What Transmission Investments Ought We Make Now?

Using Stochastic Programming for Regional Transmission Planning in the Face of Long-Run Regulatory, Economic, & Technologic Uncertainties

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Attached: Munoz et al. (2013) WECC example, van der Weijde & Hobbs (2012, excerpt) UK example

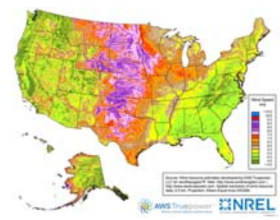
Outline

1. Introduction
2. Model Overview, Realistic Test-Case: WECC 240
3. Results
4. Conclusions

1.1 Introduction

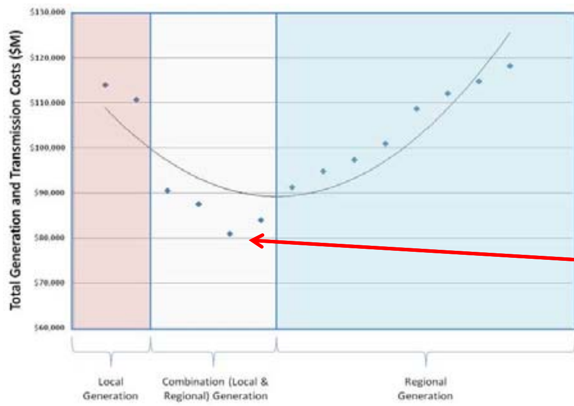
Solar Resources (NREL)

Wind Resources (NREL)



U.S. Transmission System

Zone Scenario Generation and Transmission Cost (MISO 2010)



Transmission Investments

Optimal:
Combination of Local & Regional Generation

1.2 The Challenge of Variability

January

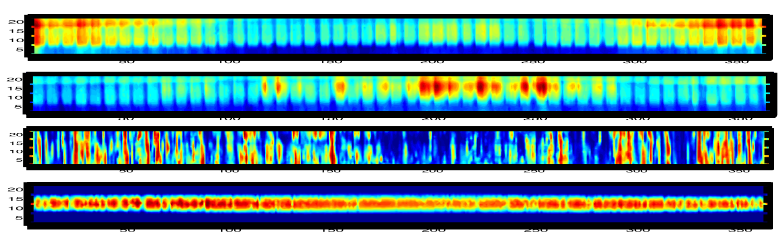
December

Load in Canada

Load in California

Wind in New Mexico

Solar in Arizona



Need to capture true economic value of renewables!

- System-wide analysis of transmission and generation investment alternatives
- Improve time resolution of operations subproblems

-> Traditional methods (e.g. load duration curves) only asymptotically valid

1.3 More Challenges

- Hyper uncertainty:
  - Fuel Costs
  - Demand Growth
  - Technology Costs
  - Carbon Tax
  - Demand Response
  - PEV
  - RPS
  - Distributed Generation
- Unbundled Electricity Market
  - Trans & gen planning separated
  - Transmission takes longer to build
  - Price signals guide gen investment

We need practical methods that can handle:

- Large-scale networks
- Renewable variability
- Long-run uncertainties
- Generators' response
- Kirchhoff's Laws

1.4 The New Paradigm

*"(c)apturing long-term benefits of transmission investments requires processes more akin to **integrated resource planning** in order to evaluate 'long-term resource cost' benefits (such as)… the ability to build new generation in lower-cost locations (and to)… find lower-cost (or higher-value) **combination of transmission and generation** investments to satisfy policy requirements, such as (renewable portfolio standards)"* (Pfeifenberger and Hou, 2012)

"Proactive" or "anticipative" planning in practice:

- FERC Order 1000 – Transmission Planning and Cost Allocation (FERC, 2013).
- California ISO (Awad et al. 2010).
- Eastern Interconnection States Planning Council (EISPC), "Co-optimization" studies (EISPC, 2013).

1.5 Transmission Planning in Practice

- Commercial tools used by ISOs and RTOs:
  - SIEMENS PSS-E
  - ABB GridView
  - Ventyx PROMOD IV

  Simulation, not optimization tools (O'Neill et al. 2012)

  - PSR NETPLAN

  Topology optimization capabilities, stochastic operations (e.g., hydro)
  Deterministic for regulatory conditions, economic drivers

- Treatment of uncertainty and hedging strategies:
  - MISO Multi-Value Projects (MISO 2010)
  - CAISO Least-Regrets Approach

"The "least regrets" approach can be summarized as evaluating a range of plausible scenarios made up of different generation portfolios, and identifying the transmission reinforcements found to be necessary in a reasonable number of those scenarios." (CAISO 2012)

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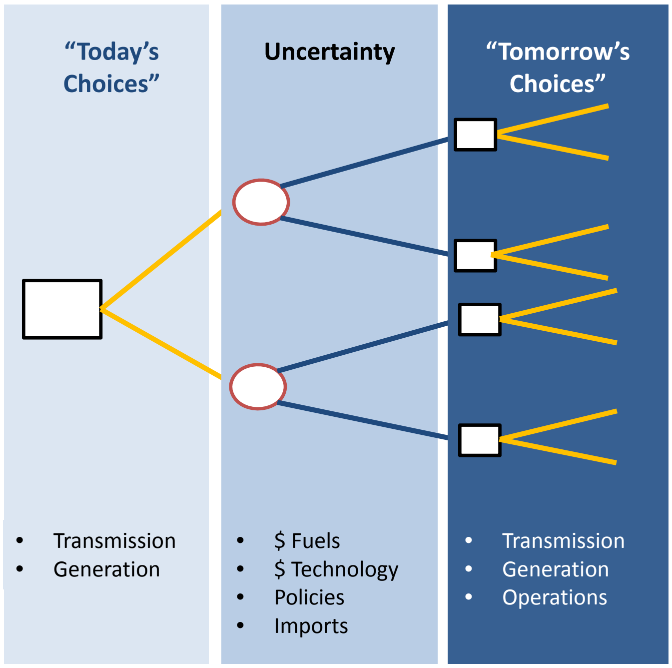
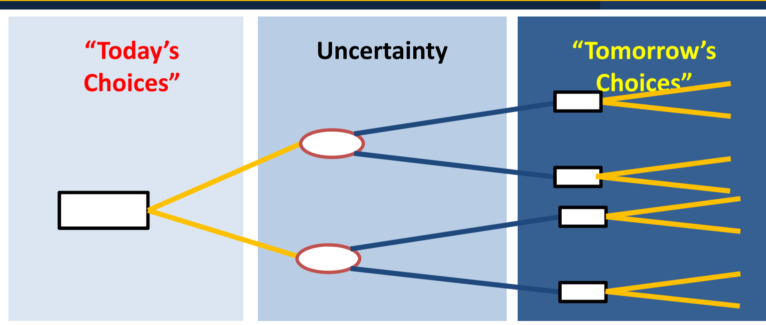
2.1 Multi-Stage Stochastic Transmission Planning



Assumptions

- **Aligned generation and transmission objectives**
  - Nodal pricing + Perfect Competition
- **Generation**
  - No unit commitment constraints/costs
- **Demand**
  - No demand response
- **Renewable targets met in most efficient way**

2.2 Multi-Stage Stochastic Transmission Planning II



$$\text{MIN} \quad C_1 X_1 + \Sigma_{\text{scenarios } S} P_S * C_2 X_{2,S}$$

$$A_{1,1} X_1 \leq B_1$$

$$A_{2,1,S} X_1 + A_{2,2,S} X_{2,S} \leq B_{2,S} \;, \forall S$$

- **Constraints include:**
  - Kirchhoff's Laws
  - Generator and transmission capacity / operating restrictions
  - Siting restrictions
  - Emissions cap, renewable portfolio standards

2.3 WECC 240-bus Test Case

WECC 240-bus system:
(Price & Goodin, 2011)

