Value of Model Enhancements: Quantifying the Benefit of Improved Transmission Planning Models

Qingyu Xu[1], Benjamin F. Hobbs[1*]

[1]Whiting School of Engineering, Johns Hopkins University, Baltimore, USA
[*]bhobbs@jhu.edu

Abstract: A framework to quantify the value of model enhancements (VOME) in transmission planning models is proposed and applied to a case study of the large-scale, long-term planning of the Western Electricity Coordinating Council (WECC) system. The VOME, which is closely related to the concept of the value of information from decision analysis, quantifies the probability-weighted improvement in the system performance resulting from changes in decisions that result from model enhancements. The WECC case study shows that it is practical to quantify VOME and illustrates the type of insights that can be obtained. The values of four types of model enhancements are compared. The results show major benefits from considering long-run uncertainty using multiple scenarios of technology, policy, and economics; these benefits are as much as 14% of total benefits of new transmission built in the first ten years. But less benefit is obtained from more temporal granularity, more complex network representations, and inclusion of unit commitment constraints and costs. This framework can be applied to quantify the value of model enhancements in any planning context, such as integrated resource planning.

Nomenclature

$C(x)$	Expected present worth of system cost of making decision x, based on the model with all enhancements
$E_i(\omega)$	Binary parameter: if $E_i(\omega)$ = 1, then enhancement i is included in the model with setting ω; if zero, then the enhancement is excluded. For instance, if there are three candidate enhancements, then $E_1(\omega^*) = 1, E_2(\omega^*) = 0, E_3(\omega^*) = 1$ indicates a model with only Enhancements 1 and 3 implemented.
I	Set of enhancements, indexed by $i, j = 1\ldots n$
x_ω	Optimal first stage transmission investments ("decision") from a model with enhancements setting specified by ω. (E.g., x_{ω^*} , where $E_1(\omega^*) = 1, E_2(\omega^*) = 0, E_3(\omega^*) = 1$, 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 the model with all enhancements (i.e., $E_i(\omega)$ = 1 for all i).
ω	Model enhancement setting, describing what enhancements are included in the model formulation.
Ω_i	The set of all possible permutations of enhancements other than i

1. Introduction

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

Planning processes for transmission are necessarily complex. Permitting and construction take on the order of a decade. This fact, 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 [2]. Also, planning should 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, although many power markets have unbundled transmission from generation, grid planners need to consider how generation mix and siting are affected by where and when lines are added. This is called "proactive" transmission planning [3].

In summary, transmission expansion planning (TEP) models are complex because they need to consider entire regions, multiple decades of costs [4], generation-transmission investment interactions [3], and uncertainty in fundamental drivers [2, 5], as well as numerous technical and economic details.

However, models for transmission planning cannot be arbitrarily complex because computation capabilities limit the size of models that can be solved. As solvers and hardware improve, planners can add features to planning models to make them more realistic, but not all desired features can be accommodated. Thus, planners always face trade-offs when 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 can easily grow to several billions of variables and constraints. Thus, a planner must choose which features of the real system to represent, which to omit, and what approximations to use. Choosing which features to include in a model is difficult and should ideally consider how much transmission plans would improve as a result of alternative model enhancements.

On the other hand, the need for TEP model enhancements has motivated a rich literature (see the review in Section 2). But which model enhancements would most improve transmission plans? This paper is concerned with the question: *Can we quantify an economic index to meaningfully compare the value that alternative model enhancements might provide to transmission planning?* To the best knowledge of the authors, a systematic and quantifiable framework to provide such information has not been proposed.

The purpose of this paper is to provide a general, systematic framework for quantifying the economic value of model enhancements (VOME). The goal is not to propose new technical or economic enhancements *per se* to TEP models; rather, the framework is intended to provide a meaningful economic index to enable planners to systematically compare and select possible enhancements, considering how they would improve the cost of the resulting plans. This is the first time that an index has been proposed for comparing the economic value of alternative enhancements of models for energy investment planning together with a practical procedure for quantifying that value.

As an illustration, we apply this framework to the Western Electricity Coordinating Council (WECC) using a realistic 300-bus network [6] based on WECC's 2024 Common Case database [7]. For the first time, the benefits of considering improved representations of long-term uncertainty and short-term variability are systematically quantified and compared. Two other enhancements are also valued in economic terms: alternative network representations and inclusion of unit commitment constraints and costs. The case study illustrates, in concrete terms, the types of useful insights and recommendations that can be obtained from applying the framework.

