 5 or 20 scenarios (Figure 3.1), as follows:

⁶ For mathematical details on the implementation of unit commitment in JHSMINE, see <http://energy.gov/sites/prod/files/2014/09/f18/06-2014RM-Hobbs-Schuler.pdf>

- “*Deterministic Planning*” (20 plans examined). A single scenario (either a base case scenario, or one of four alternative “study cases” considered in the 2013 WECC planning study). In addition, for the purposes of the “Deterministic Heuristics” we generate 15 additional deterministic solutions, one for each of the other 20 scenarios considered, but we do not analyze their individual performance.
- “*Deterministic Heuristics*” (3 approaches). The first stage decisions here are identified by comparing the deterministic solutions. “*DH: Build All*” assumes a 1st stage line is built if it appears in *any* deterministic model solution. “*DH: Majority Vote*” chooses lines that appear in a majority of the 20 deterministic solutions. “*DH: Unanimous*” builds only those lines that appear in all 20 deterministic solutions.
- “*Stochastic (5)*” (1 approach). This solution is obtained by considering only the first five scenarios (those from the 2013 Plan) in JHSFINE. Two variants are considered: one with a 20% probability for each scenario and the other considering differentiated probabilities that are chosen so that the probability-weighted values of the uncertain variables are close to their base case values.
- “*Stochastic (20)*” (1 approach). This solution is based upon including all 20 scenarios in the stochastic version of JHSFINE. In one variant, each scenario is assigned a 5% probability, while in the other, probabilities are assigned to the scenarios so that each has a probability of at least 2%, and the expected values of the variables are close the values assumed in the base case.

We then compare these plans in terms of their expected performance. This is done by inserting the values of the first stage (Year 10) decisions that represent values of the transmission investments installed by 2024 into the 20 scenario stochastic model. All other variables (including the 2024 and 2034 generation investments, and the 2034 transmission investments) are then optimized in the 20 scenario model. This means that (1) generators invest anticipating the “actual” distribution of 20 scenarios, and (2) the transmission owner makes optimal decisions in the 2nd stage when it knows what scenario is realized.⁷

⁷ This is a strong assumption for generators, in that they are assumed to have more knowledge than the transmission owner. However, to also freeze the generation investment portion of X_1 makes an even stronger assumption that the generators will make the same assumptions about the future that the transmission planner does, no matter how naïve or sophisticated the transmission planner is about uncertainty.

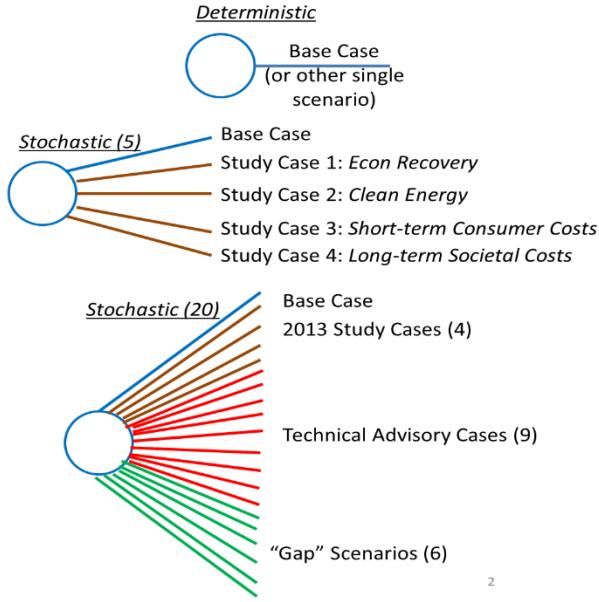


Figure 3.1 Schematic of chance node of stochastic program under one, five, or twenty scenarios

But on the other hand, to make the latter assumption would result in much larger benefits of stochastic planning, in essence because the implicit assumption would be that by adapting stochastic planning, the transmission planner will make planning by everyone, including generation owners, more rational. We therefore adopt the first assumption, which results in much smaller benefits, because only the transmission planner is assumed to “get smarter” by the adoption of stochastic planning.

The economic benefit of using stochastic programming is obtained by comparing the present worth of expected costs of (a) the naïve solution in which the 20 scenario stochastic program is solved while imposing the first stage transmission decisions from one of the suboptimal models (Deterministic, Heuristic, or Stochastic (5)) with (b) the present worth of expected costs of the unconstrained 20 scenario model, which can be no worse than the value in (a).

This difference is called the “value of the stochastic solution” in stochastic programming [17], and also has been called the “cost of ignoring uncertainty.” We have previously calculated this cost for hypothetical studies in the UK and WECC [7, 15].

By comparing the values of (a) for different solutions, we can see how well, for example, the heuristic strategies do. In [15], it was found that a heuristic strategy of building any line that appeared in any of three scenarios would do almost as well as the stochastic solution. Here, however, that is not so.

We also compare the Stochastic (5) solution performance with the other solutions to determine if a model that includes multiple scenarios, but only a small subset of them, does almost as well as the fully optimal Stochastic (20) solution. We find that this is indeed the case.

4 Data Development

We begin our review of our data assumptions by summarizing the process used to define scenarios and assign probabilities (section 4.1). Next we provide background on the smaller 21-zone Network before proceeding to discussing the development of the 300-bus network reduction (sections 4.2 and 4.3). Following this, the method used to assign load to buses within the 300-bus network is explained (section 4.4). The identification of transmission investments and their impact on path constraints is documented next (section 4.5). In section 4.6, our method for expressing the complex environmental and operational regulations involved in hydropower development in the context of an optimization problem is demonstrated and documented. Finally, the sources and analysis required to develop the properties of generation plants in the model are detailed (section 4.7).

4.1 Scenario Definitions and Probabilities

4.1.1 Scenario definition and development

We have developed 20 scenarios representing a wide range of possible future technology, policy, and economic developments over the next two decades in collaboration with a project Technical Advisory Group (TAG) that was formed by WECC. TAG included several stakeholders from power companies, public interest groups, and public agencies. Each scenario represented a distinct combination of 15 variables and is intended to represent a plausible future. The 20 scenarios consist of a base case, 4 WECC scenarios from WECC Scenario Planning Steering Group 2013 scenarios [3], 9 TAG scenarios that are specified by TAG members, and 6 “gap” scenarios that we developed to capture other possible futures that were not represented by the other scenarios. An overview of the scenario development process is shown in the figure below; further details are provided in Appendix A. Section 5.3.1 considers the impact of considering differing numbers and probabilities of scenarios.

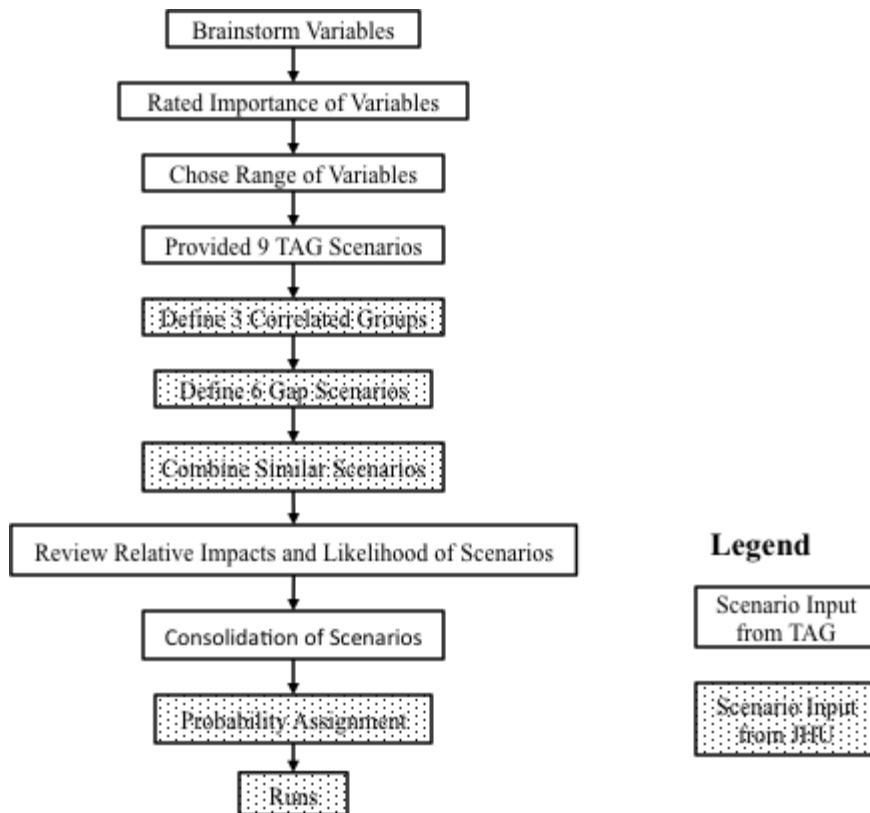


Figure 4.1 Schematic of the scenario development process

Besides these 20 scenarios, we also have defined “Failure to Launch” scenarios, that consider the effects of failure to build some of the pre-assumed (common case) transmission lines, as well as hydro year scenarios that consider the effects of climate change that results in significantly different amounts of hydropower available. The effects of considering common case transmission and hydro scenarios are examined in sections 5.3.2 and 5.3.6, respectively.

We use 15 variables to represent each of our 20 scenarios. Variables are chosen by the TAG based on their relevance to economic evaluation of transmission additions; i.e., would consideration of uncertainty in the variable’s values affect the relative attractiveness of different transmission investments? TAG members first brainstormed to derive a list of variables and then were asked classify the relative importance of those, relative to their influence on transmission economics. Importance was classified, in decreasing order, as “crucial to include”, “desirable to include”, and “less important to include”. We defined three values for each variable (low, medium, and high), based on information provided by the TAG members. Medium values represent the most likely value of this variable in 2034. The high and low values represent 90% confidence levels for the most likely value. Medium values are based on 2034 common cases values from WECC, and high and low values are calculated consistent with the average confidence intervals (low to high) that TAG members specified. Values and Importance levels of variables are

summarized in the following table. The variable values we obtained from TAG members are shown in the next table. Further details on the scenarios are provided in Appendix C.

Table 4.1 Variables selected by TAS for defining the scenarios

Group / Variables		Description	Importance	Low value (L)	Base/medium value (M)	High value (H)
Cluster 1: GAS/ CAR- BON PRICE & LOAD GROWTH	gas P	Natural Gas (\$/MMBtu)	Crucial	3.46	7.09	13.02
	carbon P	Carbon (\$/ton)	Crucial	33.38	58.00	112.84
	Load Growth	Total WECC Load Growth (%/yr)	Desirable	-0.91	1.13	3.2
Cluster 2: RENEWABLE POLICY & CAPITAL COST	State RPS	State (RPS) (% change of current policies)	Crucial	-50%	0%	50%
	Fed RPS	Federal RPS (% of load energy)	Desirable	0	0	15%
	DG	Dist. generation capacity as % of Peak Demand (%)	Crucial	3.2	11	20
	Wind Cap.	Onshore Wind(\$/kW)	Crucial	1569	1921	2065
		Offshore Wind (\$/kW)	Less Important	4707	5764	6196
	Geoth. Cap.	Geothermal(\$/kW)	Desirable	5015	5900	6490
	Solar Cap.	Solar PV(\$/kW): resid. rooftop	Desirable	2855	4007	5209
		Solar PV(\$/kW): comm. rooftop:	Desirable	2320	3256	4233
		PV(\$/kW): Fixed Tilt (1-20 MW)	Desirable	2048	2874	3736
		Solar Thermal(\$/kW): No Storage	Desirable	3560	4108	4519
		Solar Ther.(\$/kW): 6 Hr Storage	Desirable	5178	5975	6573
Cluster 3: PEAK LOAD / STORAGE	DR	DR cap as % of Peak Demand (%)	Crucial	2.2	5.5	10
	Storage	Storage cap as % of Peak Demand	Crucial	3.9	7.7	10.7
	Peak Growth	System peak demand growth rate (%/yr)	Desirable	-0.37	1.28	2.64
Other Varia- bles	In-state RPS	Requirements for State RPS to be met by in-state resources (% of RPS requirement)	Controversial	No preferences for in-state	Current in-state preferences	In-state policies, increased by 50%
	Coal P	Coal (\$/MMBtu)	Less important	1.26	1.62	1.98
	IGCC w/CCS Cap. Cost	Integrated Gasification/Combined Cycle with Carbon Capture & Storage (\$/kW)	Less important	7600	8000	10000

The next table summarizes the assumed values of the uncertain variables in the 20 scenarios. Green, yellow and blue cells correspond, respectively, for high, medium, and low values, consistent with the color scheme of the previous table.

Table 4.2 Values of uncertain variables for the 20 TAG scenarios

Scenario		Cluster 1: GAS/CARBON PRICE & LOAD GROWTH			Cluster 2: RENEWABLE POLICY & CAPITAL COST						Cluster 3: PEAK LOAD / STORAGE			Other Variables		
		Gas P	Carbon P	Load Growth	State RPS	Federal RPS	DG	Wind Cap.	Geo-th. Cap.	Solar Cap.	DR	Storage	Peak Growth	In-state RPS	Coal P	IGCC w/CCS Cap. Cost
1	Base Case															
2	WECC: 1 Econ. Recovery	Yellow		Yellow									Yellow			
3	WECC 2: Clean Energy	Green	Yellow	Yellow	Yellow	Yellow		Blue	Blue	Blue			Yellow	Blue	Green	Blue
4	WECC 3: Short-Term Consumer Costs	Green	Blue	Blue	Blue	Green		Yellow	Green	Yellow			Blue	Green	Green	Green
5	WECC 4: Long-Term Societal Costs	Blue	Yellow	Blue	Yellow	Yellow		Blue	Green	Green			Blue	Yellow	Green	Green
6	High info. tech transformation						Yellow					Yellow	Yellow			
7	High DG			Blue		Blue						Yellow	Blue			
8	Gas heavy 1	Yellow														
9	Gas Heavy 2	Yellow														
10	Nuclear Explosion	Green	Yellow		Yellow	Yellow		Green	Blue	Blue				Blue		
11	Aggressive GHG Policy	Green	Yellow		Yellow	Yellow		Yellow								
12	Carb redux + Lo Load	Yellow	Yellow	Blue	Yellow	Blue		Yellow	Yellow	Green			Blue	Blue	Green	Blue
13	High Carbon Price, Severe Climate Change Effects				Green	Green		Green	Green	Green			Yellow	Yellow	Yellow	Yellow
14	Risk Assessment of Climate Change > Water > Electricity				Yellow	Yellow		Blue	Blue	Blue			Yellow	Blue	Blue	Blue
15	HHH				Yellow	Yellow	Yellow	Blue	Blue	Blue						
16	H(M)H				Green	Green	Green	Green	Green	Green						
17	(M)HH				Green	Yellow	Yellow	Blue	Blue	Blue						
18	(M)LL				Blue	Blue	Blue	Yellow	Yellow	Yellow	Blue	Blue	Blue			
19	L(M)L				Blue	Blue	Blue	Green	Green	Green						
20	LLL				Blue	Blue	Blue	Blue	Blue	Blue	Blue	Blue	Blue			

In deriving probabilities for the scenarios, it is important not only to reflect the assumed means and standard deviations, but also any major correlations among the variables. For instance, it is reasonable to expect that higher carbon prices would be associated with lower coal prices (negative correlation). We made assumptions concerning correlations between the seven crucial variables in Table 4.3, categorizing possible correlations as either strong (negative or positive), weak (negative or positive) or absent, with associated correlations of $+/-0.6$, $+/-0.3$, and 0, respectively. Only one correlation is classified as strong, seven are weak, and thirteen are zero, as shown in the following table.

Table 4.3 Correlations of Crucial Parameters

	Gas P	Carbon P	State RPS	DG	Wind Cap.	DR	Storage
Gas P	1	0.6	0	0	0	0	0
Carbon P		1	0	0	0	0	0
State RPS			1	0.3	-0.3	0.3	0.3
DG				1	0	0.3	0
Wind Cap.					1	-0.3	-0.3
DR						1	0
Storage							1

More detailed scenario descriptions are shown in the Appendix. The above scenario definitions were used in the 300-bus models. However, although we had 16 or more Scenario Variables when we first developed the scenarios, the variables considered in 300-bus model are fewer in the following ways:

1. The Energy Efficiency, Policy-Driven Electrification, Peak Growth and Load Growth variables are combined together to give the net "Total Peak/Load Growth", which are used to reshape the load in the final model.
2. For model simplification, the National RPS, Instate RPS requirement uncertainties are dropped in the 300-bus model;
3. The "Geothermal" Capital cost uncertainty is dropped. Since investment in Geothermal is small in the model results, this omission does not affect the results appreciably.

4.1.2 Probability definition

Our analyses using stochastic programming include 5 and 20 scenario cases, where the 5 scenario stochastic solutions include only the base case plus WECC 1-5. In addition, we performed sensitivity analyses in which we had 25 scenario cases for the "failure to launch" (common case line failure to be built) in which we considered five different failure cases (including no failure) and considered every combination of those cases with the five base case plus WECC 1-4 scenarios.

We defined probabilities for the above scenarios by two approaches. One is the simple approach of assuming that every scenario considered has the same probability. Thus, in a 5 scenario case, each scenario would have a probability of 20%, while in a 20 scenario case, each would have a 5% chance. This simple procedure has the virtue of being highly practical and giving each scenario equal consideration. However, a user might have reason to believe that some scenarios are much more or less likely than others, and so might wish to differentiate the probabilities. Furthermore, it might be desirable to choose probabilities so that the mean, standard deviation, or correlations of particular uncertain variables (e.g., load growth or natural gas prices) match some assumed values.

To demonstrate the differentiated probability approach, we applied a method we adapted from the CAISO [22] called “moment-consistent optimization”. That method chooses probabilities that result in means, standard deviations, correlations, and/or other “moments” that are close to assumed values, while constraining each probability to be no less than some minimum value. The optimization minimizes some metric of the difference the moments desired and the calculated moments based on the selected scenarios and probabilities. This metric could be the sum of squared deviations between the desired and calculated moments, or the sum of absolute values of those deviations. We used this approach to assign differentiated probabilities for the 5 and 20 scenario cases that result in good matches to the base case means and the standard deviations assigned by the Technical Advisory Group. We generated different sets of probabilities to test the impact of different sets of probabilities. Below, we provide some further detail on how we generated those different sets of probabilities.

For the 5-scenario case, our objective was to spread out the probabilities and match the base case values of the crucial parameters means (medium values from Table 4.1, above). We emphasized the seven crucial parameters in the moment consistent optimization method: Natural Gas P, Carbon P, DG, Wind capital cost, State RPS, DR, and Storage (Table 4.1). The optimization model is as follows:

$$\text{Minimize } Z = \sum_{j=1}^7 \sqrt{(\widehat{\text{Mean}}_j - \text{Mean}_j)^2 / \text{Mean}_j}$$

Subject to:

$$\sum_{i=1}^5 p_i = 1; p_i \geq 0.1; p_1 = 0.2 \text{ or } 0.35 \text{ or } 0.5$$

Where p_i is the probability of scenario i , and p_1 is the probability of the base case. The probability assignments that we obtained from using the above procedure are shown in the following table. The major impact of decreasing the value of the constraint on the base case probability is to increase the probability of WECC 3, which is the short term consumer costs case (low fuel and other costs). For the stochastic model with five scenarios and differentiated probabilities, we used the second column’s probabilities, in which p_1 equals 0.35.

Table 4.4 Different Probability Assignments for 5-Scenario Case

Scenario	$p_1 = 0.2$	$p_1 = 0.35$	$p_1 = 0.5$	Equal p_i
Base Case	0.2	0.35	0.5	0.2
WECC 1	0.1	0.1	0.1	0.2
WECC 2	0.1	0.1	0.1	0.2
WECC 3	0.467738	0.35	0.2	0.2
WECC 4	0.132263	0.1	0.1	0.2

For the 20-scenario case, the objective is to choose the probability for each scenario so that the overall mean and standard deviation of certain crucial uncertain variables match the assumed values for those variables. Again, we use an optimization model to obtain the desired probabilities. There are four parts in the objective function. The first part $\frac{1}{20} \times \sum_{i=1}^{20} p_i^2$ is a penalty term for the differences of probabilities among scenarios; equal probabilities result in the lowest value of this term, while very divergent probabilities would increase it. The second part $\frac{1}{7} \times \sum_{j=1}^7 (\widehat{SD}_j - SD_j)^2$ is a penalty term for the differences of standard deviations from the desired values. The third part is a penalty term for the differences in covariance (which is the correlation between two variables times the product of their standard deviations). The fourth part is a (relatively) high penalty for differences in means; hence, this criterion receives priority in choosing the probabilities. All components in the objective function are standardized (i.e., so that their means are zero and standard deviations are 1). Meanwhile, the constraints ensure that the probabilities sum to 1 and that each scenario has a probability of at least 2.3% (this value resulted in a fairly even distribution of probabilities, while providing a good match of the moments).

Mathematically, the optimization problem is the following:

$$\text{Minimize } Z = \frac{1}{20} \times \sum_{i=1}^{20} p_i^2 + \frac{1}{7} \times \sum_{j=1}^7 (\widehat{SD}_j - SD_j)^2 + \frac{1}{21} \times \sum_{j=1}^7 \sum_{j' \neq 1, j'} > j \left(\widehat{\text{Cov}}_{j,j'} - \text{Cov}_{j,j'} \right)^2 + 10000 \times \frac{1}{7} \times \sum_{j=1}^7 (\widehat{\text{Mean}}_j - \text{Mean}_j)^2$$

Subject to:

$$\begin{aligned} \sum_{i=1}^{20} p_i &= 1 \\ p_i &\geq 0.023 \end{aligned}$$

The probability assignment that we obtain from using the procedure is shown in the table below. To obtain a good match of the means, standard deviations, and correlations, relatively high probabilities were placed on the Base Case and WECC 3 (low short-term consumer costs)

Table 4.5 Moment-matched probability assignments for 20-Scenario case

Scenario Name	Probability	Assignment
Base Case	p_1	0.197
WECC 1: Econ. Recovery	p^2	0.023
WECC 2: Clean Energy	p^3	0.023
WECC 3: Short-Term Consumer Costs	p^4	0.191
WECC 4: Long-Term Societal Costs	p^5	0.046
High info. tech transformation	p^6	0.023
High DG	p^7	0.023
Gas heavy 1	p^8	0.023
Gas Heavy 2	p^9	0.023
Nuclear Explosion	p^{10}	0.023
Aggressive GHG Policy	p^{11}	0.023
Carb redux + Lo Load	p^{12}	0.023
High Carbon Price, Severe Climate Change Effects	p^{13}	0.023
Risk Assessment of Climate Change > Water > Electricity	p^{14}	0.023
HHH	p^{15}	0.023
H(M)H	p^{16}	0.023
(M)HH	p^{17}	0.03
(M)LL	p^{18}	0.023
L(M)L	p^{19}	0.097
LLL	p^{20}	0.1165

To show how well the differentiated probabilities matched the means of the base case scenario, the following table shows the mean values of each of the uncertain variables from Table 4.1 for the five and twenty scenario cases, both for equal probabilities and for the differentiated probabilities from the above tables. The last two columns show that at least for the seven crucial variables, the probability-weighted averages for the differentiated probability cases are much closer to the base case values than the equal probability cases. In our results section, we explore the implications of using each set of probabilities.

Table 4.6 Probability weighted averages of uncertain variables across scenarios for stochastic solutions and base case (Crucial variables are indicated by an asterisk*)

Scenario Variables	Base Case	Stochastic (5 Scenario) Even Probabilities	Stochastic (20 Scenario) Even Probabilities	Stochastic (5 Scenario) Differentiated Probabilities	Stochastic (20 Scenario) Differentiated Probabilities
Natural Price (\$/MMBTU)*	7.09	7.55	8.92	7.32	7.24
Coal Price (\$/MMBTU)	1.62	1.62	1.62	1.62	1.62
Carbon Price (\$/Metric Ton)*	58	75.01	78.99	60.35	60.63
Net Load Growth (%/yr)	1.13	1.14	1.14	0.63	0.4
Net Peak Growth (%/yr)	1.28	1.16	1.23	0.81	0.68
RPS (% change of current RPS)*	0	10	17.5	-7.5	-3.52
Federal RPS (%)	0	6	5.25	3	2.87
DR (% of Peak Demand)*	5.5	5.5	7.03	5.5	5.68
DG (% of Peak Demand)*	11	11	13.82	11	11.63
Storage (% of Peak Demand)*	7.7	7.7	8.48	7.7	7.44
OnShore Wind Capital Cost (\$/kw)*	1921	1838	1859	1915	1919
Solar-PV-FixedTilt Capital Cost (\$/kw)	2847	2854	2813	3064	3049
Solar-Thermal Capital Cost (\$/kw)	4108	4081	4053	4197	4186
IGCC with CCS Capital Cost (\$/kw)	8000	7920	8040	7960	8018
Geothermal Capital Cost (\$/kw)	5900	5723	5841	5812	5921

Details on the probability values assumed for the scenarios are presented in Appendix B.

Although DR, DG and storage are identified as crucial variables by the stakeholders, they are not incorporated in the models in these demonstration runs for the following reasons:

1. Modeling challenges: DR and storage were excluded since they were difficult to represent in the load reshaping procedure of Section 4.4. Meanwhile, for DG, it is already partially represented in the form of PV solar power, but with the data available to us, we could not separate it from the already existing solar DG.
2. Assumed limited impact: DR and Storage in particular are unlikely to have a slarge impact at the levels indicated in the existing scenarios, so the effort involved in implementing them would not be justified.

However, the probabilities of the scenarios involving those variables were unchanged, even those specific variables were not modeled in the scenarios.

In the more complicated 300-bus model, the Federal RPS uncertainties are also disregarded because these constraints are never binding in the most stringent case and implementing them tended to slow down the model. Also, to lessen the complexity of the 300-bus model, the geothermal capital cost was also disregarded in that model.

4.2 WECC 21-Zone Network Definition

A 21-zone network model developed by the WECC Load Resources Subcommittee was provided by

WECC (Figure 4.2). This network significantly simplifies WECC into zones that are combinations of TEPPC areas. Flow limits on connections between zones are differentiated by direction of flow, partially representing the path constraints that are enforced on the real system. Information about line impedances is not included as part of the 21-zone model; instead, the system is modeled as a “pipes-and-bubbles” system. Existing generation was aggregated from Common Case version 1.2 [23] based upon the TEPPC area that a particular generator belongs to. Load and renewable energy profiles are aggregated following a similar procedure.