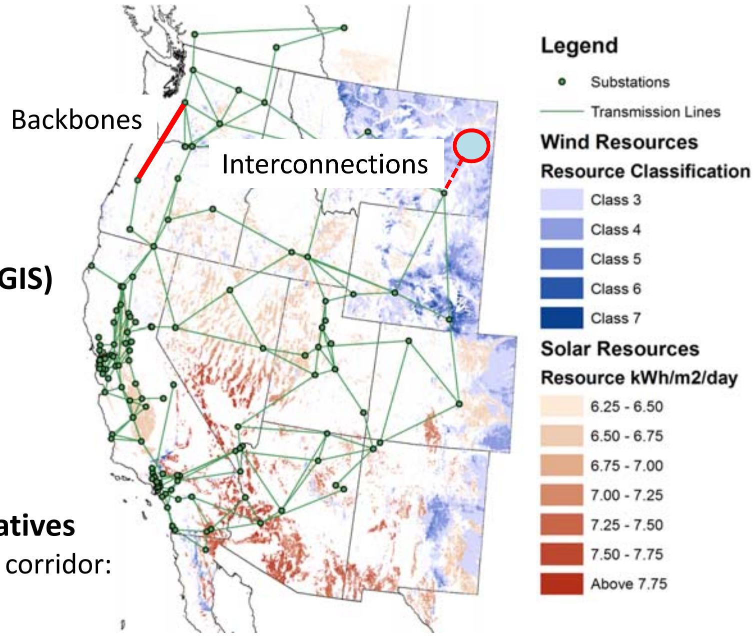
140 Generators (200 GW)
448 Transmission elements
21 Demand regions
28 Flowgates

Renewables data (Time series, GIS)
(NREL, WREZ, RETI)

54 Wind profiles
29 Solar profiles
31 Renewable Hubs (WREZ)

Candidate Transmission Alternatives
Maximum number of circuits per corridor:

2 for Backbones
4 for Interconnections to Renewable Hubs



2.4 Scenarios

- Focus on environmental policy and fuel prices

Differentiated State RPS	33% WECC-wide RPS	Carbon Cap & Trade
• State RPS • >75% from in-state resources • Average fossil fuel prices	• 33% WECC-wide RPS • Efficient REC markets • High fossil fuel prices	• 17% below 2005 levels by 2020 • 45% below 2005 levels by 2030 • Low fossil fuel prices

- Experiments
  - **Scenario Planning** (Deterministic)
  - **Stochastic Approach**
  - **Heuristics:**
    1. Heuristic I : Build lines needed in all the scenarios
    2. Heuristic II : Build lines needed in "most" scenarios (at least 2)

       "Least-regrets" or "Multi-Value Projects"

    3. Heuristic III : Build all lines

       "Congestion-free"

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3.1 Results

First-Stage Transmission Investments: Backbones

Approach	B19	B37	B56	B68	B72	B73	B74	B92	B95	B125	B133	B136	B137	B143	B151	B157	B168	B169	B201	B202	B218	B222	B237	B238
D-Carbon				1					1	1	1		1	2								2	1	2
D-33% WECC		1			1	1	2		1								1	1	1		1	1	2	
D-State RPS	2	1	1					2		2		1								1		1		2
Heuristic I																						1		
Heuristic II		1							1	1												1	1	2
Heuristic III	2	1	1	1	1	1	2	2	1	2	1	1	1	2			1							
Stochastic		1		1			2		1	2			1		1	1	1							

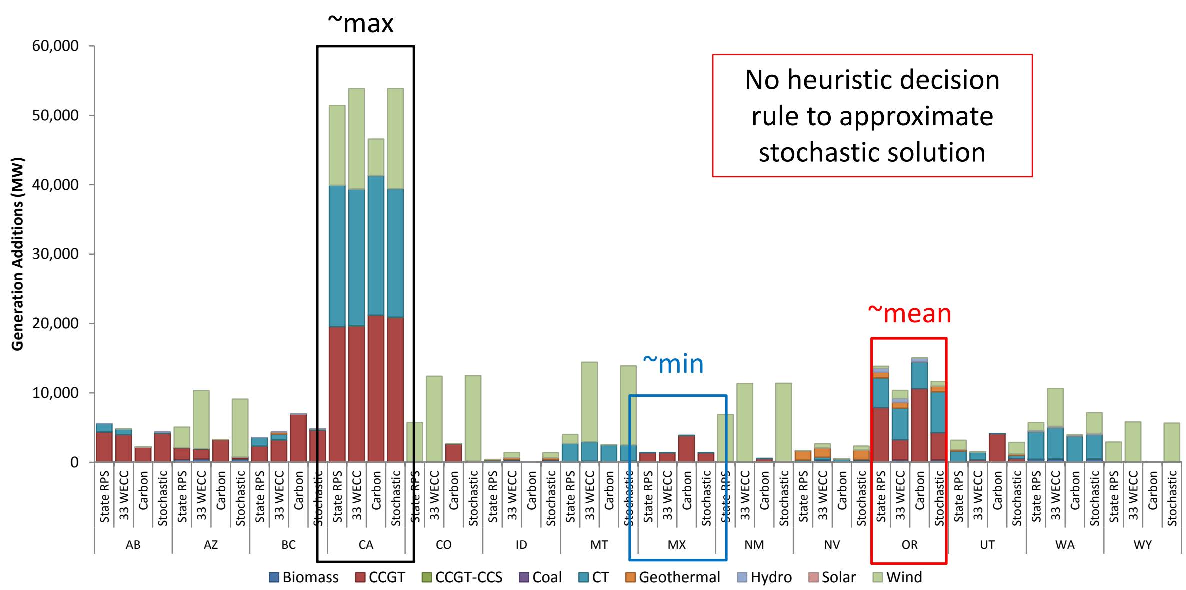
Flexible plans are suboptimal in retrospect!!

Interconnections to Renewable Hubs

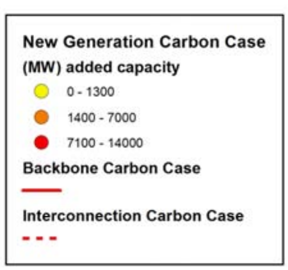
Approach	I2	I5	I6	I8	I9	I10	I11	I14	I20	I23	I24	I25	I26
D-Carbon												1	
D-33% WECC	1	4	1	3	1	1	2	1	1	1	1	1	
D-State RPS		2		2	1				1		1	1	1

