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Power Systems Infrastructure Planning with High Renewables Penetration

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Abstract

With the increasing penetration of renewable generating units, especially in remote areas not well connected with load demand, there is growing interest to co-optimize generation and transmission expansion planning (GTEP) in power systems. Due to the volatility in renewable generation, a planner needs to include the operating decisions into the planning model to guarantee feasibility. Three different formulations, i.e., a big-M formulation, a hull formulation, and an alternative big-M formulation, are reported for transmission expansion. To address the computational challenge, we propose a nested Benders decomposition algorithm and a tailored Benders decomposition algorithm that exploit the structure of the GTEP problem. Using a case study from Electric Reliability Council of Texas (ERCOT), we are able to show that the proposed tailored Benders decomposition outperforms the nested Benders decomposition. The coordination in the optimal generation and transmission expansion decisions from the ERCOT study implies that there is an additional value in solving GEP and TEP simultaneously. The detailed results of this paper has been published in Li et al. (2021).

Keywords: Power Systems, Generation Transmission Expansion, Mixed-integer Programming, Decomposition Algorithm

1. Introduction

Generation expansion planning (GEP) of power systems involves determining the optimal size, location, and construction time of new power generation plants, while minimizing the total cost over a long-term planning horizon (Conejo et al., 2016). There is a growing interest to use mathematical programming models to solve generation expansion planning problems (Lara et al., 2018; Tso et al., 2020). Conventional power units are dispatchable thermal power plants that can provide stable power output. However, with the increased penetration of renewable generation technologies, such as solar and wind, power systems nowadays need to be more flexible so as to adjust to the volatile power generation from renewables. In this case, operations decisions, such as unit commitment, ramping decisions, become important to assess system feasibility. Transmission expansion planning (TEP) refers to installing new transmission lines or expanding the capacities of existing transmission lines in a power system. Bahiense et al. (2001) propose a mixed integer disjunctive model for transmission network expansion. GEP and TEP are generally solved as two independent optimization problems. However, the significant penetration of renewables into power systems may lead to their concentration in remote areas not well connected to load demand. Therefore, installing renewables in those remote areas could compromise transmission expansion. The recognition of transmission's interaction with generation expansion has motivated the development of co-optimization methods to consider the tradeoffs between generation and transmission expansion (Krishnan et al., 2016). This paper is an extension of the GEP model reported in Lara et al. (2018) to a GTEP model. The long version of this paper has been published in Li et al. (2021).

2. Problem Statement

We are given different types of existing and known generating units and the generating units' nameplate (maximum) capacity; expected lifetime; fixed and variable operating costs; fixed and variable start-up cost; cost for extending their lifetimes; CO_2 emission factor and carbon tax, if applicable; fuel price, if applicable; and operating characteristics such as ramp-up/ramp-down rates, operating limits, contribution to spinning and quick start fraction for thermal generators, and capacity factor for renewable generators. Also given are existing and candidate transmission lines between any of the two neighboring buses. The susceptance, distance, and capacity of each transmission line are known. We use DC power flow equations to calculate the power flow in each transmission line. These equations are built based on Kirchhoff's voltage and current laws which differ from the network flow model used in the work of Lara et al. (2018). In the network flow model, the transmission network is represented similarly to pipelines where the flows only observe energy balance at each node while ignoring Kirchhoff's laws.

With the above input data, the spatial and temporal representations in Li et al. (2021), the proposed GTEP model is to decide: a) when and where to install new generators, storage units and transmission lines; b) when to retire generators and storage units; c) whether or not to extend the life of the generators that reached their expected lifetime; d) unit commitment of the thermal generators during the representative days; e) power generation of the generator clusters and power flows through the transmission lines. The objective is to minimize the overall cost including operating, investment, and environmental costs (e.g., carbon tax and renewable generation quota).

