Economic Value of Model Enhancement in Transmission Planning Optimization

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***Abstract*—A framework to quantify the value of model enhancements (VOME) in transmission planning models is proposed and applied to a case study of large-scale long-term planning of WECC system. VOME quantifies the probability-weighted improvement in system performance resulting from changes in decisions that result from model enhancements, and is closely related to the concept of value of information from decision analysis. Four types of enhancements have been investigated using the proposed framework. Our results show major benefits from considering long-run uncertainty using multiple scenarios of technology, policy, and economics; these benefits are as much as 26% of total benefits of new transmission built in the first 10 years. But less benefit is obtained from more temporal granularity, more complex network representations, and including unit commitment constraints and costs. This framework can be applied to quantify the value of model enhancements in any planning context.**

***Index Terms*—Generation planning, Economics, Power transmission planning, Mixed integer linear programming, Value of information, Stochastic programming**

I. Nomenclature

I	Set of enhancements, index i and j, with $i = 1 \ldots n$
E_i	Binary parameter: if $E_i = 1$, then enhancement i is in the model
$x_{E_i..E_n}$	Optimal first stage transmission investments ("decision") from a model with enhancements specified by subscripts. (E.g., $x_{1,0,1}$ indicates investments from a model with only Enhancements 1 and 3 implemented.)
$\underline{x}$	Decision of no transmission investments in stage 1
$\overline{x}$	Optimal decision from model with all enhancements
$C(x)$	Expected present worth of system cost of making decision x, based on the model with all enhancements

II. Introduction

Grid reinforcements are a large part of the cost of integrating renewable energy [1]. This cost is justified because they contribute to a cost-efficient, reliable, and sustainable power system by delivering renewables and reducing congestion. But they should be planned carefully to avoid unnecessary expenses.

Planning processes for transmission are necessarily complex. Permitting and construction takes about a decade. This, together with the long life of transmission assets and large policy, technology, and economic uncertainties means that benefit calculations must analyze how grid investments will perform under many different scenarios. Also, planning must consider the entire system and all alternatives for an entire region at once, because a network reinforcement in one location can strongly affect the benefits of new lines elsewhere. Further, though many power markets have unbundled transmission from generation, planners still need to consider how generation mix and siting are affected by where and when lines are added. This is called "proactive" transmission planning [2].

In summary, transmission expansion models are complex because they need to consider entire regions, multiple decades of costs, generation-transmission investment interactions, and uncertainty in fundamental drivers [3], as well as numerous technical and economic details.

However, models for transmission planning cannot be arbitrarily complex because of limited computation capabilities. As solvers and hardware improve, planners can add features to planning models to make them more realistic, but not all can be accommodated. Thus, planners always face trade-offs as they consider which model enhancements to implement. For instance, if a model has 8760 operating periods/yr, a 40-yr horizon, 10 long-run scenarios, 1000 candidate generators, and 500 candidate transmission lines, model size easily grows to several billions of variables/constraints. Thus, a planner must choose which features of the real system to represent, which to omit, and what approximations to use. For instance, a planner might decide that renewable variability is more important to model, so she might want to consider hundreds of separate operating hours per year; to make that possible, she might then sacrifice network detail, e.g., by using a "pipes-and-bubbles"/transshipment formulation instead of a linearized DC power flow.

Such choices are difficult and, should, ideally consider how much transmission plans would improve as a result of model enhancements. Our purpose in this paper is to present a framework to quantify the economic value of model improvements and apply that framework to the Western Electricity Coordinating Council (WECC) using a 300-bus network [4] based on WECC's 2024 Common Case database [5]. Thus, we can address the following question: *Can we quantify an economic index to meaningfully compare the value that alternative model enhancements might provide to transmission planning?*

The paper is organized as follows. In Section III, we briefly review some enhancements that have been proposed for transmission planning models and related models. Then in Section IV, a systematic framework for calculating the value of model enhancements (VOME) is presented. In Section V, we describe the base planning model, the WECC case study environment, and the tested enhancements. In Section VI, we show results regarding which enhancements have the most value, and in Section VII we provide some conclusions.

III. Enhancements Proposed in Recent Research

Researchers and software vendors have proposed adding various enhancements to planning optimization models (Table

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I) in an attempt to yield useful information and better performing plans. In this section, we summarize some of those enhancements. Detailed reviews can be found in [6], [7].