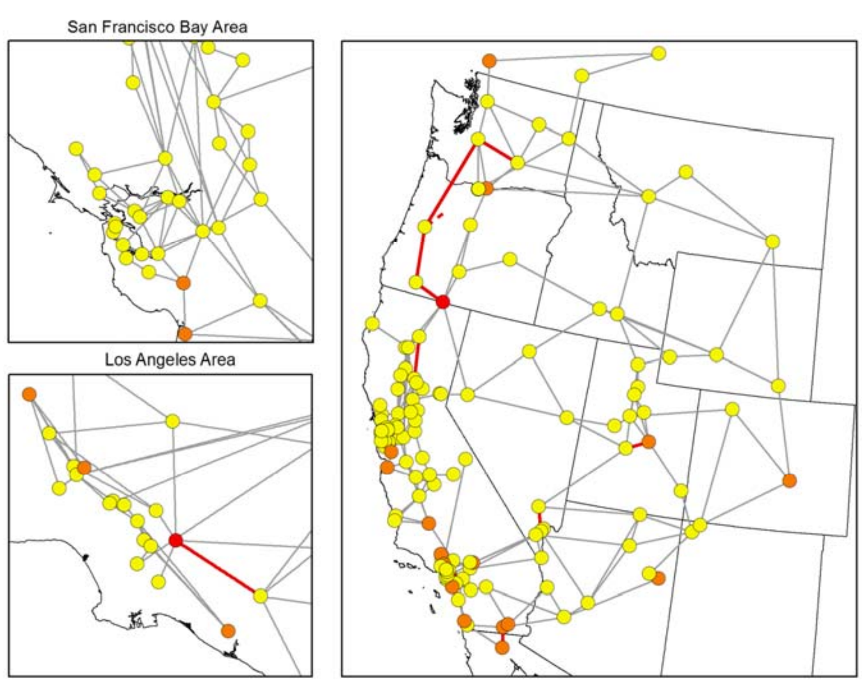
3.2 Results

First Stage Generation Investments: Deterministic vs Stochastic Solutions



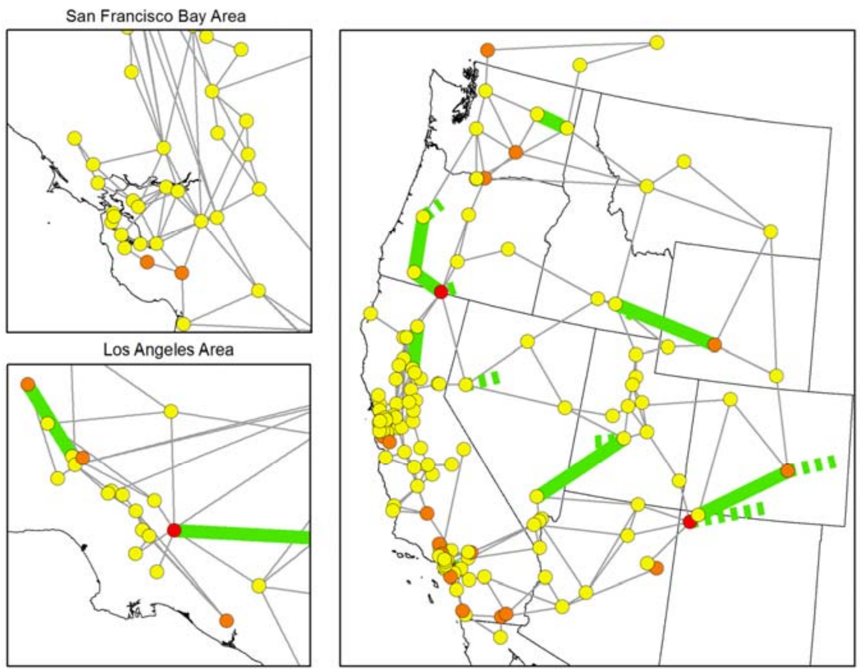
3.3 Results: Carbon Cap Case





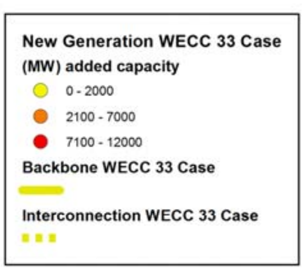
- Gen added near demand
- Low penetration of renewables
- Carbon cap only within US

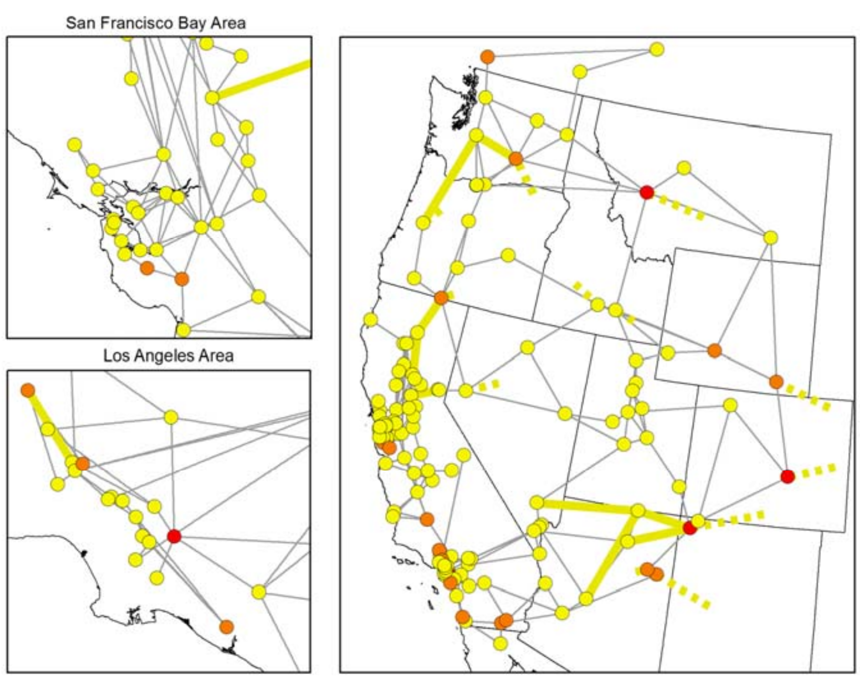
3.4 Results: State RPS Case



- High renewable penetration
  - *Mainly California*
- Why? California has highest state RPS

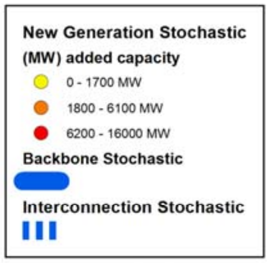
3.5 Results: WECC 33% Case



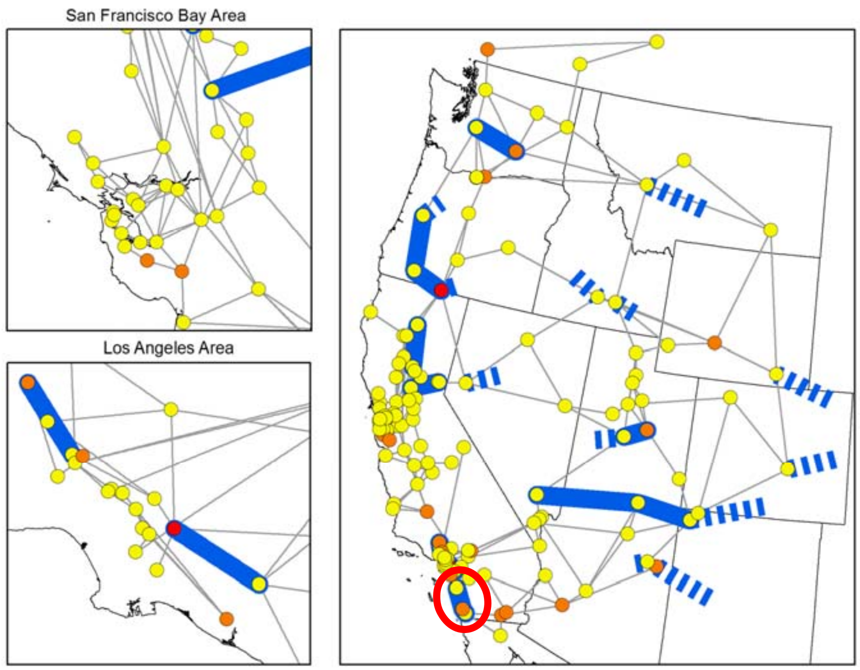


- High renewable penetration
- High quality distant resources accessed
  - *Favors population centers*

3.6 Results: Stochastic Solution



- Hi renewables
  - *Generation closer to California*
- **<u>Unique stochastic lines</u>**



3.7 Results Summary

Economic Performance of Investment Strategies

Approach	First-Stage Transmission Investments [$B]			E(System Costs) across scenarios [$B]
	Backbones	**Interconnections**	**Total**	
D-Carbon	4.0	0.1	4.1	728.2
D-33% WECC	6.1	9.3	15.4	653.6
D-State RPS	7.2	4.1	11.3	667.0
Heuristic I	0.3	0.1	0.4	951.4
Heuristic II	2.4	3.9	6.3	679.1
Heuristic III	14.7	9.5	24.2	644.5

- **Expected Value of Perfect Information (EVPI) = $45.4 Billion**
- **Value of Stochastic Solution (VSS) = $46.7 Billion**
- **WECC 10-Year Regional Transmission Plan:**
  - Estimates of $20 Billion in transmission investments to meet demand forecasts and renewable targets by 2020.

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4. Conclusions

- Scenario Planning is a weak tool for decisions under uncertainty
  - Deterministic plans don't account for flexibility
- Heuristic planning rules can perform worse than myopic deterministic plans
- Value of Stochastic Solution ~3 times the cost of transmission.
- Bounding & decomposition approaches are practical for improving granularity in operations

Questions?

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An Engineering-Economic Approach to Transmission Planning Under Market and Regulatory Uncertainties: WECC Case Study

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***Abstract*—We propose a stochastic programming-based tool to support adaptive transmission planning under market and regulatory uncertainties. We model investments in two stages, differentiating between commitments that must be made now and corrective actions that can be undertaken as new information becomes available. The objective is to minimize expected transmission and generation costs over the time horizon. Nonlinear constraints resulting from Kirchhoff's voltage law are included. We apply the tool to a 240-bus representation of the Western Electricity Coordinating Council (WECC) and model uncertainty using three scenarios with distinct renewable electricity mandates, emissions policies, and fossil fuel prices. We find that the cost of ignoring uncertainty (the cost of using naive deterministic planning methods relative to explicitly modeling uncertainty) is on the same order of magnitude as the cost of first-stage transmission investments. Furthermore, we find that heuristic rules for constructing transmission plans based on scenario planning can be as suboptimal as deterministic plans.**

***Index Terms*—Planning, Uncertainty, Stochastic Programming, Decision Analysis, WECC, Renewable Portfolio Standards.**

NOMENCLATURE

Sets and Indexes:

B	Buses, indexed b, p.
B_j	Buses within reliability region j.
FG	Flowgates, indexed a.
G	Generators, indexed k.
G_b	Generators at bus b.
G_i	Generators at zone i.
H	Hours, indexed h.
G_R	Renewable generators.
G_C	Candidate generators.
G_I	Intermittent generators.
G_{NI}	Non-intermittent generators.
L	Transmission lines, indexed l.
L_E	Existing lines.
L_C	Candidate lines.
Ω_l	Pair of nodes connected to line l.
S	Scenarios, indexed s.
T	Periods, indexed t, u, and v.
J	Reliability regions, indexed j.
R	Regions with renewable mandates, indexed i.
E	Regions with CO_2 limits, indexed e.