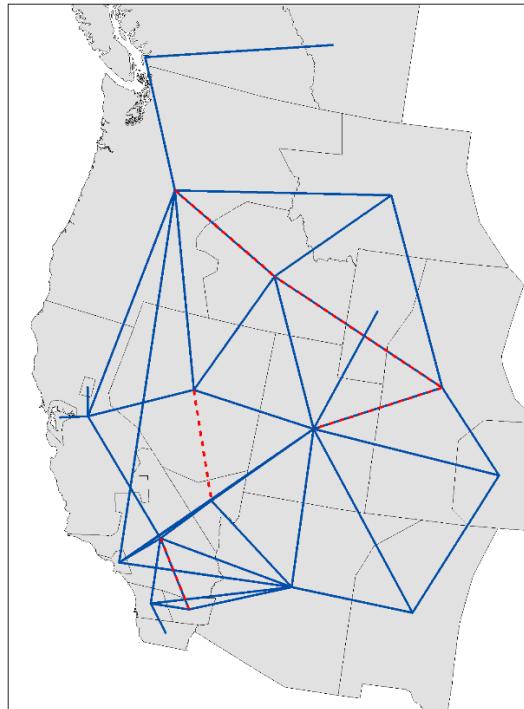


Figure 4.2 Map of the 21-zone network. The lines in dark blue reflect the initial network while dashed lines in red show common case transmission assumption (CCTA) projects that are imposed in every solution

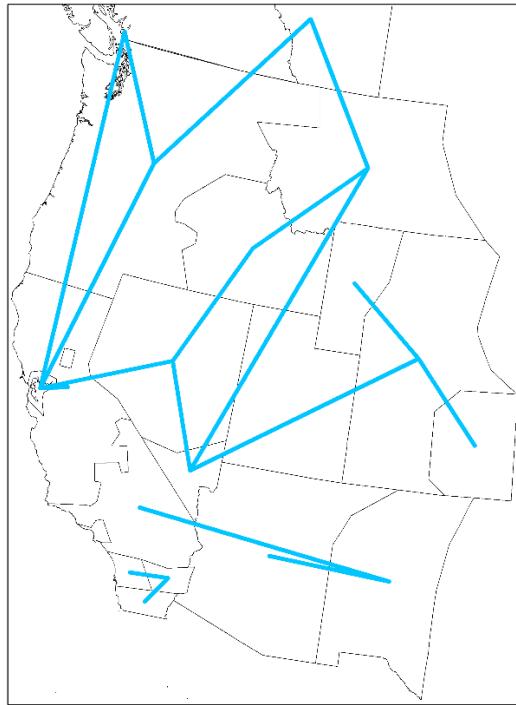


Figure 4.3 Map of the 21-zone network year 10 candidate lines

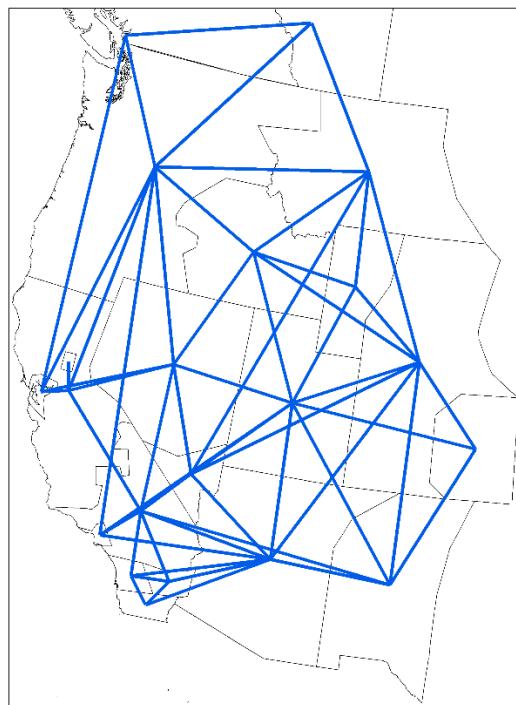


Figure 4.4 Map of the 21-zone network year 20 candidate lines

New transmission investments (Figure 4.3, Figure 4.4) have been defined using two different approaches. For TEPPC Year 10 transmission projects (identified in the Common Case Transmission Assumptions (CCTA), WECC [23]) and new transmission projects, we have identified inter-regional line candidates and

aggregated their capacities according to their thermal or other limits. CCTA projects are assumed to have been built by 2013, and are decision variables. Lines that are decision variables include transmission projects that we aggregated from the WECC project portal, which describes candidate lines that were considered in the 10 Year TEPPC planning process. Those lines are included as investment decision variables for the first stage of the transmission model (2014-2023). In addition, entirely new transmission projects directly connecting adjacent regions were added for the period of 2024-2034 on top of the previous set of transmission investments. Please refer to Section 4.5 for more details.

4.3 WECC 300 Bus Network Definition by Network Reduction

The goal of the network reduction was to create a reduced WECC network that is small enough to be computationally tractable in a multi-stage stochastic optimization. To represent inter-regional rather than intra-regional transmission expansion, the WECC footprint was divided into a set of regions between which new transmission lines could be constructed. The WECC TEPPC areas were not used due to the uneven distribution of area sizes, and in particular the small size of areas defined in the Pacific Northwest. Instead, 26 regions, shown schematically below, were constructed considering major existing inter-regional network constraints (WECC Paths) [24]. The resulting network contains 328 buses and 526 lines. Algorithmically, the network was reduced using a Ward Reduction with software from Arizona State University [20]. The network contains four distinct elements - preserved buses, preserved lines, equivalenced lines and generation hubs – which will be discussed in the following subsections.

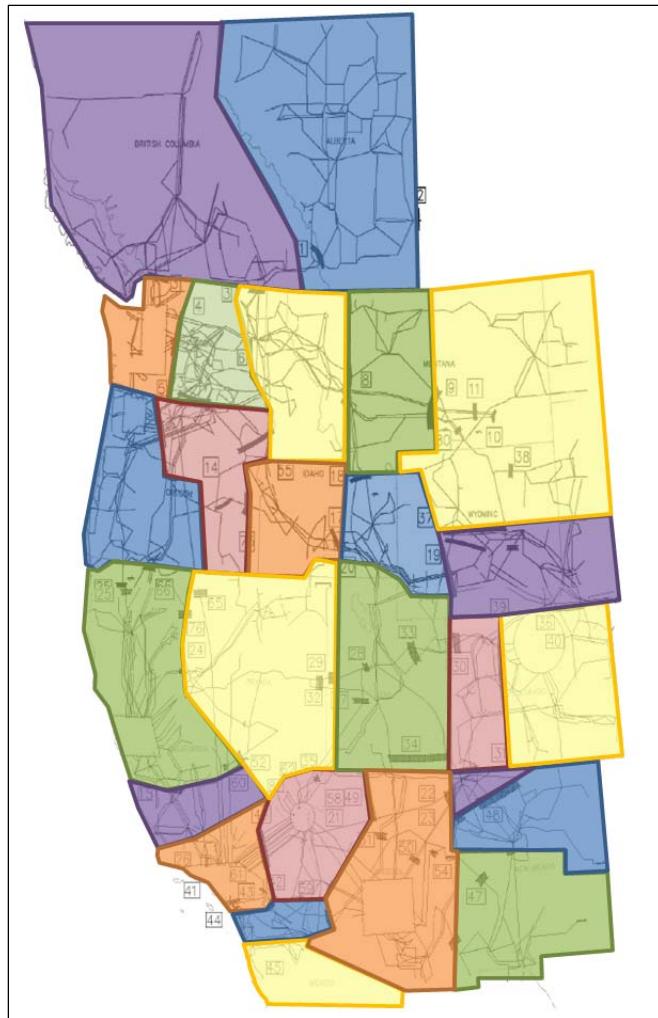


Figure 4.5 Map of 26 regions that were constructed using existing inter-regional network constraints, and that were used to define inter-regional paths in the 300-bus model

4.3.1 Preserved Bus Selection

The WECC Paths were selected to divide the network into regions. These Paths define flow limits or other operational constraints that are more restrictive than the thermal flow limits, and are defined as part of the TEPPC Common Case. Each region in the reduced network was constructed by electrically isolating an area through a series of Paths (see Figure 4.5 for a conceptual illustration). Thirty-seven Paths, including the Paths containing DC lines, were selected to subdivide the network into the 26 regions shown above. The selected paths are given below in Table 4.7.

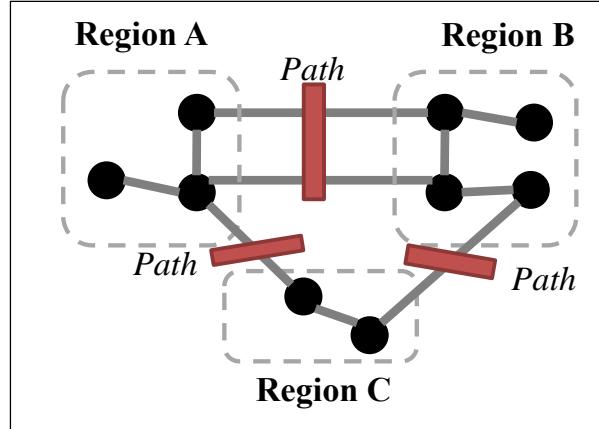


Figure 4.6 Example network showing a series of paths

Table 4.7 List of the 37 preserved paths

Path 1	Path 9	Path 20	Path 31	Path 44	Path 65	Path 83
Path 3	Path 15	Path 22	Path 32	Path 45	Path 66	
Path 4	Path 16	Path 26	Path 35	Path 46	Path 73	
Path 5	Path 17	Path 27	Path 37	Path 47	Path 78	
Path 6	Path 18	Path 29	Path 38	Path 48	Path 79	
Path 8	Path 19	Path 30	Path 39	Path 49	Path 82	

In a Ward Reduction, the buses are partitioned into the *internal* and *external* systems. The internal buses are preserved while the external buses are removed from the system. Lines connecting buses with the internal system are preserved in the reduction (both reactance and capacity), while lines connecting internal buses through the external system are transformed into equivalenced lines. In Figure 4.7 below, the shaded internal buses (1, 2, 4, and 5) are preserved. In the reduced network (*Network B*), all lines between these preserved buses are also preserved. The external buses (3, 6 and 7) are removed from the system. Their electrical properties are represented through the orange-dashed equivalent lines. These lines have a characteristic reactance but have no capacity limit.

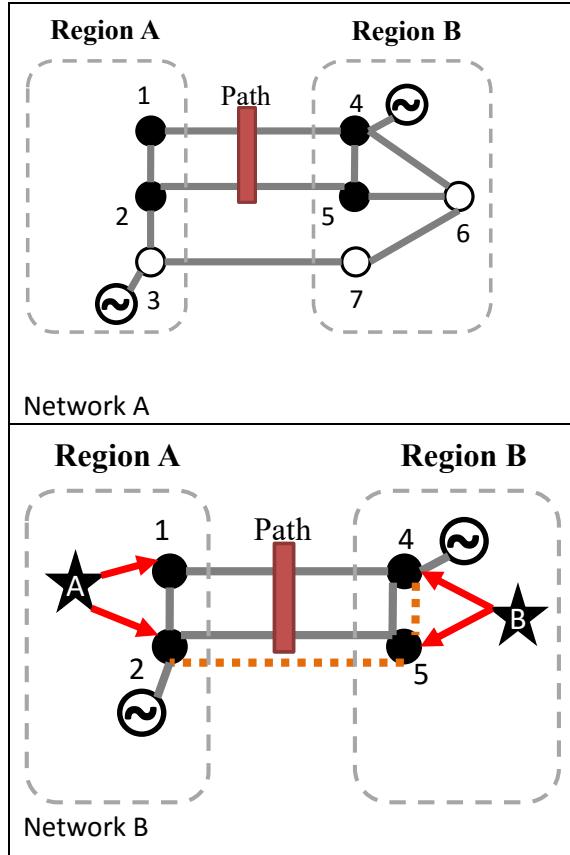


Figure 4.7 Example of path reduction

The buses contained in each Path have been defined as the internal system. This preserves the Path's reactance and capacity limits within the network reduction. In addition to the selected paths, an additional 101 number of lines was identified to attempt to divide the regions using only preserved lines. These buses were also added to the preserved nodes list. For example, in *Network A*, the line between bus 3 and bus 7 is inter-regional but is not part of a path. If buses 3 and 7 were also added to the internal system set, line 3-7 would be preserved (reactance and capacity). In *Network B*, they were not added to the internal system and as a result there is an equivalent line between buses 2 and 5. After the network reduction software was used, all equivalent lines with values of reactance higher than the highest reactance associated with any preserved line were removed. This was done in order to preserve a smaller network size. In cases where the removal of these equivalent lines created electrical islands or unrealistically separated regional networks, the lowest reactance equivalent lines were re-added to the system. The final reduced network is summarized in Table 4.8 and shown in Figure 4.8.

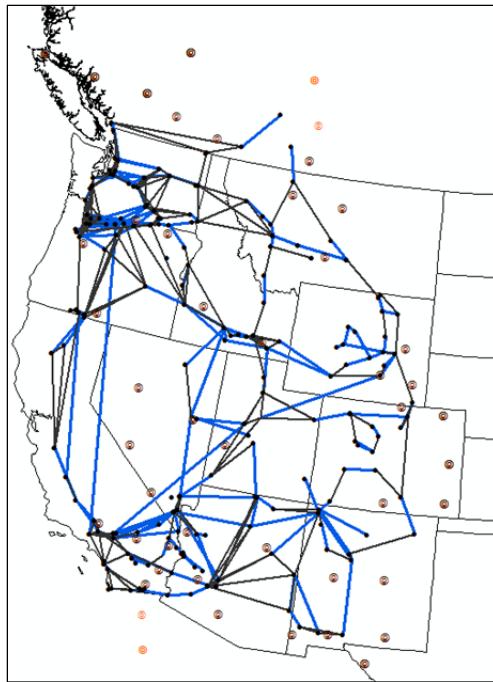


Figure 4.8 Map of the final reduced 300-bus network (dots are renewable energy zones)

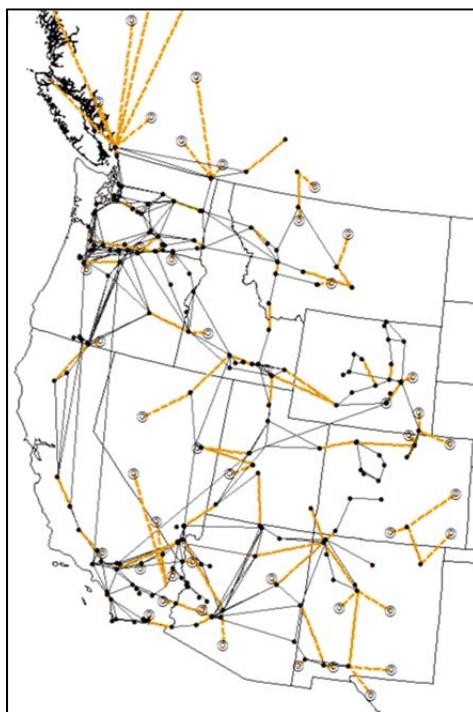


Figure 4.9 Map of the considered line investments considered in the reduced 300-bus network

Table 4.8 Summary of the final reduced network

Preserved Buses	Preserved Lines	Equivalent Lines	WREZs	Generation Hubs	Generation Hub Connectors
248	244	286	53	27	251

The use of equivalent lines in the pipes-and-bubbles models is problematic due to lack of capacity limits on lines. In the DC load flow model, the equivalent lines are effectively constrained by voltage angles resulting from the constrained preserved lines. On the other hand, in the pipes-and-bubbles model, unrealistic inter-regional flows may exist due to a capacity-constrained preserved line in parallel with a capacity-unconstrained equivalent line. To prevent these unrealistic flows, additional capacity limits were added to the equivalent lines in the transportation model. These constraints were thermal limits defined by an assumed allowable bound of phase angle differences.

4.3.2 Generation Assumptions for the 300-Bus Network

When external buses are removed from the full network, generation must be reallocated to preserved buses. In the ASU software, existing generators on external (not-preserved) buses are re-located to the electrically-nearest preserved bus. For example, in the test system shown above, the generator at bus 3 is relocated to bus 2 while the generator located at bus 4 remains at bus 4.

Rather than allowing new generation investment at each regional node, new generators are located at regional generation hubs. This approximation was made to limit the size of the model, since the number of decision variables for generation equals the average number of generators per node (bus) times the number of buses times the number of time periods. Each node within that region is connected to its hub. In *Network B* in the above schematic, these hubs are shown as stars. The hub-lines only allow flow from the hub to the node in the network. This one-way flow prevents the model from using new generation-hubs to bypass other network constraints. The hub-lines are not subject to Kirchhoff's voltage law and have no maximum capacity.

New renewable generators are the only exception to the regional hub approach. These generators were modeled instead at the location of the 53 Western Renewable Energy Zones. Each of these zones was represented as an individual bus within the system. This is because the cost of transmission interconnection to the high voltage grid is a significant cost, and that cost is an important consideration in where to site renewable developments.

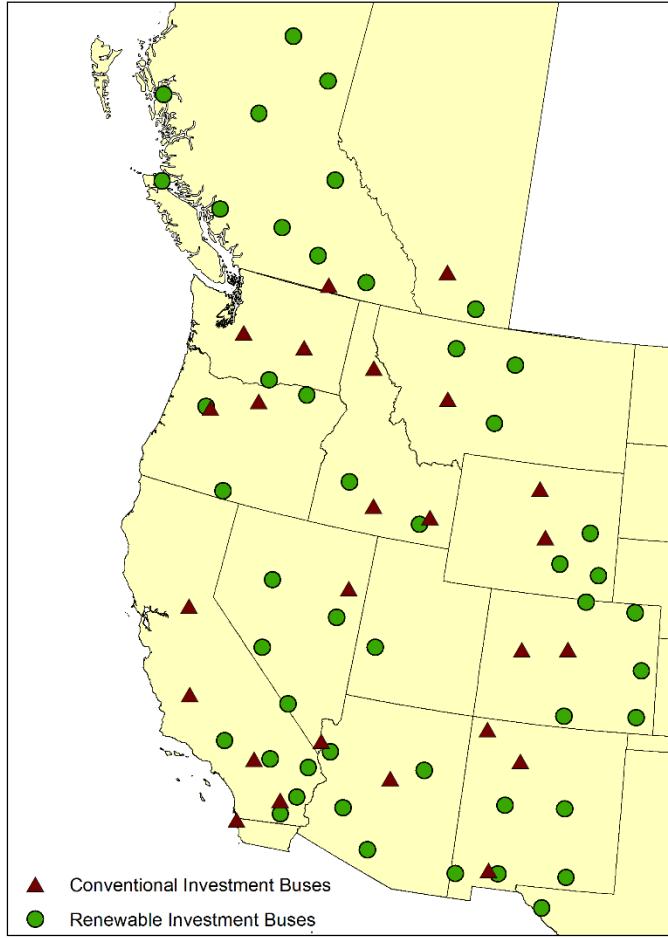


Figure 4.10 Generation hubs defined as a result of network reduction

4.4 Load Assumptions and Aggregation

The Common Case database [23] provided the year 2024 hourly load data for the TEPPC areas. We allocated the TEPPC demand data to our Buses/Zones based on the population weighting method. In order to implement the assumed peak and load growth rates for different scenarios, we developed a load-shaping method to reshape load profiles from Base Case year 2024 load back to a common year 2014 profile. Then, using scenario specific growth parameters, we were able to reshape the 2014 profile for 2024/2034 for different scenarios.

The load reshaping method is based on the load duration curve. First, by constructing the load duration curve for every TEPPC area, each hourly load will have a rank k ($k = 1, 2, 3 \dots 8784$). For instance, when $k=1$, this hour is the peak hour. Second, we designate the scenario peak growth as PG (fraction/yr), load growth rate as LG (fraction/yr), the 2014 peak as p (MW) and the 2014 average load as d (MW). Then the 2024 peak P should be $p^*(1+PG)^{10}$, and the 2024 average load D should be $D^*(1+LG)^{10}$. Third, the

core assumption of the reshaping procedure is the assumption that for any hourly load “ L_k ” on the duration curve, $L_{k,2014} = L_{k,2024} * (A+B*k)$, with $B>0$; in other worlds, the ratio is a linearly increasing function of the duration curve rank k . A and B can be calculated from the peak and average load relationship.

We considered the regional growth rates in our models. The project’s Technical Advisory Group provided TEPPC’s year 2016 to 2024 average load and peak data assumptions for WECC that we used in the scenarios. We then calculated our own regional growth rates based on our load allocation procedure.

To sample chronological data so that Unit Commitment chronological constraints on system operation could be included, the following metrics were used to ensure that the sampled data is a good representation of yearly averages:

- Expected load in Northwest
- Expected load in Southwest
- Peak load in Northwest
- Peak load in Southwest
- Expected wind in Northwest
- Expected wind in Southwest
- Expected solar in Northwest
- Expected solar in Southwest

The Northwest and Southwest WECC regions were considered separately while sampling because of the systems are winter and summer peaking respectively. Wind and solar data were also rescaled up or down so that they were within 0.1% of the annual averages.

Load data for the Common Case was available for TEPPC areas, and so has to be reallocated geographically in order to be used in the 21-zone and 300-bus models. This was performed through a population weighting analysis. The procedure was initiated by generating a Thiessen polygon analysis of the bus locations used in the 300-bus network analysis. An intersection was preformed between census tracts, the bus Thiessen polygons, and the TEPPC load areas. This process allowed us to associate a bus with a particular population and load area. The bus populations were calculated by taking the fraction of the census tract area in the intersection and multiplying by the population of the census tract. For a few buses which were located on top of one another, we assumed an even population split between the two busses. The load from a particular TEPPC area was assigned using the following equation.

$$Load_{bus,load\ area} = \frac{Population_{bus,load\ area}}{\sum_{bus} Population_{bus,load\ area}} \times Load_{load\ area} \quad \forall bus, load\ areas$$

4.5 Investable Transmission Lines

Transmission investment candidates aim to provide the list of lines that can be invested in year 2014 or 2024, and then come on-line in year 10 (2024) or year 20 (2034), respectively. There are two things to consider when making a transmission investment: the lines’ properties and their associated cost. For any candidate line, its properties include the start/end point of the line, its operating voltage and its thermal capacity. For the 21-zone application, the year 10 candidate lines are different than year 20 candidates.

On the other hand, for the 300-bus application, the year 10 candidates and year 20 candidates are the same.

The proposed candidates for the 21-zone model include the **Project lines** and **some additional year 20 lines** (Figure 4.3). **Project lines** include the transmission projects that are not CCTA lines (which are included and fixed in all model solutions, with the exception of the “failure to launch” scenarios) but are under consideration. These lines will come on-line in 2024, 2034 or 2050. All the inter-regional year on-line 2024 lines are included as the *year 10 candidates*; Inter-regional on-line 2034/2050 lines are included as the *year 20 candidates*. These lines have pre-defined start/end points, voltages and thermal capacities. Also, the year (on-line) 2024 projects are also allowed to be *year 20 candidates*, making them investable in both 2014 and 2024.

Furthermore, we defined additional *year 20 candidates* (Figure 4.4) by defining straight lines connecting the centroids of adjacent zones. To give a reasonable length, some of the centroids were moved near to the population center by adjusting the centroids to the location near to existing Common Case Resources. For instance, the centroid of British Columbia is moved to Vancouver, BC. All of these additional lines are assumed to be 500 kV voltage lines with a thermal capacity of 3000 MW. In order to reduce the integer decision variables in the second stage, after calculating the cost (see below), we calculated the Expansion Capacity/Cost ratio, and removed all the dominated lines. Dominated lines have the same start/end points but have a lower ratio, meaning that they are less cost-effective than other candidate lines per unit of capacity.

The proposed candidates for the 300-bus model include **Mirrored Backbone Lines** and **WREZ (Western Renewable Energy Zones) lines**. We “mirrored” (duplicated) the largest line (or, in some cases the second largest line) in each Path as the candidate for backbone enforcement in a Path. Thus the start/end buses and operating voltages of the candidate lines are pre-defined. There are 54 mirrored backbones in total. The expansion capacities of the mirrored backbones are calculated as follows, based on the thermal capacity and path ratings that can be found in the Common Case database:

$$\text{Expansion Capacity} = \text{Thermal Capacity} \times \frac{\sum_{\text{all lines in path}} \text{Thermal Capacity}}{\text{Path Rating}}$$

WREZ candidate lines are designed to connect their renewable resources to the existing network. The WREZ report provides the physical location of those hubs, so we define our WREZ candidate lines by connecting WREZ hubs to the nearest 500kv/300kv existing buses [25]. The thermal capacities are pre-defined as 3000 MW. There are 53 WREZ lines in total.

We calculated the cost of the candidate lines based on the length/voltage/thermal capacities and the start/end point of the lines using the cost numbers from WECC’s Long Term Planning Tool [26]. Some of the Project lines have reported costs, but some of the costs appear to be possibly underestimated, so whenever the result of our calculation came out to be higher than the reported cost, we used our cost numbers. The cost of lines has four components: base line cost, substation cost, Right of Way (ROW) cost and a 15% Allowance for Funds Used during Construction (AFUDC). Right of Way cost is calculated by the following procedure. First, the land cost is calculated in each state (using the numbers from Bu-

reau of Land Management, BLM). Then we determine the intersection of lines and the states by using the ArcGIS joint function. For a 300-bus application, many of the lines lie within a single state. The width of the line corridors is also provided by the Long Term Planning Tool. This information is combined in the following equation.

$$ROW\ cost = width \times \sum_i length_i * unit\ land\ cost_i$$

4.6 Hydro scenario development for 21-zone model

To develop alternative water scenarios, we have defined wet/dry/normal monthly multipliers that are used to adjust the hourly hydro profiles that simulate different years. Years 2011, 2001, and 2005 are identified by WECC as high, low, median hydro years respectively, and WECC provided the plant level monthly generation data for these 3 years. Hydro data was obtained directly from the WECC website [27, 28, 29]

We developed the monthly hydro multipliers by the following procedure:

1. Aggregate the plant level monthly data in to zonal monthly data
2. Calculate monthly multiplier as follows by region: High hydro multiplier = year 2011 monthly generation/year 2005 monthly generation; Low hydro multiplier = year 2001 monthly generation/year 2005 monthly generation; and normal multiplier =1;
3. For the zones of which the data is not provided by WECC, we assume that the multipliers =1 in all water scenarios

If one high water scenario happened, the high hydro multipliers will multiply all the hydro output in every zone; it is the same in low water scenario. WECC-wide, the dry year results in approximately 15% less hydropower production than in an average year, while a wet year results in about 22% more. However, these numbers vary greatly zone-by-zone and month-by-month, as the next table shows.

In the high water scenario, the high hydro multipliers will be applied to all the hydro outputs in every zone, while in the low hydro scenario, the low multipliers are applied to every zone. However, every zone can have a different multiplier, depending on the exact effects in the scenario years (2011 for high and 2001 for low). The hydro multipliers are shown in the table below.

Table 4.9 Hydro multipliers for each region and each month

Zone	Hydro Status	Month-1	Month-2	Month-3	Month-4	Month-5	Month-6	Month-7	Month-8	Month-9	Month-10	Month-11	Month-12
AB	Dry	0.99	0.97	0.84	0.75	0.68	0.53	0.66	0.9	0.59	0.55	0.56	0.74
AZNNM	Dry	0.88	1.05	0.85	0.83	0.8	0.69	0.67	0.61	0.63	0.73	0.69	0.69
BANCCA	Dry	0.35	0.09	0.23	0.18	0.19	0.11	0.2	0.27	0.17	0.08	0.24	0.23
BC	Dry	0.92	0.9	1.27	1.4	1.14	1.08	1.09	0.92	1.02	0.98	1.01	0.91
CO	Dry	0.85	0.81	0.77	0.73	0.81	0.82	0.69	0.75	0.86	0.75	0.83	1.16
ID	Dry	1.02	1.06	1.09	0.98	0.78	0.7	0.76	0.94	0.99	0.97	1.02	0.93
IIDCA	Dry	1.56	1.04	1	1.12	0.96	1.09	1.02	1.11	1.24	1.28	1.21	2.21
LADWPCA	Dry	0.22	0.38	0.43	0.15	0.59	1.02	1.39	1.14	1.33	0.83	0.1	0.53
MT	Dry	0.96	0.85	0.92	0.82	0.85	0.88	0.75	0.86	1.06	0.78	0.73	0.81
MX	Dry	1	1	1	1	1	1	1	1	1	1	1	1
NCA	Dry	0.79	0.64	0.62	0.61	0.58	0.64	0.74	0.8	0.72	0.81	0.65	0.59
NNV	Dry	1.92	2.1	2.05	1.91	1.07	1.93	1.55	2.08	2.51	2.15	1.78	1.61
PNW	Dry	0.87	0.84	0.83	0.81	0.65	0.72	0.6	0.81	0.89	0.79	0.82	0.93
SCA	Dry	0.94	0.74	0.76	0.77	0.99	0.92	0.61	0.83	0.92	0.77	0.74	0.87
SDCA	Dry	1	1	1	1	1	1	1	1	1	1	1	1
SFCA	Dry	1	1	1	1	1	1	1	1	1	1	1	1
SNV	Dry	1	1	1	1	1	1	1	1	1	1	1	1
TXNM	Dry	1.68	1.66	1.76	1.71	1.25	1.3	1.44	1.74	2.12	2.03	1.82	1.68
Utah	Dry	0.75	0.75	0.82	0.42	0.51	0.8	1.23	1.23	0.97	0.62	0.61	0.59
WWY	Dry	1	1	1	1	1	1	1	1	1	1	1	1
WYCO	Dry	1.18	1.06	0.91	0.91	0.9	0.72	0.78	1.02	1.02	0.88	0.89	0.82
AB	Wet	0.98	0.97	1.04	1.02	0.78	0.86	0.89	0.89	0.82	0.74	0.7	0.8
AZNNM	Wet	1.5	1.63	1.76	1.47	1.49	1.52	1.5	1.58	1.59	1.45	1.61	1.45
BANCCA	Wet	1.72	1.35	2.07	1.31	1.2	1.17	1.64	1.15	1.75	0.79	0.76	0.23
BC	Wet	0.91	0.98	1.2	1.29	1.01	1.02	1.05	1	1.06	1.01	0.97	0.9
CO	Wet	1.38	1.41	1.52	1.51	1.16	1.03	1.02	0.36	1.42	2.04	0.32	0.25
ID	Wet	1.99	2.44	2.39	1.91	1.19	1.59	1.81	1.58	1.97	1.46	1.31	1.25
IIDCA	Wet	2.6	0.9	1.11	1.07	1.08	1.23	1.11	1.07	1.06	0.84	0.93	1.64
LADWPCA	Wet	1	0.79	1.24	1.47	1.16	1.21	1.3	1.27	1.29	0.84	0.68	0.54
MT	Wet	1.06	1.46	1.48	1.46	1.08	1.05	1.17	1.33	1.29	1.08	0.95	1.04
MX	Wet	1	1	1	1	1	1	1	1	1	1	1	1
NCA	Wet	1.82	1.23	1.55	1.53	1.13	1.16	1.23	1.21	1.28	1.14	1.14	0.71
NNV	Wet	1.28	1.67	2.3	2.06	1.64	1.7	1.94	1.92	1.95	1.09	1.46	1.38
PNW	Wet	1.26	1.44	1.6	1.64	1.2	1.35	1.45	1.33	1.22	1.05	0.99	1.05
SCA	Wet	1.22	0.98	1.05	1.03	1.03	1.01	1.01	1.13	1.12	0.78	0.81	0.75
SDCA	Wet	1	1	1	1	1	1	1	1	1	1	1	1
SFCA	Wet	1	1	1	1	1	1	1	1	1	1	1	1
SNV	Wet	1	1	1	1	1	1	1	1	1	1	1	1
TXNM	Wet	1.03	1.31	1.48	1.55	1.19	1.39	1.61	1.58	1.45	1.05	1.02	1
Utah	Wet	1.17	1.33	1.34	1.43	1.14	1.3	1.75	1.97	2.8	2.34	2.23	1.81
WWY	Wet	1	1	1	1	1	1	1	1	1	1	1	1
WYCO	Wet	1.15	1.33	1.59	2.37	1.96	1.36	1.56	1.64	1.74	1.81	1.11	1.13

4.7 Generation Data Geographical Aggregation

The existing WECC data that we aggregated includes existing generator properties and renewable portfolio standards. We aggregated the WECC data differently in the 21-zone model and the 300-bus model. Also, we estimated investment costs and characteristics for new generation and candidate transmission investments.

