What are the Benefits of Co-optimizing Transmission and Generation Investment? Eastern Interconnection Case Study

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Abstract — **Transmission planning has traditionally followed a "generation first" or "reactive" logic, in which network reinforcements are planned to accommodate assumed generation build-outs. The emergence of renewables has revealed deficiencies in this approach, in that it ignores the interdependence of transmission and generation investments. For instance, grid investments can provide access to higher quality renewables and thus affect plant siting. Disregarding this complementarity increases costs. In theory, this can be corrected by "proactive" transmission planning, which anticipates how generation investment responds by co-optimizing transmission and generation investments. We evaluate the potential usefulness of co-optimization by applying a mixed-integer linear programming formulation to a 24-bus stakeholder-developed representation of the U.S. Eastern Interconnection (EI). We estimate cost savings from co-optimization compared to both reactive planning and an approach that iterates between generation and transmission investment optimization. These savings turn out to be comparable in magnitude to the amount of incremental transmission investment. We also evaluate three congestion metrics as screens for reducing the number of candidate transmission investments. They each improve solution times, but the Estimated Potential Benefit metric is much more effective in identifying cost-effective lines than the others.**

***Index Terms*-- Generation planning, Economics, Power transmission planning, Mixed integer linear programming**

I. Nomenclature

Sets and Indices:

- B Time blocks, indexed by b
- G Generators, indexed g
- GE Candidate generators (subset of G), indexed ge
- GI Intermittent generators (subset of G), indexed gi
- IR Intermittency region (partition of N), indexed ir
- L Transmission corridors, indexed l. Each corridor has an arbitrarily defined forward and reverse flow direction.
- N Nodes/regions, indexed n
- P Planning reserve region (partition of N), indexed p
- PS Pumped storage (subset of G), indexed ps
- R RPS constraints region (partition of N), indexed r
- S Seasons (partition of b), indexed s
- T Years, indexed t and u
- V Transmission configurations at different voltage levels, indexed by v

Parameters:

- ACP_r Compliance payment in 2010\$/MWh
- $AIC_{g,n}$ Annualized capital payment in 2010\$/MW
- $CC_{g,n}$ Capacity credit
- $CF_{g,b,n}$ Capacity factor
- DR Discount rate
- FOM_g Fixed operation & maintenance cost in 2010\$/MW
- FOR_g Forced Outage Rate
- $GI_{ge,n,t}$ Generation capital cost in 2010 \$/MW
- $GI_{l,v}$ Transmission capital cost of voltage v for interface l in 2010 \$/unit
- H_b Duration of a block in hours
- HR_l Hurdle rate in 2010 \$/MWh
- IC Initial capacity in MW with index g,n or l
- $L_{b,t,n}$ Load in MW
- $M_{g,n,t}$ Fraction of generation capacity in a region n that is past its lifetime in year t.
- MVA_v Capacity of transmission at voltage v in MW/unit
- $PL_{t,p}$ Peak load in MW
- $POR_{g,b}$ Planned Outage Rate
- $RC_{g,n,r}$ Renewable credit
- RM_p Planning reserve margin
- $RPS_{r,t}$ Renewable Portfolio Standard target
- $SL_{n,s}$ Max energy by pumped storage in MWh
- $UL_{ge,n}$ Resource potential in MW
- $VC_{g,t,b,n}$ Variable cost of generator in 2010\$/MWh
- $\Phi_{n,l}$ Element of node-line incidence matrix

Variables:

- $c_{g,t,n}$ Capacity in MW
- $ch_{t,b,n}$ Charge of pumped storage in MW
- $disc_{t,b,n}$ Discharge of pumped storage in MW
- $f^{+}_{l,b,t}$ Power flow in the forward direction in MW
- $f^{-}_{l,b,t}$ Power flow in the reverse direction in MW
- $i_{r,t}$ Unmet RPS requirement in MWh
- Inv_t Investment costs in year t in 2010\$
- $o_{g,t,b,n}$ Output of generator in MW
- Op_t Operational cost at year t in 2010\$
- $\lambda^{+}_{l,b,t}$ Shadow price for constraint (7a) in \$/MW/year
- $\lambda^{-}_{l,b,t}$ Shadow price for constraint (7b) in \$/MW/year
- $w_{l,t,v}$ Number of interfaces added by year t (integer)

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$x_{ge,n,t}$ Generation Investment at year t in MW

II. Introduction

TRANSMISSION investments have grown significantly over the past decade in the USA [1]. They are expected to be sustained at high levels in the near future [2],[3] as policy-makers and industry recognize the significant benefits of transmission upgrades and expansion [4],[5].

As a result of restructuring of electricity markets in parts of the USA, generation investments have become more market driven while transmission investments have largely continued to be made on a regulated cost recovery basis [6]. In this framework, Independent System Operators (ISOs) play a central role in identifying and/or approving transmission projects.

ISO planning procedures have mainly focused on projects addressing reliability and facilitating interconnections [7]. For those purposes, ISOs and other organizations, such as the Western Electricity Coordinating Council (WECC) [8], developed procedures that evaluate transmission expansion plans by simulating system production costs given an assumed generation mix. This approach is usually called "reactive" or "generation-first" planning, since the transmission planner responds to a pre-defined generation fleet [7]. Since then, issuance of FERC Order 1000 and the emergence of renewables driven by policy incentives have led to changes in planning processes.

In particular, the growing amount of renewables has complicated the forecasting of future generation siting. There are at least two reasons for this. First, high quality wind resources are often located at remote areas with weak or no transmission connections under the current network configuration [9]. The cost-effectiveness of such resources depends in part on the expense of the new transmission needed to deliver them, which may be highly uncertain until detailed transmission plans are made. Second, wind generators have shorter construction lead times than transmission, and generation expansion plans might change depending on where the transmission planner decides to expand the grid [10].

To overcome those challenges, transmission planners have developed new approaches to account for wind siting in reactive planning procedures. For example, the ERCOT Competitive Renewable Energy Zones (CREZ) study [11] estimated costs under four wind siting scenarios. After consulting with stakeholders, the regulator then decided to build the transmission plan identified by one scenario [12]. In contrast, MISO [13] identified wind zones and ranked them using criteria such as proximity to load and capacity factor. Then they developed wind siting scenarios by allocating equal amounts to zones starting from the top ranked zones until the renewable requirement was satisfied for each region.

These examples illustrate the efforts of planners to improve generation mix projections in generation-first transmission planning. However, as Kahn [14] points out, this general approach still does not capture the trade-offs between transmission investment costs and generation mixes. By decomposing the problem into two separate and successive sub-problems (wind siting and then transmission planning), the interactions of these decisions are only partially captured, and the planner is unable to determine if the overall strategy selected is indeed least-cost. With this approach, the planner can only conduct "what-if" analyses and simulations of the system under a few wind siting scenarios, and significant cost savings that might be gained from co-optimization may be overlooked.

Moreover, this reactive approach is also problematic since it does not account for the possibility that the optimal response of generator investors to that transmission plan might differ from the assumed generation projection. To account for this interaction, some planners adopt an iterative approach in which two optimization models, one for generation and one for transmission, are alternately applied until convergence is achieved (e.g., WECC's Long Term Planning Tool [15]).