TABLE I. SOME PROPOSED ENHANCEMENTS OF TRANSMISSION MODELS

1. Considering uncertainty	Deterministic, heuristic, stochastic [8]/ robust [11]/conditional value at risk (CVaR) [12]/adaptive [9], [10]
2. Generation representation	With/without binary/linearized unit commitment [15], [16]
3. Spatial granularity	Number of nodes in network/data aggregation level [17], [18]
4. Network representation	Hybrid DC/pipes-and-bubble, DC power flow [4], [19], [20], losses [22], AC [23]
5. Temporal granularity a. Investment stages	More investment stages over the planning horizon
b. Operating hours	More hours/yr [20]; chronological hours
6. Transmission-investment coordination	Reactive, proactive (co-optimization or multiple level) [2], [26-29]

1. Uncertainty. A major area of enhancement has been to recognize long-run uncertainties in fundamental drivers of the economic value of transmission, such as load growth, technology improvements, or policy, rather than considering just one "deterministic" or "base case" scenario. Some researchers recommend using stochastic optimization [3], [8] to model multiple scenarios representing diverse values of those drivers. Multistage stochastic programs can differentiate between immediate "here-and-now" investment decisions ("stage 1") that are made not knowing the future, and later "wait-and-see" decision stages that adapt the system depending on which scenario is realized. A variant is "adaptive planning" that defines a core multiyear plan along with changes that can be made later if the drivers change [9] (compared to stochastic optimization in [10]).

Stochastic optimization assumes planners are risk-neutral (i.e., minimizers of probability-weighted costs), while other approaches assume that planners are risk averse, i.e., more concerned with bad outcomes. Examples of the latter methods include robust optimization (minimizing the cost of the worst scenario or worst regret [11]) and conditional value of risk (CVaR) constraints [12]. Simpler heuristic methods also attempt to identify plans that are "robust" to an uncertain future. Examples are MISO's "Multi-Value Projects" [13] and the CAISO's "least regret investments" [14], which include network investments that are attractive under most scenarios.

2. Generation representation. Planning models can also be enhanced by more realistic models of generator costs and constraints. Notably, unit commitment modeling can be added to expansion models, replacing traditional load-duration curve/merit-order methods. The importance of commitment and ramp constraints, which limit generation flexibility, can improve estimates of the cost of integrating variable renewables [15]. Ho et al. [4] implemented linearized unit commitment constraints [16] in transmission optimization. Their results indicate that limiting the flexibility of generators has more impact on transmission economics in systems with slow baseload units.

3. Spatial granularity. Adding more zones or network nodes is another potential enhancement. Ref. [17] showed that more spatial aggregation can penalize photovoltaics since it mixes solar resources of good and bad quality. Shawhan et al. [18] demonstrated how increasing the level of detail for the Eastern Interconnection (from 1 node to 62,000 nodes per system) improves the accuracy of policy impacts predictions.

4. Network representation. The "pipes-and-bubbles" (transshipment) networks used in many planning models have been proposed to be replaced by more realistic approximations of power flow, such as DC OPF, that are practical to solve [19], [20]. However, as [20] shows, in a large-scale system, DC OPF modeling can dramatically slow solution times, and may have little impact on investment recommendations, compared to transshipment networks that lack Kirchhoff's voltage law. An intermediate level of complexity is the hybrid power flow [21]. There, existing AC line flows are modelled using angle difference/flow relationships (as in the linearized DC load flow), but all new lines are modelled as if they are DC circuits whose flows are controllable (as in pipes-and-bubbles models) and whose capacity can be added in continuous amounts. Other improvements could include consideration of losses [22], AC load flow [23], and N-1 contingencies [22], [24].

5. Temporal granularity. Indeed, it has been argued that having more operating hours per year in a transmission model is important than representing the voltage law [25]. However, others have studied the impact of more temporal granularity on generation expansion [20], and concluded that adding dispatch periods slows down computations while having little apparent effect on generation expansion decisions.

6. Transmission-generation investment coordination. Transmission optimization models traditionally plan against a fixed scenario of generation investment locations and types. This is "reactive" planning. However, proactive transmission planning, which considers how generation investment decision might be affected by grid reinforcements, can lead to less costly plans [26]. In the simplest proactive models, generation markets are assumed to be perfectly competitive, which allows proactive transmission planning to be modeled using a single "co-optimization" model. If instead generators behave strategically, multilevel transmission planning models can be used [27], [28], [29], but are much more computationally intensive.

The impacts of the above enhancements on transmission optimization model solutions have often been assessed [17], [18], [20], but generally with a focus on how decisions (such as generation investments) change, rather than on the improvement in economic performance of recommended plans. In one exception, the cost savings resulting from proactive transmission planning were investigated in [26], but not compared to the value of other kinds of enhancements. Here, we present and apply a framework to calculate the value of model enhancements in order to inform prioritization of model improvement efforts.

IV. VALUE OF MODEL ENHANCEMENT (VOME)

In this section, we first define the value of model enhancement. We then propose a framework for implementing this idea in transmission optimization modeling.

A. Definition of VOME

VOME is a close analogy to the idea of the "expected value of perfect information" (EVPI) from decision analysis. EVPI is the most that a planner is willing to pay for perfect information, equal to the probability-weighted (expected) improvement in the performance of the optimal solution. Similarly, VOME can be stated as: *what are we willing to pay for elaborating a planning model in a specified way?* This is the expected improvement in performance of the resulting decision. Another way to look at VOME is as the cost of simplifying the model, i.e., how much performance one must sacrifice, in expectation, if a particular simplification is made (i.e., an enhancement is omitted).