3. Transmission Expansion Formulation

One of the major constributions of this paper is to compare different formulations for transmission expansion. For the candidate transmission lines, we can write the following disjunction, where $NTE_{l,t}$ is a logic variable whose value can be True or False indicating whether or not transmission line l is installed in year t. If line l already exists in year t, the corresponding power flow has to satisfy DC power flow equation and upper and lower bounds. Otherwise, the corresponding power flow is zero. We assume that all the candidate transmission lines are standard. In other words, the susceptance of the candidate transmission lines B_l are parameters in the model.

$$\begin{bmatrix} NTE_{l,t} \\ p^{\text{flow}}_{l,t,d,s} = B_l(\theta_{s(l),t,d,s} - \theta_{r(l),t,d,s}) \\ -F^{\max}_l \leq p^{\text{flow}}_{l,t,d,s} \leq F^{\max}_l \end{bmatrix} \vee \begin{bmatrix} \neg NTE_{l,t} \\ p^{\text{flow}}_{l,t,d,s} = 0 \end{bmatrix} \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{1}$$

Standard approaches, i.e., big-M reformulation and hull reformulation (Grossmann and Trespalacios, 2013), are available to reformulate disjunctions (1) into mixed integer constraints.

The big-M formulation of the disjunction is,

$$-M_l(1-nte_{l,t}) \leq p^{\text{flow}}_{l,t,d,s} - B_l(\theta_{s(l),t,d,s} - \theta_{r(l),t,d,s}) \leq M_l(1-nte_{l,t}) \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{2}$$

$$-F^{\max}_l nte_{l,t} \leq p^{\text{flow}}_{l,t,d,s} \leq F^{\max}_l nte_{l,t} \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{3}$$

This big-M formulation is most commonly used in the literature (Conejo et al., 2016) for TEP.

The hull formulation is,

$$p^{\text{flow}}_{l,t,d,s} = B_l \Delta\theta^1_{l,t,d,s} \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{4}$$

$$\theta_{s(l),t,d,s} - \theta_{r(l),t,d,s} = \Delta\theta^1_{l,t,d,s} + \Delta\theta^2_{l,t,d,s} \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{5}$$

$$-\pi \cdot nte_{l,t} \leq \Delta\theta^1_{l,t,d,s} \leq \pi \cdot nte_{l,t} \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{6}$$

$$-\pi(1 - nte_{l,t}) \leq \Delta\theta^2_{l,t,d,s} \leq \pi(1 - nte_{l,t}) \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{7}$$

where $\Delta\theta^1_{l,t,d,s}$ and $\Delta\theta^2_{l,t,d,s}$ are disaggregated variables for the angle difference of transmission line l. Variable $\Delta\theta^1_{l,t,d,s}$ is equal to the angle difference if transmission line l has been installed in year t. Otherwise, $\Delta\theta^2_{l,t,d,s}$ equals to the angle difference. In addition to equations (4)-(7), equation (3) needs to be included in the hull formulation. The hull formulation has more continuous variables than the big-M formulation but it avoids using the big-M parameters of equations (2).

Alternative big-M formulation: Besides the big-M and hull formulations, an alternative big-M formulation is proposed by Bahiense et al. (2001). In this formulation, additional continuous variables $p^{\text{flow}+}_{l,t,d,s}$, $p^{\text{flow}-}_{l,t,d,s}$, $\Delta\theta^+_{l,t,d,s}$, $\Delta\theta^-_{l,t,d,s}$, are introduced, where the superscript '+' means that the flow is in the same direction as the nominal direction of transmission line l, i.e., from the sending-end node $s(l)$ to the receiving-end node $r(l)$; superscript '-' means the opposite direction. By defining these new continuous variables, equation (2) is replaced by equations (8a) to (8d) and equation (3) is replaced by equations (8g) and (8h).