The paper is organized as follows. In Section 2, we briefly review some enhancements that have been proposed for transmission planning models and related models. Then in Section 3, a systematic framework for calculating the value of model enhancements (VOME) is presented. In Section 4, we describe the base planning model, the WECC case study environment, and the tested enhancements. In Section 5, we summarize illustrative insights regarding which enhancements have the most value in order to demonstrate the usefulness of VOME, and Section 6 provides some conclusions.

2. Literature Review

Researchers and software vendors have recommended various enhancements to power system planning optimization models (Table 1) with the goal of providing useful information and better performing plans. In this section, we summarize some of the enhancements that have been proposed in recent years (detailed reviews can be found in [8], [9]). These can be roughly grouped into eight categories ranging from uncertainty treatment to the consideration of generation and transmission coordination. While the surveyed literature offers theoretical and case study-based arguments for the value of individual enhancements, careful comparisons across categories are rare. For example, no one has quantified whether transmission plans would be more improved by consideration of a wider range of long-term uncertainties (load-growth, etc.) or by including finer short-term variability resolution (wind and solar availability). This review highlights the need for a practical framework to make this type of comparison.

1. Long-term uncertainty: This enhancement recognizes long-run uncertainties in the fundamental drivers of the economic value of transmission, such as generation capacity mix, load growth, technology improvements, or policy, rather than considering just one "deterministic" or "base case" scenario [10]. Since restructuring has separated the responsibilities for expansion and transmission planning in many markets, some researchers have demonstrated that the generation mix can be usefully treated as uncertainties faced by transmission planners, such as in Ref. [11]. However, others have argued that generation siting and mix should not be defined as scenarios, but rather as variables in a co-optimization that respond to the transmission grid configuration [3].

Table 1 Some Proposed Enhancements to Transmission Models

Category	Examples
1. Long-term uncertainty consideration	Deterministic; multiple scenarios concerning generation capacity; load growth, policy, fuel prices, etc.
2. Short-term uncertainty/variability consideration (operating hours)	More hours/yr; load duration curve vs. chronological hours
3. Long-term temporal granularity (investment stages)	Static; dynamic: more than one investment stage over the planning horizon
4. Generation representation	Generation dispatch, with/without unit commitment
5. Spatial granularity	Number of nodes in network; bus aggregation level
6. Network representation	Pipes-and-bubbles; hybrid DC; DC OPF; linearized AC; AC OPF; line losses
7. Transmission-generation-storage investment coordination	Reactive; proactive
8. Security and others	N-K security, extreme events

A rich pool of tools has been developed to enable consideration of uncertainty within TEP. Many of these tools are applicable both to long-run uncertainties and short-run variability, discussed next. Two of the most widely cited methods are scenario-based stochastic programming [10-15] and uncertainty-budget-based adaptive robust optimization [16-20]. Other tools for modeling long-run uncertainties in planning include chance-constrained programming [21], conditional value at risk (CVaR) constraints [22], adaptive programming [23], and most recently, robust (data-driven) stochastic programming [24]. Simpler heuristic methods also attempt to identify plans that are "robust" to an uncertain future. Examples are MISO's "Multi-Value Projects" [25] and the CAISO's "least regret investments" [26], which identify network investments that are attractive under most scenarios.

2. Short-term uncertainty/variability (operating hours): We define short-term uncertainties as uncertain variables with a time scale of minutes to months. For example, with the increasing penetration of the hard-to-predict intermittent power, e.g., wind and solar, researchers have treated their availability as uncertainties, as in [12, 13]. Indeed, it has been argued that having more operating hours per year in a transmission model is more important than representing Kirchhoff's voltage law [27]. However, others who have studied the impact of more temporal granularity on generation expansion [28] have concluded that adding dispatch periods slows down computations while having little apparent effect on generation expansion decisions.

3. Long-term temporal granularity: Though many TEP models are based on a single investment decision stage ("one-shot" or "static" planning) [29], dynamic TEP models [4] have become increasingly popular because of improved computational abilities and the need for plans to include timing of investments.

4. 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. Representations of commitment and ramp constraints, which limit generation flexibility, can improve estimates of the cost of integrating variable renewables [30]. Ho et al. [6] implemented linearized unit commitment constraints [31] in transmission optimization. Their results indicate that limiting the flexibility of generators has more impact on transmission economics in systems with slow baseload units.

5. Spatial granularity: Adding more zones or network nodes is another potential enhancement. Ref. [32] showed that more spatial aggregation could penalize photovoltaics since it mixes solar resources of good and bad quality. Most recently, Lumbreras et al. [33] used a zonal model to guide nodal transmission expansion. However, the loss of fidelity was not discussed.