The aggregation process took place in three steps. The details of the aggregation methodology are provided in the following subsections.

We first identified the data sources we needed, including the WECC Common Case Database (Common Case) [23], the WECC Transmission Expansion Planning Dataset (Generation Capital Cost Calculator) [30], the Database of State Incentives for Renewables and Efficiency (DSIRE) [31], and the *Western Renewable Energy Zones – Phase 1 Report* (WREZ report) [25]. The Common Case Database provided existing generation information, fuel prices, demand information, and renewable energy hourly profiles. The Transmission Expansion Planning Dataset provided economics properties of generation investment, including capital cost, fixed O&M costs and regional cost multipliers. We obtained the renewable portfolio standard policy information from DSIRE. Finally, the WREZ report provided estimates of maximum investable renewable capacity by region.

Second we allocated the existing generators, and demand to the Buses/Zones we identified in our models. Our 300-bus network/21-zone networks provide a mapping between the network Buses/Zones and the Common Case Resources. Using this mapping, we aggregated the existing resources into the Buses/Zones by weighting all characteristics, such as heat rates, by the installed capacity. Demand allocation is based on population weighting. To further simplify the models, we also created a GridView subtype-to-type mapping for the 21-zone model and 300-bus model.

4.7.1 Existing Generator Properties (Sources: Common Case, Transmission Expansion Planning Dataset)

This part of the database includes Capacities and Retirements, Heat Rates, Intermittent Generation Profiles, Fuel IDs, Fixed O&M cost and Variable O&M cost. They are aggregated by the capacity-weighting method. Because of generation aggregation, one conventional generation plant may use more than one fuel type. So we calculated the percentage of each fuel for that type of plant at each bus/zone. The fixed and variable O&M costs are obtained from the Transmission Expansion Planning Dataset.

Below is documented the aggregation formula used.

i : index of power plant

j : index of generation type

k : index of Buses/Zones

$N_{k,j}$: set of all power plants that belongs to Bus k and type j

$X_i, R_{i,2024}, R_{i,2034}$: the capacity, retirement before 2024 and 2034 of plant i

$X_{k,j}, R_{k,j,2024}, R_{k,j,2034}$: the capacity, retirement before 2024 and 2034 of Bus k and type j

$F_i, P_{k,j}$: the other feature values of plant i (or Bus k type j), such as Heat Rate, etc.

$P_i, P_{k,j}$: Hourly profiles for renewable, motorload and pump storage of plant i (or Bus k, type j)

$$X_{k,j} = \sum_{i \in N_{k,j}} X_i, \quad R_{k,j,2024} = \sum_{i \in N_{k,j}} R_{i,2024}, \quad R_{k,j,2034} = \sum_{i \in N_{k,j}} R_{i,2034}$$

$$F_{k,j} = \frac{[\sum_{i \in N_{k,j}} (F_i * X_i)]}{X_{k,j}}$$

$$P_{k,j} = \frac{[\sum_{i \in N_{k,j}} (P_i * X_i)]}{X_{k,j}}$$

4.7.2 Regulation Rules (Sources: DSIRE, Common Case)

The sources of the Renewable Portfolio Standards (RPS) data is Database of State Incentives for Renewables & Efficiency (DSIRE) [31]; if the data is missing for year 2024 or 2034, the most recent standard was used.

To properly implement the regulation rules into our model, we made some simplifying assumptions. Eligible renewable generation types include wind-onshore, solar thermal, solar PV, biomass and geothermal; Hydro is not included. Renewable Energy Credits (REC) are assumed to be traded only inside the United States. RECs are assumed to be unbundled (i.e., these RECs are traded separately from energy, though there can in general be interstate trading of power and RECs in the same direction). Several states have REC multipliers in the RPS compliance procedures. For example, in Arizona, one MWh of solar energy from an in-state solar power plant is credited with 1.5 MWh RECs. But REC multipliers are not assumed in the 21-zone or the 300-bus applications. Most of the multiplier policies will retire before 2024 so that they won't provide incentives for the generation investment in 2024 or later. The RPS in each state is assumed to apply to all load in the state. For instance, although Arizona has a RPS of 15%, which covers 60.4% of load in Arizona [32], we assumed this RPS will covers 100% of load in Arizona, including Salt River Project (SRP) either due to voluntary participation or because of expansion of rules. The technology-specific minimums (such as for solar alone) and multipliers are not included in the 21-zone or the 300-bus model. Alternative Compliance Payment (ACP) data is missing in several states, so a value of \$100 /MWh for the ACP was assumed for the entire WECC.

Renewable Portfolio Standards (RPS) data used in our models are shown below.

Table 4.10 Assumed state RPS properties in JHSMINE

State Name	RPS 2024	RPS 2034	Instate	RPS Fine (\$/MWh)
AZ	15%	15%	100%	100
CA	33%	33%	90%	100
CO	30%	30%	0%	100
ID	0%	0%	-	-
MT	15%	15%	100%	100
NM	20%	20%	100%	100
NV	25%	25%	100%	100
OR	25%	25%	0%	100
UT	0%	0%	-	-
WA	15%	15%	0%	100
WY	0%	0%	-	-

To implement the in-state requirement policies in several states, we developed a REC trading network in our models. All interstate REC trades are assumed to be unbundled, thus some of them face stringent limitations. For example, Arizona is not limiting REC trading but does require that the RECs be bundled with power sales, which implies a 100% in-state requirement. (We do not consider imports of bundled RECs because of issues involved in requiring that balancing services for bundled renewable power be provided by the receiving balancing authority.) California is requiring the unbundled REC to a limit of 10%, which implies a 90% in-state requirement in our model; Washington State has no limitation of REC use but the REC trading is limited only with Pacific Northwest; Colorado and Oregon has no in-state requirement and can import RECs from all over WECC.

Table 4.11 Assumed REC trading paths in JHSMINE

REC trading Path (from/to)			
AZ-CA	ID-CO	NM-OR	UT-CO
AZ-CO	ID-OR	NV-CA	UT-OR
AZ-OR	ID-WA	NV-CO	WA-CA
CA-CO	MT-CA	NV-OR	WA-CO
CA-OR	MT-CO	OR-CA	WA-OR
CO-CA	MT-OR	OR-CO	WY-CA
CO-OR	NM-CA	OR-WA	WY-CO
ID-CA	NM-CO	UT-CA	WY-OR

Neither the 300-bus model nor the 21-zone model map perfectly and uniquely to individual WECC states, so the generated renewable energy is allocated by a population-based weighting procedure. E.g., in the 21-zone model, the Pacific Northwest population is assumed to be allocated as follows: 67% in Washington State and 27% in Oregon. Therefore, if the renewable energy generated by Pacific Northwest is 1000 GWh in year 2024, 270 GWh of it is allowed to be used to meet the RPS of Oregon.

We also considered the Carbon Tax policy in our model, and its data is obtained from Common Case database. The base case carbon taxes assumed in 2024 and 2034 are \$58/metric ton CO₂.

4.7.3 Investable Generation Location (Sources: Transmission Expansion Planning Dataset, WREZ report)

We developed different candidate generation investments for the 21-zone model and the 300-bus model.

In the 21-zone model, each zone can construct capacities in all investable technologies. Each technology has associated regional capital costs, which are provided by Transmission Expansion Planning Dataset. For thermal plants, we used Transmission Expansion Planning Dataset's heat rates for the new plants. The fuel patterns (fuel IDs and associated percentages) are copied from aggregated data in the same zone. For renewable (and/or intermittent) power plants, the maximum available capacity in each zone is aggregated from *Western Renewable Energy Zones – Phase 1 Report*. The hourly profiles are copied from aggregated data in the same zone.

In the 300-bus model, Renewable Investment candidate hubs (WREZ hubs) and Conventional Investment candidate hubs are designated separately. The former reflect their actual location, while one conventional investment hubs were defined as a central location in each region.

For **WREZ hubs**, we determined the locations and maximum installable solar/wind capacities according to the WREZ report. Hourly profiles of generation appropriate to each renewable generation type and location were used in each WREZ hubs. For the WREZ buses with solar capacities, we found the nearest existing buses which also have solar power, and assigned their hourly profiles to the WREZ hubs (expressed as a proportion of installed capacity by hour). The scaled hourly profile for one bus is the hourly profile divided by the capacity for one type of renewable. We did the same with wind power at WREZ hubs. One existing bus may have multiple types of solar power, e.g., Solar Thermal and Solar PV-tracking. So when assigning the profiles, if we found multiple solar power types, we allocated the installable solar capacity evenly to each solar power type. For the capital cost of potential renewable power plants, we identified the relevant states and assigned the appropriate regional capital cost provided in Transmission Expansion Planning Dataset.

In order to connect the WREZ hubs to the reduced network, we created several candidate lines, which are discussed in subsection above on network investment assumptions (Section 4.5).

For **Conventional Investment candidate hubs**, we created one investment candidate hub in each region for conventional generation investment, and this candidate hub is connected to all buses in this region by unlimited, fictional transmission lines. We assigned the heat rates provided in Transmission Expan-

sion Planning Dataset. For fuel IDs, we assigned the fuel price profiles by identifying the appropriate region's fuel price profile in the WECC data base. The mapping from the 26 regions in our model to the regions in the database is shown in the following table.

Table 4.12 Capital cost and fuel ID assumptions for conventional investment hubs

Buses	Regions	State	Capital Cost	NG Fuel	Coal Fuel
55501	Alberta	AB	AB	NG_AB	Coal_Alberta
55502	AZ	AZ	AZ	Avg(NG_AZ North, NG_AZ South)	Coal_AZ
55503	BC	BC	BC	NG_BC	Coal_PNW
55504	CA_LA	CA	CA	Avg(NG_CA SoCalGas, NG_CA SoCalB)	Coal_CA_South
55505	CA_Mid	CA	CA	Avg(NG_CA PGaE LT, NG_CA PGaE BB)	Coal_CA_South
55506	CA_North	CA	CA	Avg(NG_CA PGaE LT, NG_CA PGaE BB)	Coal_PNW
55507	CA_South	CA	CA	NG_CA SDGE	Coal_CA_South
55508	CO_East	CO	CO	NG_CO	Coal_CO_East
55509	CO_West	CO	CO	NG_CO	Coal_CO_West
55510	Four_Corners	NM	NM	NG_NM North	Coal_NM
55511	ID_North	ID	ID	NG_ID North	Coal_ID
55512	ID_South	ID	ID	NG_ID South	Coal_ID
55513	Jim_Bridger	ID	ID	NG_ID South	Coal_ID
55514	Mexico	MX	MX	NG_Baja	Avg(Coal_CA_South, Coal_AZ)
55515	MT_West	MT	MT	NG_MT	Coal_MT
55516	NM_North	NM	NM	NG_NM North	Coal_NM
55517	NM_South	NM	NM	NG_NM South	Coal_NM
55518	NV_North	NV	NV	NG_NV North	Coal_NV
55519	OR_East	OR	OR	NG_OR	Coal_PNW
55520	OR_West	OR	OR	Avg(NG_OR, NG_OR Malin)	Coal_PNW
55521	UT	UT	UT	NG_UT	Coal_UT
55522	Vegas	NV	NV	NG_NV South	Coal_NV
55523	WA_East	WA	WA	NG_WA	Coal_PNW
55524	WA_West	WA	WA	NG_WA	Coal_PNW
55525	WY_Central	WY/MT	WY/MT	Avg(NG_WY, NG_MT)	Avg(Coal_WY_PRB, Coal_MT)
55526	WY_South	WY	WY	NG_WY	Avg(Coal_WY_SW, Coal_WY_E)

5 Results and Discussion

The results of our analysis are organized around three general questions related to the motivating recommendations from the 2013 WECC Plan. The first is: What is the practicality of stochastic planning? The next question is: does stochastic planning make a difference? In particular, does stochastic programming not only result in different year 10 recommendations for new lines, but are those plans significantly less costly in expectation? And are those plans more robust against scenarios that weren't considered in developing them? The final general question is: how sensitive are those plans to various planning assumptions? These assumptions include network topology, scenarios considered and their probabilities, whether generation unit commitment costs are modeled, uncertainty in hydropower production, and other assumptions?

5.1 Is it Practical to Use Stochastic Programming in WECC?

The results of our analysis are organized around three general questions related to the motivating recommendations from the 2013 WECC Plan. The first is: What is the practicality of stochastic planning? The next question is: does stochastic planning make a difference? In particular, does stochastic programming not only result in different year 10 recommendations for new lines, but are those plans significantly less costly in expectation? And are those plans more robust against scenarios that weren't considered in developing them? The final general question is: how sensitive are those plans to various planning assumptions? These assumptions include network topology, scenarios considered and their probabilities, whether generation unit commitment costs are modeled, uncertainty in hydropower production, and other assumptions?

The below table summarizes the size and computation time required for various versions of JHSMINE used in this chapter. It shows that solution times could vary from a fraction of a second, depending on the features included in the model and its size.

Table 5.1 Comparison of Transmission Planning Models Used in Analyzing Transmission Network

Number of Scenarios	21-zone			300-Bus Network		
	Base (1)	WECC 5	WECC 5	20	Base (1)	Base (1)
Flow Model	Transportation (pipes-and-bubbles, KCL)	KCL	KCL	KCL	KCL	Linearized DC load flow (KCL+KVL)
Operations Model	Dispatch	Dispatch	Unit Commitment	Dispatch	Dispatch	Dispatch
Hours per year	24	24	72	24	6	6
Constraints	68,147	340,727	3,416,447	4,107,368	68,963	81,983
Total Variables	60,667	302,143	2,175,643	3,274,266	59,401	66,851
Binary Variables	76	288	288	1113	212	212
Mixed Integer Program (MIP) Optimality Gap	0.01%	0.01%	0.10%	0.01%	0.01%	0.01%
Solution Times (Clock)*	5 sec	56 sec	2 hrs	4.44 hrs	0.25 sec	3 hrs

Solution time on a workstation with CPU of Intel i7-5930k (3.5 GHz, 6 cores), 32GB RAM; for the unit commitment model, solution times are based on a workstation with 2 CPUs of AMD Opteron 6274 (2.2 GHz, 16 cores), 112 GB RAM. All models are solved using the AIMMS modeling system with CPLEX solver Version 12.6.2.

To be practical for application, stochastic transmission planning must be applied with an appropriate level of simplification. In our analysis we considered simplifications in three main categories:

- number of inputs (long run scenarios, operating hours per year),
- load flow model (transportation/pipes-and-bubbles or linearized DC/parallel flows), and
- modeling of generator flexibility (unit commitment constraints).

In order to solve JHSMINE on a 32 core work station, we needed to simplify the model in at least one of those categories to produce a useable model. For instance, we could solve the system with Kirchhoff's voltage law (linearized DC load flow), but it required reducing the numbers of hours and scenarios considered, and ignoring unit commitment. We were unable to solve the 300-bus network model with stochastic transmission investments to convergence in a reasonable amount of time. The solution time of the KVL model were highly sensitive to the scenario considered, and scenarios with aggressive load growth and renewable integration like WECC #2 required days to reach convergence. Or when modeling unit commitment, we were able to include a large number of input hours but needed to use a transportation model, the smaller network (21-zone), and a smaller number of scenarios. While the size of the model is an important consideration in terms of computability, the types of constraints included can even be more important. In particular, the DC linear flow constraints and the unit commitment constraints proved significantly more difficult to compute.

The parameters for the CPLEX solver were also tuned to solve the stochastic program with UC approximations to a reasonable time. The models were solved with CPLEX 12.6.2 and the linear programming solving method changed to Barrier-Dual Simplex from the default Dual Simplex method. In addition to this, the probing level was set to 3 to reduce the size of the binary tree, while cuts were generated ag-

gressively by CPLEX. This helped to solve the 21-zone 5-scenario model with 72 operating hours per year in approximately 2 hours to a MIP gap of <0.1%.

Even our most sophisticated network (300-bus) was greatly simplified relative to the true network. To apply stochastic programming without these simplifications would require the use of decomposition techniques [33], which are the subject of active research but are not yet available in commercial packages. Despite this, stochastic programming could be applied today in WECC's analysis using appropriate simplifications on the real network.

5.2 Do Stochastic Transmission Plans differ from Deterministic Plans?

It takes more time and effort to use stochastic methods for transmission planning than to use traditional deterministic methods. Expending these resources is worthwhile only if stochastic planning might result in different – and better – investment recommendations. What differences in recommendations might we anticipate?

- On one hand, we might guess that stochastic plans would *delay* investments until more is known about future load growth, prices, etc. That is, stochastic planning would consider and value the option to defer line construction.
- On the other hand, we might instead anticipate that *more* near-term investment in a diverse set of network investments would be justified so that the system in 10 years is positioned to respond to whatever load, price, technology, and policy scenario occurs. In other words, considering multiple scenarios might imply that the best approach is to spend more now in order to diversify the portfolio of transmission additions so that the system performs well no matter what happens.

In theory, either might occur--or even both at once in different sub-regions of the West, if a line is deferred in one sub-region, while additional lines are added elsewhere as a type of insurance.

5.2.1 Differences between the Stochastic Plans and the Deterministic Plans

What JHSMINE shows under the 2013 TEPPC assumptions are that a *greater* number of transmission investments are economically justified compared to a deterministic base case. We discuss the 21-zone results followed by the 300-bus results first by referring to maps of line additions in the first 10 years of the model, followed by a discussion of more detailed tabular results in later sections. This section emphasizes a comparison of the base case deterministic model results (using the 2013 TEPPC base case assumptions) with stochastic models that include either 5 or 20 scenarios.

Figure 5.1 shows the transmission investment made in the first (2024) stage in our 21-zone model, excluding the Common Case Year 10 transmission (which are treated as fixed in this setting). There are two solutions shown: the left shows the deterministic model using the 2013 TEPPC base case assumptions; the right displays the stochastic solution based on 5 scenarios (each with the same probability). The 20 scenario stochastic solution (i.e., the solution resulting from considering all 20 scenarios once) is not shown because it gives the same transmission additions as the 5 scenario stochastic solution (right side, Figure 5.1). Approximately 57% more is invested in transmission in the Year 10 solution in the stochastic solutions than the base case deterministic solution (Table 5.2, last row), although other deterministic

solutions actually have more transmission (for instance, WECC3, which has low peak/demand growth, see Table 5.2 below). The additional lines are shown in Figure 5.1 as circled lines.

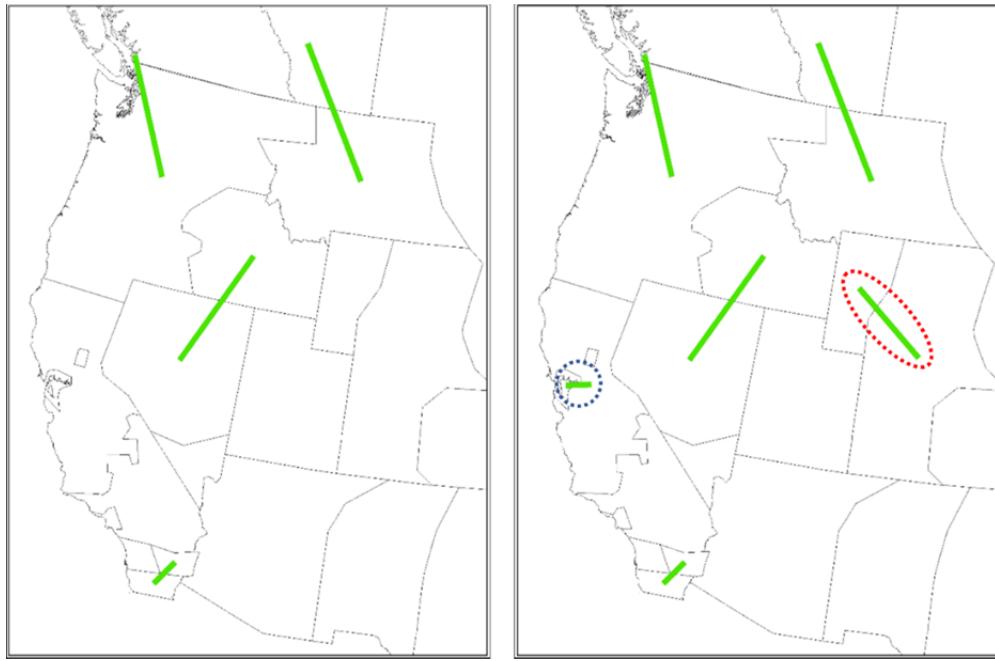


Figure 5.1 Comparison of deterministic (base case scenario), stochastic (5), and stochastic (20) solutions, 21-zone version of JHSFINE. Red circled line is not selected in any of the five deterministic models

Figure 5.2 shows the additions made in the first (2024) stage in our 300-bus model, excluding the Common Case Year 10 transmission (which are treated as fixed). There are three solutions shown in the top half of the figure: one for a deterministic model using the 2013 TEPPC base case assumptions; a second for a stochastic solution based on 5 scenarios (each with the same probability); and a third for a stochastic solution based on 20 scenarios (with various probabilities chosen so that the average values of uncertain variables, such as demand growth, are close to the base case values, but with each case having at least a 2% probability; see Table 4.5). In the bottom half, the base case solution is repeated and this time is compared to the stochastic (20 scenario) that instead results if instead equal (5%) probabilities are assumed for the 20 scenarios. Approximately 20%-50% more is invested in transmission in the Year 10 solution in the stochastic solutions than the base case deterministic solution (Table 5.3, last row), although other deterministic solutions actually have more transmission (WECC 1 and 2, which are relatively high load growth cases). The higher percentage is for the equal probability case. (This investment calculation only includes portal lines that are optional in our model; it excludes the Common Case Year 10 transmission lines.) The additional investments made with the stochastic planning model provide additional flexibility to adapt to future conditions. The stochastic planning model also delayed one backbone reinforcement until the second stage in some scenarios. In other scenarios, this line just got cancelled and was never built. The stochastic model with 20 and 5 scenarios made the same backbone enforcement decisions, but different renewable energy zone interconnections.

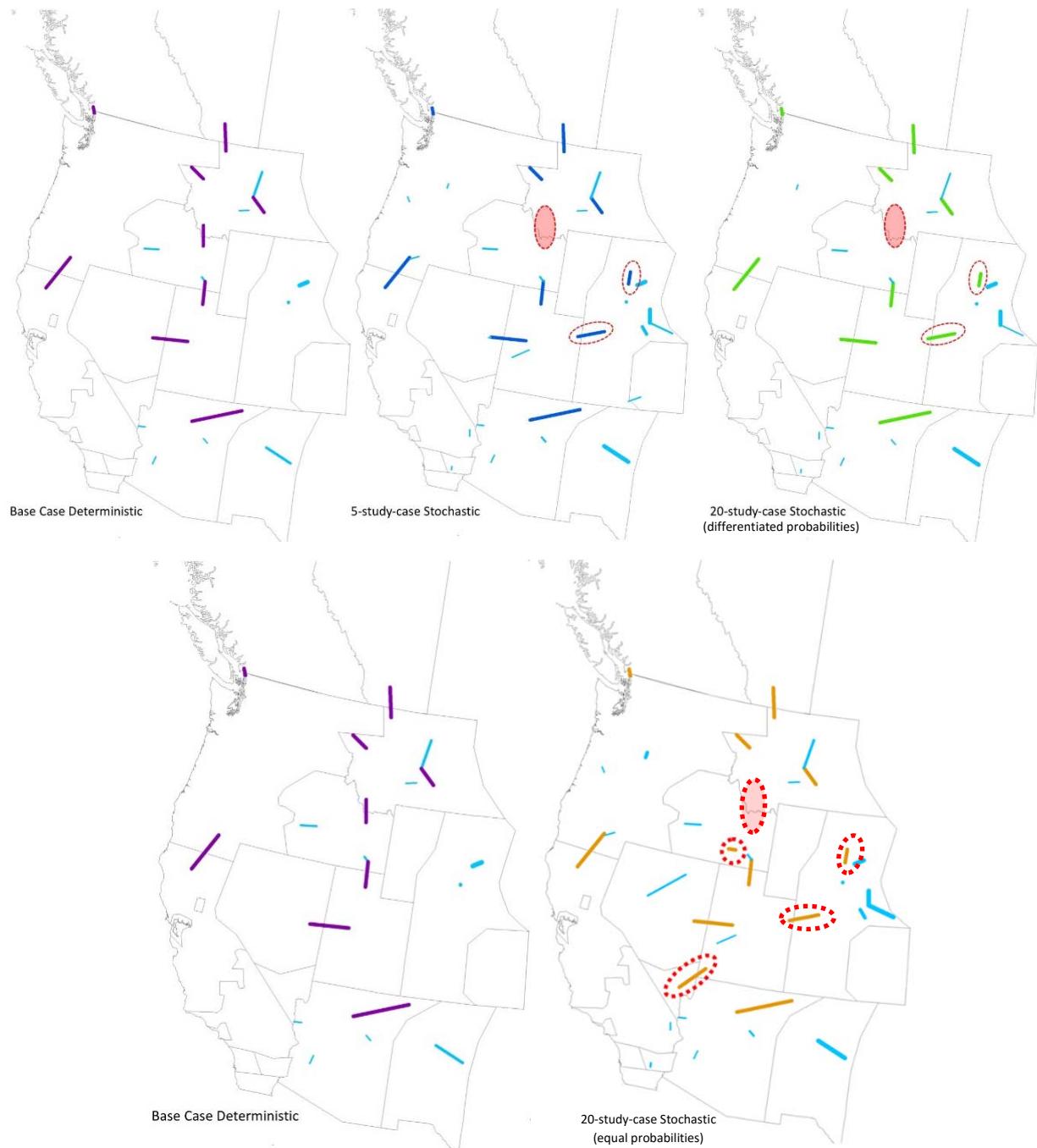


Figure 5.2 Comparison of deterministic (base case scenario), stochastic (5, equal probability), and stochastic (20) solutions, 300-bus version of JHS-MINE. Top: comparison with differentiated probability-based stochastic (20 scenarios) solution; Bottom: comparison with equiprobable stochastic (20) solution

In the top half of Figure 5.2, backbone lines connecting regions are shown in purple, blue and green, respectively, in the three solutions; light blue lines in the diagrams connect renewable energy zones to

grid. The two dotted circles without fill indicate two additional backbone reinforcement lines that the Base Case Stochastic (5) and Stochastic (20) add compared to the base case deterministic model. In contrast, the solid filled circle indicates a deterministic base case line that is not chosen by the stochastic models. In additions, decisions for lines that interconnect renewable energy zones to the grid vary among the solutions, corresponding to differences in decisions about which zones to develop. (For instance, see the line in southern Colorado that is in the 20 scenario solution but not the 5 scenario solution). In the bottom half of the figure, the brown lines in the stochastic (20) scenario are backbone lines. In that solution, four additional backbone lines are added compared to the base case solution, rather than just two.