$$p^{\text{flow}+}_{l,t,d,s} - B_l \Delta\theta^+_{l,t,d,s} \leq 0 \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{8a}$$

$$p^{\text{flow}-}_{l,t,d,s} - B_l \Delta\theta^-_{l,t,d,s} \leq 0 \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{8b}$$

$$p^{\text{flow}+}_{l,t,d,s} - B_l \Delta\theta^{+}_{l,t,d,s} \geq -M_l(1 - nte_{l,t}) \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{8c}$$

$$p^{\text{flow}-}_{l,t,d,s} - B_l \Delta\theta^{-}_{l,t,d,s} \geq -M_l(1 - nte_{l,t}) \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{8d}$$

$$p^{\text{flow}}_{l,t,d,s} = p^{\text{flow}+}_{l,t,d,s} - p^{\text{flow}-}_{l,t,d,s} \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{8e}$$

$$\theta_{s(l),t,d,s} - \theta_{r(l),t,d,s} = \Delta\theta^{+}_{l,t,d,s} - \Delta\theta^{-}_{l,t,d,s} \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{8f}$$

$$p^{\text{flow}+}_{l,t,d,s} \leq F^{\max}_l nte_{l,t} \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{8g}$$

$$p^{\text{flow}-}_{l,t,d,s} \leq F^{\max}_l nte_{l,t} \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{8h}$$

$$p^{\text{flow}+}_{l,t,d,s}, p^{\text{flow}-}_{l,t,d,s}, \Delta\theta^{+}_{l,t,d,s}, \Delta\theta^{-}_{l,t,d,s} \geq 0 \quad \forall l \in \mathcal{L}^{\text{new}}, t, d, s \tag{8i}$$

4. Proposed Algorithms

The proposed MILP GTEP model typically involves millions or tens of millions of variables, which makes the model not directly solvable by the commercial solvers. We propose two algorithms to efficiently solve this problem.

4.1. Nested Benders decomposition

Lara et al. (2018) apply a nested Benders decomposition algorithm to solve their GEP model. Like in the GEP model, the nested Benders decomposition algorithm decomposes the fullspace of the GTEP problem by year.

4.2. Benders decomposition

Instead of solving the GTEP problem sequentially by year as in the nested Benders decomposition, we treat all the investment-related variables as complicating variables and include all these variables in a single Benders master problem. The Benders algorithm iterates between the Benders master problem and the Benders subproblems.

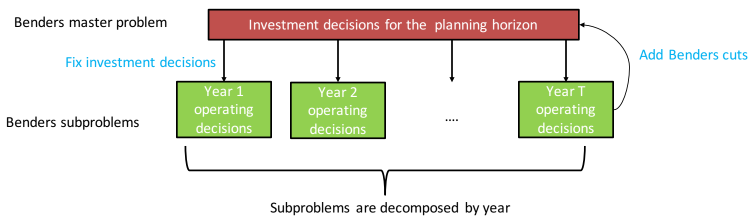

Figure 1: Tailored Benders decomposition algorithm applied to the GTEP problem

5. Results

We carry out a GTEP case study for ERCOT (Texas region in the US). It is divided into five geographical regions: Northeast, West, Coast, South, and Panhandle. We also test the two decomposition algorithms described in section 4. The nested Benders decomposition is implemented in Pyomo/Python (Hart et al., 2011). The tailored Benders decomposition implementation is from CPLEX. The computational results of the two proposed decomposition algorithms are shown in Table 1. The tailored Benders decomposition algorithm is able to solve all the three formulations to within 1% optimality gap within 10,000 seconds.

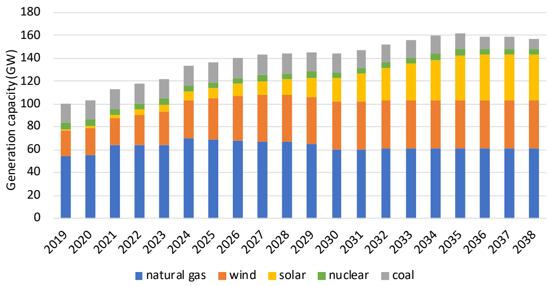

Figure 2: Aggregated generation expansion results

Table 1: Computational results of the two proposed decomposition algorithms using different formulations

Algorithm	Formulation	UB ($\$10^9$)	LB ($\$10^9$)	Gap	Wall time (secs)
tailored Benders	big-M	283.7	282.6	0.38%	5,115
tailored Benders	alternative big-M	283.9	281.6	0.82%	3,693
tailored Benders	hull	282.6	280.6	0.71%	8,418
nested Benders	big-M	295.7	268.9	9.98%	53,682
nested Benders	alternative big-M	294.2	265.5	10.81%	43,389
nested Benders	hull	288.0	269.3	6.97%	37,577