We can explain the idea as follows. Imagine a decision maker (DM) builds a model, and the model indicates that some plan x_A is optimal. Then, the DM enhances the model by improving the realism of the constraints or objective, and then gets plan x_B back instead. Finally, imagine for now that the DM can test the performance of alternative plans before implementing them by using a sophisticated and highly realistic simulation model. This simulation shows x_A would have a "true" expected cost of $C(x_A)$ while decision x_B's cost is $C(x_B)$. (We put "true" into quotes because the actual expected cost cannot be known, but this is the best estimate that can be obtained.) The VOME of this enhancement (more constraints) is then calculated as $C(x_A) - C(x_B)$, the decrease in "true" cost resulting from using the enhanced model to make decisions.

However, we must overcome at least three difficulties to successfully calculate VOME.

1. Sometimes an enhancement involves combining information from several sources. For example, we can have a model A1 based on one set of *n* operating hours/yr, and a model A2 based on a different set of *n* hours/yr. Combining the information, we have model B with 2*n* hours. Then the cost improvement can be calculated in two ways: $[C(x_{A1}) - C(x_B)]$ and $[C(x_{A2}) - C(x_B)]$. *Which should we use?*

2. There are usually multiple enhancements available. For instance, if there are 2 kinds of enhancements, from A to B (e.g., fewer to more operating hours) and from C to D (e.g., from a simple to a more sophisticated network), then there are 4 types of models: AC, BC, AD, BD. This also means that there are at two ways of calculating the savings of using B rather than A: $[C(x_{AC}) - C(x_{BC})]$ and $[C(x_{AD}) - C(x_{BD})]$. *Which should we use?*

3. The "true" cost $C(x)$ may be hard to evaluate, involving a complex or difficult to compute model, as it should ideally be capable of simultaneously evaluating all enhancements under investigation. *How should $C(x)$ be estimated?*

To address these difficulties, we propose the approach below:

1. When the enhancement involves combining information from more than one source, we calculate a weighted average of the improvements. For instance, consider the enhancement mentioned above, in which two sets of hours, each of size *n*, are combined into a *2n* hour set. Since each set contributes half of the information, we set the weights to 0.5. In that case, VOME = $[0.5C(x_{A1}) + 0.5C(x_{A2}) - C(x_B)]$[1].

2. When calculating the VOME for one particular enhancement when other enhancements are also under consideration, we consider the incremental impact given every possible combination of the other enhancements. That is, we compare solutions from two models at a time, where only the enhancement of interest *i* is changed, and all other model features are the same. This results in N_i pairs of decisions (thus N_i cost differences), where N_i equals the number of all possible permutations of other enhancements. (E.g., if there are 3 other possible enhancements, each either being present or absent, then there are $N_i = 2^3$ combinations.) Then we take the average of these N_i cost differences.

3. We define the "true" system cost $C(x)$ as the best obtainable estimate of cost of making decision x. This can be done by fixing x in the most sophisticated model that can be solved, and optimizing over other variables again. As explained in Section V.C below, it was not possible in our case study to model all enhancements at once in one model, so a compromise was made by calculating $C(x)$ by one of two sophisticated models (either with unit commitment, or with the maximum number of hours, DC load flow, and stochasticity).

With these assumptions, VOME can be formulated as follows:

$$VOME_i = \frac{1}{N_i}\sum_{\forall E_j, j\neq \mathrm{i}}\left(E\left[C\left(x_{E_1\ldots,E_i=0,\ldots E_n}\right)\right] - E\left[C\left(x_{E_1\ldots,E_i=1,\ldots E_n}\right)\right]\right) \qquad (1)$$

In this formulation, x is the decision (here, the immediate (first stage) transmission investment) obtained by a model with enhancements specified by the subscripts, and i is the enhancement under evaluation. The expectation operator accounts for both the possibility of multiple long-run scenarios (each with an assumed probability), and weighting of multiple sets of information, as described under the first difficulty above.

B. VOME Calculation in Transmission Planning

Before we implement VOME for transmission planning models, we lay out three basic assumptions.

First, all our transmission planning models are in form of transmission-generation co-optimization [2]. Thus, we obtain the optimal transmission plans anticipating generator reactions, assuming that generation investments and spot markets take place under competitive conditions.

Second, we take the viewpoint of a transmission planner, and we are interested in the cost of making mistakes in first stage (immediate or "here and now") transmission investment decisions. We define *x* for our application as the first stage *transmission* investments, and when calculating $C(x)$, we allow the most sophisticated model to choose the second stage transmission investments, as well as all generation decisions. This assumption is based on the recognition that a transmission system only commits to first stage (immediate) decisions, and has the flexibility to deviate from the solution's second stage recommendations later when there is better information. Thus, this VOME is the value of the model enhancement just for immediate transmission investments.