The lines that make up a stochastic plan can provide the system the flexibility to perform well across many scenarios. However, it is possible that a line investment that helps the system adapt to a wide range of scenarios might not be recommended by the deterministic model for any individual scenario. That is, a line might give the system flexibility, but not be better than all other lines for any particular case. Here, we examined the deterministic solutions for five distinct scenarios (base case and WECC 1-4) and compared them with the stochastic solutions to see if any lines were picked by the later that were not recommended in the former.

We found that there are indeed unique lines in the stochastic solution that are not recommended under any deterministic scenario. In particular, in the 21-zone model, the stochastic model identified a line between Western Wyoming to Wyoming & Colorado as enhancing system flexibility in the face of long run uncertainty (Figure 5.1). This line was not recommended by any deterministic plan under any of the five 2013 TEPPC scenarios (base case and WECC 1-4, identified in Table 5.2). There is no such unique line in 300-bus model results, however.

This subsection has compared stochastic solutions to deterministic solutions based on a single scenario apiece. In Section 5.2.3, below, we consider whether “robust” transmission plans constructed by looking for common elements among multiple deterministic solutions might be a good approximation of stochastic solutions.

5.2.2 But are Stochastic Plans Actually Better?

Of course, just because the stochastic solution differs from deterministic plans does not mean that these differences are important economically. The two methodologies may perform quite similarly because, for instance, different lines may have similar net benefits, or the system may readily adapt to a network that has been misconfigured in the first decision stage adjusting generation sites or later line additions.

Therefore, we quantify the (probability-weighted) cost savings resulting from implementing the near-term (year 10 plan) recommendations of the deterministic models (five scenarios) rather than recommendations from the stochastic models. In particular, what are the consequences of building the “wrong” lines now, assuming (optimistically) that (1) generation investments adapt as best they can to what lines are built, and (2) the transmission system is still optimally planned in the second decade once it is known which scenario occurs?

Table 5.2 21-zone results: economic loss from inefficient (deterministic and heuristic) year 10 plans relative to stochastic solution, and the cost of year 10 lines. All numbers are 2015 present worth

Description	PW Costs (\$ Billion)											
	Base Case (Deterministic)*	WECC 1 Study Case: Econ. Recovery (Det.)*	WECC 2 Study Case: Clean Energy (Det.)*	WECC 3 Study Case: Short-Term Consumer Costs (Det.)*	WECC 4 Study Case: Short-Term Consumer Costs (Det.)*	Heuristic 1: "Build All" (Backbone line appears in any of the 5 cases)	Heuristic 2: "Majority Vote" (Backbone line appears in >50% of cases, prob. weighted)	Heuristic 3: "Unanimous Vote" (Backbone line appears in all 5 deterministic cases)	Stochastic (5) Differentiated Probabilities**	Stochastic (5) Even Probs.	Stochastic (20) Differentiated Probs.***	Stochastic (20) Even Probs.
Increase in Cost relative to Stochastic (20) solution, Differentiated Probs	0.22	7.06	2.52	0.31	1.66	8.31	0.22	0.31	0	0	0	0
Increase in Cost relative to Stochastic (20), Even Probs	0.44	5.11	1.60	0.56	0.74	5.23	0.44	0.56	0	0	0	0
Cost of 10 Year Lines	1.23	11.70	5.87	1.15	4.53	15.01	1.23	1.15	1.94	1.94	1.94	1.94

* See subsection 4.1.1 for the definition of the individual deterministic scenarios

** See Table 4.4 third column ($p^1 = 0.35$) for the differentiated probabilities that were assumed

*** See Table 4.5 for the differentiated probabilities that were assumed

Table 5.3 300-bus results: economic loss from inefficient (deterministic and heuristic) year 10 plans relative to stochastic solution, and the cost of year 10 lines. All numbers are 2015 present worth

Description	PW Costs (\$ Billion)											
	Base Case (Deterministic)*	WECC 1 Study Case: Econ. Recovery (Det.)*	WECC 2 Study Case: Clean Energy (Det.)*	WECC 3 Study Case: Short-Term Consumer Costs (Det.)*	WECC 4 Study Case: Short-Term Consumer Costs (Det.)*	Heuristic 1: "Build All" (Backbone line appears in any of the 5 cases)	Heuristic 2: "Majority Vote" (Backbone line appears in >50% of cases, prob. weighted)	Heuristic 3: "Unanimous Vote" (Backbone line appears in all 5 deterministic cases)	Stochastic (5) Differentiated Probabilities**	Stochastic (5) Even Probs.	Stochastic (20) Differentiated Probs.**	Stochastic (20) Even Probs.
Increase in Cost relative to Stochastic (20) solution, Differentiated Probs	1.17	1.4	2.41	6.89	1.76	3.03	1.26	1.6	0.09	0.25	0	0.72
Increase in Cost relative to Stochastic (20), Even Probs	11.66	0.51	1.19	28.28	9.66	1.53	1.33	4.67	6.59	1.52	5.41	0
Cost of 10 Year Lines	3.58	5.96	6.96	3.75	3.69	8.63	5.11	3.05	4.17	4.6	4.25	5.43

* See subsection 4.1.1 for the definition of the individual deterministic scenarios

** See Table 4.4 third column ($p^1 = 0.35$) for the differentiated probabilities that were assumed

*** See Table 4.5 for the differentiated probabilities that were assumed

The discussion in this section relies on the tabular results shown in Tables 5.2 and 5.3 for the 21-zone and 300-bus models, respectively. We discuss them in reverse order, starting with Table 5.3. It shows how much better the 300-bus stochastic models perform in terms of the present worth of probability-weighted costs of transmission and generation construction and operations over the 50-year time horizon. For instance, the base case solution (based on the middle values of all the variables), which yields the solution on the left side of Figure 5.2, results in expected costs that are \$1.17B to \$11.66B higher than the Stochastic (20) solution. (The lower number results if the scenarios have differentiated probabilities, while the latter, larger penalty occurs if equal scenario probabilities are used. See rows 1 and 2 of Table 5.2.) This penalty, in the form of higher than necessary generation capital and operating costs, averaged over the scenarios, is of the same order of magnitude as the first stage (optional Year 10) lines themselves (row 3, Table 5.3).

On the other hand, planning for the other WECC deterministic scenarios in the 300-bus model results in very different total cost penalties relative the stochastic (20 scenario) optimum. On one extreme, WECC 3 scenario (which is the low growth, low fuel cost scenario) results in relatively low transmission build-out in stage 1 compared to WECC 1, 2 and 4 (only \$3.75 billion), which leaves the system vulnerable to the high growth rates, high renewable installation, or high fuel costs that can occur in other scenarios. Consequently, operating costs in stage 1 (2024) are much higher in those scenarios than they would be otherwise, and there is a relatively large (\$6.89B or \$28.28B) penalty for planning based on the WECC 3 scenario. On the other extreme, WECC 1 and 2 scenarios, which have more robust load growth, result in roughly twice the transmission additions of the base case or WECC 3, and appreciably more than the stochastic solutions. However, this early expenditure is a form of insurance, at least in the case of equiprobable solutions. If the 20 scenarios have equal probabilities, WECC 1 and 2 incur only about one-tenth the cost penalty as the base case (\$0.51B and \$1.61B for the WECC 1 and 2 study case solutions, compared to \$11.66B for the base case and similar or higher numbers for the WECC 3 and 4 cases).

The differences in expected costs in the 300-bus case may appear relatively small at first glance. For instance, the \$6.89 billion in present worth terms is ~1% the present worth of generation investment and operating costs in WECC footprint; the latter, summed over 50 years at a 5% interest rate, amount to about one trillion dollars. However, the cost penalties of inefficient planning turn out to be of the same order of magnitude as the construction cost of the year 10 plan lines (shown in the last line of Table 5.3). This shows that the economic losses from suboptimal (deterministic) planning can be highly significant relative to the cost of transmission.

Turning to the 21-zone results, the monetary value of improvements from stochastic planning are smaller than for the 300-bus case because, we believe, the value of transmission additions within regions are not considered and congestion is not as accurately represented. In monetary terms, the 21-zone model adds less than half as much transmission investment in the first 10 years as the 300-bus model, so it is unsurprising that the benefits of stochastic planning are less.

Just as in our discussion of the 300-bus results in Table 5.3, we treat the 10 year (first stage) recommendations of the two stochastic (20) 21-zone solutions (differentiated or equal probabilities) as the "gold standard" against which the quality of 10 year recommendations by other solutions are evaluated. Each

set of recommendations (from the five deterministic models, including the base case and WECC 1-4; the three heuristics; and four stochastic solutions, two under 5 scenarios and two under 20 scenarios) is evaluated by constraining the 20 scenario model to choose the recommended lines in the first stage, and then allowing the model to optimize generation investments in both stages as well as transmission investments in the second decade. By this procedure, the year 10 recommendations of the base case deterministic plan perform worse than the stochastic (20) solutions by one-quarter to one-half billion dollars in present worth (first column, Table 5.2). These cost penalties are 5-20 times smaller than the 300-bus results in Table 5.3. However, the other deterministic solutions do much worse than the base case, with the WECC 1 solution (in which ten times as much transmission is built as in the base case in response to load growth) performing over an order of magnitude worse. The resulting "stranded assets" cause the performance of the WECC 1 solution to be much worse.

Meanwhile, the stochastic (5) solutions for the 21-zone model incur no penalty relative to the stochastic (20) case because their recommendations for \$2 billion of additional transmission investment in the first 10 years are identical. This is in contrast to the 300-bus model, where the stochastic (5) solutions did less well than the stochastic (20) solutions, although not dramatically so.

We now return to our discussion of the 300-bus results to consider whether stochastic planning based on just 5 scenarios results in 10 year recommendations that are more robust against scenarios that haven't been considered. The expected increase in total system costs by \$1.17B-\$11.66B resulting from deterministic planning based on the base case, compared to a 20 scenario stochastic plan, is not the only benefit of stochastic planning. Another key benefit of a stochastic plan is how it improves the overall robustness of the system. This can be examined by considering the total cost realized in a wide range of scenarios, including scenarios not considered in building a particular plan.

To quantify the robustness of stochastic solutions, Figure 5.3 and Figure 5.4 each compare two solutions: the costs of the deterministic base case solution against the 5 scenario stochastic plan's costs, compared for all 20 scenarios. (Figure 5.3 shows the situation in which differentiated probabilities were considered in the 5 scenario solution, as well as in the 20 scenario solution, while Figure 5.4 summarizes robustness results if instead equal probabilities are assumed in each.) Each bar charts shows, for each of the 20 solutions, the total system cost of the base case deterministic solution (in particular, the present worth of costs resulting from implementing its year 10 recommendations) minus the cost of the year 10 recommendations of the considered 5 scenario solution.⁸ Thus, we are comparing how the two solutions

⁸ The values shown in the bar charts were calculated as follows. First, the Year 10 (first stage) transmission decisions in the base case were imposed in the 20 scenario stochastic model, and then the model optimized the first stage generation investments, plus generation operations and both generation and transmission investments in the subsequent years. In other words, the 20 scenario stochastic models' "hands were tied", assuming that the naïve (base case) transmission additions were made. This yields 20 costs, one per scenario, whose probability-weighted average is the objective function of the stochastic model. Then this calculation was repeated, except using the 5 scenario stochastic Year 10 (first stage) lines instead, also yielding 20 scenario-specific costs. Finally, we subtracted, for each scenario, the stochastic 5 solution's cost from the base case deterministic solution's cost, yielding the twenty bars in Figure 5.3 and Figure 5.4. The difference between those two bar charts is that Figure 5.3 made the naïve running using differentiated probabilities, while Figure 5.4 used equal probabilities.

fare not only against the five scenarios considered in that stochastic solution, but also the other 15 scenarios that were included in the 20 scenario solution, but not in the base case or 5 scenario solution.

The results in the figures lead to the conclusion that the 5 scenario solutions do much better in the 15 other scenarios than the base case, and so are conclusively more robust. While the base case plan does perform better than the 5 scenario plan in 8 of the 20 scenarios in both figures, it performs worse in the other 12, including 10 out of the 15 scenarios not considered by either solution. In particular, in the high growth, high renewable integration cases, the base case performs far worse, with a penalty of up to \$40B compared to the 5 scenario stochastic solution in Figure 5.4. (The values are somewhat less than half those levels if instead differentiated probabilities are considered, but are still well in excess of the quantity of transmission investments in the first stage, as shown in the last row of Table 5.3.) Therefore, in addition to improving the expected costs, the stochastic planning method helps hedge against losses in the most expensive scenarios, even for scenarios that were not considered. This means that stochastic planning likely provides robustness to the system against scenarios not considered in the planning procedures.

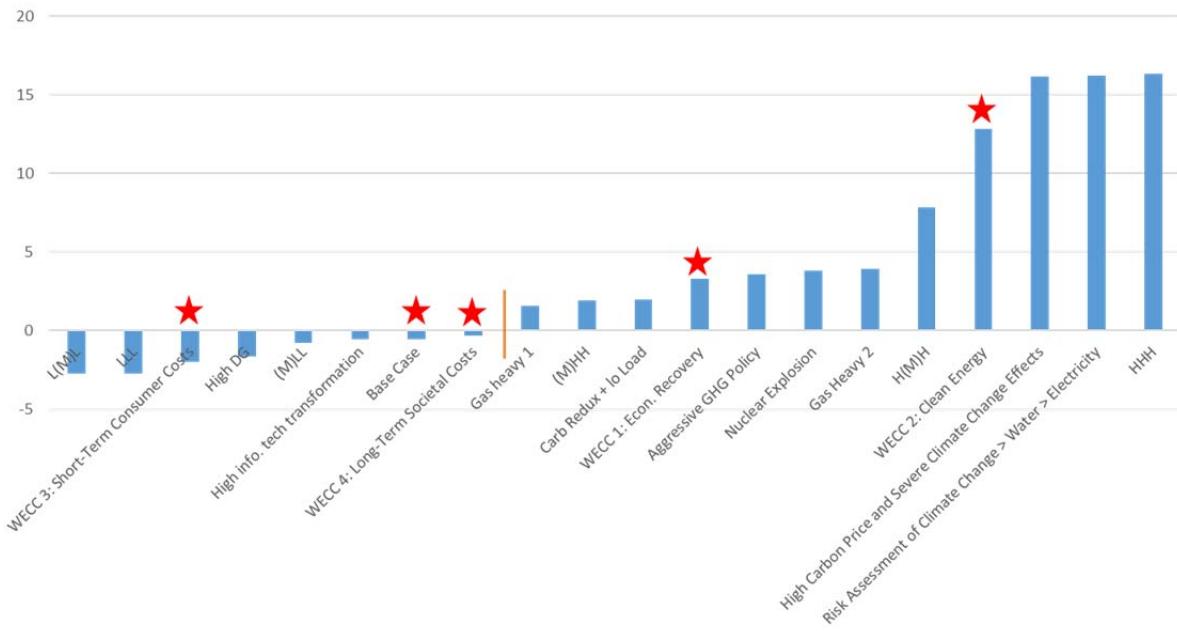


Figure 5.3 The cost difference between a deterministic base case plan and the 5 scenario plan for each of 20 scenarios, assuming differentiated scenario probabilities (300-bus model)

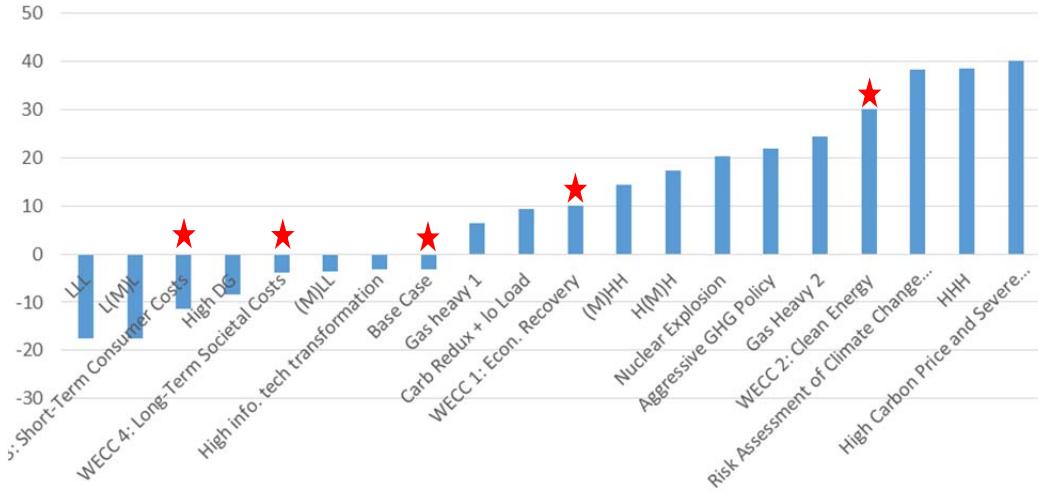


Figure 5.4 The cost difference between a deterministic base case plan and the 5 scenario plan for each of 20 scenarios, assuming equal scenario probabilities (300-bus model)

5.2.3 Robust Planning: Can Good Plans be Defined by Identifying Lines Chosen by Multiple Deterministic Models?

Because of the extra effort required to do stochastic programming, the California and Mid-Continent ISOs have instead tried to identify “robust” lines by applying deterministic planning for each of several scenarios, and then recommending lines that are chosen in some or all of the scenarios [4, 5]. For instance, a line that is chosen by most or all deterministic models, each based on a different scenario, might be concluded to be a potentially worthy investment. This is what mathematicians call a “heuristic”, which is defined as a procedure, sometimes based on rules of thumb, that is relatively easy to execute and is expected to yield good recommendations, but won’t necessarily produce the overall best solution. Might this approach, based on analyzing deterministic model results, do almost as well as deterministic planning?

As mentioned in Section 4.3, we evaluate three such heuristics to assess whether they might yield plans whose scenario-averaged costs are low as the optimal stochastic solution. Table 5.2 and Table 5.3 compare their results. “*Heuristic 1: Build All*” assumes a year 10 backbone line is built if it appears in *any* deterministic model solution, as shown in the left panels of Figure 5.5 and Figure 5.6. “*Heuristic 2: Majority Vote*” chooses backbone lines that appear in a majority of the 5 deterministic solutions (probability weighted) and this solution is shown in the middle panels of Figure 5.5 and Figure 5.6. “*Heuristic 3: Unanimous*” builds only those backbone lines that appear in *all* 5 deterministic solutions, and are shown in the right panels of Figure 5.5 and Figure 5.6.

Because we had to relax the binary decision variables of WREZ interconnection lines, so that the amount of WREZ transmission capacity is a continuous variable, defining the amount of WREZ capacity resulting from each heuristic requires some assumptions. Here, we adopt the following rules. For the “Build all” strategy, we picked the maximum of WREZ solutions over 5 scenarios. For the “Majority Vote” heuristic,

we picked the largest 3 solutions in 5 scenarios and took the average. For the “Unanimous” case, we just took the average of solution over all 5 scenarios.

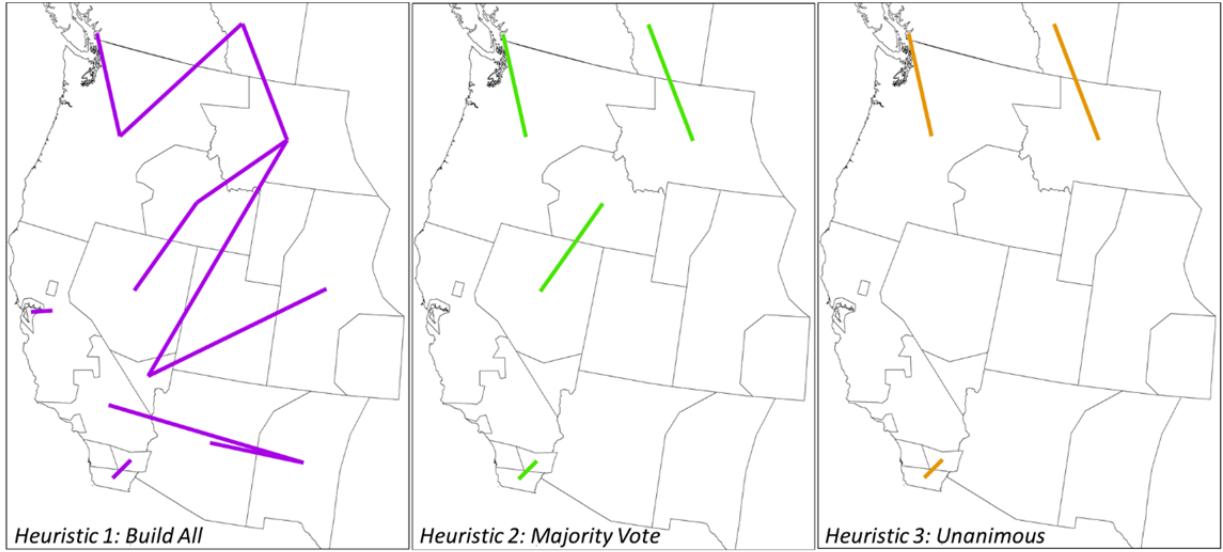


Figure 5.5 The year 10 recommendations of three heuristic strategies in the 21-zone model

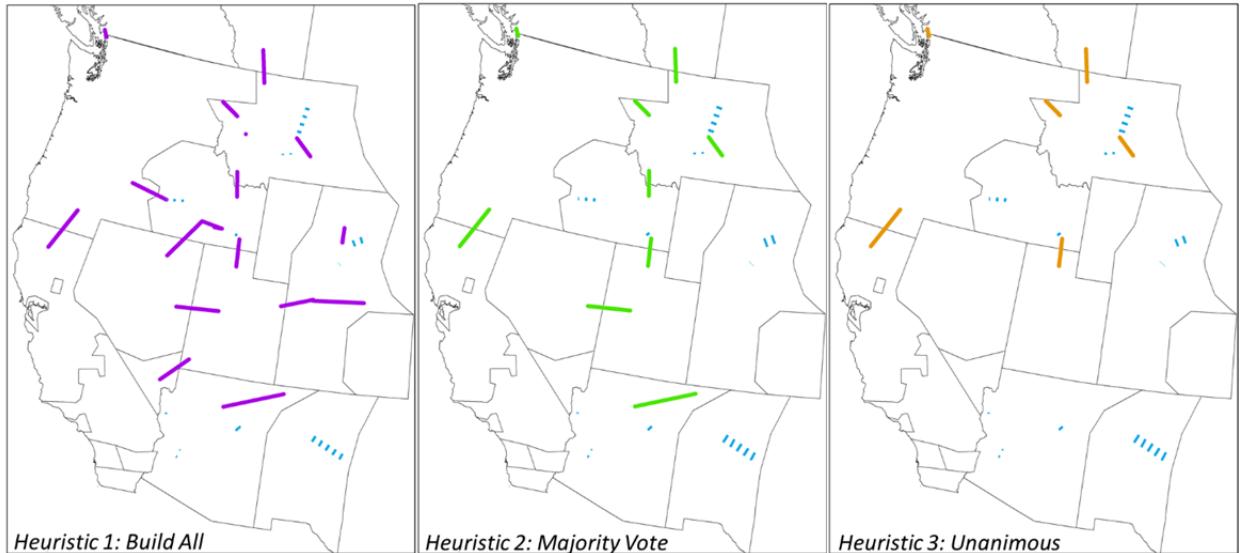


Figure 5.6 The year 10 recommendations of three heuristic strategies in the 300-bus model

Table 5.2 and Table 5.3 show that of the three possible heuristics we define, the best was “Majority Vote” (i.e., lines that appear in a majority of the 5 deterministic solutions) for both the 21-zone and 300-bus models. For the 300-bus model, the cost penalty for the Majority Vote approach relative to the optimal 20 scenario stochastic solution is \$1.3B in both the differentiated and equal probability cases. For

the differentiated probabilities, this heuristic is actually worse than the deterministic solution based on just the base case (penalty of \$1.17 billion), but for the equal probability case, it is far better than the base case solution (whose penalty is ten times larger under those probabilities). In contrast, for the 21-zone model, the “Heuristic 2: Majority Vote” solution is exactly the same as base case solution.

Interestingly, the two other heuristics perform inconsistently. The “Build All” heuristic does almost as well as the “Majority Vote” case (in terms of expected penalty relative to full 20-scenario stochastic programming) if equal probabilities are assumed in the 300-bus case, but much worse in the differentiated probability case. Therefore, “build everything” as an insurance policy does not necessarily perform well compared to other heuristics or even deterministic planning. The reverse is true for the “Unanimous Vote” heuristic in 300-bus solution. In 21-zone model, since the “Build all” strategy is very different compared to the “Majority Vote” heuristic, it actually incurs a much larger (\$5.23B-\$8.31B) penalty compared to the penalty of \$0.22B-\$0.44B for the “Majority Vote” heuristic. Thus, we cannot depend on any particular heuristic to do as well as stochastic programming. Indeed, heuristics may actually do much worse than even the base case deterministic solutions, as the first two rows of Table 5.2 and Table 5.3 demonstrate.⁹

5.3 Sensitivities to Model Structure, Uncertainties, and Assumptions

In this section, we discuss the sensitivities of JHMINE to various assumptions about model structure, and consider the impact of some additional uncertainties not included in the 20 scenarios modeled above. In particular, we ask the following questions. First, in subsection 5.3.1, we ask: “Are stochastic solutions sensitive to the number or the probabilities of scenarios (study cases)?” Then in subsection 5.3.2, we consider the question: “How does uncertainty in line completion affect the results? Especially, what if we consider the possibility that some CCTA lines fail to be completed?” In subsection 5.3.3, we take generator flexibility (in particular, unit commitment constraints) into account and show the resulting effects on year 10 recommendations. In the same section, we will also discuss the effect of different carbon tax assumptions on generation and transmission investment.

In subsection 5.3.4, we then compare the 21-zone and 300-bus considering alternative power flow models (linear DC and transportation). We ask: “Will these different network representations affect the result much?” And: “What are insights do they provide?” In subsection 5.3.5, we discuss the sensitivities of our model to different procedures for selecting operating hours (which capture within-year variation in loads as well as solar and wind availability). Finally, in subsection 5.3.6, we examine the impact of year-to-year variability of hydropower availability, by examining whether transmission recommendations for the year 10 (first) stage are affected by whether dry, medium, or wet years are considered.

5.3.1 Are Stochastic Solutions Sensitive to the Number or the Probabilities of the Scenarios

Stochastic planning is more complicated than deterministic planning because planners have to define scenarios and the associated probabilities of occurrence. Does the stochastic solution depend strongly on which—and how many—scenarios (study cases) are considered? If so, this is a problem, since stake-

⁹This was also the conclusion of an earlier study of WECC using a different network model [15].

holders and planners will naturally disagree on what scenarios should be considered and their probabilities. This was the case, for instance, with this project's Technical Advisory Committee when we asked them to create scenarios and assess their relative likelihood.