The capacities of different generation technologies from 2019 to 2038 are shown in Figure 2. The results include high capacities of solar and wind. The aggregated natural gas capacity of the five regions increases in the first few years, reaches its peak in 2024 and gradually decreases afterwards due to the retirement of old generators and the increase in carbon tax, which makes the natural gas generators less competitive compared with solar and wind generators. The nuclear capacities are unchanged throughout the planning horizon. The coal capacities are unchanged in the first few years

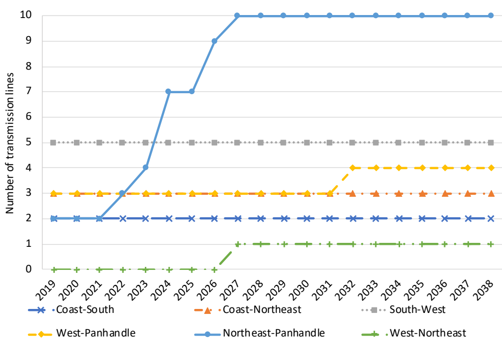

Figure 3: Transmission expansion results

and start decreasing in 2029 because of reaching their nominal lifetimes. No storage unit is installed. Therefore, the renewable generation when the net load is negative has to be curtailed. The total discounted renewable curtailment cost is \$1.64 billion in 20 years. The number of transmission lines built over the planning horizon are shown in Figure 3. Most of the transmission lines are built for Northeast-Panhandle and South-West in order to transfer the power generated by the renewable sources in West and Panhandle to other regions.

6. Conclusions

We have developed models and algorithms for capacity expansion of power systems with high penetration of renewables. For PSE researchers, the capability to analyze power systems enables to study hybrid energy systems that have both electricity generators and electricity/heat consumers, such as chemical plants.

References

L. Bahiense, G. C. Oliveira, M. Pereira, and S. Granville. A mixed integer disjunctive model for transmission network expansion. *IEEE Transactions on Power Systems*, 16 (3):560–565, 2001.

A. J. Conejo, L. Baringo, S. J. Kazempour, and A. S. Sissiqui. *Investment in Electricity Generation and Transmission - Decision Making under Uncertainty*. Springer International Publishing, 2016. ISBN 978-3-319-29501-5. doi: 10.1007/978-3-319-29501-5.

I. E. Grossmann and F. Trespalacios. Systematic modeling of discrete-continuous optimization models through generalized disjunctive programming. *AIChE Journal*, 59(9): 3276–3295, 2013.

W. E. Hart, J.-P. Watson, and D. L. Woodruff. Pyomo: modeling and solving mathematical programs in python. *Mathematical Programming Computation*, 3(3):219, 2011.

V. Krishnan, J. Ho, B. F. Hobbs, A. L. Liu, J. D. McCalley, M. Shahidehpour, and Q. P. Zheng. Co-optimization of electricity transmission and generation resources for planning and policy analysis: review of concepts and modeling approaches. *Energy Systems*, 7(2):297–332, 2016. ISSN 1868-3975.

C. L. Lara, D. S. Mallapragada, D. J. Papageorgiou, A. Venkatesh, and I. E. Grossmann. Deterministic electric power infrastructure planning: Mixed-integer programming model and nested decomposition algorithm. *European Journal of Operational Research*, 271(3):1037–1054, 2018.

C. Li, A. J. Conejo, P. Liu, B. P. Omell, J. D. Siirola, and I. E. Grossmann. Mixed-integer linear programming models and algorithms for generation and transmission expansion planning of power systems. *European Journal of Operational Research*, 2021.

W. W. Tso, C. D. Demirhan, C. F. Heuberger, J. B. Powell, and E. N. Pistikopoulos. A hierarchical clustering decomposition algorithm for optimizing renewable power systems with storage. *Applied Energy*, 270:115190, 2020.