6. Network representation: The "pipes-and-bubbles" (transshipment) networks used in many planning models have been proposed to be replaced by more realistic but practical to solve approximations of power flow, such as the DC OPF [34]. However, as Ref. [28] 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 [35]. There, existing AC line flows are modeled using angle difference/flow relationships (as in the linearized DC load flow), but all new lines are modeled 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 linearized AC power flow [36], high-voltage DC power flow [37], and consideration of losses [36, 38]. With present computational capabilities, TEP optimization models with full AC power flow can only be solved by meta-heuristic [39] or constructive heuristic methods [40].

7. Transmission-generation-storage investment coordination: Transmission optimization models traditionally treat generation investment locations and types as exogenous "build out" scenarios [16-19, 21, 29, 41]. This is termed "reactive" planning. However, proactive transmission planning [3], which considers how generation investment decision might be affected by grid reinforcements, can lead to less costly plans because they consider how grid reinforcements can lead to savings in both capital and operating costs of generation [42]. 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 [3, 10, 42]. If instead generators behave strategically, multi-level transmission planning models can be used [3, 12, 43-45], but are much more computationally intensive. Most recently, researchers started to add storages investment as an option into TEP to captured the mutual impacts between transmission and storage investment [46]. Researchers have also expanded the scope of TEP beyond the electricity sector to include the representations of upstream gas network constraints [47].

8. Security and Other Enhancements: These include proposals to incorporate N-1 security constraints [14], N-K security constraints [48], and extreme events such as blackouts [49] and earthquakes [50].

The impacts of the above enhancements on solutions to TEP optimization models have often been assessed through sensitivity analyses [6, 28, 32, 51]. These analyses usually focus on changes in decisions (such as locations or amounts of investments), rather than on the improvement in economic performance of recommended plans; i.e., the improvement in expected costs if solutions from the more sophisticated model were to be implemented. In one exception, the cost savings resulting from proactive transmission planning were investigated in [42], but they were not compared to the value of other kinds of enhancements.

To the best of our knowledge, a systematic framework for researchers and planners to compare the economic value of alternative modeling enhancements has not been proposed previously. The contribution of this work is to present such a framework to prioritize model improvement efforts and to illustrate its potential usefulness through a realistic case study.

3. Value of Model Enhancement (VOME)

In this section, we first define the value of model enhancement (Section 3.1). We then propose a framework for implementing this idea in transmission optimization modeling (Section 3.2). Finally, in Section 3.3 a metric is proposed that compares VOME to the overall benefits of transmission expansion, which is useful for gauging the practical significance of VOME.

3.1 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 if perfect information is provided about future conditions. 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 the deterioration in the solution if the model is simplified, i.e., how much solution performance is sacrificed, 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 a different 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 "true" cost is $C(x_B)$. (We put the "true" into quotes because the actual expected cost cannot be known, but this is the best estimate that can be obtained. These "true" costs are of course subject to uncertainty because of the inability to consider all possible scenarios and because the probabilities used are themselves uncertain. Further, any estimate of such costs is itself subject to error because of model and data limitations even in the most sophisticated model.) The VOME of this enhancement (more constraints) is then calculated as $C(x_A) - C(x_B)$, which is the decrease in "true" cost resulting from using the enhanced model to make decisions.

However, we must overcome at least three conceptual difficulties to successfully calculate the 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 (what we call "enhancement settings" ω): AC, BC, AD, BD. This also means that there are at least 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* = $[0.5C(x_{A1}) + 0.5C(x_{A2}) - C(x_B)]$. A 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 of the scenarios and their probabilities gives a plan x_s. Then the value of this enhancement is $[p_1C(x_1) + p_2C(x_2)] - C(x_s)$. This is the same as the definition of the expected cost of ignoring uncertainty (ECIU) (also known as the value of the stochastic solution) in classical decision analysis [52].
2. When calculating the VOME for one particular enhancement when other enhancements are also under consideration, we *calculate 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 $N_i = 2^3$ possible combinations of those features.) Then we average these N_i cost differences.
3. We *define the "true" system cost $C(x)$ as the best obtainable estimate of the 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 5.3 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:

$$VOME_i = \frac{1}{N_i}\sum_{(\omega_0,\omega_1)\in\Omega_i}\left(E\left[C\left(x_{\omega_0}\right)\right] - E\left[C\left(x_{\omega_1}\right)\right]\right) \quad (1)$$

In this formulation, x is the decision (here, the immediate (first stage) transmission investment) obtained by a model with formulation setting ω. The set Ω_i is composed of all the pairs of model formulations (ω_0, ω_1) in which:

- $E_i(\omega_0) = 0$, $E_i(\omega_1) = 1$ (i.e., the two model formulations being compared are without and with enhancement i, respectively), and
- $E_j(\omega_0) = E_j(\omega_1), \forall j \neq i$ (i.e., enhancements other than i are the same in the two models whose costs are compared).