Parameters:

$CAP_{e,s}^t$	Carbon emissions limit.
$CX_{l,s}^t$	Capital cost of line.
$CY_{k,s}^t$	Capital costs of generator.
δ	Discount rate.
$D_{b,h,s}^t$	Forecasted demand.
$ELCC_k$	Effective Load Carrying Capability factor.
EM_k	Carbon emissions rate.
$\overline{F_l}$	Line capacity.
$\overline{FG_a}$	Flowgate limit.
h^*	Peak demand hour.
M_l	Large positive number.
$MC_{k,s}^t$	Generation marginal cost.
NC_s^t	Noncompliance penalty.
p_s	Probability of scenario s.
$\Phi_{b,l}$	Element of node-line incidence matrix.
$\Psi_{a,l}$	Element of flowgate-line incidence matrix.
RM_j	Reserve margin requirement.
$RPS_{i,s}^t$	Renewable obligation.
S_l	Line susceptance.
V_t	Period length.
$VOLL$	Value of loss load.
$W_{k,h}$	Hourly capacity factors for wind and solar.
$\overline{Y_k}$	Maximum resource potential.
Y_k^0	Installed generation.
YR_k^t	Retirement of generation capacity.

Variables:

$x_{l,s}^t$	Transmission investment decision.
$y_{k,s}^t$	Generation new build.
$g_{b,k,h,s}^t$	Generation.
$r_{b,h,s}^t$	Load curtailment.
$n_{i,s}^t$	Noncompliance of renewable target .
$f_{l,h,s}^t$	Power flow.
$\theta_{b,h,s}^t$	Phase angle.

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I. INTRODUCTION

ELECTRICITY transmission networks are large interconnected systems used to ensure the reliable and economic delivery of power from generators to consumers. Recently, the National Academy of Engineering recognized electrification as *"the single most significant engineering achievement of the 20th Century"* [1]. With an installed capacity of 1,100 GW and more than 160,000 miles of high-voltage transmission lines, the U.S. electricity system serves approximately 130 million customers with annual revenues totaling over $350 billion in 2010. Transmission comprises 10% of the total system assets of $800 billion [2].

Historically, transmission investments were driven by load growth, remote siting of large thermal plants, and opportunities for inter-system exchanges of economy energy and reserves. Today, transmission is also seen as a key enabler of renewable energy integration, since the best renewable resources are often far from load centers and the existing grid. Considerable investment will be needed in the coming decade. WECC estimates that $20 billion in foundational transmission investments are needed by 2020 in the western U.S. to meet load projections and state Renewable Portfolio Standards (RPSs) [3]. A similar study for California estimates that transmission investments to meet just that state's 33% RPS target by 2020 will cost approximately $16 billion [4], which is double the annual cost of wholesale power in the CAISO market in 2011.

Complying with renewable goals at minimum cost to consumers will require careful consideration of trade-offs between the cost of transmission investments to remote resources and the quality and diversity of those resources. In vertically integrated markets, a central decision maker can, in theory, select the optimal combination of generation and transmission investments to meet demand and renewable mandates at minimum cost under the Integrated Resource Planning paradigm. But such coordination is a challenge in restructured markets where only transmission assets are centrally planned. Although transmission planning has been traditionally "reactive" to generation investments (i.e. generation investments first, transmission afterwards), transmission planning authorities increasingly recognize two facts. First, transmission investments influence the profitability of investment decisions concerning generation, demand-side management (DSM) and other resources, and therefore affect the siting of those investments. Second, because large transmission projects can have longer lead-times than natural gas-fueled and renewable power plants and DSM, transmission commitments must be made before generation is constructed. Therefore, *"(c)apturing long-term benefits of transmission investments requires processes more akin to integrated resource planning in order to evaluate 'long-term resource cost' benefits (such as)...the ability to build new generation in lower-cost locations (and to)...find lower-cost (or higher-value) combination of transmission and generation investments to satisfy policy requirements, such as (renewable portfolio standards)"*[5] [6]. This has resulted in an "anticipative" or "proactive" philosophy being embodied in FERC Order 1000 [7] and a growing interest among planning authorities (such as the California ISO [8]) to use transmission planning to steer the generation market towards potentially better social outcomes compared to the old reactive approach.

Proactive or anticipative planning doesn't come without challenges though. Planning for long-lived infrastructure before it is needed involves making assumptions about the timing, size and location of future generation investments, which will depend strongly on network characteristics as well as on highly uncertain market and regulatory conditions (e.g. technology and fuel costs, environmental regulation, and renewable mandates). Disregarding any of these features can result in myopic plans and the risk of stranded transmission assets [9] [10] [11].

Methods now used in transmission planning studies have two limitations. First, planners usually rely on detailed production cost modeling tools and Monte Carlo simulation to assess the economic performance of a set of pre-defined transmission and generation configurations (e.g., PSS-E [12], GridView [13], and PROMOD IV [14]). However, these commercial packages lack topology optimization capabilities and cannot suggest potentially better transmission configurations [15] [16]. The few commercial packages that can optimize topology (e.g., NETPLAN [17]) account for neither the generators' responses to transmission investments nor uncertainties in market and regulatory conditions.

A second limitation arises from using scenario planning to cope with uncertainty. In scenario planning, several scenarios are defined that represent alternative future economic and regulatory conditions, and then a separate plan is developed separately for each scenario using either deterministic network optimization or a production costing-based comparison of pre-defined plans. Then investments that are attractive in all or most scenarios are identified as robust. Examples of such planning approaches are the Multi-Value Projects by the Midwestern ISO (MISO) [18], and the least-regret investments by California ISO (CAISO) [19]. The underlying assumption of these approaches is that investments needed for all or most scenarios provide a hedge against uncertainty and, thus, correspond to the projects that should be developed now. However, it has been proven theoretically that optimal stochastic investment strategies (i.e., ones that minimize probability-weighted costs across scenarios) cannot in general be constructed by such heuristics. Stochastic optima are rarely optimal for any individual scenario, and may include projects that would not be in the deterministic optimal plan for any particular scenario [20] (an example is shown later in this paper for WECC.) For instance, a somewhat more expensive route for a circuit between two buses might keep more options open later for additional circuits in that corridor or connections to other circuits; the cost of this additional adaptability must be suboptimal for any particular scenario, but could be worthwhile under uncertainty. For these reasons, scenario planning and heuristics are limited for planning under uncertainty.

In this paper we propose a model for adaptive transmission planning that takes into account generators' response, Kirchhoff's Voltage Law (parallel flows), and uncertainty. We also include recourse or "wait-and-see" investment decisions, since in reality not all decisions must be made today, as some can be delayed until there is more information available. We apply our approach to a 240-bus representation of the WECC adapted from [21] to illustrate the insights that can be gained. Uncertainty is modeled with three scenarios with diverging environmental policies and fuel costs. We compare the economic performance of the optimal stochastic solution with deterministic investment strategies as well as heuristic rules used in current transmission planning studies. We also calculate the Expected Value of Perfect Information (EVPI) and the Expected Cost of Ignoring Uncertainty (ECIU, equal to the expected loss from using deterministic rather than stochastic programming). We find that in this case they both have the same order of magnitude for the WECC case study, and that the ECIU is approximately three times the cost of transmission investments in the first-stage.

The rest of the paper is organized as follows. In Section II we review the existing literature on multi-stage transmission planning under uncertainty, considering the response of generator investment and operations. Our two-stage stochastic transmission planning model is formulated in Section III. In Section IV we describe our case study and assumptions regarding candidate renewable resources and scenarios. In Section V we present our results and discuss the limitations of the current approaches. Finally, we offer conclusions in Section VI.

II. Literature Review

Transmission planning using optimization is an active research area [22]. Initial approaches to finding cost-effective transmission plans were based on linear programming [23]. However, due to scale economies, transmission capacity additions are better represented with discrete variables instead of continuous ones [24]. This is an advantage if power flows are modeled using a linearized dc approximation [25], since Kirchhoff's Voltage Laws for candidate transmission lines can be enforced with linear disjunctive constraints instead of nonlinear ones [26] [27] [28]. The resulting problem is formulated as a mixed integer linear problem and solved with commercial MIP solvers ([29], [30], [31] and [32]).