However, as proven mathematically [16], such an iterative approach cannot guarantee convergence to the joint transmission-generation optimum. This joint optimum, though, can in theory be identified by a co-optimization planning approach (also called proactive or anticipative transmission planning) [7][16]. That approach optimizes generation and transmission investment simultaneously on a system-wide basis, and so endogenously accounts for any interdependency between transmission and generation investments. We implement the proactive transmission planning concept, which is further explained in Section III, as a mixed integer linear programming (MILP) model in Section IV. Because the number of transmission candidates in transmission planning can be large relative to the capabilities of existing software [17], we also evaluate the performance of three alternative screening metrics for limiting the number of candidates considered.

We present an application of the co-optimization model to the Eastern Interconnection (EI), using the EI Planning Collaborative (EIPC) database [18]. This allows us to address the following question: *How do plans and total system costs resulting from traditional planning approaches (generation-first or iterative) compare to costs under full co-optimization of transmission and generation investment?* Thus, our first contribution is to estimate the benefits co-optimization can achieve for a 24-bus representation of a real system (the EI).

Our second contribution is to address the question: *Can congestion-based screening metrics be used as screening metrics in order to reduce the pool of candidate transmission investments without diminishing the benefits of co-optimization?* Most screening metrics rely on shadow price information, which may mis-estimate the benefit of the expansion of an interface because they do not consider the extent of the interface expansion and its interaction with potential augmentation of other interfaces. To quantify the potential inefficiencies introduced by those screening procedures, we compare the solution of the co-optimization model considering a full set of alternatives with solutions that only consider subsets of interfaces that survive the three screening methods considered.

The rest of the paper is structured as follows. Section III reviews recent research on methods to consider generation-transmission investment interactions. Section IV defines the theoretical basis for applying co-optimization in a restructured electricity market and summarizes our model. Section V describes the experimental design of our EIPC case study and presents the definitions of the screening metrics that we compare. Section VI presents the results of the optimization and screening analyses, followed by conclusions in Section VII.

III. Theoretical Transmission Planning Frameworks

Two basic frameworks aiming at net benefits maximization have been proposed as alternatives to reactive (generation-first) transmission planning: (1) proactive transmission planning and (2) iterative or coordinated transmission planning.

A proactive or anticipative transmission planner expands transmission while anticipating how generation investment and operations will respond. In [7], Sauma and Oren assume that the transmission planner has an objective of maximizing net market surplus and prove that the proactive planner will lead to superior solutions in terms of market surplus compared to the reactive network planner's approach but inferior compared to an integrated (or composite) resource planner [19].

Under the assumptions of perfect competition among generators and efficient transmission pricing (locational marginal pricing), the proactive transmission planning problem is equivalent to integrated resource planning, which can be solved as a single-level maximization of market surplus problem [20]. But in the most general case, in which generators may possess market power, the proactive planner has to solve a hierarchical, multi-level optimization problem in order to maximize social welfare [7].

The authors of [21] assume that generators add capacity strategically but operate under perfect competition. Thus they formulate the three-level problem (transmission planning—generation planning—market clearing) of [7] as an equivalent MILP under a binary expansion discretization assumption. Changing the perfect competition assumption of [21] to Cournot competition, the problem is formulated as a Mixed Integer Non Linear Program (MINLP) in [22], [23]. In [24],[1] Cournot competition is relaxed and a fourth level is introduced representing generator's bidding problem. There, an iterative solution method employing search-based techniques and agent-based models is proposed. However, the reader should be aware that in case strategic behavior is assumed, questions of existence or multiplicity of generation equilibria can arise [22],[25].

The second alternative to reactive planning that has been proposed in the literature assumes coordination of generation and transmission planning through a multi-step, iterative process that iterates between investment decisions by different parties. The authors in [26] consider merchant transmission, generation investors, and a system planner, the latter being responsible for the security of the network. The planner broadcasts capacity payment signals if security criteria are not met; if on the other hand those criteria are met, she broadcasts LMPs and FMPs (Locational and Flowgate Marginal Prices). Investors react to those signals, and the procedure iterates until a defined stopping criterion is met.

A more realistic iterative approach, given present US market designs and tools, has been proposed by Gu et al. [27]. Their planning procedure starts with generation planning; then, given the generation investments identified, the procedure continues with transmission planning. After defining a tentative set of transmission investments, it adjusts the generation investment plan, and continues iterating between the two planning modes (generation, transmission) until a convergence criterion is satisfied (similar to WECC's LPTP model [15]).

Despite the proven result [7] that proactive planning, *in theory,* leads to superior results compared to traditional approaches, papers estimating the practical improvements in net benefits compared to traditional planning practice are lacking. The existing literature has instead focused on: 1) resolution of the computational problems arising because of the MINLP nature of the generation and transmission planning problem in case strategic behavior is assumed [21], [22], [24] and 2) model enhancement through addition of new features such as outage contingencies [28]. However, transmission planners should consider the benefits of more complex models, in terms of improved plans, before changing existing transmission planning practice. To the best of our knowledge, only one paper presents relevant benefit estimates [16] and reports up to 5% savings for co-optimization relative to reactive planning for a simplified 13-zone US network. In contrast to [16], our analysis employs a more detailed network and scenario assumptions that were developed by EIPC stakeholders [29].

IV. Model Description

Because of the size of the EI problem in terms of number of zones, companies, and resources, our analysis assumes perfect competition and efficient transmission pricing. As mentioned above, this allows us to solve the problem using an efficient single-level model that co-optimizes generation and transmission expansion [30]. Another simplifying assumption that makes computation easier is that of perfectly inelastic demand. As a result, maximization of net market surplus or benefits (which is a nonlinear objective function under elastic demand) reduces to minimization of cost, which is a linear objective in our formulation.

In summary, our model identifies a set of transmission and generation investments over a multiyear planning period in order to achieve minimum system cost. Specifically, the costs considered include investment expenses along with fuel, variable and fixed maintenance costs for generators, carbon taxes, Renewable Portfolio Standards Alternative Compliance Payments, and hurdle rates that apply to power trade between regions.[2] The problem is formulated as a MILP with decision variables for generation and transmission investments in each year from 2011 to 2030. Transmission investments are modeled as discrete, integer variables to consider the lumpiness in line additions, while all other variables are modeled as continuous. Transmission expansion is possible only for existing interfaces, consistent with the EIPC study. Dispatch is modeled for three seasonal load duration curves, defining a total of 20 periods per year, representing a range of load and renewable output conditions.

[1] In [24] the transmission planner does not maximize market surplus. Instead, she minimizes a function based upon the maximum regret across planning criteria.

[2] We assume that carbon tax and hurdle rate taxes reflect actual costs for the society.