Finally, in calculating $C(x)$ we assume that generation in-

[1] Similar idea is applied to assess the enhancement from deterministic to stochastic planning. For example, consider two possible scenarios with probability p_1 and p_2, resulting in plans x_1 and x_2. A stochastic model considering both scenarios and their probabilities gives plan x_s. Then the value of this enhancement is $[p_1 C(x_1) + p_2 C(x_2)] - C(x_s)$. This is the same as the definition of expected cost of ignoring uncertainty (ECIU) in classical decision analysis [30].

vestors make decisions with full information, including the information that would be provided by all enhancements, even if transmission plans *x* are based on more naïve assumptions from a simpler model. However, generation owners make their decisions assuming that they cannot affect prices of transmission services (nodal price differences). This can be viewed as the competitive market's reaction to decisions *x*.

Combining all three assumptions, we calculate VOME thus:

1. x is the first stage transmission investments from a model with an assumed set of enhancements.
2. $C(x)$ is the "true" system cost obtained by simulating the optimal generation decisions and second-stage transmission investments in response to *x*. We treat $C(x)$ as the actual system cost associated with *x*.
3. VOME for an enhancement is then calculated by (1).

Fig. 1 presents this procedure as a flow chart.

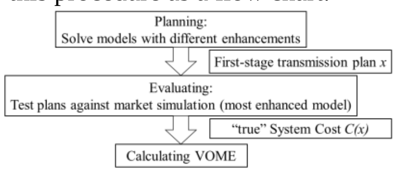

Fig. 1. Procedure for Calculating VOME in Transmission Planning Model

C. *Metrics of Economic Benefit of Transmission Planning*

To place VOME in context, we compare it to the overall benefit of transmission expansion. If VOME for a particular enhancement is a significant fraction of the total benefit of adding transmission, then we conclude that the enhancement is potentially important to include in the model.

The benefit of expansion is calculated as follows. Assume that it is feasible to build no lines at all in first stage, and let $\underline{x}$ stand for this null plan. The resulting null plan cost (*NPC*) will be $NPC = C(\underline{x})$. Then we can define any other plan *x*'s net benefit (*NB*(*x*)) as $NB(x) = NPC - C(x)$.

By the definition of "true" cost $C(x)$ as the cost from the most sophisticated model (i.e., the one with all enhancements), we can define the best possible optimal plan cost (*OPC*) as $OPC = C(\overline{x})$, where $\overline{x}$ is the solution from that model. We can then define the upper bound of economic benefit (*UPB*) transmission planning as $UPB = NPC - OPC$.

Any plan *x*, other than the optimal plan, can be viewed as achieving some but not all of the possible benefits. Thus, we can define economic benefit recovery as $BR(x) = NB(x)/UPB$. The $BR(x)$ metric is useful when comparing different transmission plans, since the change in the objective function is usually a small part of total system cost, which is large because it includes all generation capital and operating costs.

V. Experimental Design

We now describe how we implemented VOME in a realistic transmission planning study. First, we briefly describe the basic model for the VOME calculation, and then we give an overview of the enhancements we investigated. We then summarize the case study environment, a 300-bus network for WECC. Finally, we describe how the four enhancements are added to the model.

A. *Summary of Basic Planning Model*

The basic planning model is the Johns Hopkins Stochastic Multi-Stage Integrated Network Expansion (JHSMINE). Its mathematical formulation can be found in the on-line Appendix (http://hobbsgroup.johnshopkins.edu/home.html), and is based on [8] as elaborated in [4]. JHSMINE is a scenario-based, two-stage stochastic programming model, in which first-stage (here-and-now) decisions made today (year 0) include immediate transmission and generation investments that will be on-line in year 10, while recourse decisions are new transmission/generation investments that come on-line in year 20, as well as optimal generation dispatch and power flows in years 10 and 20, the latter being used to estimate costs in years after 20. These decisions are subject to network, unit commitment and other constraints. Renewable portfolio standards and renewable credit trading are also modeled. Uncertainties can be handled through multiple scenarios for year 10 and 20 model parameters. Examples include capital cost uncertainties caused by technology advances (i.e., scenarios of objective function coefficients), load/peak growth uncertainty (represented by scenarios of constraint right-hand sides), and policy uncertainties, such as carbon prices.

B. *Case Study Environment: 300-bus WECC system*

We discuss four sets of assumptions: network reduction, existing generation mix, new generation investment opportunities, and network investment possibilities. First, the system is a reduction of the WECC Common Case 2024 [5] (details in [4]). The reduced network includes 328 nodes and 530 lines (Fig. 2), in which 249 of the nodes were preserved existing nodes in the original network (230 kV or above), while 244 lines were preserved existing lines from the original network. The whole network can be divided into 26 regions by the preserved paths [31].