In other words, Ω_i is the set of all possible pairs of models involving permutations of enhancements other than i. N_i is the number of model pairs within Ω_i. 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.

3.2 VOME Calculation in Transmission Planning

Before we implement VOME for transmission planning models, we lay out three basic assumptions of the VOME calculation procedure.

First, all our *transmission planning models are in the form of transmission-generation co-optimization* [3]. Thus, the optimal transmission plan anticipates how generator investment and spot markets will react to grid changes, under the assumption that generation decisions 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 the 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 investors make decisions with full information on how the grid design would affect prices*, based on the information that would be provided by a model with all enhancements, even if transmission plans *x* are based on more naïve assumptions from a simpler model. This can be viewed as the competitive energy market's reaction to grid reinforcements *x*, in which generators use the most sophisticated possible model to project prices, even if the transmission planner is naive.

Alternative assumptions are possible when calculating VOME. For instance, oligopoly could be assumed instead of competitive energy markets. Or first stage generation investments could also be included in x, in which case VOME would quantify the value of better models for combined transmission-generation planning.

Combining all three assumptions, we calculate VOME following the procedure in the flowchart in Fig. 1, where:

- x is the first stage transmission investments from a model with an assumed set of enhancements.
- $C(x)$ is the "true" system cost obtained by simulating the optimal generation decisions and second-stage transmission investments in response to x.

VOME for an enhancement is then obtained by (1).

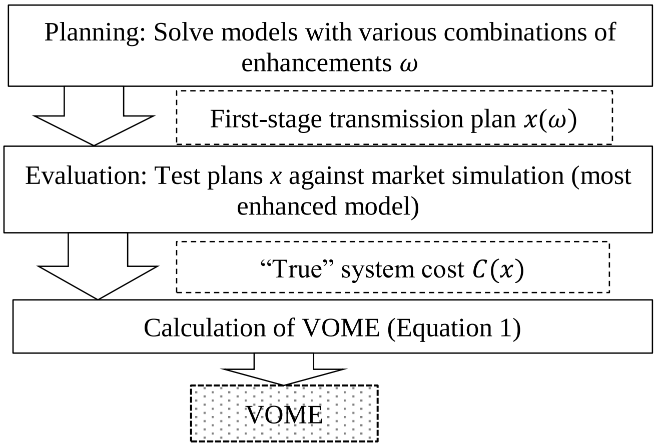

Fig. 1. *Procedure for calculating VOME in multistage transmission planning*

3.3 A Benefit Metric for Transmission Planning

To place VOME in context, we compare it to the overall benefit of building new transmission. If VOME for a particular model feature 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 new transmission is calculated as follows. Assume that it is feasible to build no lines at all in the 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 the reduction in system cost relative to the null plan: $NB(x) = NPC - C(x)$.

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

Any plan x, other than the optimal plan, might achieve some but not all of the possible benefits. Thus, we can define the proportion of possible benefits that are realized by building x ("economic benefit recovery") as $BR(x) = NB(x)/UPB$. The $BR(x)$ metric is a useful relative metric when comparing different transmission plans, since the change in the overall objective function resulting from transmission investment is usually a small part of total system cost, which is much larger because it also includes all generation capital and operating costs. However, the calculation of VOME, which can be solely conducted by following Fig. 1, does not rely on the benefit recovery metric; rather this metric is a simple tool to help the reader interpret the significance of the benefits of enhancement, i.e., VOME.

4. Experimental Design

We now describe how we implemented VOME in a realistic transmission planning study. Results form that study are provided in Section 5 that illustrate the types of insights that can be obtained about the economic value of improved model features. 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, which is a 300-bus network for WECC. Finally, we describe how the four enhancements are added to the model.

4.1 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 [53], and is based on [10] as elaborated in [6]. JHSMINE is a scenario-based, two-stage stochastic programming model (Fig. 2, where one of the scenarios is explicitly shown), in which first-stage (here-and-now) decisions made today (year 0) include immediate transmission and generation investments that will be online in year 10, while recourse decisions are new transmission/generation investments that come online 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.