There is also a broad literature on transmission planning under uncertainty (e.g., [33], [34], [35], [36]). However, most of it focuses on single-stage (or open loop) planning, assuming that all investment decisions must be made today, and ignoring the option of delaying commitments until more information is available. A number of studies have quantified option value by considering later decision [37]. But these studies have usually been of individual transmission investments, without considering alternatives elsewhere in the network. Multi-stage network planning models have been proposed in [38], [39] and [40], but the former studies take generation investments as exogenous, therefore ignoring interactions of transmission and generation investments. Game-theory approaches, on the other hand, can account for market power and generators' responses [10], but network optimization based on such methods is computationally intractable for real-world applications.

Recently, [40] proposed a two-stage stochastic transmission planning approach that takes into account generators' response, but applied to a small, seven-bus, radial representation of the UK ac transmission system, and only considered dc or radial ac links, thus ignoring the parallel flow impacts of Kirchhoff's Voltage Law. Here we improve [40] by extending the formulation to include ac transmission lines and flowgate constraints. We also model the effect of having differentiated state renewable mandates and the effect of the geographical definition of renewable certificate markets on the optimal configuration of transmission and generation investments. Our model is applied to a network that is two orders of magnitude larger than the one in [40], and employed to compare the performance of heuristic rules that are commonly utilized in current transmission planning studies (e.g. MISO [18] and CAISO [19]) to the optimal stochastic plan. No such comparison was made in [40], even though heuristics are increasingly used in practice.

III. Model Description

We model transmission and generation investment decisions in two stages, each followed by market operations (see Figure 1). The two stages are divided into three periods, one before it is known which scenario will occur, and two after uncertainty is revealed. Investment decisions made in one period do not become available until the beginning of the following period.

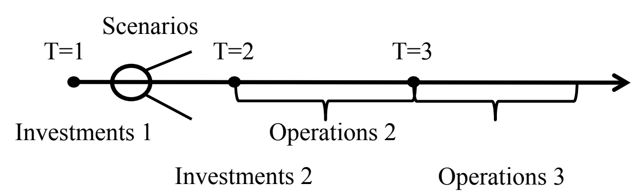

Fig. 1. Timeline

Power flows are modeled using a linearized dc approximation [25]. Generation intermittency and load variations are modeled by including a sample of hours chosen so that the averages, standard deviations, and correlations of wind and load across different locations are well approximated. As in [40], we assume perfect competition and nodal pricing; as a result, the generation market equilibrium can be simulated by minimizing the present worth of total investment and operating costs, which is the same objective we assume for transmission planners. Because the objectives are consistent, the bilevel transmission planning-generation market planning problem can be reduced to a single combined transmission-generation optimization model.[1] Thus, our model is mathematically equivalent to an Integrated Resources Planning approach [42], except that in a deregulated market, generation investments represent the optimal market response to the transmission planner strategy, rather than a result of an integrated plan. Other examples of "co-optimization models", which consider how generation investments react to transmission investment, include [43] [44] [45] [46].

We assume that demand can always be met at cost $VOLL$ and ignore the possibility of lines or generation outages, which should be analyzed using a probabilistic production cost simulation. The focus of this article is on transmission additions that are motivated by economics: resource investment and operating cost savings, and the need to develop least-cost strategies to achieve renewable integration and other policy goals (as in FERC Order 1000 [7]). Although reliability is, and will remain, an important driver of some transmission additions, these economic factors are the primary drivers

[1]The conditions for equivalence of market equilibria to the solution of a single optimization model are discussed in [41].

behind large interregional transmission proposals today.[2]

Objective Function: We define investment costs for a single scenario, before uncertainty is revealed, in $t = 1$ and for multiple scenarios, after uncertainty is revealed, in $t = 2$, as the sum of transmission and generation investments:

$$I_s^t = \sum_{l \in L_C} CX_{l,s}^t x_{l,s}^t + \sum_{k \in G_C} CY_{k,s}^t y_{k,s}^t \tag{1}$$

Operating costs O_s^t for periods $t = 2, 3$ and scenario s account for generators operating costs OC_s^t, and penalties OP_s^t for load curtailments and noncompliance with renewable targets. To maintain a manageable model size, we simulate market operations for a single year at the beginning of periods 2 and 3, and assume that they represent operations for the remaining years in each period.[3]

$$OC_s^t = \sum_{v=1}^{V_t} \left(\frac{1}{1+\delta}\right)^{v-1} \sum_{h \in H} \sum_{k \in G} MC_{k,s}^t g_{k,h,s}^t \tag{2}$$

$$OP_s^t = \sum_{v=1}^{V_t} \left(\frac{1}{1+\delta}\right)^{v-1} \left[\sum_{b \in B} VOLL\ r_{b,h,s}^t + \sum_{i \in R} NC_s^t n_{i,s}^t\right] \tag{3}$$

$$O_s^t = OC_s^t + OP_s^t \tag{4}$$

The cost-minimization problem is then defined as:

$$min\ I^1 + \sum_{s \in S} p_s \left[\left(\frac{1}{1+\delta}\right)^{V_1} (I_s^2 + O_s^2) + \left(\frac{1}{1+\delta}\right)^{V_1+V_2} O_s^3\right] \tag{5}$$

Constraints. The above objective is optimized subject to:

Kirchhoff's Current Law:

$$\sum_{l \in L} \Phi_{b,l} f_{l,h,s}^t + \sum_{k \in G_b} g_{k,h,s}^t + r_{b,h,s}^t = D_{b,h,s}^t \quad \forall b, h, s \tag{6}$$

Kirchhoff's Voltage Law for existing and candidate lines, respectively:[4]

$$f_{l,h,s}^t = S_l(\theta_{b,h,s}^t - \theta_{p,h,s}^t) \quad \forall (b,p) \in \Omega_l, l \in L_E, h, s, t \tag{7}$$

$$|f_{l,h,s}^t - S_l(\theta_{b,h,s}^t - \theta_{p,h,s}^t)| \le M_l(1 - \sum_{u=1}^{t} x_{l,s}^u) \quad \forall (b,p) \in \Omega_l, l \in L_C, h, s, t \tag{8}$$

Note that the right hand side is equal to zero if a line is built, but otherwise is a very high number so that the constraint doesn't bind [26] [29].

Thermal limits on existing and candidate lines:

$$|f_{l,h,s}^t| \le \overline{F_l} \quad \forall l \in L_E, h, s, t \tag{9}$$

$$|f_{l,h,s}^t| \le \overline{F_l} \sum_{u=1}^{t} x_{l,s}^u \quad \forall l \in L_C, h, s, t \tag{10}$$

Flowgates. We assume that the capacity of interfaces between neighboring systems are defined as a fraction of the aggregated capacity of the lines, so the constraints can be updated depending on reinforcements to existing corridors:

$$\sum_{l \in L} \Psi_{a,l} f_{l,h,s}^t \le \overline{FG_a} \left[\sum_{l \in L_E} |\Psi_{a,l}| \overline{F_l} + \sum_{l \in L_C} \sum_{u=1}^{t} |\Psi_{a,l}| \overline{F_l}\ x_{l,s}^u\right] \quad \forall a, h, s, t \tag{11}$$

Maximum generation:

$$g_{k,h,s}^t \le W_{k,h}(Y_k^0 + \sum_{u=1}^{t} [y_{k,s}^u - YR_k^u]) \quad \forall k, h, s, t \tag{12}$$

Installed reserve margins: We enforce installed reserve margins in predefined reliability areas. Intermittent generators are included using Effective Load Carrying Capability Factors (ELCCs).

$$\sum_{k \in G_{NI} \cap G_j} (Y_k^0 + \sum_{u=1}^{t} y_{k,s}^u) + \sum_{k \in G_I \cap G_j} ELCC_k(Y_k^0 + \sum_{u=1}^{t} y_{k,s}^u) \ge (1 + RM_j) \sum_{b \in B_j} D_{b,h,s}^t \quad h = h^* \quad \forall j, s, t \tag{13}$$

Generation resource constraints that limit construction in each region:

$$\sum_{u=1}^{t} y_{k,s}^t \le \overline{Y_k} \quad \forall k \in G_C, s \tag{14}$$

Renewable Portfolio Standards that place a lower bound on renewable energy output in a defined region, accounting for

[2]Transmission additions that are primarily motivated by improvements in reliability require a different set of techniques. When assessing the reliability implications of new transmission, reliability metrics such as the "one day in ten year" loss of load expectation (LOLP) or the expected energy not served (EENS) are relevant [47]. They are generally modeled in industry practice using probabilistic simulations considering, for instance, line outages, generator forced outages, the full distribution of load, and wind variability. Examples of such simulation models include Concorda MARS [48] and CRUSE [49]. Such modeling has not yet been integrated in economic optimization models for transmission but is an important topic for future research.