However, it turns out that the specific number of scenarios considered by the stochastic plan is less important than the fact that multiple scenarios are considered. The key is to consider a range of possible futures in the first place. This can be observed in our comparisons of the stochastic solutions for the 5 and 20 scenario cases, as well in comparisons of stochastic solutions with different probabilities. When planning for a single scenario, both the 21-zone and 300-bus models showed appreciably higher expected costs relative to the stochastic model solution for the 5 or 20 scenario case (Table 5.2, Table 5.3). That is, when taking the 1st stage (Year 10) transmission decisions and imposing them in the full 20 scenario model as described at the end of the last section, the resulting costs are higher than if the full 20 scenario model could choose the optimal lines in that stage. However, the cost increase resulting from imposing the 5 scenario stochastic solution in the 20 scenarios model is an order of magnitude smaller for the 300-bus case under equal probabilities.¹⁰ In the 21-zone case, the Year 10 transmission additions in the 5 scenario and 20 scenario solutions are the same (whether differentiated or equal probabilities are considered), so clearly it is much more important to include some uncertainty by having 5 scenarios representing a range of conditions than to finesse the stochastic model by expanding the scenario set from 5 to 20 scenarios. That is, while it is important that your scenarios span the range of possibilities, it is not necessary to represent all possible futures.

¹⁰In particular, imposing the base case Year 10 lines upon the 20 scenario stochastic model increases costs by \$1.18B to \$11.66B (differentiated and equal probability cases, respectively), while imposing the 5 scenario stochastic Year 10 lines upon the 20 scenario stochastic model only inflated costs by \$0.09B to \$1.52B (differentiated and equal probability cases, respectively).

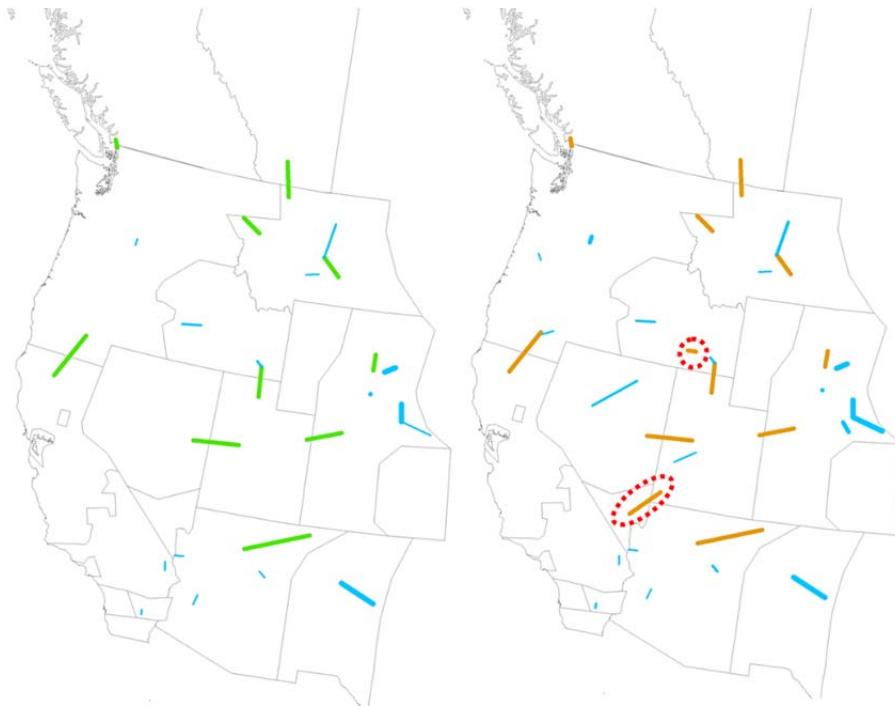


Figure 5.7 Comparison of Year 10 transmission line investments for the 20 scenario stochastic solution with equal probabilities (left) and for differentiated probabilities (right) (300-bus case), with the circled lines indicating additional backbone enforcement investment

Turning to the question of the effect of probabilities, does it matter what probabilities are assumed for the scenarios? We tested this, and we found that although there were some changes in the year 10 recommendations if we gave different weights to different scenarios, but these differences were not as large as the differences between the base case and stochastic solutions. Figure 5.7 shows a difference of two backbone lines for the 300-bus case, and Table 5.3 indicates that the penalty of using the “wrong” probabilities to choose 10 Year lines under the 20 scenario case. This penalty is roughly half the penalty incurred if instead deterministic planning (with the base case scenario) is used to choose the initial investments.¹¹

However, the impact of different probabilities was much less in the 21-zone case. We tested the 21-zone model with four distinct sets of probabilities for the five 2014 study cases (base case and WECC 1-4). The stochastic solutions result in exactly the same transmission investment pattern (Table 5.4) even though the generation investments differ appreciably (Table 5.5). In particular, with a decreased weight upon the WECC 3 study case (short-term consumer costs), the total capacity installed in the first ten

¹¹The second row of Table 5.3 shows that imposing the stochastic (20 scenario, even probability) 1st stage lines (Figure 5.7, left) in the stochastic model (20 scenario, differentiated probability) results in \$0.7B higher costs, whereas using the base case lines increases cost by \$1.2B. Going the other way (third row), if we impose the stochastic (20 scenario, differentiated probability) 1st stage lines (Figure 5.7, right) in the stochastic model (20 scenario) with equal probability, costs go up by \$5.4B, compared to the \$11.7B penalty from imposing the base case lines.

years increased by a significant amount, mainly in the form of new wind (and to a lesser extent geo-thermal) investment. The fact that generation mixes change but transmission investment does not indicate that the same between-region transmission investments can accommodate quite varying generation mixes.

Table 5.4 Alternative sets of probabilities and their associated 10-year transmission investment

Prob ability	Base Case	WECC 1	WEC C 2	WECC 3	WECC 4	MX-IIDCA	MT-AB	NNV-ID	PNW-BC	SFCA-NCA	WYO-WYCO
A*	0.2	0.1	0.1	0.47	0.13	1	1	1	1	1	1
B	0.35	0.1	0.1	0.35	0.1	1	1	1	1	1	1
C	0.5	0.1	0.1	0.2	0.1	1	1	1	1	1	1
D	0.2	0.2	0.2	0.2	0.2	1	1	1	1	1	1

* Probability set A is the differentiated probability case shown in other figures

Table 5.5 Different sets of probabilities & associated 10-year generation investment (WECC wide)

Probability Set	Study Case/Scenario					WECC-wide Year 10 Investment (MW)					
	Base Case	WECC 1	WECC 2	WECC 3	WECC 4	Geo	Wind	Bio	Gas CT	Gas CCGT	Total
A*	0.2	0.1	0.1	0.47	0.13	512	17783	329	4658	17595	40877
B	0.35	0.1	0.1	0.35	0.1	1259	22229	329	3388	18412	45617
C	0.5	0.1	0.1	0.2	0.1	1292	28211	329	2165	19600	51597
D	0.2	0.2	0.2	0.2	0.2	2583	33211	329	2785	17789	56697

* Probability set A is the differentiated probability case shown in other figures

5.3.2 Failure to Launch: How Does Uncertainty in CCTA Line Completion Affect Transmission Plans?

In this project, we also consider the importance of a particular type of uncertainty that has not been examined before in transmission planning. In particular, there is great uncertainty regarding whether lines that are planned for construction in the near future (what we will call “10 year lines”) will actually be completed.¹² Therefore, we also considered models with scenarios in which some of the near-term

¹² In WECC’s planning process, which was last completed in 2013 and is now underway for 2015, its Transmission Expansion Planning Policy Committee (TEPPC) oversees an analysis a detailed process of identification of transmission investment alternatives for the year 10 and year 20 time-frames. The result of the year analysis is a set of recommended lines, called the “Common Case Transmission Assumptions” (CCTA). In our analysis, with the exception of defined “failure to launch” scenarios (in which one or more CCTA lines do not actually materialize), we assume that the CCTA lines are built in the first 10 years. In addition, JHSMINE can identify additional lines for implementa-

planned lines do not actually materialize. This part of the project responds to Recommendation #9 of the WECC 2013 report that recommended that uncertainty concerning completion of 10-year study transmission projects (“CCTA projects”) be considered [3].

More specifically, we ask: “How might the failure of certain planned lines change the recommendations for other near-term lines as well as lines that are planned for later (‘20 year lines’)?” On one hand, a significant risk of non-completion of one line might enhance the value of a potential parallel line that would deliver the same resources or serve the same load, so perhaps the model would recommend more lines. We call this an “insurance” or “substitution” effect. On the other hand, non-completion of a line might instead diminish the economic value of other potential lines in series with that line—a “broken chain link” or “complementary” effect.

We examined this question with the 21-zone model. The 25 study cases we considered are shown below, each with the same probability of 0.04 (Figure 5.8). The map of 4 CCTA inter-zonal corridors that are assumed to have a probability of not being completed is given in Figure 5.9.

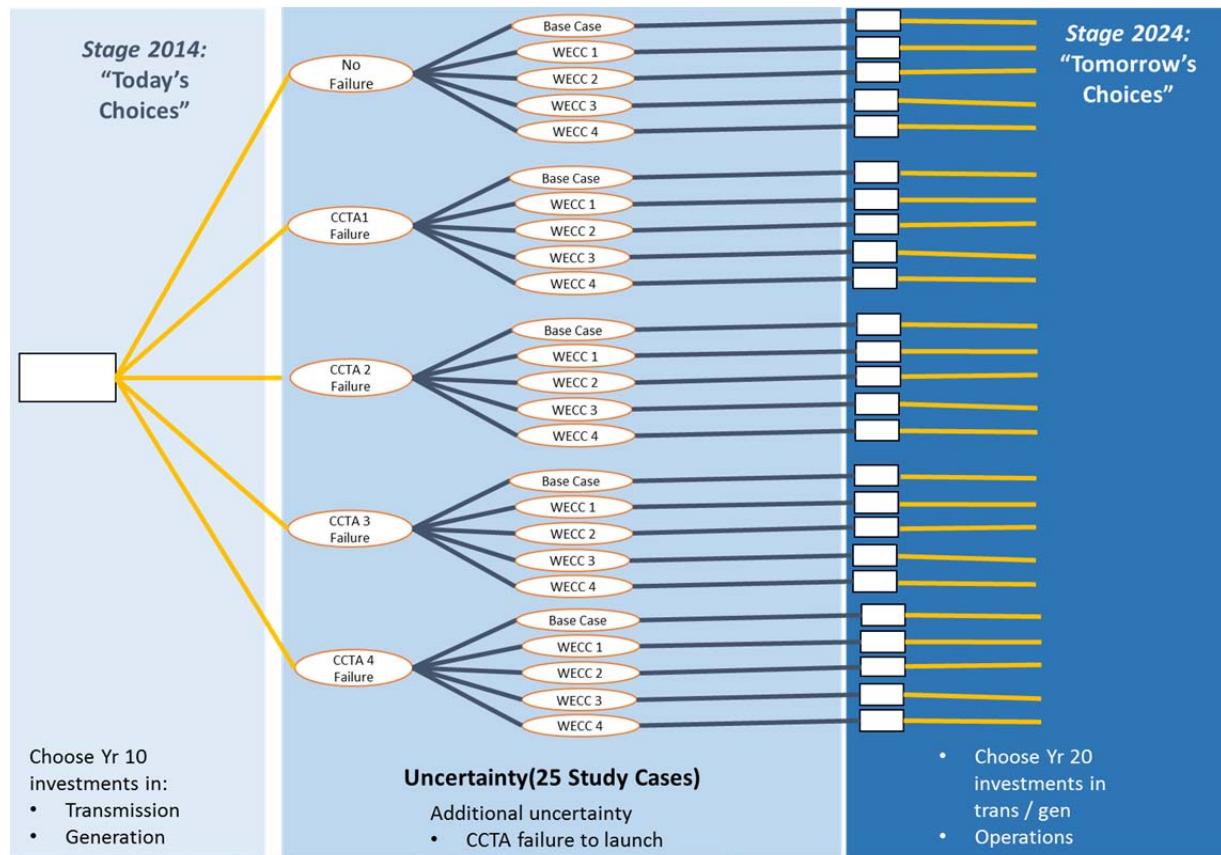


Figure 5.8 Decision tree for 25 study cases considered in the failure to launch analysis for CCTA lines

tion by year 10. In this paper, both CCTA and any additional near-term lines are collectively called “10 year lines”, while lines built later for implementation the end of the second decade are called “20 year lines”.

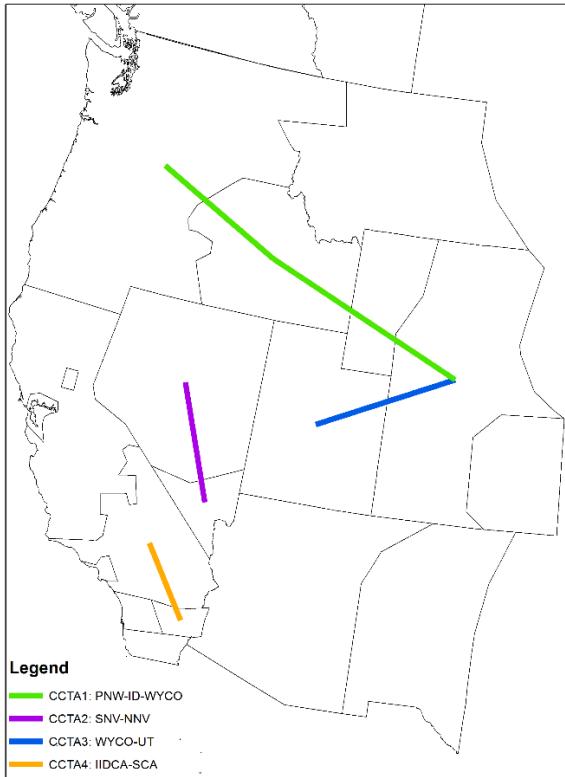


Figure 5.9 Four sets of CCTA inter-zonal lines that are each assumed to have a 20% probability of not being completed by 2024. Each set can include several lines in series that perform the same function.

In fact, however, we found evidence of neither the insurance or broken link effects, at least in the 10 year plans. In particular, even if we assume that there is a 20% probability that a set of planned year 10 lines won't actually be built, the model still recommended exactly the same set of 10 year lines. The subsequent 20 year lines, however, did change, at least in scenarios with reasonable load growth. In those cases, the model would often build "replacement" lines that serve a similar function as the cancelled year 10 line (for instance, to deliver Colorado wind to the southwest). We now discuss the shift in year 20 line investments in more detail for each of the four sets of CCTA lines that we assumed are subject to "failure to launch" risk. We also summarize the changes in generation investment in year 20 (2nd stage) the WECC 1 (economic growth) study case, which is the study case with the most vigorous load growth and generation investment. These shifts provide insight on the role of the CCTA lines in interregional electricity trade and siting decisions.

The shift in second state (year 20) transmission investments differs depending upon the specific CCTA failure in question. The following figures (Figure 5.10-Figure 5.13) show the 25 scenario stochastic solution. In particular, we compare the year 20 investments that follow if none of the CCTA lines are cancelled with the lines that are instead added if one of the sets of CCTA lines in Figure 5.9 is not built. This comparison is made for each of the four sets of such lines. The left panels are the year 20 transmission decision changes: the broader a red line is, the more times it is added across the five WECC scenarios

(base case, WECC 1-4) compared to the no CCTA failure scenarios for those five study cases. The right panels are the generation investment changes in year 20 as a result of a “failure to launch” of a set of CCTA lines, considering only the WECC 1 scenario (high peak/load growth) year 20 decisions as an example.

A loss of CCTA set 1, which would provide a connection between the Pacific Northwest and Colorado (Figure 5.9), has a small impact on the second stage decisions, as shown in Figure 5.10. The unavailability of this line led to several second stage lines being added; however, these changes only appeared in single scenario and did not result in a widespread reduction of investments (Figure 5.10). Of the new investments that appear in response to the CCTA1 failure to launch, two appeared in one of the five scenarios. This one scenario was subject to high demand growth (WECC 1 study case). Regarding generation investments, failure of CCTA1 lines to appear has the greatest impact on investments in Idaho, Wyoming, Utah and Colorado, especially in study case WECC 1. Without the CCTA1 project, the generation investment moved southeast from the northwestern states and Montana to Utah, Wyoming and Colorado (Figure 5.10, right). This indicates that CCTA1 would have facilitated power transfers from the northwest to the latter states.

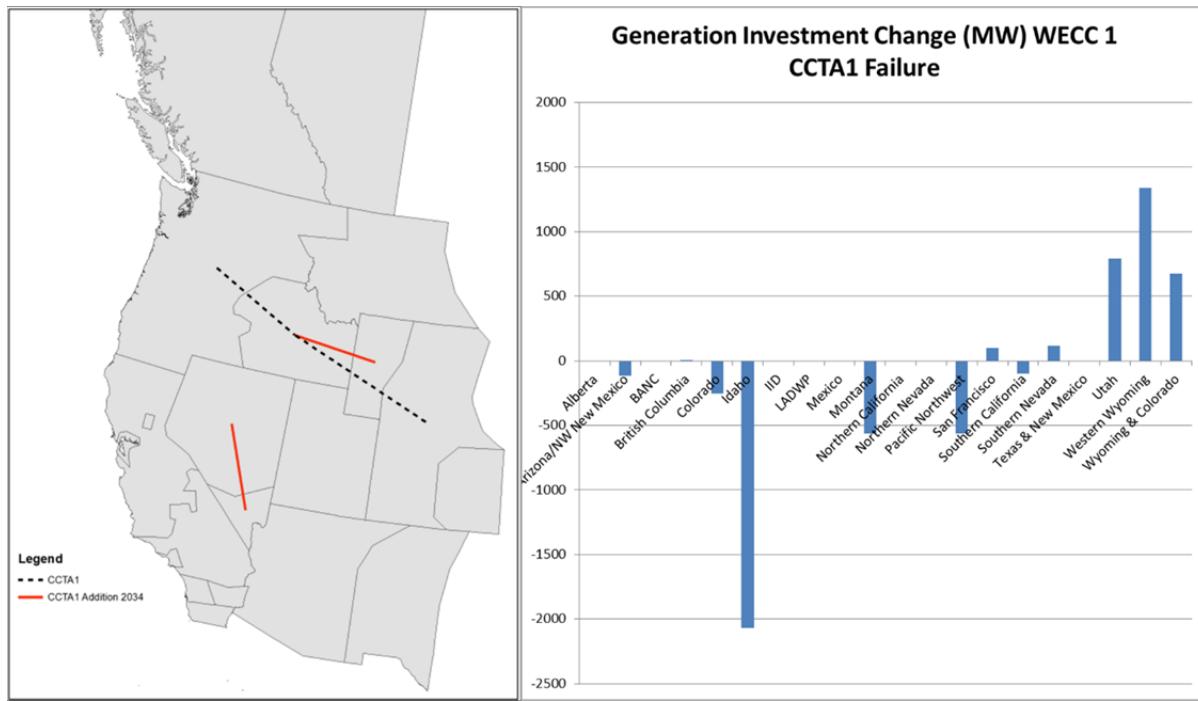


Figure 5.10 Left: Changes in “Year 20 Lines” as a result of CCTA set 1 “failure to launch.” Right: Changes in generation investments by region as a result of CCTA 1 failure (WECC 1, comparison with year 20 generation investment in WECC 1 with no failure to launch)

The failure of CCTA 2 (Figure 5.11), connecting Northern and Southern Nevada, has a much clearer impact on the second stage decisions. In response, the model chooses to build a similar project in three out of the five scenarios in the second stage along the same corridor (the Base Case, WECC 1 and WECC 2 study cases). The greatest change in generation investment relative to the “no failure to launch case” is a shift from Western Wyoming to Wyoming & Colorado zone in the High Load Growth Rate case (WECC 1 study case).

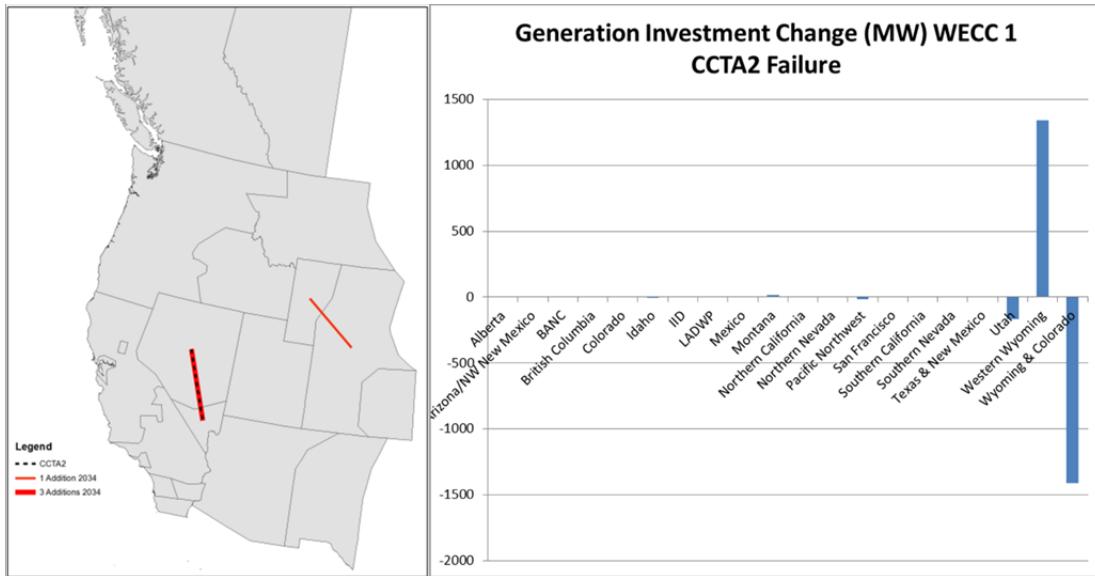


Figure 5.11 Left: Changes in “Year 20 Lines” as a result of CCTA 2 failing to launch. Right: Changes in generation investments by region as a result of CCTA 2 failure (WECC 1, comparison with year 20 generation investment in WECC 1 with no failure to launch)

A failure to launch for CCTA 3 connecting Utah to Wyoming and Colorado has a relatively small impact on second stage decisions. As Figure 5.12 shows, it results in second stage investment in a line from Western Wyoming to Wyoming & Colorado (WECC 1). The missing CCTA project caused a corresponding change in generation investment from Utah to Western Wyoming in the WECC 1 study case in year 20.

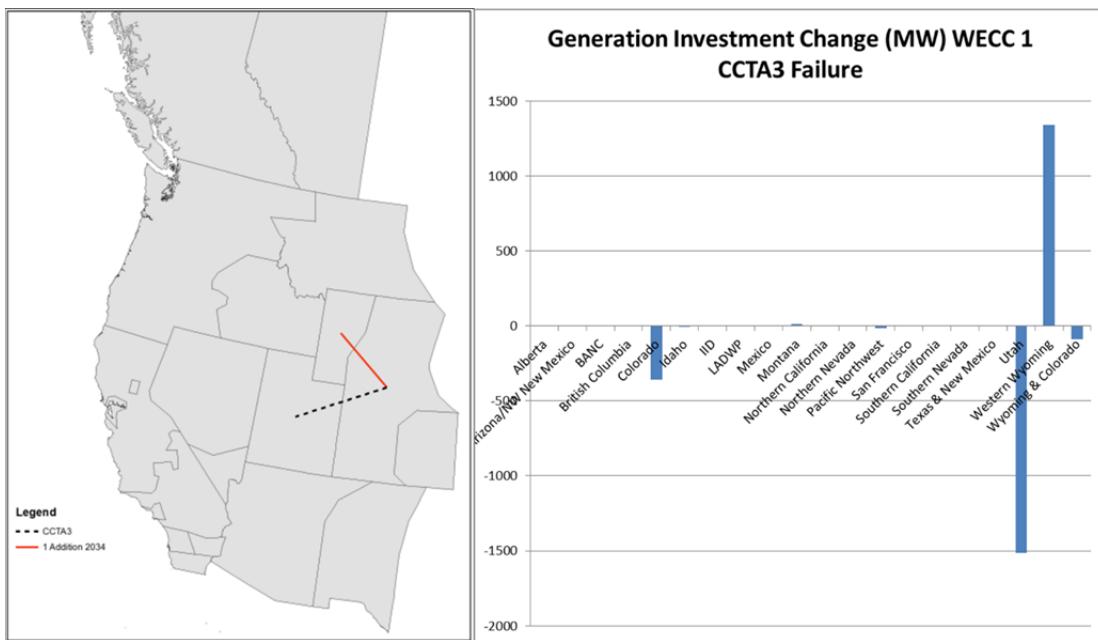


Figure 5.12 Left: Changes in “Year 20 Lines” as a result of CCTA 3 failing to launch. Right: Changes in generation investments by region as a result of CCTA 3 failure (WECC 1, comparison with year 20 generation investment in WECC 1 with no failure to launch)

For a failure of CCTA 4 connecting Southern California to IID (Imperial Irrigation District), there was a clear response in the year 20 plan, with a line being selected between Mexico and San Diego in three scenarios (Base Case, WECC 2 and WECC 4). This line is also chosen in WECC 1 and WECC 2 scenario even if CCTA 4 doesn't fail. But the generation investment shift in the region is relatively small (loss of 500 MW in Southern California), which indicates that the market might adapt to the CCTA 4 failure by transmission planning rather than shifts in generation siting.

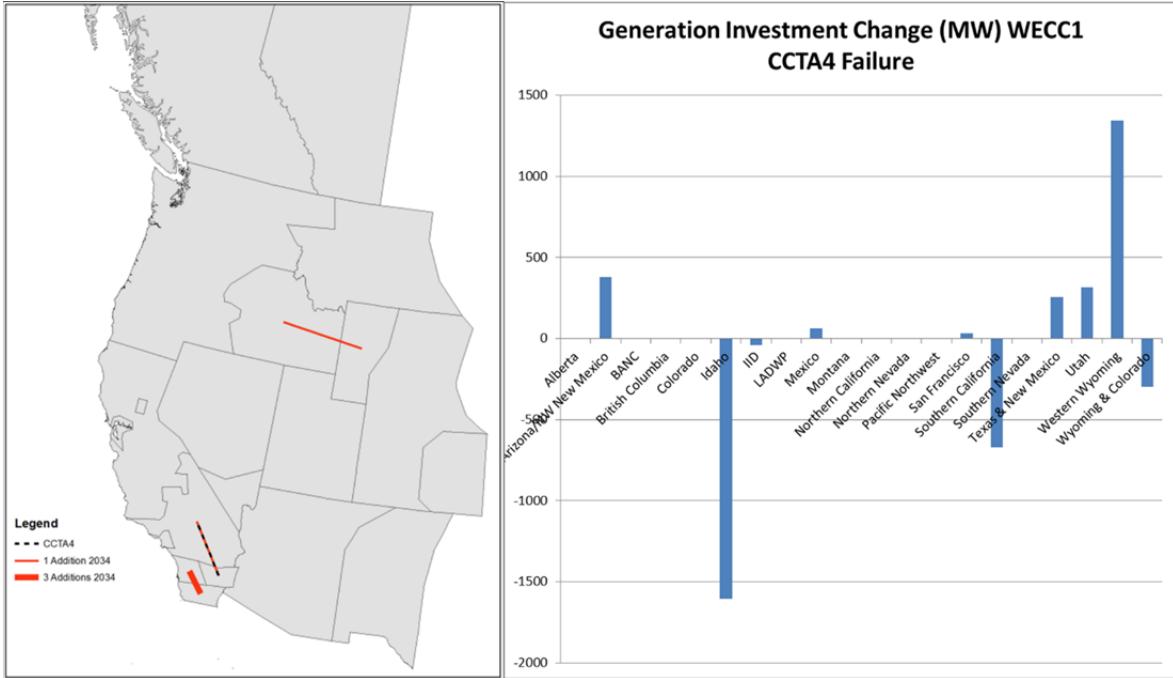


Figure 5.13 Left: Changes in “Year 20 Lines” as a result of CCTA 4 failing to launch. Right: Changes in generation investments by region as a result of CCTA 4 failure (WECC 1, comparison with year 20 generation investment in WECC 1 with no failure to launch)

5.3.3 Does Representation of Generator Flexibility affect Transmission Plans?

Considering uncertainty affects transmission plans, as we show above. How important are other approximations in transmission planning? A potentially important approximation is the representation of generator flexibility. In traditional transmission planning, production costing — the calculation of generation operation costs — is undertaken using load duration curve-based methods that ignore inter-temporal operational phenomena such as start-ups, minimum run capacities, and ramp constraints. But such unit commitment (UC) considerations, and their impact on operational flexibility, are becoming increasingly important with the growing penetration of renewable generation [34, 35, 36]. Unfortunately, representing UC constraints in capacity expansion models poses computational problems. These computational problems arise from the structure of Unit Commitment models. In particular, the problems are Mixed Integer Programs (MIPs) in which the decision to switch on or commit a unit in a particular hour is modeled as a binary variable. Solving such a MIP as a part of a larger MIP (the transmission investment problem) causes a binary variable explosion, which can lead to intractable solution times. The question we explore here is: Can disregarding these inter-temporal operational considerations, and thus overestimating the flexibility of thermal generators, bias transmission plans? And if so, what are the benefits of better models of generator flexibility in transmission planning?