Investment decisions for 20 years are modelled, which is a typical long term planning horizon. Because investments have benefits beyond year 20 and full overnight capital costs are included in the cost objective for new infrastructure, there could be large "end effects" distortions in cost calculations and investment decisions if no years after year 20 are simulated [31]. Therefore, we adopt an end-effects correction approach similar to EGEAS [32]. Specifically, we model a 40-year extension period with stationary conditions identical to year 20, essentially assuming that the last year's capacity and dispatch are maintained in years 2031-2070. We also include annualized capital payments for any generation infrastructure that would exceed its lifetime over the 2031-2070 period, assuming that retired plants are replaced with similar facilities. This end effects treatment is captured in the second term of the objective function, shown below:

$$\sum_{t=1}^{20}\frac{Inv_t+OP_t}{(1+DR)^t}+\sum_{t=21}^{60}\frac{Op_{20}+\sum_{g,n}AIC_{g,n}*M_{g,n,t}}{(1+DR)^t} \quad (1)$$

where:

$$Inv_t = \sum_{ge,n} GI_{ge,n,t}x_{ge,n,t} + \sum_{l,v} GI_{l,v}*(w_{l,t,v}-w_{l,t-1,v}) \quad (2)$$

$$Op_t = \sum_{b,g,n} H_b VC_{g,t,b,n} o_{g,t,b,n} + \sum_{g,n} FOM_g c_{g,t,n} + \sum_{b,l} H_b HR_l (f^+_{l,b,t}+f^-_{l,b,t}) + \sum_r ACP_r i_{r,t} \quad (3)$$

This objective is minimized subject to the constraints below:

$$\sum_l \Phi_{n,l}(f^+_{l,b,t}-f^-_{l,b,t})+\sum_g o_{g,t,b,n}+disc_{t,b,n}=L_{b,t,n}+ch_{t,b,n}, \forall t,b,n \quad (4)$$

$$o_{g,t,b,n}\le(1-FOR_g)(1-POR_{g,b})CF_{g,b,n}c_{g,t,n}, \ \forall g,t,b,n \quad (5)$$

$$c_{g,t,n}\le c_{g,t-1,n}+x_{ge,n,t}, \forall g,t,n$$

$$where \quad c_{g,0,n}=IC_{g,n} \quad (6)$$

$$f^+_{l,b,t}\le IC^+_l+\sum_v MVA_v*w_{l,t,v}, \ \forall l,b,t \quad (7a)$$

$$f^-_{l,b,t}\le IC^-_l+\sum_v MVA_v*w_{l,t,v}, \forall l,b,t \quad (7b)$$

$$c_{ge,t,n}\le UL_{ge,n}, \quad \forall t,ge,n \quad (8)$$

$$\sum_{n\in P,g} CC_{g,n}c_{g,t,n}\ge(1+RM_p)PL_{t,p}, \qquad \forall p,t \quad (9)$$

$$0.75*\sum_{b\in S} ch_{t,b,n}H_b \ge \sum_{b\in S} disc_{t,b,n}H_b, \ \forall s,t,n \quad (10)$$

$$ch_{t,b,n}\le c_{ps,t,n}, \ disc_{t,b,n}\le c_{ps,t,n}, \ \forall t,b,n \quad (11)$$

$$\sum_{b\in S} disc_{t,b,n}H_b\le SL_{n,s}, \qquad \forall s,t,n \quad (12)$$

$$i_{r,t}+\sum_{b,g,n} H_b RC_{g,n,r}o_{g,t,b,n}\ge RPS_{r,t}*\sum_{b,n} H_b L_{b,t,n}, \forall t,r \quad (13)$$

$$\sum_{b,gi,n\in IR} H_b o_{g,t,b,n}\le 0.35*\sum_{b,n\in IR} H_b L_{b,t,n}, \ \forall t,ir \quad (14)$$

In addition, all variables are assumed to be nonnegative, and the transmission planning variable $w_{l,t,v}$ is integer.

The constraints modeled include a load balance constraint for each zone and time period (4), generator capacity constraints taking into account forced and planned outages along with output profiles for intermittent resources (5), interface flow limits (7), limits on resource construction (8), planning reserve constraints (9), storage operational constraints (10-12), and renewable policy constraints (13-14). Constraint (6) allows units to retire in any year, which might be optimal if a unit is not dispatched often and its fixed O&M costs are high enough. For storage constraints, a 75% efficiency was assumed (10). Since pumped storage's energy capability was not available, an upper bound constraint (12) was imposed on its discharge based on EIPC study results [33]. A similar approach was followed for hydro units. Constraint (13) models Renewable Portfolio Standards (RPS) and (14) imposes an upper bound on wind and solar generation in each intermittency region equal to 35% of annual load, which was considered by EIPC to be a plausible penetration level.

Additional constraints, which are mainly slight modifications of constraint (8), are imposed to take into consideration licensing issues for nuclear, lead time issues (e.g., for all generators, except natural gas, no investment is considered the first 4 years), maximum amount of investment per transmission interface (set to 20,000 MW), and limits on regional concentrations of investments (e.g., wind capacity installed in the SPP region cannot be higher than 50% of the total EI wind capacity). Many of these constraints represent stakeholder judgments concerning the feasibility of different resource development patterns. Consistent with the original EI study, Kirchhoff's Voltage Law is not included in the constraints as the stakeholders agreed to represent the EI as a transshipment model. As pointed out in [34], omission of KVL constraints might lead to different than the true optimal plan. However, according to results presented in [34, Fig. 11] it appears that the discrete transportation model, which we essentially assume here, performs well in approximating the cost of the discrete+KVL model. If reactances are available for the reduced network, it is possible to impose the voltage law at the expense of additional binary variables [30]. However, data from [35] for 2010 indicates that loop flows occur frequently (e.g., more than half of the time flows are from TVA to SOCO, SOCO to VACAR, and then from VACAR back to TVA), suggesting that KVL does not hold for this zonal model.

Other widely used continental-scale planning tools such as IPM [36], which is used for both policy making and planning, and ReEDS [37], which is applied by NREL to investigate power system futures, employ similar formulations to the one described above. While both of those models have some additional features such as more detailed representations of air pollution control options in IPM, both of them are linear problems. In contrast, our model treats transmission as discrete investments using binary variables, which Ref. [34] concludes is more realistic. While in this particular application, we focus on benefits society might enjoy if the proposed model is adopted by transmission planners, other parties might find it useful in their policymaking or decision making processes. Examples include generation investors who might apply the model for market intelligence purposes, and regulators who could use the model when reviewing applications for new transmission facilities.

The problem is modeled in AIMMS. The CPLEX 12.6 solver is used to solve the model with a MIP gap tolerance of 10^{-6} (expressed as a fraction of the objective function).

V. Experimental Design

A. Eastern Interconnection representation

For all results reported in this paper, we use the 24-bus representation of the Eastern Interconnection from the original study [28]. We omit regions outside of the EI in this case as the interchanges between them and the EI are relatively small. The EI is represented with 24 nodes (set N) where Balancing Authorities are aggregated to nodes. Nodes are connected through 47 interfaces (set L). Transfer limits[3] are approximate estimates of the maximum power that could be transmitted between any adjacent nodes in 2020.

The network was defined by knowledgeable experts from planning coordinators through a transparent multi-stakeholder process. In the original study, this network was judged sufficient for generating conceptual transmission plans that would capture the fundamental economics of interregional transmission and be of sufficient interest to justify further study.