[3]Here we define the model for a full year (H=1..8760). A sample of hours can be used instead by weighting each sampled hour's variables by $\frac{|H|}{8760}$ in Equations 2, 3, 15, and 16.

[4]An ideal choice of M_l is equal the maximum angle difference times the susceptance of candidate line l. Thus, if the line is not built, the left-hand-side of equation (8) is unconstrained. Values of M above this minimum would still enforce constraint (8), but can cause numerical difficulties in branch-and-bound algorithms [31]. Here we only consider reinforcements to the trunk transmission system and radial interconnections, therefore, the maximum angle difference is bounded by the maximum power flow in any line connecting buses b and p. Bounds for candidate lines that create new loops in the system, or that interconnect initially disconnected systems, can be computed by solving shortest- or longest-path problems, respectively [29].

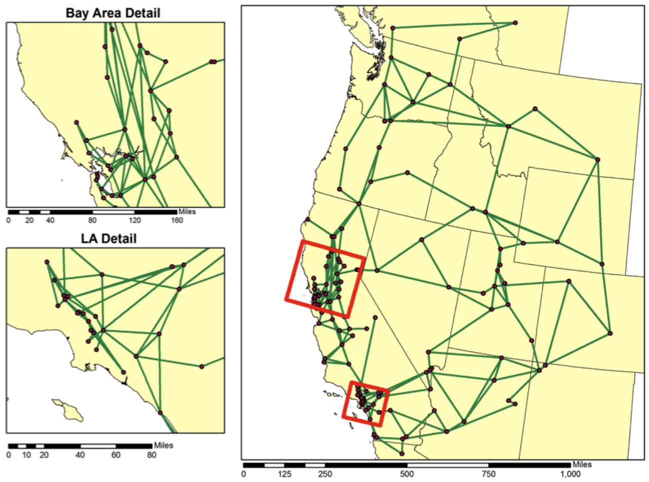

Fig. 2. WECC 240-Bus System

credits that are allowed to be imported from other regions:

$$\sum_{k\in G_R\cap G_i}\sum_{h\in H} g^t_{k,h,s} + n^t_{i,s} \geq RPS^t_{i,s}\sum_{k\in G_i}\sum_{h\in H} g^t_{k,h,s} \quad \forall i,s,t \tag{15}$$

Emissions constraints that limit total emissions of CO_2 within defined areas:

$$\sum_{k\in G_e}\sum_{h\in H} g^t_{k,h,s}EM_k \leq CAP^t_{e,s} \quad \forall e,s,t \tag{16}$$

Nonnegativity and integrality:

$$g^t_{k,h,s}, y^t_{k,s}, n^t_{i,s}, r^t_{b,h,s} \geq 0 \qquad \forall k,b,h,i,s,t \tag{17}$$

$$x^t_{l,s} \in \{0,1\} \qquad \forall l,s,t \tag{18}$$

IV. Case Study: WECC 240

The WECC 240-bus test-case is a network reduction of the synchronized western North American interconnection [21]. It consists of 240 buses, 448 transmission elements, and 157 aggregated generators with a total installed capacity of 224 GW. The model also includes limits for 28 flowgates that are normally enforced during operations in the WECC. Since the original WECC 240 test-case was created to replicate present market operations, it lacks information about candidate renewable resources or transmission alternatives that is necessary to test our transmission-planning approach.

For this example, we assume a ten-year lag between decisions to build transmission and generation, and project completion. Therefore, we model investment decisions at the beginning of years 2013 and 2023 (period 1, $V_1 = 10$). Market operations are modeled between years 2023 and 2033 (period 2, $V_2 = 10$), and between years 2033 and 2063 (period 3, $V_3 = 30$).

Here we describe our main assumptions in adapting this test-case for the long-term transmission planning study.

TABLE I
Candidate Generation

Technology	Overnight Capital Cost [M$/kW]	Fixed O&M Cost [$/kW]	Variable O&M Cost [$/MWh]	Heat Rate [MMBtu /MWh]
Coal CCS	4,579	63.21	9.05	12.0
CCGT	978	14.39	3.40	7.1
CCGT CCS	2,060	30.25	6.45	7,5
CTGT	665	6.70	9.87	9.8
Hydro	3,500	15	6	-
Wind	2,438	28	0	-
Solar PV	5,400	22	0	-
Biomass	3,860	103	5	12.5
Geothermal	4,141	84	9	-

A. Generation Assumptions

We use projections of both capital and fuel cost data from the Energy Information Administration (EIA) [50]. Capital costs of new generation (CX) include both overnight capital costs and the sum of the discounted fixed operation and maintenance costs. We use a geographic information system (GIS) to spatially analyze renewable resource potential from the Western Renewable Energy Zones study [51] and the Renewable Energy Transmission Initiative in California [52]. Wind generation variability is represented using 54 spatially aggregated hourly profiles from NREL's Western Wind Resources Database [53]. Similarly, solar intermittency is included in 29 regions with hourly profiles generated using NREL's PVWatts tool [54]. In terms of conventional generation, we assume that no new nuclear or large hydroelectric power plants are going to be built in the WECC. EPA's new carbon pollution standard makes it difficult to build new conventional coal power plants [55], so we only allow for new coal generation that has CCS technologies. We retire 11,752 MW of once-through cooling power plants in California and 1,572 MW in the rest of the WECC, as projected in the WECC 10-Year Regional Transmission Plan [3]. Table I summarizes the costs for candidate generators.

We impose installed reserve margins of 12% within 8 different regions of the WECC. Intermittent generators are included in reserve margins with derated capacities using typical ELCC values. Finally, we assume that hydroelectric operations will be consistent with those in the WECC 240 profiles for the year 2004. Operations of hydroelectric power plants are constrained by both the technical characteristics of the power plants and by environmental constraints specific to each basin. Flexible dispatch of hydropower, as well the introduction of other energy storage technologies, can be used to provide energy, capacity, and ancillary services [56] [57], all of which could result in potential savings in transmission and generation infrastructure and improve the economics of renewable generation. Capturing these benefits, however, would require chronological simulation of operations and consideration of multiple scenarios of hydrological conditions [58] [59], both of which are beyond the scope of this article, but should be the subject of future research.

B. Transmission Assumptions

The original WECC-240 test case does not include ratings for all transmission elements. For unconstrained lines, we approximate thermal limits based on line lengths, voltage levels, and St. Clair line loadability curves [60]. However, we assume that all transformers are unconstrained, since their capital costs are relatively low compared to transmission upgrades. Based on the Western Renewable Zones Study, we group candidate resources into 31 renewable hubs distributed throughout the WECC that require new transmission capacity to deliver power to the existing grid. Consequently, we consider two types of transmission upgrades: backbones and interconnections. Trunk reinforcements are capacity additions parallel to existing corridors, while interconnections are radial links from initially disconnected renewable hubs to the nearest existing high voltage buses. For illustration purposes, we limit the availability of rights-of-way to a maximum of two new 500 kV circuits for the trunk system, and four for interconnections. This assumption can be relaxed to include more alternatives of different voltage levels, but at the expense of a larger model.

C. Scenarios

Environmental policies and renewable mandates in the U.S. vary greatly among states. While California, for example, has a stringent renewable goal of 33% by 2020, neither Wyoming nor Idaho now have renewable mandates [61]. Furthermore, some states allow Load Serving Entities (LSEs) to meet a fraction of the state mandates using out-of-state renewable generation through Renewable Energy Certificates (RECs), which are tradable financial instruments created from electricity generated from qualifying renewable resources [62]. Although there is currently neither a national nor a WECC-wide REC markets, their implementation would relax the geographic heterogeneity between state RPS goals and result in renewable generation investments in the most cost-effective locations [63]. In contrast, a shift in the focus of future environmental regulation from state renewable mandates towards carbon emissions limits would give generators fewer incentives to invest in renewables and would, instead, promote the use of clean conventional generators, especially in our scenario of low natural fuel prices.