First, however, let us consider how unit commitment constraints can change operations at the generating unit level. Figure 5.14 and Figure 5.15 illustrate these unit level changes showing generation opera-

tions at two locations in the 21-zone model (Arizona/NW New Mexico and Colorado) with and without UC constraints.

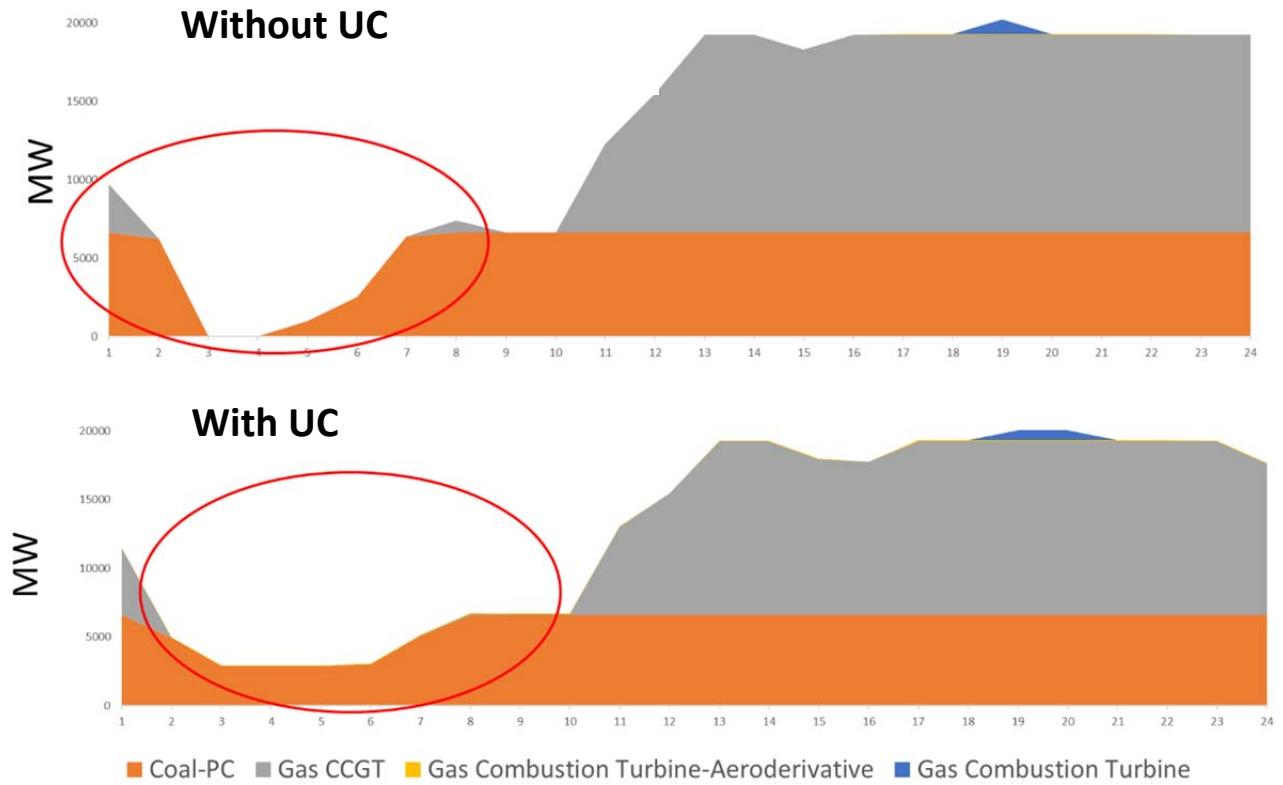


Figure 5.14 Select operations without UC and with UC constraints at AZ/NW-NM (2024, WECC 1 study case, 21-zone model)

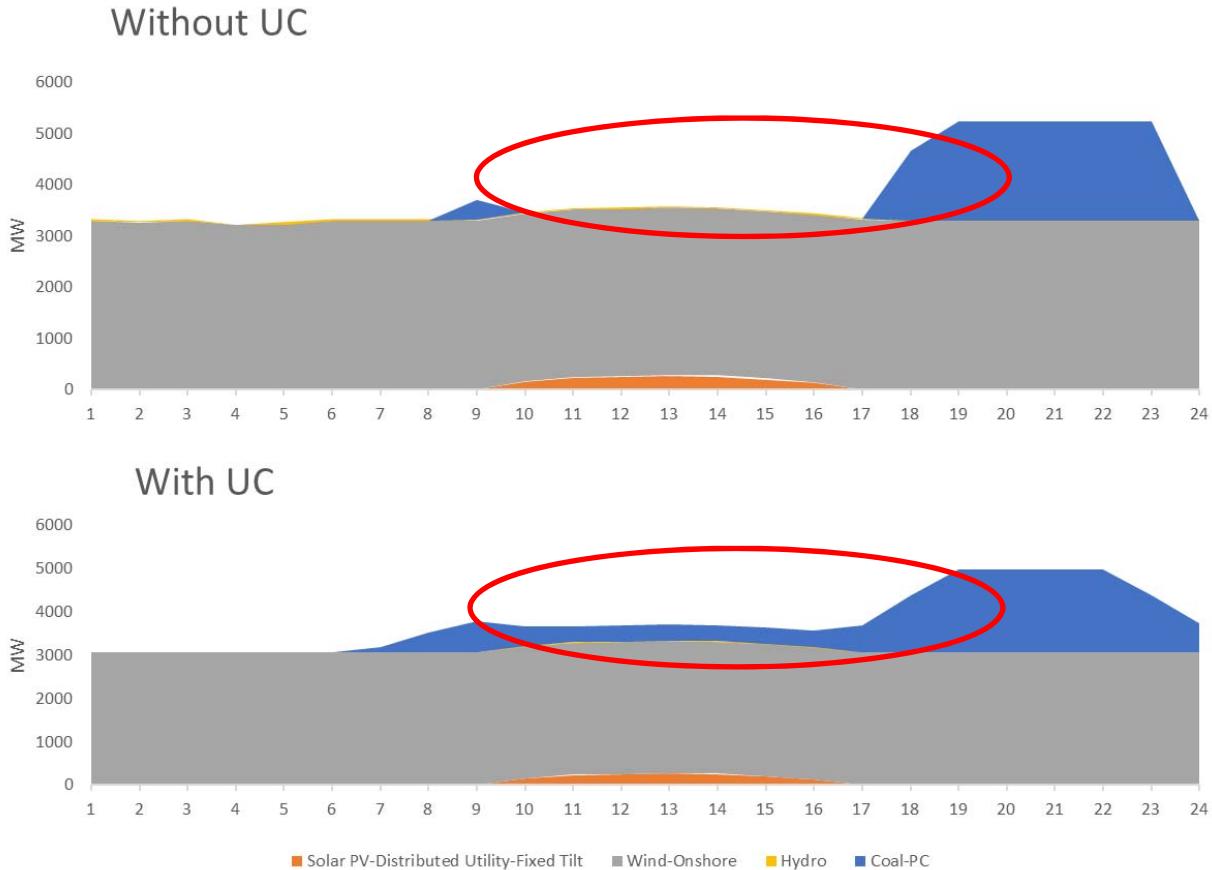


Figure 5.15 Select operations with UC in Colorado zone (2024, WECC 1 study case, 21-zone model)

In Figure 5.14, we can clearly see the effect of considering UC constraints on the coal unit between the hours 3 and 6 in this sample day. In the model where operations are represented using a traditional load-duration curve (Figure 5.14, top), the coal unit goes from producing more than 5 GW in hour 2 to being shut down in hour 3. It then stays shut for only 2 hours before being quickly ramped up to produce its maximum output in hour 7. In reality, coal units are slow moving and cannot be ramped up and down so quickly. It is also unrealistic that they are shut for only 2 hours between operations. Including UC constraints rectify this by constraining how fast these units can move up and down. Furthermore, UC also constrains generation with minimum-run capacity. We see this in Figure 5.14 (bottom) where the unit is slowly ramped down from hour 1 and instead of shutting down in hour 3, it runs at its minimum-run capacity while ramping up again evenly to reach its maximum output by hour 7. The ramps are more even and we do not see short-spanned shutdowns. Figure 5.15 shows similar behavior for Colorado's coal units, which operate in cycling mode in this particular day because of the nearly constant wind conditions; unit commitment constraints (bottom of figure) result in shallower ramps for the coal capacity and more continuous operation. This is a closer representation of how coal units really behave.

These fundamental changes to operations' representation have the potential to change the relative economic attractiveness of different technologies in all hours and at all buses, which in turn can change the investments needed to meet demand there economically. For instance, slow ramp ability means that price spikes upwards and downwards can occur during or near those ramp periods. This can increase the profitability of quick-start units, while harming the revenues received by renewable generation if it exacerbates the ramps.

We now consider how those constraints can affect the economics of transmission, as reflected in the JHSMINE model. We start with a simple deterministic example to show that this additional operational detail indeed has the potential to affect both the year 10 and year 20 transmission and generation investments suggested by the model under certain conditions. We use the WECC 21-zone model to run a deterministic two-stage model with the WECC 1 (Economic Recovery) study-case from the 2013 TEPPC database.

With the inclusion of UC constraints, both the immediate and future generation investments change in this high load growth, low carbon cost scenario. When it comes to transmission investment, with UC, we build one extra line today (year 10) and build two fewer lines tomorrow (year 20). These results are shown in Figure 5.16 and Figure 5.17 respectively.

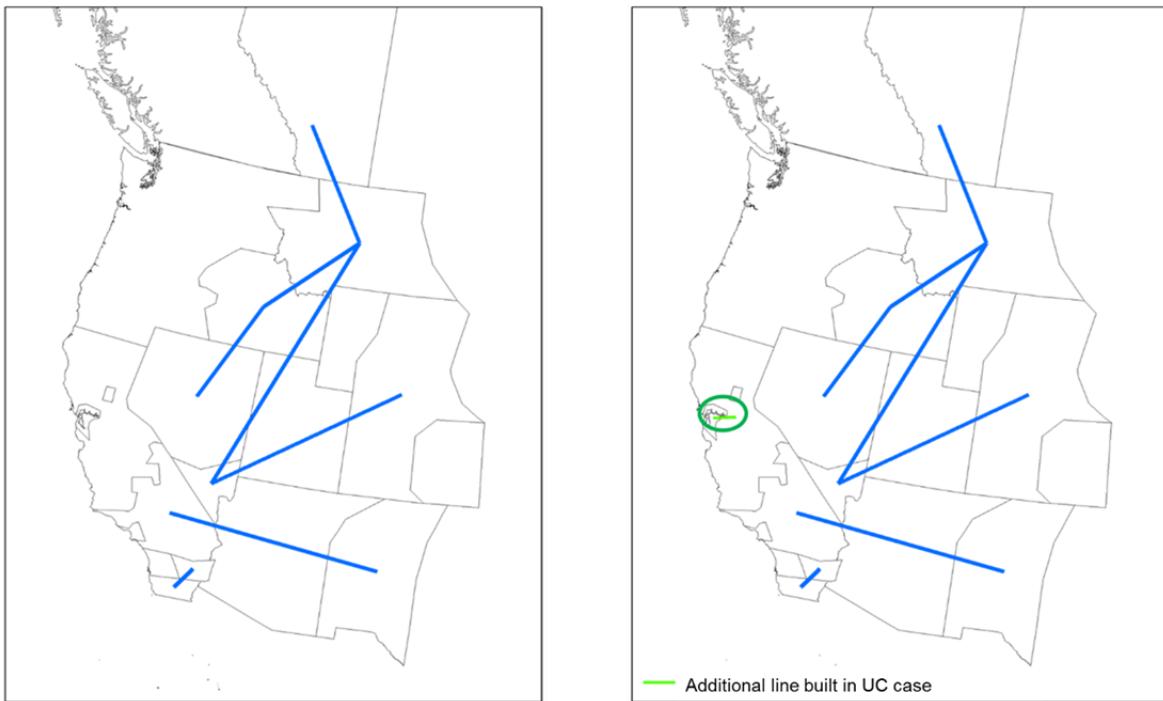


Figure 5.16 Changes in Stage 1 transmission investment (WECC 1 Economic growth, deterministic model). Left panel shows investments without UC and right panel shows investments with UC. One additional line is built in the UC case

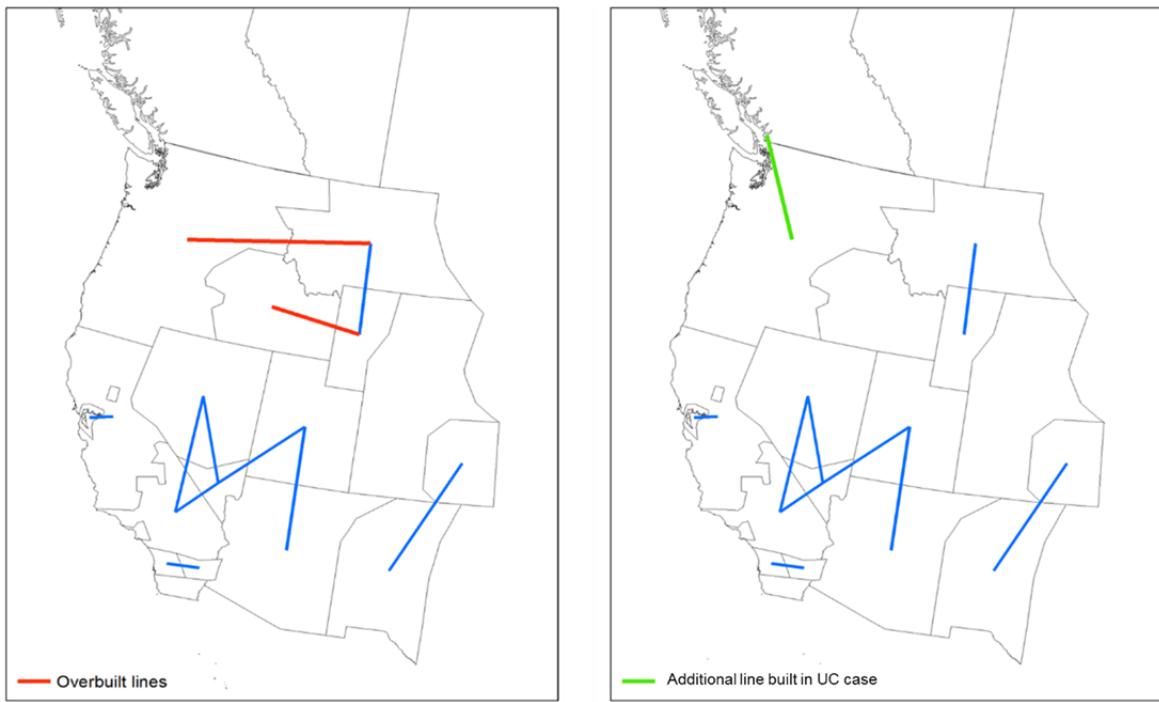


Figure 5.17 Changes in Stage 2 transmission investment (WECC 1 Economic growth, deterministic model). Left panel shows investments without UC and right panel shows investments with UC. Red represents lines that are not built in the UC case, but the no-UC model recommends because it does not account for UC constraints. Green lines are additional lines that the UC model builds

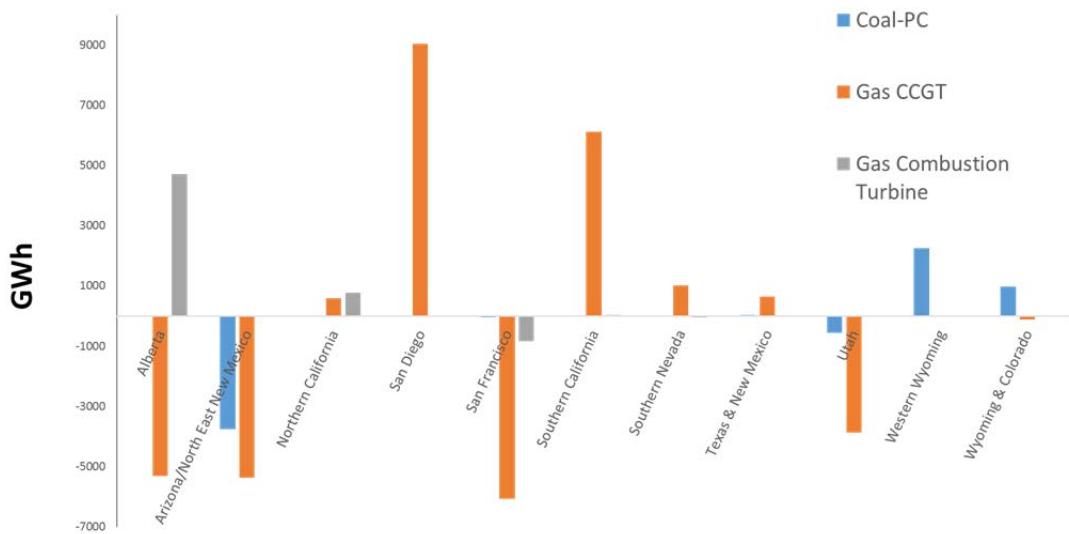


Figure 5.18 Changes in Stage 1 operations by generator type and zone (With UC – Without UC) (WECC 1 Economic growth, deterministic model)

In addition to generation and transmission investments, the overall energy mix changes both in terms of fuel type and location. As an example, year 10 major energy mix changes (with UC – without UC) are shown in Figure 5.18 for the WECC 1 deterministic model. In Alberta, with UC, we see an increase in CT generation as opposed to CCGT generation. We see less coal operated in Arizona/NW New Mexico while more coal is operated in Western Wyoming and Wyoming/Colorado. Overall there is a slight increase in CT operations, reflecting its less stringent unit commitment constraints.

In addition, we also ran a stochastic version of the UC model with the five WECC scenarios from the 2013 TEPPC report, each with the same probability. While we did not observe any changes in the Stage 1 transmission investments decisions as a result of including UC constraints, we saw that year 10 generation investments and year 20 generation and transmission decisions changed with UC constraints. We specifically observed that these changes were significant when there were significant amounts of slow-moving generators (i.e., coal units) in the energy mix that were being cycled. This makes sense because Unit Commitment constraints such as ramping, start-up costs and minimum run capacities affect these units the most. To confirm this hypothesis, we ran our deterministic two-stage model (WECC 1 study case) under varying carbon prices. Some changes in year 10 transmission investments are summarized in Figure 5.19. They show changes in year 10 transmission investments as a result of UC constraints depends on carbon prices. The left panel of Figure 5.19 shows today's investments when the carbon tax is 30\$/ metric ton CO₂ and right panel shows today's investments when the carbon tax is \$35/metric ton CO₂. For the lower tax, UC constraints cause one fewer line to be built; for the higher tax, the constraints instead incent one additional line.

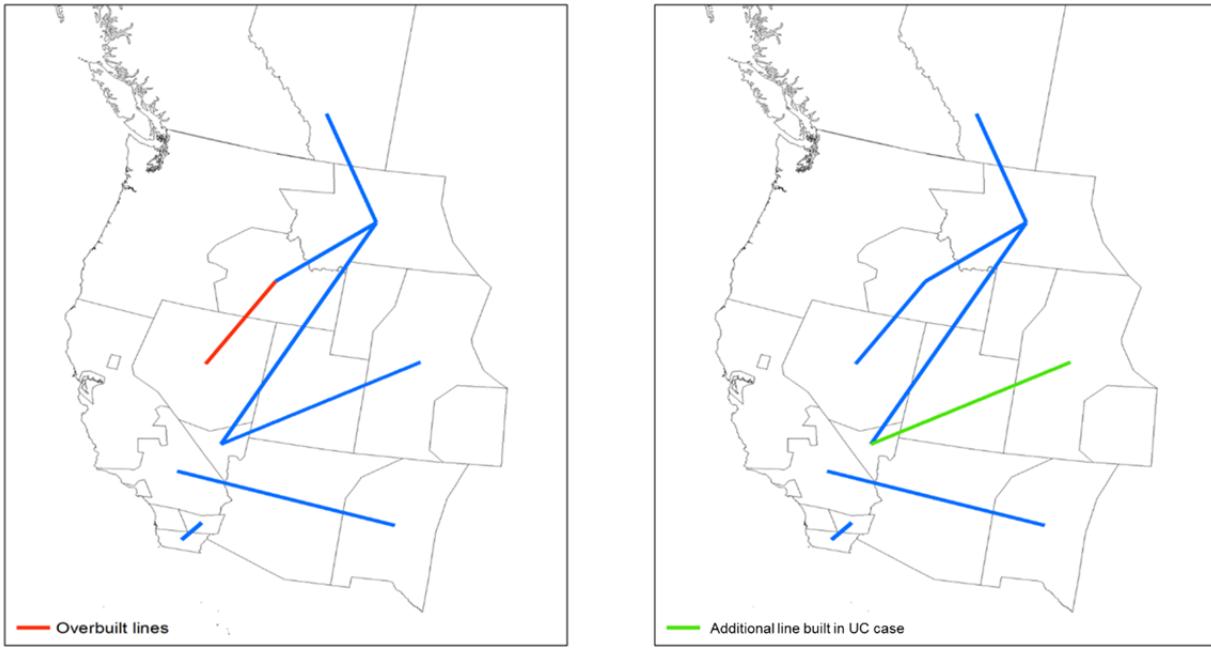


Figure 5.19 Change in year 10 transmission investments as a result of UC constraints under different carbon prices. Left panel shows today's investments when carbon tax is 30\$/metric ton CO₂ and right panel shows today's investments when carbon tax is \$35/metric ton CO₂

Turning to Figure 5.20 and Figure 5.21 (both of which are based on the deterministic model using the WECC 1 scenario), we see that Unit Commitment has the potential to change today's investment decisions under medium carbon prices (bottom of figure). With a low carbon price of \$20/metric ton CO₂ or a very high one of \$100/ metric ton CO₂, though, we see that today's transmission investments do not change. With the low price, this is because the cost of fuel and CO₂ are sufficiently low that the coal units tend to be base-loaded (top of figure). When there is no need to cycle the slow-moving plants very much, the ramping constraints and start-up/shut-down costs figure into operations very rarely. There is then no major effect of UC constraints on the relative economic attractiveness of different technologies. In the high carbon price, coal capacity factors are very low to begin with, and unit commitment constraints only have a small effect. In that situation, the few coal plants that operate are often operating in peak mode, and their operating hours are extended to accommodate ramp ups and downs. However, their usage has low (Figure 5.20). Thus, under the extreme carbon prices, unit commitment restrictions on coal plant operations have are unlikely to impact long-term transmission investments.

On the other hand, for medium carbon prices, coal plant output remains significant, but the plants operate in cycling model. The figure shows that unit commitment constraints have the effect of restricting such operations and thus decreasing their capacity factors. In that case, transmission investments are affected, as shown in Figure 5.19.

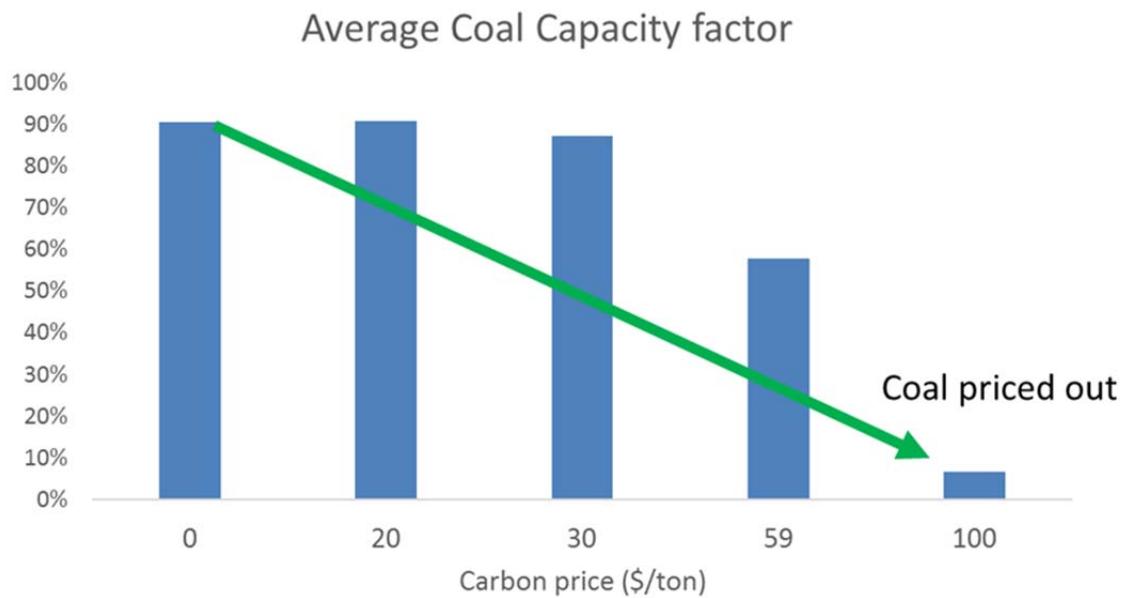


Figure 5.20 Effects of CO₂ prices upon the capacity factor (CF) of coal plants (2024, WECC 1 Economic Growth scenario, no unit commitment constraints)

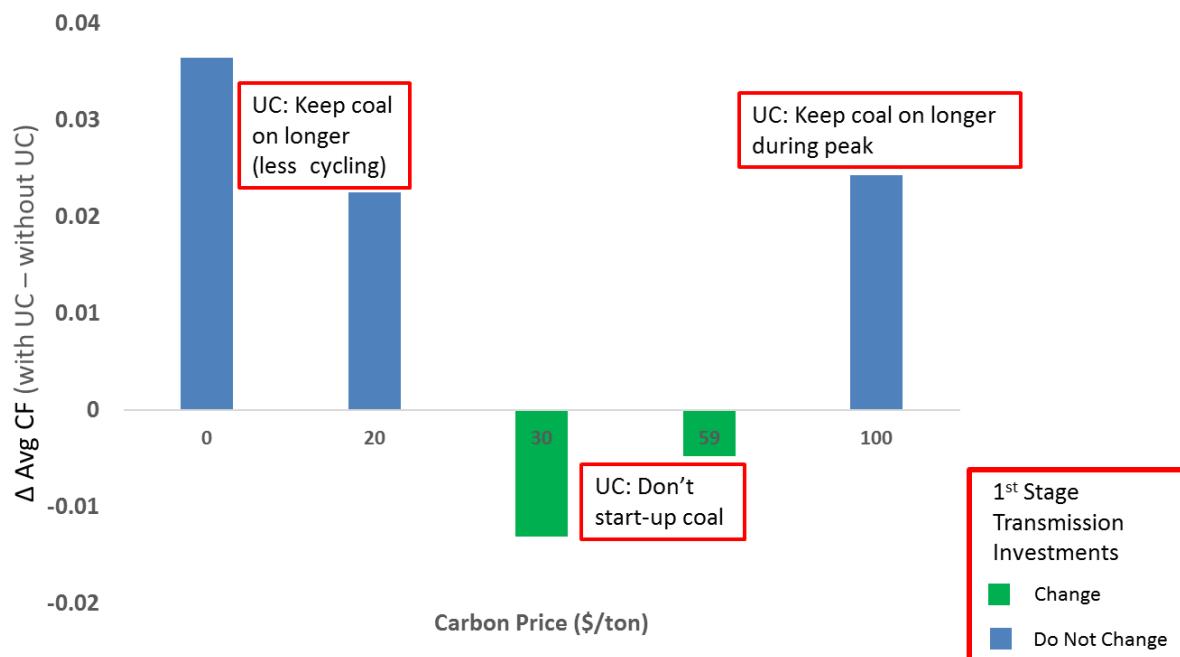


Figure 5.21 Effects of unit commitment constraints upon the capacity factor (CF) of coal plants under alternative CO₂ prices, and the resulting impacts on transmission investments (Deterministic model based on WECC 1 scenario: economic growth)

In sum, we have shown the impact of chronological operational constraints on long-term multi-stage transmission planning. Unit commitment has the potential to change today's (year 10) and tomorrow's (year 20) transmission and generation investments in some situations. Specifically, if slow-moving generators are a large part of the energy mix with the potential of being cycled (for example, in scenarios with a medium carbon-tax in which coal is cycled), it is more important to consider UC constraints as these are the scenarios where transmission investments are most likely to change.