The objective function is the net present value of the system cost, which is composed of discounted cash flow in each operating year (year 10 and year 20 in Fig. 2). The cash flows include the overnight cost of building generation and transmission assets, as well as the system operating cost including the unit commitment and dispatch expenses. 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, each with a different set of 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 right-hand sides of constraints), and policy uncertainties, such as carbon prices.

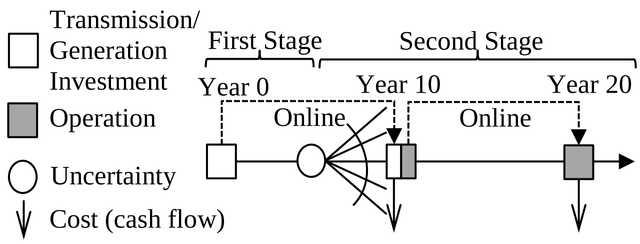

Fig. 2. *Diagram of JHSMINE chronology*

4.2 Case Study Environment: 300-bus WECC system

We discuss four sets of assumptions: network reduction, existing generation mix, new generation investments, and network investment possibilities.

First, the system is a reduction of the WECC Common Case 2024 [7] (details in [6, 54]). The reduced network includes 328 nodes and 530 lines (Fig. 3), in which 249 of the nodes are preserved existing nodes in the original network (230 kV or above), while 244 lines (red lines in Fig. 3) are preserved existing lines from the original network. The preserved paths divide the whole network into 26 regions [55].

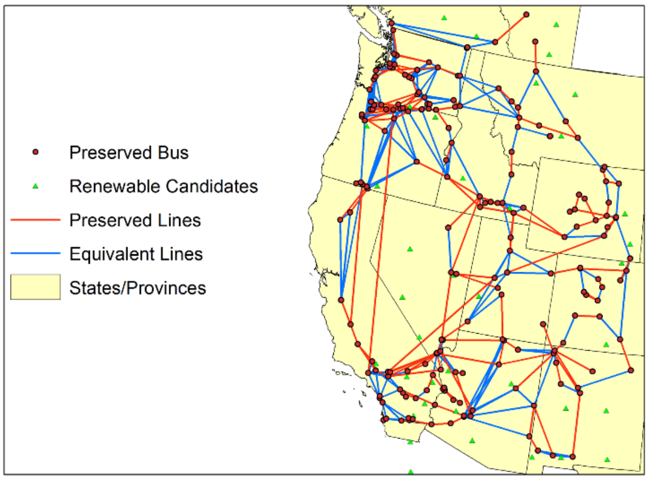

Fig. 3. *WECC case study network reduction*

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 of the 26 regions just mentioned. The remaining 53 nodes in the network are candidate sites for renewable investment (green triangles in Fig. 3). Their locations and potential capacities are derived from [56]. 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 [57].

Finally, transmission investment candidates can be divided into two categories: backbone reinforcements and renewable access. Backbone reinforcements are defined as having the characteristics of the existing line with the 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 reinforcements in the WECC "Common Case" [7] have been brought online by 2024, all transmission investment variables in our model are incremental over and above the Common Case.

4.3 Candidate Model Enhancements

We compare the economic value of four possible model enhancements using VOME.

4.3.1 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 modeling by defining a new continuous decision variable as the in-operation minimum run capacity (in MW), and linearizing every set of unit commitment constraints (start up, shut down, ramp rate limit and minimum startup and shutdown time) around it [31]. The effect of linearized unit commitment is two-fold: fewer binary variables, thus speeding up solution times; and enabling the model to include generation capacities as decision variables. Only thermal generation technologies are subject to these flexibility constraints.

4.3.2 Network Modelling: More physical realistic models of power flows will help the TEP model to better characterize how grid reinforcements affect transmission capability, dispatch, and, ultimately, costs.

The basic model is a pipes-and-bubbles (P&B, or transshipment) power flow model that does not enforce Kirchhoff's voltage law. This model can be enhanced by implementing a linearized DC power flow model using a "B-theta" formulation, which includes the voltage law by explicitly modeling phase angles, but assumes unit voltage and negligible resistance [58]. Flow on a line equals the phase angle difference across the line divided by impedance; we enforce this for new lines by disjunctive constraints [34] that use 0-1 variables to represent absence/presence of the line. An intermediate level of enhancement is hybrid flow modeling [35], as defined in Section 2, above.

4.3.3 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 yield a better representation of load and renewable temporal distributions and correlations.