However, the EIPC study recognized that this representation has a number of simplifications rendering more detailed analyses necessary in an actual planning process. [4] Some of those simplifications included disregarding of internal congestion within the regions, the assumption of a single interface between any two regions instead of multiple lines at different voltages and locations, and the absence of physical correspondence of interfaces to lines, thus making contingency analysis impractical.

Another major simplification of the previous study was the employment of heuristics, which ignore transmission expansion costs, to decide on conceptual transmission build-outs. In this paper, we attempt to overcome this simplification by co-optimizing the planning of transmission and generation. However, we also had to simplify some other assumptions, including the following:

1) Transmission capital costs are estimated based on EIPC data on costs per MW-mile for eligible configurations (345 kV single and double circuits, 500 kV, 765 kV), adjusted for regional differences.[5]
2) We approximated interface lengths using distances between the region's center points.[6]
3) To represent wheeling cost and power trading frictions between regions, hurdle rates are considered and vary between 0 and 10 $/MWh.

B. *Case study: data assumptions*

The purpose of this study is to explore and illustrate the benefits of co-optimization. Because the database for the original EIPC study were developed by a collaborative stakeholder process [38] and the assumptions and results of that study have been used or analyzed in follow-on studies [39], [35], [40], we retain the original EIPC assumptions, except where noted, in order to make our results as comparable as possible. [7] For instance, we keep the same horizon (2011-2030) as the original study so stakeholders can better assess the benefits of co-optimization.

Twelve types of generators *G* are considered for new investments. These include combustion turbines, combined cycle (CC), hydro, pulverized coal, integrated gasification combined cycle (IGCC), IGCC with carbon capture and sequestration (IGCC_CCS), onshore/offshore wind, nuclear (Nuc), biomass, landfill gas, and photovoltaics.

All dollar values are in 2010$. A 5% real discount rate is used in present worth calculations in line with the original study and industry practice[41]. Since the purpose of this study is to explore and illustrate the benefits of co-optimization rather than to replicate the full EIPC study or come up with an actual transmission plan, we focus on one of the EIPC planning scenarios, the EIPC CO_2+ scenario (also known as "Future 8 Sensitivity 7"). This scenario was chosen because of its relatively high investments in transmission and renewable generation in the original EIPC study. A high assumed CO_2 price is the key driver of those investments (Table I).

We omit three other policies modeled in the EIPC study in order to simplify the model: these include renewable incentives, NO_x and SO_2 caps, and other EPA rules (such as once-through cooling restrictions) that may require plant retrofits.

Table I: Indicative CO_2 prices (Source: EIPC [18])

Year	2015	2020	2025	2030
Carbon tax (2010$/tn)	26.83	38.1	62.39	139.74

In brief, some basic characteristics of the case study are:

1) Energy demand falls by 4% from 2011 to 2030 due to growth in energy efficiency and distributed generation.
2) A high amount of Demand Response (DR) (152 GW in 2030) is installed. That DR is given full credit in the planning reserve constraint and is dispatched as a pseudo-generator with a variable cost of 750 $/MWh.
3) Renewable portfolio standards are applied to eight aggregated zones, and 6 zones are used specifically for solar.
4) Generation capital costs are reduced annually to account for learning effects. They are also adjusted for regional differences and financing costs for various technologies.

C. *Modeling of alternative planning approaches*

1) Proactive transmission planning/ Co-optimization

This planning approach is implemented by solving the MILP presented in Section IV, which allows transmission and generation investments to be jointly optimized.

2) Iterative planning approach

This planning approach is similar to the iterative planning approach used in [16], [27]. The model of Section IV is used iteratively, switching between generation-only and transmis-

[3] Several methods were used to specify the transfer limits based on stakeholder preferences. In brief, the following methods were used: linear transfer analysis, first contingency incremental transfer capability (FCITC), operating limits (actual or augmented) to account for additions, and historical data.

[4] Phase 2 of the EIPC study [47] partially addressed this concern by simulating the system in detail for one peak hour and one off-peak hour.

[5] Interface expansion costs vary between 1,261 and 11,836 $/MW-mile.

[6] Given the absence of information on the precise lines, substations or other constraints by interface, it is hard to determine the exact investment cost required to increase transfer limits. We assumed that relieving the constraint requires investment in transmission lines for the entire distance between the centers of the regions being connected. However, the investment required could be lower in case the congestion is concentrated at border bottlenecks between the two regions, or possibly higher in cases in which transmission is limiting for power transfers between buses that are far more distant than the centers. We have tested the latter assumption, for example, and found that co-optimization remains beneficial in that case, although the magnitude of benefits is smaller.

[7] Current paper is a successor of the study completed in 2015, where interested reader can find more detailed analysis and comparisons [48].

sion-only investment modes. In the former mode, the transmission investment decisions are fixed at the levels decided at the previous iteration, and the only investments optimized are generation. Similarly, when the mode is transmission-investment only, generation capacity in each zone is fixed at the levels decided at the previous iteration. The first iteration is the generation investment mode, given the present grid. We stop iterating between the two modes when convergence is achieved in that the objective function does not improve.

3) Reactive planning approach

This planning approach attempts to model traditional practice. In the introduction, we define reactive transmission planning as transmission planning under a pre-defined scenario of the generation fleet. The definition is quite broad and might correspond to different methods for identifying the assumed generation mix (e.g., the MISO and ERCOT cited in Section II, above) and/or different methods of transmission planning (e.g., assessment of lines individually or optimization of a portfolio of lines). In our application, we assume that the generation mix scenario has been identified through optimization of generation investments given the existing transmission network. Then, transmission planner designs conceptual transmission plans by solving an optimization problem for the whole system given that generation mix. In brief, the reactive planning approach is simulated by the first two iterations of the iterative approach. First, generation capacity is optimized to create a generation build-out scenario, and then transmission is optimized subject to the generation scenario.

D. Congestion metrics/Restricted proactive model

Congestion metrics are frequently used by transmission planners to reduce the set of candidate transmission lines to a subset that appears particularly promising and so can be studied in more detail. In particular, ISOs employ those metrics to identify or/and screen transmission projects that could improve market efficiency. For example, PJM uses total congestion cost and binding hours [42], SPP uses the total shadow price of each transmission interface [43], and MISO has proposed a new metric called Estimated Potential Benefit (EPB) [44]. The authors of [44] assess the metrics based on their ability to reflect the rank order implied by the Actual Potential Benefit (APB) of interface expansions, and conclude that EPB outperforms the other metrics. APB is defined as the reduction in system cost estimated by a production costing model after expanding an interface. We consider three metrics related to those ISO methods, defined as follows.

ISOs usually calculate those metrics by extracting flows and shadow prices based on extensive production cost simulations they run under a specific generation siting scenario. In our case, we use the same definitions but obtain the flows and shadow prices from the planning model. In particular, we run the generation-only planning model (1st iteration of the iterative approach). Generation investments are represented through continuous variables and the transmission network is fixed. So the first iteration is a linear program and shadow prices for the transmission flow limit constraints (7) are provided by the solver. The flows are also recorded and used for calculation of metric (15). Moreover, instead of the year-by-year calculations ISOs use, we apply the metrics to all years at once by summing them over the entire planning horizon.