5.3.4 How Does Network Representation Affect Investments?

As mentioned, we considered networks with two different levels of granularity: 21 zones and 300 aggregated buses. Path limits are included in each as well as line thermal limits. Here, we compare the results of these two representations, as well as the impact of including Kirchhoff's Voltage law in the network rather than just a pipes-and-bubbles representation. We also describe the effect of omitting path constraints in the linearized DC load flow version of the 300-bus model, wherein only line thermal constraints limit flow.

To examine the impact of network granularity we compare solutions between the 21-zone and the 300-bus networks solved using a transportation flow. One possible comparison is to examine the differences in costs between the two systems. Costs are noticeably higher in the 300-bus model compared to the 21-zone model runs with a ~20% increase over the 21-zone counterpart (Table 5.6). This difference is mainly due to higher operation costs in the 300-bus network due to differences in the network. This is evident because the generation mix is the same in each, and they would produce similar costs if all transmission constraints were removed. First stage (Year 10) generation investments in the 300-bus network are also roughly twice as large as in the 21-zone system. This increase in investment is likely in response to these higher operation costs as well as network congestion.

Table 5.6 Objective costs broken down by type for stochastic models and base case deterministic model solved using the 21-zone and 300-bus networks (transportation model)

Time Period	Cost Type	Cost \$ Billion (Present Worth)					
		300-bus			21-zone		
		20 Scenario	5 Scenario	Base Case	20 Scenario	5 Scenario	Base Case
2014-2024	Transmission	4.25	4.60	3.58	1.94	1.94	1.23
	Generation	135.36	160.75	115.38	69.30	102.32	66.8
2024-2033	Transmission	1.40	2.21	0.86	3.20	4.08	1.07
	Generation	26.52	42.10	17.80	60.74	67.52	24.03
	Operations	220.37	253.94	210.62	202.17	227.99	190.84
2034-2063	Operations	313.90	413.11	326.94	247.24	353.01	292.70

Additional differences can be seen between the first stage generation investment decisions between the two networks in Table 5.6. Models solved using the 300-bus network built more than twice the genera-

tion capacity (in MW) compared to the 21-zone investment decisions, mainly gas generation. This is a product of how new conventional generation is modeled in the 300-bus network. Here new generation capacity is built at a fictional generation hub which is connected to all buses within its area (see Figure 4.5 for the areas assumed in the 300-bus model). This flexibility regarding delivery of power might contribute to output from new CCGT replacing production from existing conventional generation which is modeled at individual busses. This explanation is consistent with the higher observed contribution of CCGT to the generation mix, at the expense of combustion turbines and coal (Figure 5.22). The more congested network drives the model to generate more electricity using local CCGT and less electricity using wind turbines.

Table 5.7 First stage generation investment decisions for models solved using the 21-zone and 300-bus networks

Network	Model	Added Capacity (GW)					
		Biomass	Gas CCGT	Gas CT	Geothermal	Solar PV	Wind
21-zone	5 Scenario	0.33	17.79	2.78	2.58	0.00	33.21
	20 Scenario	0.33	19.26	2.66	0.83	0.00	19.55
300-bus	5 Scenario	0.06	63.76	32.19	2.02	0.50	19.91
	20 Scenario	0.05	59.53	37.97	0.59	0.46	10.91

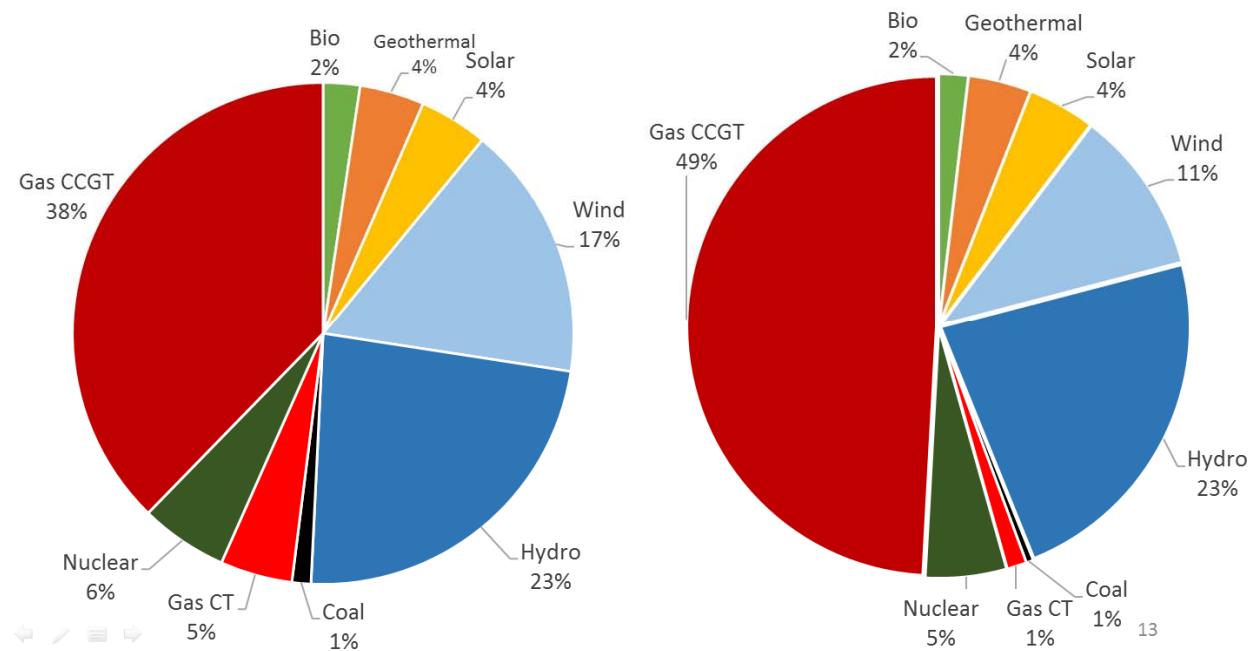


Figure 5.22 Comparison of energy (MWh) generation mix, 2024 (1.04 trillion MWh), between 21-zone and 300-bus network, base case deterministic model

Direct comparisons of transmission additions between these two networks are complicated since the two networks exact true points of reference. The 300-bus network was developed from the using a network reduction from the real WECC network provided with the common case. In contrast, the 21-zone LRS network provides information related to large geographic zones. In order to make this comparison possible, the 300-bus network was aggregated to the 21-zone geography. For transmission, any projects in the 300-bus model that cross zones are counted as inter-zonal connections. Generation in the 300-bus model is aggregated to the zones that the investment buses were connected to. While this approach is imperfect, it allows us to gain some insight with regards to how the locations of investments in the two models compare to one another.

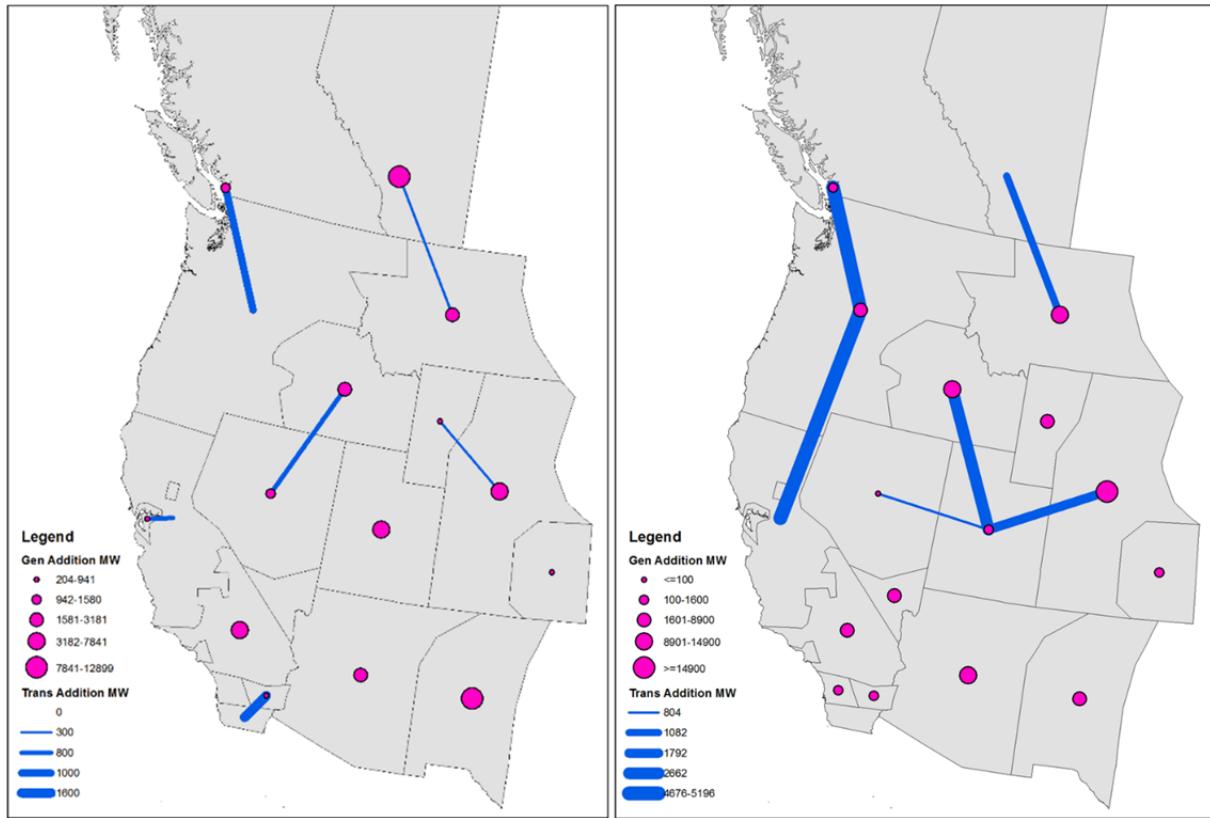


Figure 5.23 Comparison between inter-zonal investments between the 21-zone (left) and the 300-bus (right) models under the 5 scenario (even probabilities) stochastic solution (year 10 lines)

Figure 5.23 compares the differences between the 21-zone and the 300-bus Year 10 transmission investments for a 5 scenario (with even probabilities) stochastic solution. Here a common pattern of transmission investments along the coast connecting the British Columbia to Pacific Northwest as well as Alberta to Montana appear. But there are also deviations between the two in terms of the exact pattern of transmission investments. Such differences are expected due to the different types of investments available in each network. For example, the 300-bus model allows reinforcements between "Wy-

oming & Colorado" and "Utah" and in the "Idaho to Utah" corridor, but the 21-zone model does not have any Year 10 candidate lines connecting Utah (see Section 4.5). These two particular lines are highly favorable in the 300-bus 5 and 20 scenario models, and are the major deviation of the 300-bus solution from the 21-zone results.

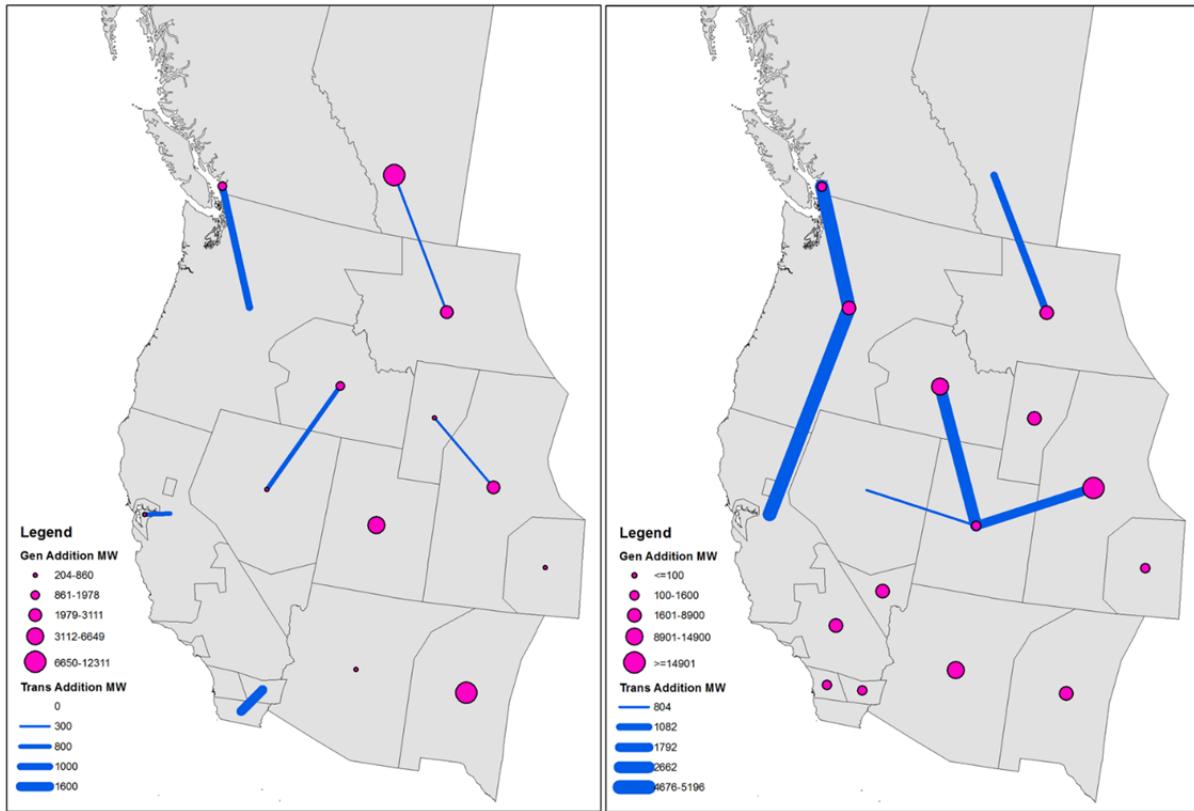


Figure 5.24 Comparison between inter-zonal investments between the 21-zone (left) and the 300-bus (right) models under the 20 scenario (differentiated probabilities) stochastic solution (year 10)

Comparing the above two figures, between the 5 and 20 scenario stochastic solutions there were no differences in the 21-zone network investment decisions, and some changes in generation siting (mainly less investment in Arizona and California). For the 300-bus network, the year 10 backbone reinforcements between regions are also the same for 5 and 20 scenario stochastic solutions. Thus, the differences that we reported earlier in this chapter between the 5 and 20 scenario solutions for the 300-bus case are renewable interconnections.

As would be expected, the added detail (and thus transmission congestion) in the 300-bus network increased generation costs of the system relative to an equivalent scenario set in the 21-zone model (compare Figure 5.23 and Figure 5.24). Additionally, there were some differences in anticipated siting

and mixes of new generation. The additional congestion in the 300-bus network resulted in a small investment shift from remote renewable resource investment towards conventional resources.

The inclusion of path constraints in the 300-bus model was also a driving force behind transmission and generation investments. We compared the 300-bus model base case deterministic solution with the KVL constraints enforced (i.e., linearized DC load flow) (Figure 5.25 left), which included path constraints, and a base case deterministic solution in which the path constraints are omitted and only thermal constraints are enforced (Figure 5.25 right). This showed shifts in the pattern of transmission and generation investment decisions. Table 5.8 as well as Figure 5.25 below compares the between-region investments that result in these two models, while Table 5.8 also shows the differences for the pipes-and-bubbles versions. Omitting the path constraints results in two more lines in the Wyoming-Colorado zone, while the Alberta-Montana and AZ/NM-COLORADO corridors lose lines. These differences show that it is critical to include path constraints in the transmission planning process.

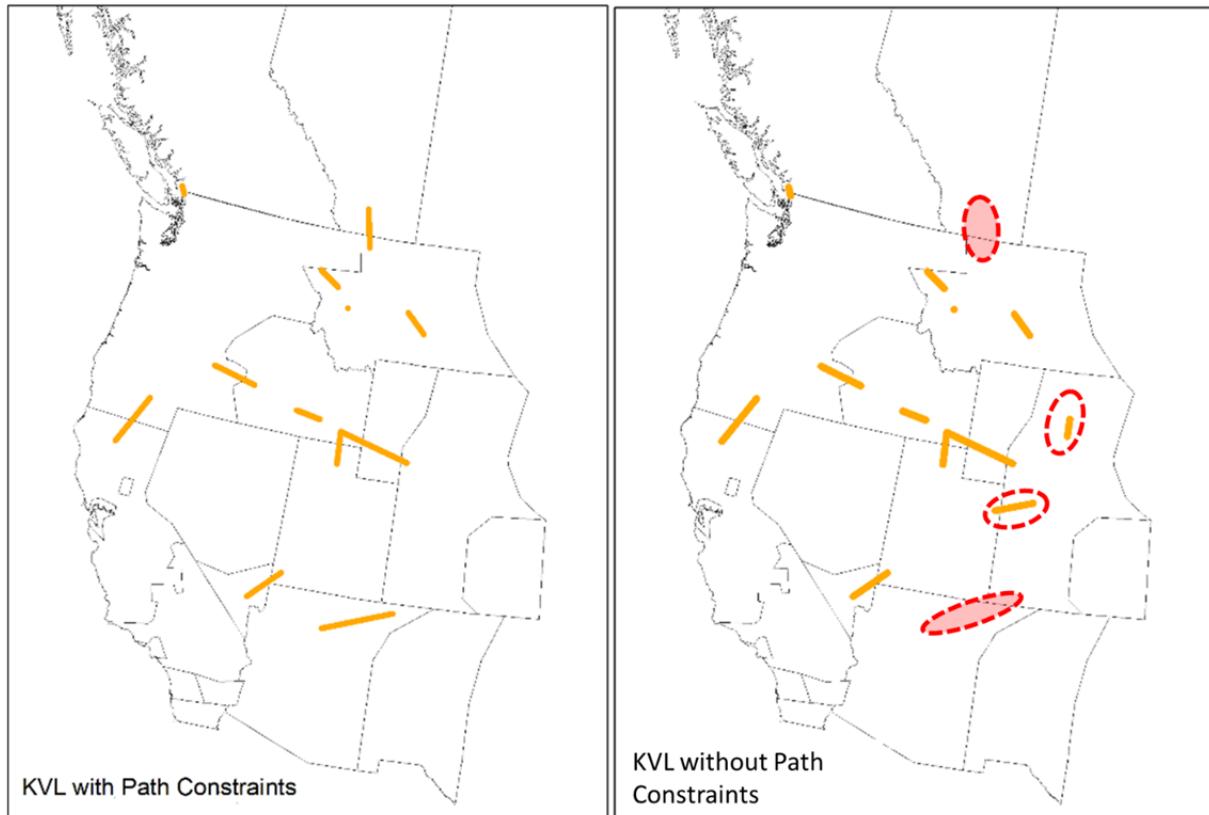


Figure 5.25 Year 10 transmission decision. Left: KVL with Path Constraints. Right: KVL without Path Constraints (Base case deterministic 300-bus model)

Table 5.8 First stage transmission investment decisions for models solved with and without path constraints

Transmission Line	KVL (Linearized DC) Model		Transportation (Pipes-and-Bubbles) Model	
	Path	No Path	Path	No Path
1000639	X		X	
1001035	X	X	X	X
1002922			X	X
1006606	X	X	X	X
1006716	X	X		
1006792	X	X	X	X
1008329	X	X	X	X
1012665	X	X		
1012705	X	X		
1013037	X	X	X	X
1013301	X		X	X
1013688	X	X	X	
1013784		X		
1014398	X	X		
1015720		X		

Modeling the flow of power in the transmission expansion model can be done with varying degrees of simplification in order to make the model computationally feasible. Ideally one would use the full AC power flow equations modeling both real and reactive power, but this is impractical in a planning model. A more computationally practical method is to model only real power flow subject to Kirchhoff's current and voltage laws using a linearized DC approach. The DC linear approach can be further simplified to a pipes-and-bubbles model which considers only real power flows subject to energy balances in each bubble.

We are able to solve our 300-bus planning model with both a linearized DC load flow (KVL) approach as well as the pipes-and-bubbles (transportation) approach. We now compare these two approaches for the base case deterministic model (Figure 5.26), considering only six rather than 24 hours because of the computational limitations of the KVL model. As the next two figures (Figure 5.26) show, under the KVL model, more transmission lines are built compared to the transportation model, involving 30% more capital investment. But as long as the path constraints were enforced in the KVL model, most of the lines built in the first stage by the transportation model also appeared in the KVL transmission expansion plan. Of the twelve transmission lines that appeared in the year 10 decisions of the KVL model, eight were also built in the transportation model. This suggests that if the underlying network is well defined and includes the reliability-based path constraints, a transportation model may be useful for identifying the

most attractive transmission lines. The advantage of the simpler model is that it is much quicker to execute, thus allowing many more long-run scenarios as well as operating hours (load/renewable output combinations) to be considered.

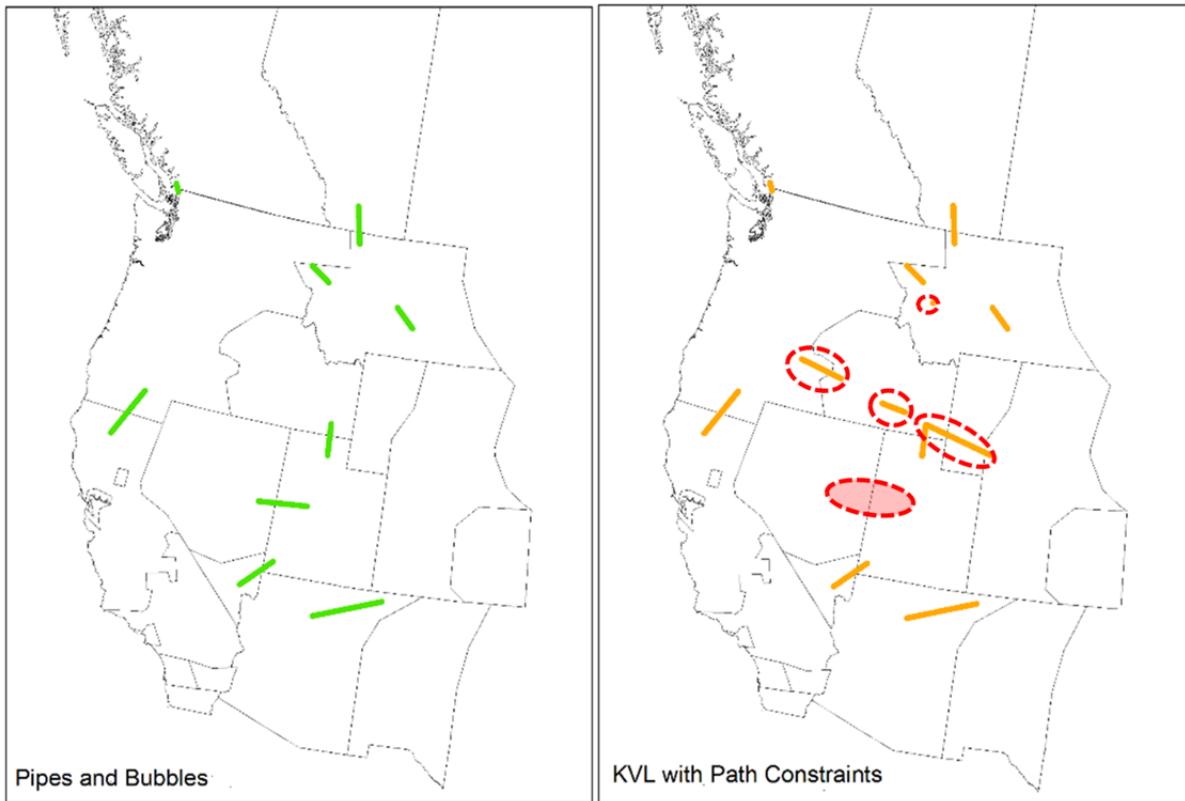


Figure 5.26 Year 10 transmission decision. Left: Pipes and Bubbles. Right: KVL with Path Constraints (Deterministic base case 300-bus solutions)

5.3.5 Does Choice of Operating Hours Matter?

Transmission and generation investment optimization models have to make simplifications to represent load, solar, wind etc. Simplifications are necessary because even when an entire years' worth of data is available, it cannot be included in the model because large models (even linear programs without binary variables) can take a very long time to solve. One of the questions we want to answer is: "Do two good, but different approaches to sample hourly data that represent the yearly data yield the same investments?" In other words, does the choice of hours used affect investments? The answer is yes, which implies that (1) operating hours should be chosen carefully; and (2) more hours will improve the representation.

The two choices of hours we used were:

- the 24 hours that were generated using k-means clustering [37] where k=24, which we used to generate the results presented in Sections 5.2.1 and 5.2.2, and
- 72 hours (three different days, as described in Section 4) that matched the North-West's and South-West's annual averages in terms of load, wind, and solar, which we used in the Unit Commitment part of the study (subsection 5.3.3).

Both models omitted unit commitment constraints and were similar in every way except the choice of hours and their weights. Although both sets of hours were generated using criteria that are regularly used in investment studies, we find that there are significant changes in total costs, Year 10, and Year 20 transmission investments between the two models based on those sets of hours.

While 8 transmission lines were built with the two models based on these sample hours, only 6 individual lines were common to the two solutions. The total cost also rose by 7.62% when the 24-hour non-chronological data was replaced with the 72-hour chronological data. One of the reasons could be that the hydro, solar, and wind data is less likely to be overestimated when we consider chronological data. So, choice of hours makes a difference to the investments and care should be taken while sampling.

5.3.6 What is the Impact of Changed Hydropower on the Solutions?

We tested the impact of uncertain future hydropower by developing two new scenarios “Base Case – Dry” and “Base Case – Wet” using the regional hydro modifiers described in section 4.6. These represent possible climate scenarios describing typical hydropower production in the future. In the Dry year, the available hydro resource is 15% less, while in the Wet year, the available hydro resource is 22% more than the base case year. These are WECC-wide averages, and the percentages vary by region, as described in section 4.6.

The hydro uncertainty is tested by considering three scenarios in a stochastic version of the model: one-third probability each in 2024 and afterwards of the base case with high hydro, base case with low hydro and base case with medium hydro. These are modeled as permanent climate changes, such that all years in a given scenario will have those hydro conditions; thus these are extreme cases, since in reality hydro conditions will still vary year-to-year, although with lower or higher averages.

We conclude that the impact of uncertain hydropower on the stochastic solutions is insignificant. In terms of transmission investment: JHSMINE gave the same solution considering uncertain hydropower conditions or not, as shown in the below table.

Table 5.9 Comparison of Year 10 Transmission Investments between Base Case and Uncertain Hydro Case

Corridor:	MX-IIDCA	MT-AB	NNV-ID	PNM-BC
Base Case	1	1	1	1
Uncertain Hydro (all three scenarios)	1	1	1	1

A cost comparison also shows that there are insignificant differences between the Base Case and Uncertain Hydro cases, which are documented in the next table.

Table 5.10 Cost Comparison between Base Case and Uncertain Hydro (\$Billion)

	Base Case	Uncertain Hydro (One-third chance of each hydro sce- nario)*
Total Cost	576.70	575.43
2014 Transmission Investment	1.23	1.23
2014 Generation Investment	66.83	64.00
2024-2033 Operation Cost	190.84	191.73
2024 Transmission Investment	1.07	1.98
2024 Generation Invest	24.02	22.17
2034-2063 Operation Cost	292.70	294.32

*The exact investments in 2024 and exact operations in 2024 and 2034-2063 depend on which climate/hydropower scenario occurs, but the results are similar among the dry, medium, and wet scenarios

Table 5.11 Generation Investment Comparison between Base Case and Uncertain Hydro

Scenario	Wind (GW)	Gas CCGT (GW)	Gas CT (GW)	Geothermal (GW)
Base Case only	30.89	4.80	0.37	0.19
Uncertain hydro	28.25	6.67	0.37	0.19

But we should note that the occurrences of “Dry year” or “Wet year” do have some impact on the Energy Mix and the generation capacity investment. Considering hydro uncertainty, the model chose to build less wind power and more gas comparing to the generation investment considering no hydro uncertainty. Besides the changed generation investment portfolio, the energy mixes in “dry”, “normal” and “wet” year are also different (Figure 5.27). In dry year, the model generated more gas to cover the missing hydro, and in wet year, the additional hydro substituted gas.