The two 24-hour sets are generated using a methodology combining clustering and random sampling. First, based on the 8760-hourly profiles of load and intermittent resources availability (e.g., hydroelectricity, wind, solar, etc.), the 8760 hours are grouped into 24 clusters, each of which has a different size ($N_c, c = 1\ to\ 24$) . Second, one hour from each cluster is randomly selected to generate a single sample hour set, and this step is repeated 80,000 times. When using a 24-hour sample in the TEP model, each hour is assumed to be repeated N_c times. Finally, two mutually exclusive 24-hour samples are selected. Each sample set of hours is chosen by minimizing the deviation of first and second moments of all profiles between the 24-hour sample sets and the original 8760 hourly data, while constraining the sampled coincident peak to be at least of 85% of the peak of 8760 hourly data. The 48-hour set is the union of these two 24-hour sets, with the duration of each hour halved. Examples of the resulting load duration curves are shown in Fig. 4.

4.3.4 Multiple Long-Run Scenarios: Reasons for considering long-run uncertainty are discussed in Sections 2 and 3, above, and in more detail in [9]. Here, we take stochasticity into consideration by two-stage stochastic programming [52]. This method uses an expected cost objective to decide which stage 1 investment commitments ("here and now" decisions) to make before it is known how uncertainties such as load growth will be resolved, while making "wait and see" (stage 2) decisions afterward. Although, as mentioned in Section 2, 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.

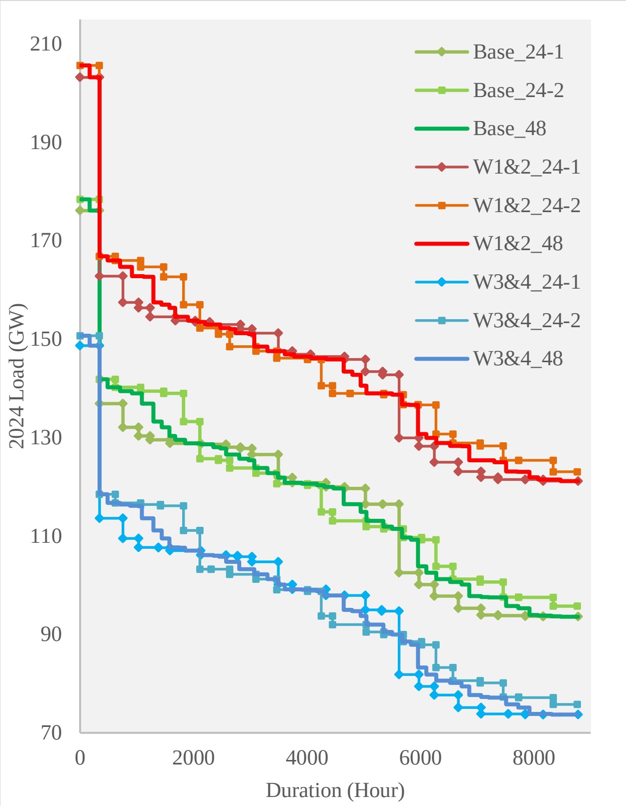

Fig. 4. *WECC-wide year 2024 load duration curves for different hour sets (red, green, blue = Scenario W1 and W2, Base Scenario, and Scenario W3 and W4, respectively)*

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, with 5 second stage scenarios). In the latter model, we assume the 5 scenarios are equally likely. Parameters values for these five scenarios (Table 2) are either directly from WECC's 2013 study cases [59] or developed with the help of a WECC technical advisory group [6]. As an example of the long-run scenario definitions, the load duration curves of different hour sets in different scenarios in 2024 is shown in Fig. 4.

Table 2 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

For the above four enhancements, two groups of experiments were undertaken as follows. First, the effect of generator unit commitment 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 analysed 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.

5. 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 inclusion of long-run uncertainties via multiple scenarios.

5.1 Model Size and Computation Time Comparison

First, in Tables 3 and 4, we display the change in model size and solution times under alternative enhancements.

Table 3 Model Size and Solution Time with Various Enhancements (Deterministic/Single Scenario Cases)

	Deterministic (14 candidate backbone lines x 2 stages)					
Network	P&B	Hybrid	DC OPF	P&B	Hybrid	DC OPF
Hours	24	24	24	48	48	48
# Constr. (million)	0.23	0.26	0.26	0.46	0.51	0.52
# Vars. (million)	0.18	0.19	0.19	0.36	0.36	0.36
Solution Time (minutes)	0.5	6.67	13.94	1.17	23.19	51.79

Table 4 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
#Constr. (million)	1.15	1.25	1.26	2.25	2.49	2.51	4.97	17.5
#Vars. (million)	0.90	0.93	0.93	1.74	1.86	1.86	4.19	7.61
Sol. Time (hours)	0.06	1.97	15.46	0.25	13.49	34.67	0.77	25.8

All these models are mixed integer linear programs (MILPs) and are solved to a MILP gap of 10^{-4} (relative to the objective function value) to avoid possible biases in our conclusions introduced by large gaps. All models were solved on a 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 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 30 seconds.