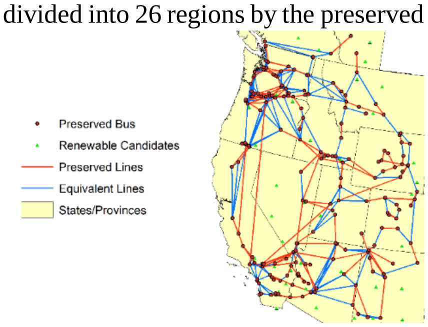

Fig. 2. Case study network reduction

Second, the system includes 544 existing generators of 16 types distributed among 249 existing nodes.

Third, the other 79 nodes are designed as candidate sites for generation expansion. 26 of the 79 nodes are location-irrelevant conventional generation expansion sites in each region mentioned above. The remaining 53 nodes in the network were candidate sites for renewable investment. Their locations and potential capacities are derived from [32]. Four types of renewables (wind, utility-level solar, geothermal and biofuels) can be constructed along with two types of conventional generation (gas combined cycle and combustion turbines). Capital costs assumptions vary based on the location of candidate sites [33].

Finally, the transmission investment candidates considered can be divided into two categories: backbone reinforcements and renewable access. Backbone reinforcements are defined as having the characteristics of the line with largest capacity in a given WECC transmission path. Such lines relieve congestion and path limits. Radial renewable access lines connect renewable developments to the closest nodes in the existing network. Since we assumed all transmission lines in the WECC "Common Case" [5] have been brought on line by 2024, all transmission investment variables in our model are incremental over and above the Common Case.

C. Candidate Model Enhancements

We compare the economic value of four possible model enhancements using VOME, as described above.

1) Generating Unit Commitment

This enhancement enables the model to consider limits upon generation flexibility, such as start-up costs, minimum running capacity, and ramp limits. This would penalize slow-moving steam generators relative to single and combined cycle plants. Such limits are relevant to transmission planning because, for example, delivery of distant renewables will be less valuable if their fluctuating output cannot be fully used by the grid.

In our model, this enhancement is modeled by relaxing the binary constraints on commitment variables so that they can take on values in the range of 0-1, which reduces computational time [16]. The variables can be interpreted as the fraction of generation capacity of a given type that is committed in a given hour. The assumed commitment parameters (WECC averaged) are shown below (Table II). Other technologies such as hydro/wind and solar are not subject to these flexibility constraints.

TABLE II. GENERATOR UNIT COMMITMENT ASSUMPTIONS

Generation Type	Minimum Run (% capacity)	Ramp Rate (% of capacity/hr)	Startup Cost ($/MW)
Coal	51%	29%	61.26
Gas Combined Cycle	51%	44%	59.68
Gas Combustion Turbine	41%	75%	24.32
Nuclear	87%	12.5%	81.81

2) Network Modeling

More physical realistic models of power flow benefits planning by better characterizing how grid reinforcements affect transmission capability, dispatch, and, ultimately, costs.

The basic model is a pipes-and-bubble (P&B) power flow modeling. This can be enhanced by implementing a linearized DC power flow model using a "B-theta" formulation, which includes Kirchhoff's voltage law by explicitly modeling phase angles, but assumes unit voltage and negligible resistance [34]. Flow on a line equals the phase angle difference across the line divided by impedance; we enforce this for new lines by disjunctive constraints [19], that use 0-1 variables to represent absence/presence of the line. An intermediate level of enhancement is hybrid flow modeling [21], defined above.

3) More Short-Run (Within-Year) Temporal Granularity

Computational limits mean that it is not possible to model 8760 hrs/yr in a multi-decadal transmission optimization model, even without any other enhancements. Thus, we must choose the number of distinct operating periods. More periods/yr can result in a better representation of load and renewable temporal distributions and correlations.

Here, two levels of with-in year temporal granularity, 24-hrs/yr and 48 hrs/yr, are considered. To make the 24 and 48 hour solutions comparable, the set of 48 hours is defined as the union of two 24 hour sets. The load duration curves for different sets hour sets (24, 48, and 8760) are shown in Fig. 3 to show the load pattern captured by the hour sets.

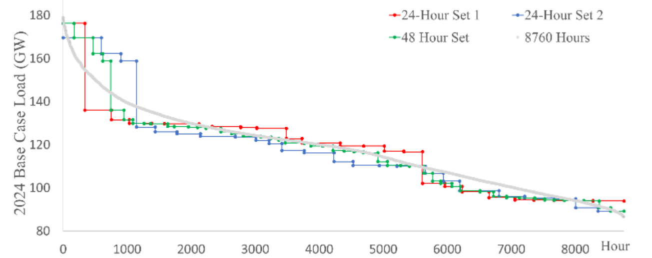

Fig. 3. WECC-wide load duration curves for different hour sets

4) Multiple Long-Run Scenarios

Reasons for considering long-run uncertainty are discussed in Section II, and in more detail in [7]. Here, we take stochasticity into consideration by two-stage stochastic programming [30]. This method uses an expected cost objective to decide which stage 1 investment commitments to make before it is known how uncertainties such as load growth will be resolved, while making "wait and see" (stage 2) decisions afterwards. Although there are other uncertainty planning methods, stochastic programming has the advantage of representing system adaptations over time as well as the state-of-knowledge when commitments are made. Further, the objective (MIN expected cost) is consistent with the definition of $C(x)$ used by VOME.