1. *Total congestion cost (TCC):* defined as the product of hourly shadow price and hourly flow on the interface, summed over all hours of the year (in \$/yr):

$$TCC_{t,l} = \sum_b (|{\lambda^{+}_{l,b,t}}^{8}| + |\lambda^{-}_{l,b,t}|) * (f^{+}_{l,b,t} + f^{-}_{l,b,t}) \qquad (15)$$

2. *Total shadow price (TSP):* defined as the sum of hourly shadow prices for the interface (in \$/MW/yr).

$$TSP_{t,l} = \sum_b (|\lambda^{+}_{l.b.t}| + |\lambda^{-}_{l,b,t}|) \qquad (16)$$

3. *Estimated Potential Benefit (EPB):* defined as the product of the hourly shadow price of the original model and the maximum overflow (flow over the capacity) that is recorded in a second run of the model if the congested interface is unconstrained (constraint (7) is relaxed). In its practical application by MISO, congested interfaces are sorted into groups and one simulation per group is conducted in which (7) is deactivated and the unconstrained flow (f^{un}) is recorded for all interfaces of the group.

$$EPB_{t,l} = \sum_b (|\lambda^{+}_{l,b,t}| + |\lambda^{-}_{l,b,t}|) * |f^{+,un}_{l,b,t} + f^{-,un}_{l,b,t} - IC_l| \qquad (17)$$

All three metrics consider the benefit of additional capacity through shadow prices or overflows, but they ignore the investment cost of the line. This omission could lead to retention of high value but very costly candidate interfaces, but exclusion of lower value interfaces that have a higher net benefit. As an attempt to counter this weakness, we apply a charge to any overflow. We assumed a charge that would be a lower bound to the fixed charge (in \$/MWh) required to recover the investment cost. For that purpose, we calculated the discounted sum of hours included in the model (174,112 hours). Then assuming that the interface will be used all 8760 hours at full capacity, we divided the investment cost per MW of the least expensive configuration for each interface by ~2*10^5 hours.

VI. Results

A. Benefits of co-optimization/proactive planning compared to iteration and reactive planning

By construction of the experiment, co-optimization of generation and transmission planning cannot have a higher cost than the iterative approach. This is because the latter has the same objective function but a smaller feasible region since some of the decision variables are fixed at each iteration (e.g., generation investments are fixed for the 2nd iteration). Since reactive planning is equivalent to the iterative approach with the maximum number of iterations set at two, and since the cost cannot be worsen from iteration to iteration, reactive planning cannot have a lower cost than the iterative method.

Here we quantify the extent to which co-optimization outperforms the reactive and iterative methods. Co-optimization results in cost savings of \$4.5bn compared to the reactive ap-

[8]Note that in all calculations we assume that there is one hourly shadow price per time block b and its relationship with the shadow price for constraint (7) is $\lambda_{l.b.t} = H_b * hourly\ shadow\ price$.

proach and $3.5bn (0.10% of the objective function) compared to the iterative approach (see Table II). The iterative method converged in only 4 iterations. In particular, it identified the same transmission investments as the reactive approach but as part of iteration 3, generation investment changed slightly responding to the transmission investments of iteration 2. So, in this case the two approaches have quite similar solutions. For that reason, we will only present and discuss the results of the iterative approach in the following tables. This similarity of the iterative and the reactive approaches is not generally the case, however, as we demonstrate in one of the sensitivity runs in section VI-B.

Contrasting the composition of costs of the two approaches, we see that co-optimization makes more investments in order to save operational costs. In particular, co-optimization decides to invest in transmission that connects regions with wind capacity factors high enough to compete with conventional resources to high load regions that lack high quality wind resources. In that manner, co-optimization integrates approximately one-third more wind both in terms of capacity and energy (see Table III). This generation mix change is significantly driven by the carbon tax cost savings (which make up $51.5bn out of the $907bn-$818bn = $89bn savings in extension period operational costs in Table II).

Table II: Objective function components

Metric ($bn NPV in 2010$)		Co-optimization	Iterative (4th iteration)
Years: 2011-2030	Generation Operation	1,583	1,592
	Generation Investment	692	633
	Transmission Operation (Hurdle Rates)	9	8
Years: 2031-2070	Extension period annualized capital costs	500	473
	Extension period operational costs	818	907
Total	Transmission Investment	9	1
	Objective function	3,610.9	3,614.4

Table III: EI Capacity mix in 2030, GW/TWh

Capacity Type	Co-optimization	Iterative 4th
CC	220/770	233/921
CT	49/7	45/7
Nuc, Hydro, IGCC_CCS	219/1501	219/1505
Wind	194/622	143/458
DR	152/1	152/1
Other	18/94	19/102

The majority of the investments are concentrated in the late 2020's since a high carbon tax[9] is necessary to make wind competitive with CC, even in regions with high quality wind. For example, 2020 is the first year that wind has a lower levelized cost in 4 regions. The number of such regions reaches 6 in 2030 (Fig.1). Other reasons that could explain the concentration of investments in the late 2020's could be negative load growth in the near future in combination with abundant existing capacity that is not due to retire until the 2030's and the declining capital costs of renewables due to the learning rates assumed. As a result, much of the savings achieved by co-optimization are observed towards the end of the model horizon. In particular, converting the overnight capital payments to annualized costs, we observe that the majority of the savings achieved by co-optimization are concentrated in years 2029, 2030 and the extension period.[10]

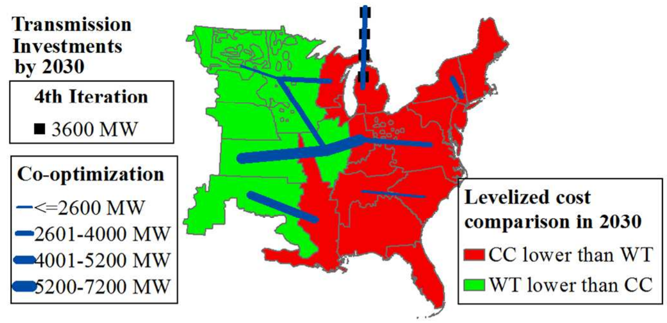

Figure 1: EI transmission investments by 2030 (MW)

Transmission investment is significantly lower in the iterative approach compared to co-optimization (see Fig. 1). To explain this difference, we describe the iterative mechanism in more detail. In the first iteration, which invests in generation only, tight transmission constraints and the lack of a clear economic advantage for wind means that investment in gas-fired plants occurs even in regions with high quality wind. Wind integration is modest and no curtailment is observed. Then the 2nd iteration identifies which transmission lines are justified by operational cost savings, given the generation build-out from the 1st iteration. The presence of gas generation and absence of wind curtailment leads the model to avoid new connections to regions with high quality wind. Thus, the iterative approach fails to recognize that operating cost savings can arise from simultaneously investing in remote wind and the interregional transmission needed to access it. In economic terms, those two investments are complementary, in that the presence of one increases the economic value of the other. Co-optimization is needed to capture this interdependency.