For illustration purposes, we develop three scenarios that represent uncertainty in regulatory and market conditions. [5] Although load growth and technology costs are also important sources of uncertainty, here we assume they are constant across all scenarios. We also assume that load patterns will be the same as in 2004, although changes in load shapes, due to, e.g., demand response and electric vehicles, can change the optimal transmission and generation investment plans [65] [66] [67] [68]. Multiple scenarios for load growth and load shapes can be included in additional scenarios as in [40], while demand management can be included as a resource and decision variable in the model, but at the expense of computational efficiency. The three scenarios, assumed equally likely, are defined as follows:

- **State RPS**: This is the reference case. We assume that renewable goals remain as projected and differentiated by state [61], but allow 25% of each state's RPS to be met with out-of-state resources. The fuel prices we use are average projections from the EIA.
- **33% WECC**: This is an analog to the scenario modeled in [69]. In this case there is a strong pressure on renewables with a 33% WECC-wide RPS goal together with high fuel prices. Unlike the State RPS scenario, here we assume the existence of an efficient WECC-wide REC market allowing renewable generation to be built in the most cost-effective locations.
- **Carbon**: In this scenario, environmental regulation focuses on carbon emissions reductions instead of renewable mandates, and fuel prices are lower than average projections. We set emissions limits based on the Waxman/Markey bill that passed the U.S. House of Representatives in 2009, which sets carbon reduction targets of 17% below 2005 levels by 2020 and of 42% below 2005 levels by 2040 [70].

TABLE II
SUMMARY OF SCENARIOS

	Scenarios		
	State RPS	33% WECC	Carbon
Probability	1/3	1/3	1/3
Natural Gas prices [$\$/MMBtu$]			
2023	5.01	6.81	3.96
2033	6.06	7.82	4.81
Coal prices [$\$/MMBtu$]			
2023	1.89	2.38	1.51
2033	2.02	3.14	1.34
Total renewable goals [$TWh/Year$]			
2023	229	336	0
2033	290	417	0
Emissions limits [$MMTCO_2/Year$]			
2023	No limit	No limit	292
2033	No limit	No limit	183
Certificate trading	$\leq$25% of state goals	Yes	Yes

V. Results

All model runs reported in this article were done in the AIMMS 3.12 modeling language using the CPLEX 12.4 solver on a 32-core workstation with 112 GB of RAM. In order to keep the model size small, we simulated market operations using a sample of only 10 hours and ignored ramping limits, which resulted in a model with 110,000 variables (2,040 binary variables for transmission investments) and 240,000 constraints for the stochastic case. The solution time to solve the deterministic equivalent of the stochastic formulation of the problem was of 2.5 hours, and of 1 hour for the deterministic cases. Larger transmission networks, more scenarios, or more granular representation of operations, however, will

[5] The scenarios defined in our study are only used to illustrate an application of our methodology and do not constitute an attempt to represent the full range of scenarios that might be used in an actual application (e.g. MISO [18] and CAISO [19] studies), which is the reason why we treat parameters independently. In real-world studies, scenarios can be defined by managers and stakeholders using techniques for expert elicitation. Since Royal Dutch Shell's primary use of scenarios in 1960's, a number of systematic approaches have been proposed and applied to develop sets of scenarios [64].

increase the size of the problem significantly, and the approach of solving a single deterministic equivalent might then be computationally prohibitive. Decomposition might then be the most practical approach to solving these problems. Examples of alternative decomposition-based solution methods include Benders decomposition [29], which divides the problem into a master or investment problem and subproblems, and Progressive Hedging [71], which relies on scenario decomposition instead. These alternative methods were, however, unnecessary for the WECC model described here. As in [29], we first relaxed all the disjunctive constraints and used that solution as a starting point for the full formulation. We stopped computation once we reached a MIP gap of 1%. To ensure electricity load and renewable energy targets are met, we used a high noncompliance penalty of 500 \$/MWh.

A. *Planning Based on Deterministic Scenario Models*

Scenario planning is a common practice in industry when important investment decisions must be made under uncertainty. By developing a set of scenarios that represent the uncertain future, decision makers can analyze different investment strategies for each scenario, and also assess the performance of other investment strategies resulting from heuristic planning procedures. Here we find the optimal deterministic plan for each scenario s^* by setting its probability p_s^* to 1 and removing all constraints for $s \neq s^*$. Tables III and IV summarize the optimal first-stage transmission investment strategies for different planning approaches. Note that for the 33% WECC scenario, it is optimal to build multiple lines to access distant renewable hubs, while for the Carbon scenario it is cost-effective to build only one such line and instead meet emissions targets using a combination of near-load renewable resources and natural gas generators. The minimum system costs for each deterministic scenario (CPI_{s*}) are \$565.5 Billion for State RPS, \$711.9 Billion for 33% WECC, and \$495.0 Billion for the Carbon scenario. We refer to the probability-weighted sum of these costs as the Expected System Costs under Perfect Information ($EC|PI$), which provides a lower bound upon the expected cost under uncertainty for any actual strategy:

$$EC|PI = \sum_{s \in S} p_s CPI_{s*} = \$590.8 \text{ Billion} \tag{19}$$

However, the minimum cost under perfect information is overly optimistic, since, in reality, other scenarios for which the deterministic plans are suboptimal can still occur.

In Table V we summarize the costs of first-stage transmission investments in backbones and interconnections, as well as the performance of different first-stage transmission investment strategies. We estimate expected system costs for deterministic approaches ($ECDS_s$) by imposing their first-stage transmission investment decisions onto the stochastic model, which is then free to choose second-stage investments that differ among the scenarios, but assuming that generators still take uncertainty into account in the first-stage. Because the first stage decisions are constrained in this manner, the objective function must be no better than that for the full stochastic model, since the latter is free to choose the first stage decisions to minimize cost. Note that of the three deterministic alternatives, the D-33% WECC is the one requiring the highest investment in transmission in the first stage, but these are the investments that will result in the lowest expected system costs when tested against all scenarios (see out-turn scenarios in Table V). In contrast, planning the grid using the D-Carbon strategy results in high regrets, compared to the system costs under perfect information, if the out-turn scenarios are 33% WECC or State RPS

A common practice today in transmission planning studies is to construct investment strategies by combining deterministic results using heuristic rules. For example, one approach used both at CAISO [19] and MISO [18] is to recommend projects chosen by deterministic models in all or most scenarios. Here we emulate these approaches with two heuristic rules for choosing lines to build immediately.

- *Heuristic I:* Select lines that are built in the first stage in each and every scenario-specific deterministic model.
- *Heuristic II:* Select lines that are built in at least two out of the three scenario-specific deterministic models.

A more ambitious approach followed by the Alberta System Operator (ASO) is to plan for a congestion-free network so that any possible scenario of generation investment is accommodated [72]. Therefore, as a proxy for the ASOs planning approach, we consider an additional heuristic:

- *Heuristic III:* Select any lines that are built in the first stage of any scenario-specific deterministic model.

Table V shows that the heuristics modeled after the procedures proposed by the CAISO and MISO actually do worse than most plans created using traditional deterministic methods. In particular, *Heuristic I* yields higher expected costs than planning myopically for any one deterministic scenario. This is evidently because the marginal value of new transmission is very high for the first few additions (because of avoided noncompliance penalties), and that heuristic constructs the fewest lines. Meanwhile, *Heuristic II* does better than planning using the deterministic Carbon scenario, but still is worse than the deterministic D-33% WECC and D-State RPS plans. In contrast, *Heuristic III* (build all lines identified in any scenario) gives lower expected system costs compared to any of the deterministic plans or other heuristics. Note that this advantage is not a necessary result, and depends on the data. But III requires nearly twice as much first-stage transmission investment as any other plan (\$24.2B, Table V) and therefore has a high risk of stranded assets. In sum, since scenario planning as well as heuristics based upon scenario plans do not attempt to identify network designs that optimize performance across all scenarios simultaneously, they are a weak approach for planning under uncertainty.

B. *Optimal Stochastic Planning*

In contrast, the model described in Section III provides a single recommendation for transmission investment commitments now (here, 2013, for implementation by 2023). Our approach also models recourse (second-stage) decisions, which are investments that should not start until 2023 when there

TABLE III
FIRST-STAGE INVESTMENTS IN RADIAL INTERCONNECTIONS TO RENEWABLE HUBS

Approach / Corridor N	I2	I5	I6	I8	I9	I10	I11	I14	I20	I23	I24	I25	I26
D-Carbon												1	
D-33% WECC	1	4	1	3	1	1	2	1	1	1	1	1	
D-State RPS		2		2	1				1		1	1	1
Heuristic I												1	
Heuristic II		2		2	1				1		1	1	
Heuristic III	1	4	1	3	1	1	2	1	1	1	1	1	1
Stochastic	1	4	1	3	1	1	2	1	1		1	1	1

TABLE IV
FIRST-STAGE INVESTMENTS IN TRANSMISSION BACKBONES

Approach / Corridor N	19	37	56	68	72	73	74	92	95	125	133	136	137	143	151	157	168	169	201	202	218	222	237	238
D-Carbon				1					1	1	1		1	2								2	1	2
D-33% WECC		1			1	1	2		1								1	1	1		1	1	2	
D-State RPS	2	1	1					2		2		1								1		1		2
Heuristic I																						1		
Heuristic II		1							1	1												1	1	2
Heuristic III	2	1	1	1	1	1	2	2	1	2	1	1	1	2			1	1	1	1	1	2	2	2
Stochastic		1		1			2		1	2			1		1	1	1				1	1		2

TABLE V
FIRST-STAGE TRANSMISSION INVESTMENTS COSTS AND ECONOMIC PERFORMANCE OF PLANNING STRATEGIES. ALL COSTS IN BILLION USD.