Note that only about 30 seconds are needed to generate an optimal plan for the most simplified model, while more than one day was required to solve a model with the most enhancements.

5.2 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 5. 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* = $890.38B (2014 present worth). In contrast, with about $3.18B of first-stage transmission investment x resulting from the unit commitment model with 5 scenarios, the system's "true" cost $C(x)$ is $35.39B lower, which we treat as the upper bound *UPB* of the net benefit of transmission.

In contrast, if unit commitment is *not* included, more renewable interconnection transmission is constructed, with a total first stage transmission investment of $3.52B, and a $C(x)$ that is $35.28B lower than *NPC*. Thus, the model enhanced with unit commitment gave a more conservative plan x, whose benefits are $0.11B billion higher (= $35.39B-$35.28B) 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 5 Costs and Expected Benefits of First Stage Transmission Plans Generated by Model without/with Unit Commitment Enhancement (billion 2014 US$).

Planning Model	No UC	With UC
Backbone Transmission	0.80	0.80
Renewable Transmission	2.72	2.38
"True" Cost $C(x)$	855.11	854.99
Net Benefit (*NB(x)*) relative to null plan	35.28	35.39
Benefit recovery *BR(x)*	99.7%	100%
Null plan cost (*NPC*)	890.38	

5.3 VOME of Temporal Granularity, Power Flow Representation and Stochasticity

To estimate the VOME of the three other 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).

(Also for the same reason, requirements for spinning reserves, which would double the number of operating variables for conventional generators, are not modeled in this section. However, the inclusion of generation spinning reserves can be viewed as an enhancement of TEP, and therefore can be investigated by VOME as well. The results showed a nearly negligible VOME of $0.007B (0.02% of the $35.39B benefit of transmission) for including spinning reserves compared to, for instance, a VOME for UC of $0.11B (0.32%).)

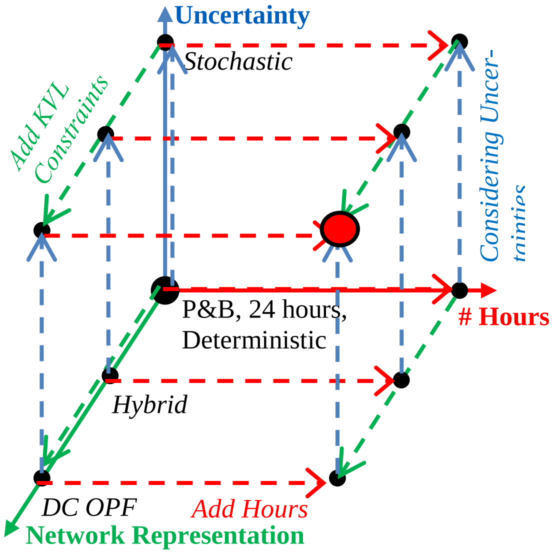

Fig. 5. *The conceptual framework for VOME calculation of Temporal Granularity, Network Representation and Stochasticity*

Fig. 5 is a visualization of how we implemented the definition of VOME from Section 3 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 (across the four to six arrows with the same color) is the VOME for the particular enhancement represented by the direction of the arrow (i.e., equation (1), above).

Table 6 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 UPB = \$40.58B (the value of the plan from the model with all enhancements, last entry in the next-to-last row). (Note that this differs slightly from the UPB for the model with unit commitment in Section 5.2.)

Several trends are noticeable in Table 6. 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 the five deterministic models in a given row shows that choosing the wrong scenario for planning can result in large regret. On average, stochastic plans achieved \$5.59B more benefits compared to deterministic plans, which represents 13.8% of the maximum benefits UPB.