However, the iterative method does recognize operational savings due to regional fuel cost differences or/and differences in the marginal resource. Nevertheless, the former does not justify transmission investments here due to the wheeling charges exceeding fuel cost differences for the same type of resource. The latter, however, motivates the iterative method's only transmission investment, which is also identified by co-optimization. Ontario has spare low cost capacity during most load periods. As a result, 3.6 GW of expansion is justified for one interface to facilitate export of its cheap capacity (Fig. 1).

[9] We have also run sensitivities with lower carbon tax prices. A ~ 0.02% savings were observed for a carbon tax of 100 $/tn applied to 2015-2030, while a higher carbon price (140 $/tn) produced a higher co-optimization savings (0.12%).

[10] Note that this concentration of investments and savings in the final years of the horizon would lead to negligible savings in terms of % of the objective function (~0.03%) if annualized investment costs were used to correct end effects. However, the benefits would still be considerable for the years 2029 and 2030 (~0.2 to 0.5%, respectively).

Finally, the amount of trade in the EI increases significantly under co-optimization compared to the iterative solution. This is expected since gas-fired plants can be developed in any region with fairly similar costs while high quality wind is found only at specific regions. To measure trade, we divide the EI into zones by combining regions that have zero hurdle rates between them, and then calculate flows among those zones. Co-optimization increases the sum of net trade between these zones by 150% (from 64 TWh to 152 TWh) in 2030.

B. Sensitivity analyses

We also quantified co-optimization's benefits for two sensitivity cases. In the first, we replace the carbon tax with an EI-wide renewable portfolio standard. In the second, we extend through 2030 a production tax credit (PTC) of 22$/MWh of wind production for the first 10 years of a wind investment. Please note that the results of the first sensitivity analysis depend on the flexibility allowed for trading renewable energy credits as shown in [45]. In our sensitivity, enforcement at the EI-level assumes full flexibility for credit trading within EI.

For the first sensitivity, we enforced an EI-wide renewable energy target that we calculated to match the TWh of renewables generated by year in the base case co-optimization results, and then we removed the carbon tax. The iterative model now needs 10 iterations to converge. The result is that the iterative and co-optimization solutions have a more similar pattern of transmission development, with 7,506 GW-miles built under co-optimization vs. 5,598 GW-miles in the iterative case. At that point, the co-optimization solution costs $1bn less. Although both methods procure the same amount of renewable energy, the co-optimization approach builds more wind at the expense of biomass and wood. High quality of wind in specific regions compensates for the additional transmission investment needed to access them, and makes those remote wind resources competitive compared to local renewables.

In the second sensitivity case, the PTC yields more wind investment in both approaches. However, the cost saved by co-optimization resembles that in the base case (section VI-A). Co-optimization costs $4.3bn less than the iterative solution, corresponding to 0.12% of the total objective. However, the number of iterations required for convergence increases from 4 to 24. As a result, we now observe a more pronounced cost improvement resulting from using iterative rather than reactive planning (Table IV).

Table IV: 2nd Sensitivity solution comparison of three planning approaches

Transmission planning approach:	Reactive (2nd iteration)	Iterative (24th iteration)	Co-optimization
System cost after PTC receipt ($2010bn)	3,581.2	3,558.8	3,554.5
By 2030: Transmission Investment (GW-mile)	1,554	19,161	33,896

C. Co-optimization performance when candidate transmission investments are pre-screened

Computational time is a disadvantage of the full co-optimization. Here, co-optimization took 5-9 times as long to solve as the iterative approach, even though the latter involved multiple model solutions. So we evaluate whether pre-screening of investments in order to reduce model size could improve solution times, and whether restricting the options considered decreases the benefits of co-optimization.

We identified the 10 most congested interfaces in the EI using the three metrics defined in Section V-C. Thus, the set of candidate interfaces is greatly reduced from the original 47 interfaces. Using the three sets of interfaces identified by the metrics as the reduced sets of transmission candidates (noted S_R), we then co-optimized the EI system three times, once for each metric. Even though all metrics use the same shadow prices in their definition, the sets of interfaces they identify are very different because of the different roles of existing flows (in the case of metric TCC) and overflows (for EPB), as shown in Table V. Only three interfaces appear in all three sets of 10 interfaces and one of them is the interface that expands under the iterative approach (Fig. 1).

Table V: Intersections of reduced sets of candidate interfaces

Set	Size	Set	Size
$S_{TCC} \cap S_{TSP}$	5	$S_{TSP} \cap S_{EPB}$	4
$S_{TCC} \cap S_{EPB}$	5	$S_{TSP} \cap S_{EPB} \cap S_{TCC}$	3

Pre-screening lines results in a smaller number of integer variables for new lines, and reduces solution time by two-thirds for the co-optimization model, when using the same gap tolerance (10^{-6}). Unfortunately, however, by restricting which lines can be chosen by co-optimization, the cost savings obtained from co-optimization are reduced (see Table VI).

Table VI: Performance of different screening metrics

Co-optimization with S_R based on:	TCC Metric	TSP Metric	EPB Metric	Full set of lines
Cost increase vs. full set of lines ($bn)	1.8	1.6	0.6	0
Cost savings vs. iterative ($bn)	1.7	1.9	2.9	3.5
Time to solve (sec)	411	608	490	2081
No. of integer variables	480	384	480	1968

Note: The number of continuous variables is the same in each model (218,164). The LP Barrier method is used at each node of the Branch-and-Bound algorithm. The priority feature of integer variables for branching and full probing are adopted. These solution times are achieved on a desktop with Intel core processor i7-5930K at 3.50GHz and 32 GB Ram.

Cost savings achieved vary (Table VI) depending on the metric used. EPB outperforms the other two metrics: it captures the highest portion (82%) of co-optimization's cost savings without taking more time. Given that the interface expanded by the iterative approach is part of all three reduced sets, the iterative approach is the same across all metrics. So, EPB also incurs the least cost increase (+$0.6bn) compared to co-optimization with the full set of lines, while TCC and TSP incur an increase approximately three times as high.

Digging further into the metrics' performance, we examine the number of interfaces at the intersection of two sets: 1) set O_F, defined as the set of interfaces expanding under co-optimization with the full set of lines and 2) set S_R. Then, the number of false positives is defined as the size of $S_R \cap (S_R \cap O_F)^C$ and the number of false negatives is equal to the size of the set $O_F \cap (S_R \cap O_F)^C$. Given that in our application, the sizes of S_R and O_F are identical, the numbers of false positives and negatives are equal (Table VII). We see that EPB also performs best (fewest false positives/negatives).

Table VII: Comparison of sets $\boldsymbol{S_R}$ and $\boldsymbol{O_F}$

Reduction metric	Size of $S_R \cap O_F$	False positives/negatives
TCC	4	6
TSP	4	6
EPB	7	3

There are two reasons for the success of the EPB metric. First, the overflow analysis indicates which interfaces might experience the greatest increase in use if all interfaces are expanded simultaneously. In that manner, it identifies economically attractive multi-interface paths. Second, the overflow charge guides the flow and prevents some false positives. For example, in the case of two parallel paths with same shadow prices, EPB will favor the one with the lowest cost.