We quantify the value of considering long-run uncertainties in the case study by considering the first stage decisions x that are made considering either each of 5 scenarios separately (deterministic model) or jointly in an enhanced model (stochastic programming). In the latter model, we assume the 5 scenarios are equally likely. Parameters of these five scenarios (Table III) are either directly from WECC's 2013 study cases [35] or developed with the help of a WECC technical advisory group [4].

Considering the above four types of enhancements, two groups of experiments were undertaken as follows. First, the effect of generator unit commitment modeling is investigated by itself, with the model including stochasticity (5 scenarios) but only the pipe-and-bubbles network. Then the other three enhancements (temporal granularity, network representation and stochasticity) are compared together. Unit commitment is analyzed in a separate experiment mainly because it requires sequential hourly data. This requirement, which requires representative days instead of hours, renders the planning model with other features, especially DC OPF, computationally intractable. On the other hand, the three days (72 hours) we used in the unit commitment analysis are not as accurate a representation of cross-region load and renewable output correlations as the sets of hours investigated in the second experiment.

TABLE III. VALUES OF UNCERTAIN VARIABLES BY SCENARIO

Scenario:	Base	W1	W2	W3	W4
Gas Price (% change from base)	0	+86	0	0	-51
Carbon Price ($/ton)	58	58	113	33	113
Load Growth (%/yr)	1.13	3.20	3.20	-0.91	-0.91
Peak Growth (%/yr)	1.28	2.64	2.64	-0.37	-0.37
State RPS (% change)	0	0	+50	0	+50
Federal RPS (% of Load)	0	0	+15	0	+15
Wind Cap. Cost (% change)	0	+7.5	-18.3	+7.5	-18.3
Geoth. Cap. Cost (% change)	0	0	-15	0	0
Solar Cap. Cost (% change)	0	0	-28.7	+30	0

VI. RESULTS

In this section, we will show the outcomes of the VOME experiments for the case study WECC system. First, we summarize model sizes and computation times to help the reader appreciate the "curse of dimensionality" that arises from attempts to include all possible enhancements. Then we show the VOME for adding unit commitment to the planning model, and, finally, compare the values of VOME across the enhancements of increased temporal granularity, improved network representation, and including long-run uncertainties via multiple scenarios.

A. Model Size and Computation Time Comparison

First in Tables IV and V, we display the change in model size and solution times under alternative enhancements.

TABLE IV. MODEL SIZE AND SOLUTION TIME WITH VARIOUS ENHANCEMENTS (DETERMINISTIC/SINGLE SCENARIO CASES)

	Deterministic (15 candidate backbone lines x 2 stages)					
Network	P&B	Hybrid	DC OPF	P&B	Hybrid	DC OPF
Load slices/yr	24	24	24	48	48	48
# Constraints (million)	0.23	0.26	0.26	0.46	0.51	0.52
# Variables (million)	0.18	0.19	0.19	0.36	0.36	0.36
Solution Time (minutes)	0.25	4.25	5.78	0.78	21	35

TABLE V. MODEL SIZE AND SOLUTION TIME WITH VARIOUS ENHANCEMENTS (STOCHASTIC/5 SECOND STAGE SCENARIOS)

	Stochastic (Same Candidates, 5 WECC scenarios)							
Network	P&B	Hybrid	DC OPF	P&B	Hybrid	DC OPF	No UC	With UC
Hours	24	24	24	48	48	48	72	72
#Constraints (million)	1.15	1.25	1.26	2.25	2.49	2.51	3.17	14.6
#Variables (million)	0.90	0.93	0.93	1.74	1.86	1.86	2.41	6.67
Solution Time	3 mins	3 hours	4 hours	0.25 hours	16.8 hours	24 hours	0.67 hours	6.89 hours

All these models are mixed integer linear programs (MILPs) and are solved to a MIP gap of 10^{-5} % (relative to the objective function value) to avoid possible biases in our conclusions introduced by large gaps. Also, all models were solved on the same workstation with an Intel® Core™ i7-5930K CPU and 32 GB of core memory using solver CPLEX 12.6.3. All solution times shown here are approximate averages, since, for example, there are 10 deterministic runs using the P&B network together one of the two 24-hour sets (5 scenarios times 2 sets of 24 hours), for which the average solution time is 15 seconds.

Note that only about 15 seconds are needed to generate an optimal plan for the most simplified model, while 24 hours were required to solve a model with the most enhancements.

B. VOME of Unit Commitment

In this part of the analysis, first-stage plans x are generated from two planning models, both with the stochasticity enhancement (5 scenarios), but one without linearized unit commitment constraints and costs, and the other with those features. The network was assumed to be P&B for computation tractability. Three 24-hour days were considered per year (72 hrs/yr).