Table 6 Net Benefits $NB(x)$ of First Stage Transmission x Generated by Different Models (Billion 2014US\$)

Power Flow/ Hour Set	Deterministic (Single Scenario) Plans						Stochastic
	Base	W1	W2	W3	W4	Avg.	
P&B/24-Set 1	36.84	37.91	38.40	21.93	34.75	33.97	39.67
P&B/24-Set 2	38.56	38.53	38.94	22.39	36.28	34.94	39.74
P&B/48 hrs	38.45	38.19	38.60	23.48	35.89	34.92	39.87
Hybrid/24-Set 1	37.54	38.47	38.81	19.60	35.71	34.03	39.66
Hybrid/24-Set 2	38.98	38.81	39.17	17.44	35.95	34.07	40.17
Hybrid/48 hrs	39.43	38.59	38.94	20.36	36.30	34.72	40.46
DCOPF/24-Set 1	37.69	38.87	38.92	19.64	35.17	34.06	39.79
DCOPF/24-Set 2	39.02	39.19	39.30	17.40	36.16	34.21	40.24
DCOPF/48 hrs	39.48	39.04	39.06	19.79	36.32	34.74	40.58
Null Plan (x =0) Cost (NPC)				788.93			

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, on average, for a model with deterministic and 48-hour enhancement, "true" benefits actually *decrease* when hybrid power flow is modelled instead of P&B power flow, resulting in a negative number in column 4, last row of Table 7. Hybrid modelling may distort plans by exaggerating the benefits of new lines (which are modelled as controllable DC lines whether or not they are actually AC) relative to existing AC circuits that are subject to Kirchhoff's voltage law. On the other hand, however, when stochasticity is considered, the benefit of adding hours is always positive.

Table 7 VOME for Three Enhancements (Stochasticity, Hours, Network) and Associated Ranges (Billion 2014US\$)

Enhancement	Stochas-ticity	Temporal Granularity	P&B to Hybrid Network	Hybrid Network to DCOPF
VOME (\$)	5.59	0.50	0.049	0.080
Fraction of total benefit	13.8%	1.24%	0.121%	0.198%
Max (\$)	5.88	0.68	0.59	0.12
Min (\$)	4.95	0.17	-0.41	0.014

The third trend is that a simple stochastic model (P&B network/24 hrs) can achieve most (98%) of the potential benefit.

The results from Table 6 are used to derive the VOME values (Table 7). Consistent with the trends just discussed, the inclusion of multiple scenarios (stochasticity) is the most valuable enhancement by over an order of magnitude. Its value of \$5.59B (present worth) is also far greater than the VOME of including unit commitment (\$0.11B) and spinning reserves (\$0.007B), calculated earlier.

Of course, for other planning problems, the relative value of these enhancements may be quite different; for instance, for a system with many slow moving coal plants and a much higher renewable penetration, the number of hours and inclusion of unit commitment would likely have a significantly increased VOME. The conclusion of this section is not that long run stochasticity is necessarily more important than other enhancements, but that TEP model improvements can have large tangible benefits in general, and that those benefits can be estimated.

6. Conclusion

This paper has presented a framework to calculate the economic value of model enhancements (VOME), in terms of expected improvement 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 compared.

We now return to the question raised at the beginning of this paper: *Can we quantify an economic index to meaningfully compare the value that alternative model enhancements might provide to transmission planning?* The answer, provided by the VOME methodology, is *yes*. The results for this particular case 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 13.8% (approximately \$5.59B) 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 [7].

These results imply that considering long-run uncertainties is potentially highly beneficial in transmission planning. To the best of knowledge of the authors, this is the first time that the benefits of considering long-term uncertainty versus short-term variability or other model enhancements have been systematically quantified and compared. This quantification framework and its result is particularly important in power systems with rapidly increasing renewable penetration and can be informative for planners who must trade off the number of futures and the number of hours to consider. However, only the stochastic programming technique for representing long-run uncertainties is discussed in this paper. Therefore, applying the VOME framework to compare and evaluate plan improvements resulting from other uncertainty-based planning techniques, e.g., robustness optimization, is a desirable extension of this research.

The results also imply that 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.

However, these particular VOME results do not necessarily apply to other regions or planning problems. Nonetheless, they indicate that systematically quantifying the economic value of model improvement is practical. The applications of VOME are not limited to the enhancements discussed in this work. For example, enhancement of TEP models by considering distributed energy resources (including generation, demand response and storage) is appealing given the increasing importance of those resources. Furthermore, VOME 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.

VOME can also be a very beneficial tool in transmission expansion processes that regularly update plans, e.g., the CAISO's annual transmission expansion planning process [60]. VOME can show which enhancements would be beneficial to the current TEP and therefore should be considered for the inclusion in the next planning cycle. For example, if the consideration of the long-run scenarios has significantly higher VOME than other candidate features, planners should put more effort into defining and enriching long-run scenarios in subsequent plans, such as what is currently being done in MISO [25], CAISO [60] and WECC [59].

7. Acknowledgment

This work is funded by the U. S. Department of Energy, U.S.A, the Western Electricity Coordinating Council, Utah, U.S.A., and the U.S. National Science Foundation.

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