However, the success of EPB in our case does not result from its ability to better approximate actual potential benefits (APB, defined above), contrary to the claim in [44]. Even if we identify the most promising interfaces using APB and co-optimize with this reduced set, we only get 77% of the full co-optimization savings because APB focuses on benefits from individual expansions, ignoring interactions among interfaces.

Examining the false positives of each S_R, we now consider the reasons for their inclusion. First, all three metrics employ shadow price information. Those prices are useful but they do not quantify the extent (in GW) of expansion that would be beneficial, nor do they provide information on how those benefits would be affected by expanding other interfaces. In particular, the false positive line that all three screening methods share seems to be beneficial for a much lower number of MW than the size of a new line for that interface. Also, the TCC and TSP metrics may include all the interfaces connecting two adjacent regions with large price differences while in practice it may be optimal to expand just the least costly interface. Finally, although the adjusted EPB does account for interface interactions, it could yield false positives because allowance of an overflow in one interface may cause overflows on other interfaces in series, not all of which may be optimal to expand.

Reviewing the false negatives, we see that all metrics tend to miss interfaces that consist of the next-most limiting element on a multi-interface serial path. EPB seems to suffer the least because the simultaneous release of the flow limits might lead to significant overflow in the multi-interface path, prioritizing even lines with low shadow prices. However, in case of zero shadow prices, EPB would expect no improvement and might miss an optimal series of lines to expand. To correct this, grouping techniques might be adopted [46].

VII. Conclusions

We apply co-optimization, or “proactive transmission planning”, to a 24-bus representation of the Eastern Interconnection, using a dataset for the entire EI developed in a stakeholder process. Savings from co-optimization are ~0.1% of system cost, compared either to reactive (generation-first) planning or a model that iterates between generation and transmission expansion. Given the high total system cost (several trillion dollars in present worth for the EI), this magnitude of savings is considerable. Those savings are on the same order of magnitude as incremental transmission investment costs. Transmission investments increase access to remote high quality wind resources and achieve savings through increasing trade between EI regions and recognition of the complementarity of transmission and remote generation investment.

However, model size and solution times are a challenge for practical implementation of co-optimization. We apply and evaluate congestion metrics as screening criteria in order to reduce the number of transmission options considered. However, we observe that two widely used congestion metrics have a high rate of failure, in terms of overlooking lines that would actually be expanded in a co-optimization with the full set. These metrics fail to achieve more than half of the cost savings of co-optimization with the full set. In contrast, a version of the estimated potential benefit (EPB) metric proposed by MISO performs better, capturing ~82% of the savings while reducing solution times by more than 75%.

Future work could test the benefits of co-optimization and the success of EPB as a screening criterion based upon more detailed representations of the EI network that include Kirchhoff’s Voltage Laws. Also, co-optimization benefits could also be quantified assuming strategic players rather than perfect competition. This would require use of large-scale multi-level optimization models.

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IX. References

[1] L. Aniti, “Investment in electricity transmission infrastructure shows steady increase,” EIA, Today in Energy. [Online]. Available: http://www.eia.gov/todayinenergy/detail.cfm?id=17711.

[2] International Energy Agency, “World Energy Investment Outlook,” Int. Energy Agency, Paris, Fr., vol. 23, 2014.

[3] Edison Electric Institute, “Transmission Projects : At A Glance,” 2015. [Online]. Available: ttp://www.eei.org/issuesandpolicy/transmission/pages/transmissionprojectsat.aspx

[4] J. Pfeifenberger, J. Chang, and J. Tsoukalis, “Investment Trends and Fundamentals in US Transmission and Electricity Infrastructure,” 2015. [Online]. Available: http://www.brattle.com/system/publications/pdfs/000/005/190/original/Investment_Trends_and_Fundamentals_in_US_Transmission_and_Electricity_Infrastructure.pdf?1437147799.

[5] J. Pfeifenberger, J. Chang, and A. Sheilendrananth, “Towards more effective transmission planning: addressing the costs and risks of an insufficiently flexible electricity grid,” 2015. [Online]. Available: http://www.wiresgroup.com/docs/reports/WIRES%20Brattle%20Rpt_TransPlanning_042315.pdf

[6] J. Pfeifenberger, J. Chang, M. Davis, and M. Geronimo, “Contrasting Competitively-Bid Transmission Investments in the U . S . and Abroad.” 2014. [Online]. Available: http://www.brattle.com/system/news/pdfs/000/000/719/original/Contrasting_Competitively-Bid_Transmission_Investments_in_the_U.S._and_Abroad.pdf?1408140050