Since the planning model that includes unit commitment is closer to reality, the calculation of $C(x)$ is performed with both unit commitment and stochasticity. That is, "true" cost $C(x)$ for a given set of first-stage transmission investments x is calculated by optimizing all the other decision variables while including unit commitment and 5 second-stage scenarios.

The resulting cost of transmission plans and their benefits is shown below in Table VI. The "true" cost $C(\underline{x})$ of the null plan $\underline{x}$ (no first stage transmission other than the WECC Common Case lines) is *NPC* = $993.75B (2014 present worth). In contrast, with about $3B of first-stage transmission investment x resulting from the unit commitment model with 5 scenarios, the system's "true" cost $C(x)$ is $24.05B lower, which we treat as the upper bound *OPC* of the net benefit of transmission. In contrast, if unit commitment is *not* included, more backbone and renewable interconnection transmission is constructed, with a total first stage transmission investment of $3.85B, and a $C(x)$ that is $23.54B lower than *NPC*. Thus, the model enhanced with unit commitment gave a more conservative plan x, whose benefits are $0.51B billion higher (= $24.05B-$23.54B) than the x resulting from the model without unit commitment. This is our estimate of VOME for including unit commitment in the WECC-wide transmission planning model.

TABLE VI. COSTS AND EXPECTED BENEFITS OF FIRST STAGE TRANSMISSION PLANS GENERATED BY MODEL WITH/WITHOUT UNIT COMMITMENT ENHANCEMENT (BILLION 2014 US$).

Planning Model	No UC	With UC
Backbone Trans.	1.62	1.00
Renewable Trans.	2.23	2.00
"True" Cost $C(x)$	970.21	969.70
Net Benefit (*NB(x)*) relative to null plan	23.54	24.05
Benefit recovery *BR(x)*	97.9%	100%
Null plan cost (*NPC*)	993.75	

C. VOME of Temporal Granularity, Power Flow Representation and Stochasticity

To estimate the VOME of these three enhancements, the impracticality of solving a unit commitment model together with all three other enhancements means that each model in this section omits unit commitment (i.e., assumes that generators can be ramped up and down without restriction and can be freely started up or shut down).

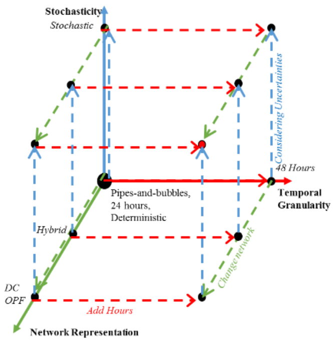

Fig. 4. Conceptual framework for VOME calculation of Temporal Granularity, Network Representation and Stochasticity

Fig. 4 is a visualization of how we implemented the definition of VOME from Section IV. in this experiment. Let the origin of the three-dimensional plot represent the outcome of a highly-simplified model with just a P&B network, 24 operating hours/yr, and a single long-term scenario. Then one can imagine enhancing the planning model along any or all of three dimensions, anticipating that the enhancement(s) will generate a more beneficial first-stage transmission plan *x*. Each node in the diagram represents one possible model formulation (combination of enhancements), for which we obtain the first-stage transmission plan *x* whose "true" cost $C(x)$ is calculated using the most sophisticated set of assumptions (linearized DC network, 48 hours/yr, and stochasticity with 5 scenarios). Then we calculate the differences between adjacent nodes, which is equivalent to calculating the cost savings resulting from enhancing the model in one direction. The average of cost differences (arrows with same color) is the VOME for the particular enhancement represented by the direction of the arrow (i.e., equation (1), above).

TABLE VII. NET BENEFITS *NB*(*x*) OF FIRST STAGE TRANSMISSION *x* GENERATED BY DIFFERENT MODELS (BILLION 2014US$)

Power Flow/ Hour	Deterministic (Single Scenario) Plans						Stochastic
	Base	W1	W2	W3	W4	Avg.	
P&B/24-Set 1	21.28	23.75	21.16	1.85	23.09	18.22	24.38
P&B/24-Set 2	20.29	23.00	22.13	2.43	23.27	18.23	24.50
P&B/48	20.20	23.76	22.41	1.95	23.73	18.41	25.09
Hybrid/24-Set 1	22.43	22.80	21.13	1.93	22.47	18.15	24.44
Hybrid/24-Set 2	21.09	23.54	22.54	2.58	23.96	18.74	24.97
Hybrid/48	20.34	23.10	21.31	2.05	24.49	18.26	25.40
DCOPF/24-Set 1	22.36	22.05	21.43	2.30	22.78	18.18	24.85
DCOPF/24-Set 2	21.32	23.55	22.57	2.92	24.33	18.94	25.17
DCOPF/48	20.42	22.57	21.58	2.41	24.77	18.35	25.69
Null Plan (*x* =0) Cost (*NPC*)				887.90			

Table VII shows the benefits achieved by different plans obtained by comparing their "true" cost $C(x)$ to that of the null plan $C(\underline{x})$. The upper bound of benefit is $25.69B (the value of the plan from the model with all enhancements, last entry in next-to-last row). Several trends are noticeable. First, deterministic models (especially based on scenario W3) often perform poorly relative to stochastic models. The benefits of plans generated by stochastic models are consistently higher than plans from the five deterministic models (one per scenario) in the same row. The large variation among deterministic models shows that choosing the wrong scenario for planning can result in large regret. On average, stochastic plans achieved $6.68B more benefits compared to deterministic plans, which represents 26% of the maximum benefits.