	First Stage Transmission Investments			Out-turn Scenarios			Expected
Approach	Backbones	Interconnections	Total	Carbon	33% WECC	State RPS	System Costs
D-Carbon	4.0	0.1	4.1	553.1	1,000.4	631,1	728.2
D-33% WECC	6.1	9.3	15.4	598.7	724.6	637.4	653.6
D-State RPS	7.2	4.1	11.3	558.6	857.0	585.4	667.0
Heuristic I	0.3	0.1	0.4	777.0	1,217.7	859.3	951.3
Heuristic II	2.4	3.9	6.3	574.0	853.8	609.8	679.1
Heuristic III	14.7	9.5	24.2	590.5	721.2	621.9	644.5
Stochastic	5.6	9.2	14.8	575.2	716.9	616.5	636.2
System Costs Under Perfect Information (CPI_s) (Both transmission and generation have perfect information)				495.0	711.9	565.5	

is more clarity about market and regulatory conditions. This is analogous to a Real Options approach, where the cost difference between the first-stage transmission investments of the stochastic plan and a reference strategy (e.g. a deterministic or heuristic-based plan) constitute the price of the option, which can be exercised later depending on the state of the system [73].

By definition, the investment plan recommended using our two-stage stochastic approach yields the lowest expected system costs compared to both deterministic and heuristic approaches (see Table V). The optimal stochastic solution recommends only \$14.8 Billion in transmission investments in the first-stage, \$9.4 Billion less than *Heuristic III*, and results in expected system costs of \$636.2 Billion ($ECSS$), or \$8.3 Billion less than *Heuristic III*. Note that the set of transmission investments recommended by the stochastic approach includes projects (B151 and B157) that would not be chosen for any scenario under perfect information. In other words, these two projects are suboptimal in retrospect for any of the three scenarios; however, they are optimal in an expected value sense since they are physical hedges that impart more flexibility to the system than projects selected under the deterministic approaches.

Besides the optimal strategy, we can also use the stochastic approach to calculate two indices from the decision analysis literature [74] of the economic consequences of uncertainty, the Expected Value of Perfect Information ($EVPI$) and the Expected Cost of Ignoring Uncertainty ($ECIU$). The $EVPI$ provides an upper bound on the value of better forecasts for the uncertain parameters, and is calculated as:

$$EVPI = ECSS - EC|PI = \$45.4 \text{ Billion} \tag{20}$$

That is, this is the cost of the optimal stochastic solution $ECSS$ minus (the necessarily no worse) expected cost across scenarios if generation and transmission planners could perfectly foresee which scenario would occur ($EC|PI$).

The $ECIU$ is, on the other hand, a measure of the expected cost savings from using the stochastic approach for transmission planning instead of a naive deterministic one, but assuming that generators still consider all scenarios.[6] It is formally defined as the difference between the expected performance of the deterministic solutions minus the expected costs of the stochastic plan [74]:

$$ECIU = \sum_{s \in S} p_s ECDS_s - ECSS = \$46.7 \text{ Billion} \tag{21}$$

[6]A more detailed description of how to calculate $EVPI$ and $ECIU$ for both transmission and generation, and transmission only is given in [40].

VI. Conclusions

We describe a tool for transmission planning under gross economic and policy uncertainty. It is formulated as a two-stage stochastic mixed-integer linear program, and we solve it with a commercial optimization package. It improves upon [40] in that we model a system that is two orders of magnitude larger with a meshed network in which Kirchhoff's Voltage Law as well as interface (flowgate) constraints are considered. Using the WECC 240-bus test case and three scenarios representing carbon and renewable policy uncertainties, we compare the economic performance of transmission strategies based on deterministic scenario planning, heuristic combination of scenario plans, and stochastic optimization. The transmission investments recommended by our stochastic approach outperform the deterministic plans by \$46.7B in the expected value of the present worth of costs ($ECIU$), and by \$17.4B compared to the best deterministic solution (D-33% WECC), which is triple the cost of first-stage transmission investments in the stochastic solution. Thus, better transmission planning can yield cost savings exceeding the cost of the lines themselves.

Since deterministic approaches do not value flexibility [20], heuristic rules that select lines based on the common elements of deterministic scenario plans may perform no better than deterministic strategies. Indeed, in our case study, they perform worse. However, investing in all the lines found in the deterministic solutions as a heuristic to hedge against uncertainty can, in turn, yield lower expected system costs compared to other heuristics, but requires nearly double the transmission investment in the first stage and thereby posing a higher risk of stranded transmission assets.

In contrast, stochastic planning explicitly considers the flexibility of a system to adapt to uncertain developments. Plans that incur extra costs for flexibility are unlikely to be found to be optimal for any individual scenario, and so would be overlooked in deterministic planning [15] [20]. As our results illustrate, the optimal stochastic strategy not only differs from all deterministic and heuristic solutions, but also includes line additions not identified in any of the deterministic plans. Thus stochastic transmission planning that considers optionality and flexibility from the entire network's perspective are needed.

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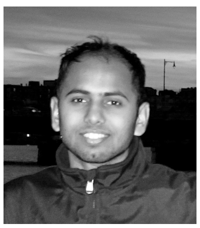

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The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty

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ABSTRACT

Aggressive development of renewable electricity sources will require significant expansions in transmission infrastructure. We present a stochastic two-stage optimisation model that captures the multistage nature of transmission planning under uncertainty and use it to evaluate interregional grid reinforcements in Great Britain (GB). In our model, a proactive transmission planner makes investment decisions in two time periods, each time followed by a market response. Uncertainty is represented by economic, technology, and regulatory scenarios, and first-stage investments must be made before it is known which scenario will occur. The model allows us to identify expected cost-minimising first-stage investments, as well as estimate the value of information, the cost of ignoring uncertainty, and the value of flexibility. Our results show that ignoring risk in planning transmission for renewables has quantifiable economic consequences, and that considering uncertainty can yield decisions that have lower expected costs than traditional deterministic planning methods. In the GB case, the value of information and cost of disregarding uncertainty in transmission planning were of the same order of magnitude (approximately £100 M, in present worth terms). Further, the best plan under a risk-neutral decision criterion can differ from the best under risk-aversion. Finally, a traditional sensitivity analysis-based robustness analysis also yields different results than the stochastic model, although the former's expected cost is not much higher.

1. Introduction

Over the last two decades, the electricity industry has seen several important developments, each of which has impacted transmission planning and increased uncertainty (Shahidehpour, 2004; Thomas et al., 2005). Firstly, many electricity markets previously dominated by a few large vertically integrated utilities have been restructured so that generation investment and operations decisions are made by individual, profit-maximising companies whose power is transmitted on a grid run by an independent system operator. In these markets, transmission and generation investment decisions are not made simultaneously by the same entity. Grid planning now has to account for the independent reactions of the generation market (Awad et al., 2010; Motamedi et al., 2010; Tor et al., 2008). Secondly, increasing interregional and international trade in electricity meant that greater amounts of electricity have to be transported further distances (Pollitt, 2009). Thirdly, concern about climate change has led to increased use of renewable sources of power, which are built in different locations and whose availability is generally more intermittent than conventional generators. Moreover, technological changes over the next two decades could result in very different patterns of renewable development than today.

Until now, with a few exceptions (de la Torre et al., 1999), transmission planners have relied upon deterministic transmission planning models, which are often run several times with different assumptions to assess the robustness of the proposed decisions. However, such a deterministic robustness analysis may reveal that the optimal plan is highly sensitive to the assumptions, in which case no unambiguous recommendation can be made; further, even if there are investments that are seemingly optimal under all or most scenarios, they may not constitute the optimal stochastic plan — i.e., the plan that minimises expected cost over the range of possibilities.

Thus, in light of these developments, a new modelling framework is needed, which satisfies three requirements. First, it should take into

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