[7] E. E. Sauma and S. S. Oren, “Proactive planning and valuation of

transmission investments in restructured electricity markets," J. Regul. Econ., vol. 30, pp. 358–387, 2006.
[8] WECC, "WECC TEPPC 2007-08 Study Plan," 2007. [Online]. Available: http://www.oatioasis.com/csu/csudocs/teppc_tasswg_study_plan_v3_4-07.doc
[9] R. Piwko, D. Osborn, R. Gramlich, G. Jordan, D. Hawkins, and K. Porter, "Wind energy delivery issues [transmission planning and competitive electricity market operation]," IEEE Power Energy Mag., vol. 3, no. 6, pp. 47–56, 2005.
[10] M. Madrigal and S. Stoft, "Transmission Expansion for Renewable Energy Scale Up: Emerging Lessons and Recommendations," Washington DC, 2012.
[11] ERCOT System Planning, "Competitive Renewable Energy Zones (CREZ) Transmission Optimization Study," 2008. [Online]. Available: http://pbadupws.nrc.gov/docs/ML0914/ML091420467.pdf
[12] Public Utility Commission of Texas, "Texas Public Utility Commission Approves Wind Transmission Plan," News Release, 2008. [Online]. Available: http://www.puc.texas.gov/agency/resources/pubs/news/2008/071708.pdf
[13] MISO, "Regional Generation Outlet Study." [Online]. Available: https://www.misoenergy.org/Planning/Pages/RegionalGenerationOutletStudy.aspx.
[14] E. Kahn, "Wind Integration Studies: Optimization vs. Simulation," Electr. J., vol. 23, no. 9, pp. 51–64, 2010.
[15] WECC Staff, "2013 Interconnection-wide Plan Tools and Models," 2013.
[16] A. Liu, B. F. Hobbs, J. Ho, J. D. McCalley, and Q. P. Krishnan, Venkat; Shahidehpour, Mohammad; Zheng, "Co-optimization of Transmission and Other Supply Resources," 2013.
[17] R. Bo, C. Wu, J. Yan, L. Hecker, and Z. Zhou, "LODF - based Transmission Solution Screening Method In Economic Transmission Planning," in 2015 IEEE Power & Energy Society General Meeting, 2015, pp. 1–5.
[18] "Eastern Interconnection Planning Collaborative (EIPC)." [Online]. Available: http://www.eipconline.com/.
[19] R. M. Sawey and C. D. Zinn, "A mathematical model for long range expansion planning of generation and transmission in electric utility systems," IEEE Trans. Power Appar. Syst., vol. PAS-96, no. 2, pp. 657–666, 1977.
[20] A. H. van der Weijde and B. F. Hobbs, "The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty," Energy Econ., vol. 34, no. 6, pp. 2089–2101, 2012.
[21] D. Pozo, E. Sauma, and J. Contreras, "A Three-Level Static MILP Model for Generation and Transmission Expansion Planning," IEEE Trans. Power Syst., vol. 28, no. 1, pp. 202–210, 2013.
[22] S. Jin and S. M. Ryan, "A Tri-Level Model of Centralized Transmission and Decentralized Generation Expansion Planning for an Electricity Market — Part I," IEEE Trans. Power Syst., vol. 29, no. 1, pp. 132–141, 2014.
[23] S. Jin and S. M. Ryan, "A tri-level model of centralized transmission and decentralized generation expansion planning for an electricity market-Part II," IEEE Trans. Power Syst., vol. 29, no. 1, pp. 142–148, 2014.
[24] A. Motamedi, H. Zareipour, M. O. Buygi, and W. D. Rosehart, "A transmission planning framework considering future generation expansions in electricity markets," IEEE Trans. Power Syst., vol. 25, no. 4, pp. 1987–1995, 2010.
[25] D. Pozo, J. Contreras, and E. Sauma, "If you build it, he will come: Anticipative power transmission planning," Energy Econ., vol. 36, pp. 135–146, 2013.
[26] J. H. Roh, M. Shahidehpour, and Y. Fu, "Market-based coordination of transmission and generation capacity planning," IEEE Trans. Power Syst., vol. 22, no. 4, pp. 1406–1419, 2007.
[27] Y. Gu, J. D. McCalley, and M. Ni, "Coordinating Large-Scale Wind Integration and Transmission Planning," IEEE Trans. Sustain. Energy, vol. 3, no. 4, pp. 652–659, 2012.
[28] J. Aghaei, N. Amjady, A. Baharvandi, and M.-A. Akbari, "Generation and Transmission Expansion Planning: MILP–Based Probabilistic Model," IEEE Trans. Power Syst., vol. 29, no. 4, pp. 1592–1601, 2014.
[29] Eastern Interconnection Planning Collaborative, "Phase 1 Report : Formation of Stakeholder Process , Regional Plan Integration and," 2011. [Online]. Available: http://nebula.wsimg.com/44f0897683f915dac648f22ac80624b5?AccessKeyId=E28DFA42F06A3AC21303&disposition=0&alloworigin=1
[30] F. D. Munoz, B. F. Hobbs, J. L. Ho, and S. Kasina, "An engineering-economic approach to transmission planning under market and regulatory uncertainties: WECC case study," IEEE Trans. Power Syst., vol. 29, no. 1, pp. 307–317, 2014.
[31] V. Krishnan and J. D. McCalley, "Building Foresight in Long-Term Infrastructure Planning Using End-Effect Mitigation Models," IEEE Syst. J., vol. 99, pp. 1–12, 2015.
[32] Electric Power Research Institute, "EGEAS Capabilities Manual, v11."
[33] EIPC, "EIPC Phase I MRN-NEEM Model Inputs," 2011. [Online]. Available: http://www.eipconline.com/phase-i-documents.html
[34] F. D. Munoz, E. E. Sauma, and B. F. Hobbs, "Approximations in power transmission planning: Implications for the cost and performance of renewable portfolio standards," J. Regul. Econ., vol. 43, no. 3, pp. 305–338, 2013.
[35] Open Access Technology International Inc, "Assessment of Historical Transmission Schedules and Flows in the Eastern Interconnection," 2014. [Online]. Available: http://eetd.lbl.gov/sites/all/files/assessment-of-historic-transmission-schedules-and-flows-2014.pdf
[36] US Environmental Protection Agency, "Power Sector Modeling." [Online]. Available: https://www.epa.gov/airmarkets/power-sector-modeling.
[37] W. Short, P. Sullivan, T. Mai, M. Mowers, C. Uriarte, N. Blair, D. Heimiller, and A. Martinez, "Regional Energy Deployment System (ReEDS)," 2011. [Online]. Available: http://www.nrel.gov/analysis/reeds/pdfs/reeds_documentation.pdf
[38] Eastern Interconnection Planning Collaborative, "Working Draft of MRN-NEEM Modeling Assumptions and Data Sources for EIPC Capacity Expansion Modeling."
[39] S. W. Hadley, D. J. Gotham, and R. L. Luciani, "Additional EIPC Study Analysis: Final Report," 2014. [Online]. Available: http://info.ornl.gov/sites/publications/files/Pub52176.pdf
[40] A. Bloom, A. Townsend, and D. Palchak, "The Eastern Renewable Generation Integration Study : Flexibility and High Penetrations of Wind and Solar," in IEEE PES General Meeting, 2015.
[41] California ISO, "ISO 2013-2014 Transmission Planning Process Supplemental Assessment : Harry Allen-Eldorado 500 kV Transmission Project Economic Need," 2014. [Online]. Available: https://www.caiso.com/Documents/HarryAllen-EldoradoProjectAnalysisReport_AppendixA.pdf
[42] PJM, "2014 PJM Regional Transmission Expansion Plan: Book 3," 2015. [Online]. Available: http://www.pjm.com/documents/reports/rtep-documents/2014-rtep.aspx
[43] SPP, "ITP 10 2015 Integrated Transmission Plan 10-Year Assessment Report." [Online]. Available: http://www.spp.org/publications/Final_2015_ITP10_Report_BOD_Approved_012715.pdf
[44] R. Bo, L. Hecker, Y. Gu, J. Okullo, J. Bakke, and M. Ni, "A new congested flowgate ranking strategy in MISO Market Efficiency Planning Study," IEEE Power Energy Soc. Gen. Meet., pp. 1–5, 2013.
[45] A. P. Perez, E. E. Sauma, F. D. Munoz, and B. F. Hobbs, "The Economic Effects of Interregional Trading of Renewable Energy Certificates in the U . S . WECC," Energy J., vol. 37, no. 4, pp. 267–296, 2016.
[46] R. Bo, S. Member, J. Yan, C. Wu, L. Hecker, M. Tackett, and M. Ni, "Novel Congested Flowgate Grouping Methods In Economic Transmission Planning," in 2014 IEEE PES General Meeting | Conference & Exposition, 2014, pp. 1–5.
[47] Eastern Interconnection Planning Collaborative, "EIPC Phase II Documents," 2015. [Online]. Available: http://www.eipconline.com/phase-ii-documents.html.
[48] R. Johnson, A. Baechert, S. Koppolu, E. Spyrou, J. Ho, B.F. Hobbs, J. McCalley, A. Figueroa, and S. Lemos-Cano, Co-optimization of Transmission and Other Resources Study, Final Report, Prepared by Energy Exemplar, LLC, The Johns Hopkins University, and Iowa State University, Submitted to the Eastern Interconnection States Planning Council and National Association of Regulatory Utility Commissioners, Washington, DC, January 26, 2015, [Online]. Available: pubs.naruc.org/pub/536E6296-2354-D714-51E2-0762AD9121F7

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