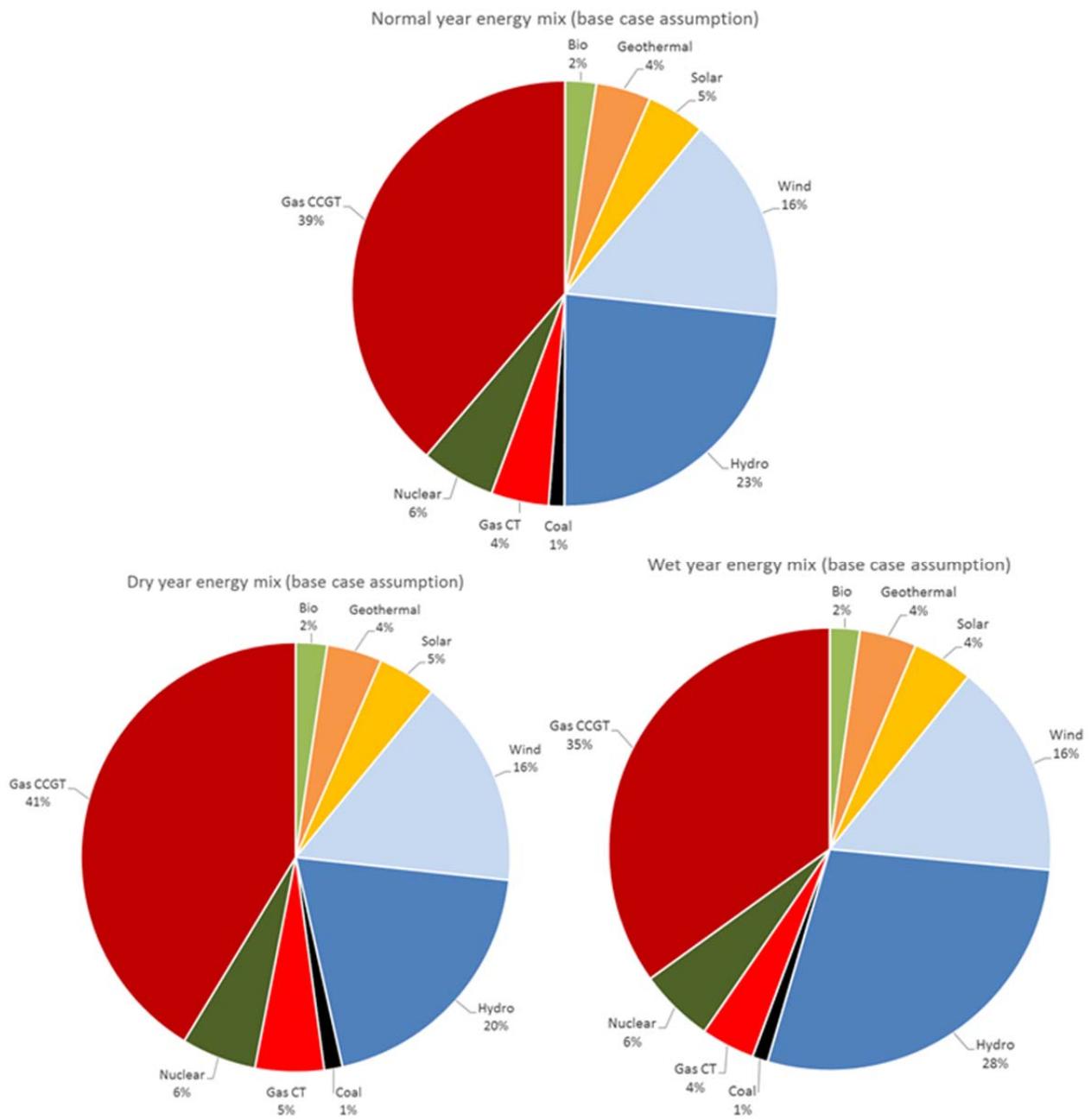


Figure 5.27 Energy mix comparison between dry year, normal year and wet year in uncertainty hydro model

6 Conclusions

Our experience running stochastic planning models indicates that they are practical for 21-zone or 300-bus models of the WECC system under multiple scenarios, and that considering more than one scenario simultaneously in a planning model results in distinctly different plans. The reduction in probability weighted cost that would result from implementing the stochastic model's recommendations is on the same order of magnitude as the size of the first stage (year 10) investment.

The analyses show that some compromises are required to keep solution times within reasonable bounds (minutes, rather than hours). If multiple scenarios are to be considered, then running the full 300-bus model with Kirchhoff's voltage law together with 24 sample hours within a year for the multi-year problem is not yet practical. Executing the voltage law model with that number of sample hours was successful only for a model with one study case as a scenario. The voltage law model selects more lines as economic because of the greater amount of congestion, but in our test case, the lines it selected also included all the lines that the simpler pipes-and-bubbles model chose, as long as both models represent path constraints.

We conclude that appreciably different recommendations are made by the 300-bus model relative to the 21-zone model, so that the larger network is preferred if the effort can be made to build the larger data base it requires. We also find that selection of operating hours to simulate within a given year can make an important difference, and so should be done carefully in order to capture the variations as well as correlations of loads, wind output, and solar output over the region. On the other hand, incorporating unit commitment constraints in the production costing part of the model is less important, making no difference in year 10 line recommendations in most cases tested.

We recommend that WECC consider implementation of a stochastic model as part of its next planning cycle in order to build confidence that near term (year 10) transmission reinforcements will contribute to an adaptable and robust network. Adaptability and robustness is best assessed with a model that recognizes that some line additions will be more effective in poising the system to accommodate future changes in fuel costs, loads, technologies, and policies. Such a model must consider multiple possible futures at once and how a system can adapt to them over multiple decades. Finally, because the generation siting responds to transmission availability, a co-optimization formulation, such as used here, should be adopted. This is essential for capturing the savings in generation capital costs as well as production expenses that can be realized from transmission additions.

Appendices

Appendix A. Scenario Development Process Details

Several WECC stakeholders gave generously of their time by participating in several web-based meetings of this project's Technical Advisory Committee. During the meetings of this group, several tasks were undertaken that lead to the definition of the 20 scenarios used in the analysis. These tasks are summarized in the following subsections. Results (averaged across participants) are reported.

A1. Identifying Variables and Rating Their Importance

Stakeholders first brainstormed in a webinar meeting, identifying 18 variables that would have impacts on transmission lines siting. They individually grouped the 18 variables into three categories concerning their degree of relevance to economic evaluation of transmission additions; i.e., would consideration of uncertainty in their values affect the relative attractiveness of different transmission investments? Based on those responses, we group the 18 variables into categories of “crucial,” “desirable to consider,” controversial and “less important” according to the voting results:

- **Crucial:** Natural Gas prices; expansion of DG, DR, and storage; capital cost reductions in wind farms; as well as environmental related policies (**State RPS** and **Carbon prices**) are considered as crucial variables.
- **Desirable:** Other capital costs; changes in net energy for load and peak demand; **federal RPS**; as well as **climate and policy impacts** are the variables that are desirable to consider.
- **Controversial:** Stakeholders held conflicting views when considering the importance of state RPS to be met by in-state resources and the importance of new interconnections between WECC and either ERCOT or the EI.

A2. Choose Range of Variables

Subsequently, stakeholders provided likely ranges of values (90% confidence intervals) for the variables. We adjusted 2034 reference case values to “low” and “high” values in scenarios based on percentage changes that were provided by the stakeholders' specified ranges. (As a hypothetical example, stakeholders' mean values for natural gas price might be low: 3, medium: 5, and high: 9 \$/MMBTU. Since the 2034 reference case value is 7, our adjusted range for scenarios is low = $3/5*7=4.2$, medium=7, high= $9/5*7=12.6$.)

There is no value for DG, DR, and Storage percentage in 2034 reference case. We use value specified by TAG for these variables.

A3. Provide 9 TAG Scenarios

Stakeholders were asked to define scenarios. Each scenario includes a brief description and recommended values for associated variables. For instance, once stakeholder identified a

“nuclear” scenario with variable values that might support significant new construction of that technology.

A4. Define 6 Gap Scenarios

To capture a wide range of possibilities in the uncertainty space, we generated gap scenarios representing variations among 3 clusters of variables. Variables in the same clusters are “related” to each other. Correlations between clusters are also shown below. In this clustering, we left out “Coal P”, “IGCC w/ CCS capital cost”, and “In-state RPS”, because they are rated as less important in previous discussions with the Technical Advisory Committee. These three variables are set to their medium values in the 6 gap scenarios.

- **Cluster 1: GAS/CARBON PRICE & LOAD GROWTH CLUSTER**
 - (+) Gas P; Carbon P; Load Growth, Policy-driven load electrification
 - (-) Policy-driven load reduction
 - Rationale: The increase of Carbon price leads to decrease in coal demand. As a result, the demand and prices of Natural gas increase; and as load growth increases, demand for gas will increase, thus the price for natural gas will also increase.
- **Cluster 2: RENEWABLE POLICY & CAPITAL COST CLUSTER**
 - (+) State & Federal RPS, DG
 - (-) Wind, Geothermal, and Solar Capacity Cost
 - Rationale: Wind, Geothermal and Solar capital costs are related because the types of technology improvements that lead to lowered costs for one technology would likely (but not necessarily) lead to decreases in capital costs for the other technologies. Because we consider solar DG in this cluster, decreases in capital costs would also promote the implementation of DG. Finally, if the capital cost for renewable generation decreases, governments are more likely to implement more ambitious RPS policies.
- **Cluster 3: PEAK LOAD / STORAGE CLUSTER**
 - (+) DR; Storage; Peak Growth, Policy-driven peak electrification
 - (-) Policy-driven peak reduction
 - Rationale: Increases in peak growth will increase economic and perhaps regulatory pressures for more DR and storage.
- **Correlation between Clusters:**
 - Load growth in cluster 1 and peak growth in cluster 3 are positively correlated, thus cluster 1 and cluster 3 are considered to be positively related. Increase of state RPS and the increase of renewable energy integration in cluster 2 may make it more desirable to have storage in system, thus cluster 2 and cluster 3 are also positively related.

Table A-1 Identified correlations between clusters

	Cluster 1	Cluster 2	Cluster3
Cluster 1	1	0	+
Cluster 2		1	+
Cluster 3			1

Six gap scenarios are listed as combinations of high, medium, and low values of the three clusters. We emphasize these more likely combinations of these clusters in defining the scenarios. Therefore, as examples, we disregard HHL, and LLH, and replace HLH with HMH due to positive correlations between clusters.

Table A-2 Gap scenarios

Cluster 1: GAS/CARBON PRICE & LOAD GROWTH CLUSTER	Cluster 2: RENEWABLE POLICY & CAPITAL COST	Cluster 3: PEAK LOAD / STORAGE CLUSTER
H	H	H
H	H	L
H	L	H
H	(M)	H
H	L	L
(M)	L	L
L	H	H
(M)	H	H
L	H	L
L	(M)	L
L	L	H
L	L	L

Appendix B. Review of Relative Impacts and Likelihood of Scenarios

TAG members were asked to review relative impacts and likelihood of scenarios for the whole scenarios set. The following table shows the average results across the participants. Likelihood and importance are highly correlated in the voting results. Scenarios are sorted descending by likelihood and are grouped into 3 groups, as shown below.

Table B-1 Impacts and likelihood of scenarios

Group	# of Scenarios	Name of Scenarios	Likelihood	Importance	Overall
1	3	WECC 2: Clean Energy	3.6	4.6	8.2
	7	High DG	3.6	4.2	7.8
	12	Carbon Redux + Low Load	3.6	4.2	7.8
	5	WECC 4: Long-Term Societal Costs	3.6	4	7.6
	6	High Tech/Information Transformation	3.4	3.6	7
	9	Gas Heavy 2	3.4	3.6	7
	17	MHH	3.4	3.4	6.8
2	13	High Carbon Price, Severe Climate Change Effects	3.2	4.2	7.4
	11	Aggressive GHG Policy	3.2	4	7.2
	14	Risk Assessment of Climate Change > Water > Electricity	3.2	3.4	6.6
	15	HHH	3	3.8	6.8
	2	WECC 1: Econ. Recovery	3	3.6	6.6
	4	WECC 3: Short-term Consumer Costs	2.8	3.4	6.2
3	16	HMH	2.8	3.4	6.2
	19	LML	2.8	3.4	6.2
	8	Gas Heavy 1	2.6	3.4	6
	18	MLL	2.4	2.8	5.2
	20	LLL	2.2	2.2	4.4
	10	Nuclear Explosion	2	2.8	4.8

And then we can assign probabilities to the scenarios following the procedure outlined in section 4.1.2. (Probabilities Assignment).

B.1 Overall Growth Calculation

The objective of this section is to document the procedure for determining the High/Medium/Low values of Net Growth Rate using the High/Medium/Low values of Gross Growth Rate, Policy-driven Reduction rate and Policy-driven Electrification rate. The following procedure applies to both average load and peak load. The formula to calculate Net Growth Rate is as follows:

$$\begin{aligned} \text{Net Growth} &= \text{Gross Growth} - \text{Policy Driven Reduction} \\ &\quad + \text{Policy Driven Electrification} \end{aligned}$$

Step 1. Simplification of the probability mass function (PMF) from the survey's value: The survey asked for the mean value and 90% confidence interval (CI) of Gross Growth rate, Policy-driven Reduction rate and Policy-driven Electrification rate. We simply define High/Low values as having probabilities of 95% and 5%, respectively, of being exceeded, while the Mean value has an exceedence probability of 90%.

Step 2. Obtain the PMF for Net Growth Rate: By considering the formula above, the PMF of Net Growth Rate is based on the joint PMF of Gross Growth rate, Policy-driven Reduction rate and Policy-driven Electrification rate. Considering Gross Growth rate, Policy-driven Reduction rate and Policy-driven Electrification rate as independent variables, we calculated the PMF of Net Growth rate by multiplying the probabilities together of each variable.

Step 3. Determine the High/Medium/Low values: We calculated the standard deviation from the PMF above, and determining the High/Medium/Low value by using 95% CI and mean value. The results are shown below.

Table B-2 Net load/peak growth rate

	Net Load Growth rate (%)	Net Peak Growth rate (%)
High	-0.91	-0.37
Mean	1.13	1.28
Low	3.2	2.64

B.2 Peak Growth Value Adjustment

The Load Duration Curve (LDC) in 2024 and 2034 resulting from a particular set of load and peak growth assumptions might be flat or even nonmonotonic (increasing for some hours rather than monotonically decreasing from the assumed peak hour to the assumed low load hour). Such nonmonotonicities can occur in some scenarios with high energy growth but low peak growth, resulting in some hours having higher loads than the assumed peak hour. So we have checked all scenarios, and found one case where there was a nonmonotonicity (Scenario 18, MLL). There, we increased the peak growth value to -0.0037/yr to +0.0074/yr. The checking procedure is shown below:

Indicator: "2024/2034 Load Factor" = "2014 Average Load" * "2024/2034 Load Multiplier" / ("2014 Peak Load" * "2024/2034 Peak Multiplier")

in which:

Load Multiplier = $(1+Load\ Growth)^{10}$ for 2024; $(1+Load\ Growth)^{20}$ for 2034

Peak Multiplier = $(1+Peak\ Growth)^{10}$ for 2024; $(1+Peak\ Growth)^{20}$ for 2034

The criterion is **IF the indicator is higher than [(1-2014 Load Factor)/2 + 2014 Load Factor]**. If yes, then it is problematic, we need to make a change.

Appendix C. Scenario Descriptions

- **Base Case:** This is the business-as-usual expected scenario. All variables are set to medium values and follow the 2034 reference case from WECC.
- **WECC 1 Economic Recovery:** This scenario focuses on economic recovery with widespread economic growth in the WECC region and increasing standards of living. There is no overriding policy theme, and technology improvements are steady.
- **WECC 2 Clean Energy:** This scenario emphasizes rising economic growth and breakthroughs in technology development. It also includes aggressive policies to reduce greenhouse gas emissions and develop new technologies.
- **WECC 3 Short-Term Consumer Costs:** This scenario describes a future world with restrained economic growth, stagnated standards of living, and incremental technology improvements that follow current patterns. The scenario's theme of slow growth and a focus on keeping consumer costs low.
- **WECC 4 Long-Term Societal Costs:** This scenario also describes a world with slow economic growth in the WECC region but includes breakthroughs in technology improvement in electric supply and distribution technologies. The overall focus of this scenario is controlling long-term societal costs.
- **High information and Technology transformation:** This scenario focuses on effective adoption of smart grid technologies with improvements in information, communications and control technology. This effectively increases the value of customer resources (EE, DR, and DG) as well as variable resources and storage. Market forces dominate, so policy drivers are less important.
- **High Distributed Generation:** This scenario describes a world with a large amount of distributed generation. As a result, load growth becomes flat or negative.
- **Gas Heavy 1:** This scenario assumes gas prices start out low but skyrocket due to heavy demand. Policy, load and peak growth, and technology improvements follow current pattern.
- **Gas Heavy 2:** This scenario describes a world with greater dependence on gas to accommodate intermittent generation. As a result of this dependence, gas prices are high. With technology improvements on smart grid and control technology, DG, DR, and storage play an important role in this world. In this scenario, the renewable generation technology developments are slow, and capital costs of renewable generation are high. Additionally, this scenario includes aggressive policies to reduce greenhouse gas emissions.
- **Nuclear Explosion:** In this scenario, nuclear power becomes politically palatable, and there is a push to replace coal with nuclear generation. A national approach is taken to address climate goals as opposed to state-specific plans, and the scenario includes a federal carbon-pricing program (cap and trade or carbon tax). This scenario encourages resource sharing and the optimization of low-carbon resources between states.
- **Aggressive Greenhouse Gas (GHG) Policy:** This scenario focuses on strong policy action to reduce GHG with high carbon prices and high RPS requirements at both state and federal levels. DG, DR, and storage also play an important role in this world.
- **Carbon Reduction + Low Load:** This scenario focuses on mandatory policy-driven carbon reduction requirements (RPS will likely vary considerably by state) coupled with flat to declining con-

sumption (as metered at the customer interface with the utility).

- **High Carbon Price and Severe Drought:** High carbon price or other policies drive generation decisions toward low climate impact alternatives. With a high carbon prices, more people use electric vehicles, adding to load and shaving some of the excess solar generation. There is assumed to be moderate to severe drought in most years across California, the intermountain west and the southwest states.
- **Risk Assessment of Climate Change > Water > Electricity:** This scenario assesses the economic and reliability risks to electricity due to the impacts of climate change. With tight water supplies, higher peak and energy demands (for air conditioning), lower plant efficiencies, gas and carbon prices are high. This also assumes aggressive policies to reduce greenhouse gas emission.
- The following six scenarios highlight groups of correlated inputs (e.g. increased peak load will also likely be correlated with increased use of storage technologies). These scenarios do not include specific narrative themes, but are designed to cover possible scenarios that have not been captured above.
 - **HHH:**
 - High value in cluster 1: Gas/Carbon Price & Load Growth Cluster
 - High value in cluster 2 (+): Renewable Policy & DG
 - Low value in cluster 2 (-): Capital Cost Cluster
 - High value in cluster 3: Peak Load Storage Cluster
 - **HMH:**
 - High value in cluster 1: Gas/Carbon Price & Load Growth Cluster
 - Median value in cluster 2: Renewable Policy & Capital Cost Cluster
 - High value in cluster 3: Peak Load Storage Cluster
 - **MHH:**
 - Median value in cluster 1: Gas/Carbon Price & Load Growth Cluster
 - High value in cluster 2 (+): Renewable Policy & DG
 - Low value in cluster 2 (-): Capital Cost Cluster
 - High value in cluster 3: Peak Load Storage Cluster
 - **MLL:**
 - Median value in cluster 1: Gas/Carbon Price & Load Growth Cluster
 - Low value in cluster 2 (+): Renewable Policy & DG
 - High value in cluster 2 (-): Capital Cost Cluster
 - High value in cluster 3: Peak Load Storage Cluster
 - **LML:**
 - Low value in cluster 1: Gas/Carbon Price & Load Growth Cluster
 - Median value in cluster 2: Renewable Policy & Capital Cost Cluster
 - Low value in cluster 3: Peak Load Storage Cluster
 - **LLL:**
 - Low value in cluster 1: Gas/Carbon Price & Load Growth Cluster
 - Low value in cluster 2 (+): Renewable Policy & DG
 - High value in cluster 2 (-): Capital Cost Cluster
 - Low value in cluster 3: Peak Load Storage Cluster

Appendix D. Unit Commitment Mathematical Formulation

The “tight relaxed unit commitment” (TRUC) model used to include unit commitment constraints in JHSMINE is stated in mathematical terms below.

Notation: Sets

B	Set of buses b
H	Set of hours h
L	Set of lines l
T	Set of (time) stages t
R	Set of internal-regions r (For RPS calculation)
G	Set of generators g
GR	Set of renewable generators gr ($GR \subset G$)

Notation: Parameters

$CZ_{l,t,s}$	Cost of building line l in stage t and scenario s
$CX_{b,g,t,s}$	Cost of building unit g at bus b in stage t and scenario s
$CY_{b,g,t,s}$	Marginal Cost of generating energy from unit g , bus b , stage t , scenario s
$VOLL_{b,t,s}$	Value of Lost Load in bus b , stage t , and scenario s
$QP_{b,g}^{min}$	Minimum-run capacity as a fraction of total capacity
$\bar{X}_{b,g,t,s}$	Maximum capacity of generator g allowed at bus b
R_g	Fraction of load that needs to be in reserves
$RP_{b,g}$	Fraction of maximum capacity that can be ramped up or down for unit g
$M_{b,l}$	Line-incidence matrix mapping buses to lines
$D_{b,h,t,s}$	Load at bus b , hour h , stage t , and scenario s
RPS_r	State-mandated fraction of yearly load that must come from renewables
$\bar{F}_{l,t,s}^{E/N}$	Maximum flow on existing (E) and new lines (N)
$\underline{F}_{l,t,s}^{E/N}$	Minimum flow on existing (E) and new lines (N)

Notation: Variables

$z_{l,t,s}$	$\{0, 1\}$ Invest in line l in stage t , scenario s
$x_{b,g,t,s}$	Capacity of generator g built at bus b
$q_{b,g,h,t,s}$	Output from g in hour h in stage t and scenario s
$p_{b,g,h,t,s}^{min}$	Minimum-run capacity online in hour h from g in stage t and scenario s
$r_{b,g,h,t,s}$	Reserves in hour h from generator g in stage t and scenario s
$X_{b,g,h,t,s}$	Upper-limit on generator g 's capacity in stage t and scenario s
$p_{b,g,h,t,s}^{SU}$	Capacity started up in hour h from generator g in stage t and scenario s
$p_{b,g,h,t,s}^{SD}$	Capacity shut down in hour h from generator g in stage t and scenario s
$f_{l,h,t,s}^{E/N}$	Flow on existing (E) and new (N) lines in hour h , stage t , scenario s
$\theta_{b,h,t,s}$	Angle at bus b , hour h , stage t , and scenario s

$$\text{MIN} \sum_{l,t,s} CZ_{l,t,s} z_{l,t,s} + \sum_{b,g,t,s} CX_{b,g,t,s} x_{b,g,t,s} + \sum_{b,g,h,t,s} CY_{b,g,t,s} q_{b,g,h,t,s} +$$

$$\sum_{b,h,t,s} VOL_{b,t,s} l_{b,g,h,t,s} + \sum_{b,g,h,t,s} \frac{C_{b,g,t,s}^{SU}}{Q_{b,g,t,s}^{\min}} p_{b,g,h,t,s}^{SU} + \sum_{b,g,h,t,s} \frac{C_{b,g,t,s}^{SD}}{Q_{b,g,t,s}^{\min}} p_{b,g,h,t,s}^{SD}$$

$$\text{s.t. } p_{b,g,h,t,s}^{\min} \leq q_{b,g,h,t,s}$$

$$p_{b,g,h,t,s}^{\min} \leq QP_{g,i}^{\min} X_{s,h,gc,i}$$

$$r_{b,g,h,t,s} + q_{b,g,h,t,s} \leq (1 - POR_g)(1 - FOR_g) \frac{p_{b,g,h,t,s}^{\min}}{QP_{g,i}^{\min}}$$

$$X_{b,g,h,1,s} = X_{g,i}^0 + X_{g,i}^1 - X_{h,g,i}^R$$

$$X_{b,g,h,1,s} = X_{g,i}^0 + X_{g,i}^1 + X_{s,g,i}^2 - X_{h,g,i}^R$$

$$X_{b,g,h,t,s} \leq \bar{X}_{b,g,t,s}$$

$$r_{b,g,h,t,s} \leq R_g \frac{p_{b,g,h,t,s}^{\min}}{QP_{g,i}^{\min}}$$

$$p_{b,g,h,t,s}^{\min} - p_{b,g,h-1,t,s}^{\min} = p_{b,g,h,t,s}^{SU} - p_{b,g,h-1,t,s}^{SD}$$

$$(r_{b,g,h,t,s} + q_{b,g,h,t,s} - p_{b,g,h,t,s}^{\min}) - (q_{b,g,h-1,t,s} - p_{b,g,h-1,t,s}^{\min}) \leq RP_{g,i} \left(\frac{p_{b,g,h,t,s}^{\min}}{QP_{g,i}^{\min}} - p_{b,g,h,t,s}^{\min} \right)$$

$$(q_{b,g,h,t,s} - p_{b,g,h,t,s}^{\min}) - (q_{b,g,h-1,t,s} - p_{b,g,h-1,t,s}^{\min}) \geq -RP_{g,i} \left(\frac{p_{b,g,h-1,t,s}^{\min}}{QP_{g,i}^{\min}} - p_{b,g,h-1,t,s}^{\min} \right)$$

$$q_{b,g,h,t,s} - p_{b,g,h,t,s}^{\min} \leq \frac{p_{b,g,h,t,s}^{\min}}{QP_{g,i}^{\min}} - \frac{p_{b,g,h,t,s}^{SU}}{QP_{g,i}^{\min}}$$

$$q_{b,g,h,t,s} - p_{b,g,h,t,s}^{\min} \leq \frac{p_{b,g,h,t,s}^{\min}}{QP_{g,i}^{\min}} - \frac{p_{b,g,h,t,s}^{SD}}{QP_{g,i}^{\min}}$$

$$\sum_g q_{b,g,h,t,s} - \sum_l M_{b,l} (f_{l,h,t,s}^E + f_{l,h,t,s}^N) + l_{b,h,t,s} = D_{b,h,t,s} \quad \forall b, h, t, s$$

$$\sum_{b,g} r_{b,g,h,t,s} \geq X_R D_{b,h,t,s} \quad \forall h, t, s$$

$$\underline{F}_l^E \leq f_{l,h,t,s}^E \leq \overline{F}_l^E \quad (\xi_{l,h}^-, \xi_{l,h}^+) \quad \forall l \in E, h$$

$$z_l \underline{F}_{l,t,s}^N \leq f_{l,h,t,s}^N \leq z_l \overline{F}_{l,t,s}^N \quad (\beta_{l,h}^-, \beta_{l,h}^+) \quad \forall l \in N, h$$

$$f_{l,h,t,s}^E - B_l^E \sum_b M_{b,l} \theta_{b,h,t,s} = 0 \quad \forall l \in E, h, t, s$$

$$-(1 - z_{l,t,s})M \leq f_{l,h,t,s}^N - B_l^N \sum_b M_{b,l} \theta_{b,h,t,s} \leq (1 - z_{l,t,s})M \quad \forall l \in N, h, t, s$$

$$\sum_{r,gr,h} q_{r,gr,h,t,s} \geq RPS_r \sum_r D_{r,h,t,s} \quad \forall r, h, t, s$$

$$q_{b,g,h,t,s}, q'_{b,g,h,t,s}, r_{b,g,h,t,s} \geq 0 \quad \forall b, g, h, t, s$$

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