Second, for the enhancements of temporal granularity and power flow representation, the improvements in "true" cost are consistently small and their sign can vary. For example, for both 24-hr plans generated from the base-case deterministic/DCOPF model, "true" benefits actually *decrease* when using higher temporal granularity (48 hrs). However, when stochasticity is considered, the benefit of adding hours is always positive.

The third trend is that a simple stochastic model (P&B network/24 hrs) can achieve most (95%) of the potential benefit.

The results from that table are used to derive the VOME values (Table VIII). Including multiple scenarios (stochasticity) is the most valuable enhancement by over an order of magnitude, and also greatly exceeds the benefit of unit commitment.

TABLE VIII. VOME AND ASSOCIATED RANGES (BILLION 2014US$)

Enhancement	Stochasticity	Temporal Granularity	P&B to Hybrid	Hybrid to DCOPF
VOME ($)	6.68	0.30	0.16	0.20
Fraction of total benefit	26.0%	1.18%	0.62%	0.78%
Max ($)	7.34	0.695	0.310	0.305
Min ($)	6.22	-0.21	-0.15	0.090

Although space does not permit us to describe the individual transmission plans *x* in detail, we can note one important pattern. This pattern is that hybrid models tend to over-invest in backbone reinforcement. Table IX shows the backbone reinforcement cost of plans generated by different models: hybrid models universally invest more lines than the P&B and DCOPF models. This is likely because the hybrid model treats all new grid reinforcements as controllable DC lines, while imposing Kirchhoff's voltage law on the existing grid. This could result in an exaggeration of the value of new transmission and thus over-encourage investment. In contrast, The simpler P&B model is not so biased towards new investment because it treats all lines (albeit incorrectly) as having controllable flows.

TABLE IX. FIRST STAGE BACKBONE INVESTMENT GENERATED FROM DIFFERENT MODELS (BILLION 2014US$)

Power Flow/ Hour	Deterministic					Stochastic
	Base	W1	W2	W3	W4	
P&B/24-Set 1	0.53	0.88	1.16	0.37	0.53	0.55
P&B/24-Set 2	0.37	0.52	1.46	0.37	0.37	0.53
P&B/48	0.37	0.70	1.16	0.37	0.37	0.55
Hybrid/24-Set 1	1.20	2.72	1.95	1.20	1.20	1.98
Hybrid/24-Set 2	1.20	1.02	1.66	1.20	1.20	1.84
Hybrid/48	1.18	2.72	2.28	1.20	1.20	1.84
DCOPF/24-Set 1	0.56	1.35	1.16	0.56	0.56	0.72
DCOPF/24-Set 2	0.56	1.00	1.64	0.56	0.56	0.72
DCOPF/48	0.56	1.05	1.16	0.56	0.56	0.72

VII. CONCLUSIONS

This paper has presented a framework to calculate the economic value of model enhancements (VOME), in terms of expected improvements in the probability-weighted present worth of system costs resulting from changes in immediate transmission investments. We apply the concept to a large-scale, long-term planning model for the WECC transmission network. Four types of enhancements, including stochasticity (multiple long-run scenarios), finer temporal granularity (operating hours), improved network modeling, and inclusion of unit commitment costs and constraints, are investigated.

The results show major benefits from considering uncertainty using multiple scenarios of technology, policy, and economics, but less benefit from the other potential enhancements. These benefits are as large as 26 percent of the overall benefit of building new transmission lines between 2015 and 2024 over and above the lines already included in the WECC Common Case [5].

These results imply that considering long-run uncertainties is potentially highly beneficial in transmission planning. Also, a simple model with a small set of hours and a pipes-and-bubbles power flow simulation can potentially yield a plan that achieves most of the potential economic benefits. On the other hand, planning deterministically based on the wrong scenario concerning future policy, economics, or technology can result in a huge economic regret. These results suggest the following practical approach to optimizing network reinforcements: start with a plan generated by optimizing a simple stochastic model, and then use it as a starting point for heuristic search for a better set of first-stage network reinforcements, using the most sophisticated model available to test the solution.

These particular VOME results do not necessarily apply to other regions or planning problems. Nonetheless, they indicate that quantifying the economic value of model improvement is practical and can provide useful insights not only for users of transmission planning models but also for other types of planning optimization problems in power and other infrastructure systems.

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