Mario R. Eden, Marianthi Ierapetritou and Gavin P. Towler (Editors) Proceedings of the 13th International Symposium on Process Systems Engineering – PSE 2018
July 1-5, 2018, San Diego, California, USA 

# Expanding the Scope of Electric Power Infrastructure Planning

Cristiana L. Lara[a]*, Ben Omell[b], David Miller[b], Ignacio E. Grossmanna[a]

[a]*Department of Chemical Engineering, Carnegie Mellon University, 5000 Forbes Avuenue, Pittsburgh, PA 15213.*
[b]*National Energy Technology Laboratory, 626 Cochrans Mill Rd, Pittsburgh, PA 15236.*
*grossmann@cmu.edu*

## Abstract

This paper addresses long-term generation expansion planning considering a high penetration of renewables and the possibility of investing in advanced fossil fuel energy systems and multiple energy storage technologies. We propose a deterministic multi-scale mixed-integer linear programming (MILP) formulation that includes annual investment decisions and hourly unit commitment. We adopt time sampling and clustering techniques to reduce the size of the model and improve its tractability. Additionally, we use the Nested Decomposition algorithm for mixed-integer multi-period problems proposed by Lara et al. (2017) to solve the problem more efficiently. We apply the proposed formulation to a case study in the ERCOT region, and show that for this case study it makes sense to invest in small capacities of lithium-ion utility batteries in systems with increasing share of renewables.

**Keywords**: generation expansion planning, energy storage, advanced fossil fuel.

## 1. Introduction

Generation expansion planning models consist of finding the optimal investment strategy for building new generation capacity while meeting load demand and satisfying technical and economic requirements. Such models are used to support decision making in power systems, study the impact of new technology developments, identify resource cost trends, and evaluate the impact of policy shifts on the projected generation mix to meet future demand. The increasing penetration of renewable generation in the grid brought new challenges for the long-term planning models. Due to their intermittent and non-dispatchable nature, it becomes crucial to include operating details at the hourly level to ensure flexibility in the system. Therefore, recent publications such as Flores-Quiroz et al. (2016), Heuberger et al. (2017), and Lara et al. (2017) have focused on integrating unit commitment, ramping limits and operating reserves into long-term planning models.

A number of flexible, environmentally sustainable fossil energy systems are under development which can help maintain grid stability by providing baseload power as well as help manage fluctuations that occur with high penetrations of renewables. Such new systems are expected to have increasing flexibility and achieve lower costs over the next several years. In addition, energy storage can play a pivotal role in the future of renewable generation to smooth out the variability of wind and solar power output. Several stationary, large-scale energy storage technologies are under development and are projected (Schmidt et al., 2017) to significantly decrease in capital cost over the next few decades. Liu et al. (2017) considers a generic energy storage technology in their capacity expansion model, which was represented as a multistage stochastic linear programming model, and applied to a case-study in the ERCOT region.

In this paper, we extend the work by Lara et al. (2017) to address long-term planning of electric power infrastructure considering an increasing share of power generation from renewables and the possibility of having new, advanced fossil energy systems and/or electricity storage units incorporated to the grid. The modeling framework, which is based on mixed-integer linear programming (MILP), takes the viewpoint of a central planning entity whose goal is to optimize the generation expansion planning. This model is very comprehensive in terms of alternatives considered, identifying the source, generation technology, electricity storage technology, location, and capacity of future generation and storage units that can meet the projected electricity demand while taking into account detailed operational constraints (i.e., unit commitment), the variability and intermittency of renewable generation sources, and the power flow between regions. The major goal of this model is to help understanding the characteristics needed to develop new advanced energy generation and storage technologies that can be competitive in the anticipated future market considering all sources of competition.

In addition to the challenge of comprehensive grid modeling and solving the resulting MILP, another challenge lies in the multi-scale integration of detailed operating decisions at the hourly level with investment planning decisions over a few decades, significantly exacerbating the computational burden. Therefore, we adopt judicious approximations and aggregations, such as time sampling and generator clustering (Palmintier and Webster, 2014) to reduce the size of the model. In the algorithmic front, we use the Nested Decomposition algorithm for mixed-integer multi-period problems proposed by Lara et al. (2017) to solve the problem efficiently.

## 2. Problem Statement

For the proposed planning model, an area with a set of existing and potential generators is given. Regarding these generators, their source (nuclear, coal, natural gas, wind, and solar), generation technology (e.g., steam, combustion and wind turbines, photo-voltaic, concentrated solar panels, solid oxide fuel cells) are known. Also known are: their nameplate capacity; expected lifetime; capital cost; fixed and variable operating cost; maximum yearly installation limit; start-up costs (fixed and variable); cost for extending their lifetimes; $CO_2$ emission factor; age in the beginning of the planning horizon; location (regions); and operating characteristics such as ramp rates, operating limits, maximum contribution to spinning and quick-start fraction for thermal generators, and capacity factor in an hourly basis for the renewable generators.

Also given is a set of potential storage units, with specified technology (e.g., lithium-ion, lead-acid, and flow batteries), capital cost, power rating, rated energy capacity, charge and discharge efficiency, and storage lifetime. Additionally, the projected load demand is given for each location on an hourly basis, as well as the distance between locations, transmission loss factor per mile, and transmission line capacity between locations.

The objective is to find the location, year, type and number of generators and storage units to install; when to retire the generators, and whether or not to extend their lifetime; the approximate power flow between locations; and the approximate operating schedule in order to meet the projected load demand while minimizing the overall operating, investment and environmental costs.

Modeling strategies are adopted to handle the problem size and its multi-scale nature. Regarding the time scale, we use *k*-means clustering approach to select representative days from historical data that best represent the load demand and renewable capacity factor for each region (Lara et al, 2017). This reduced set of representative days with hourly resolution is multiplied by a weight to account for the entire year. For the spatial representation, the area considered is divided into regions that have similar climate and load demand profiles, and it is assumed that the potential locations are the midpoints in each region. Additionally, generators and storage units that have the same status (existing or potential) and the same technologies are grouped in clusters per region (Palmintier and Webster, 2014), such that the discrete decisions associated with generators and storage units are integer instead of binary variables, representing the number of units under a specific status in each cluster at each time period. To simplify even further the model, the transmission is determined by an energy balance between nodes, as in the "truck-route" model representation. This approximation ignores Kirchhoff's voltage law, but it is commonly used in long-term planning models that consider a large area.

## 3. MILP formulation and solution strategy

This section presents the proposed deterministic MILP formulation. For the sake of space, we only include in this paper the constraints that were modified or added to the original model by Lara et al. (2017). In addition to the set of regions $r \in R$, generator clusters $i \in I$, time periods (years) $t \in T$, representative days $d \in D$, and sub-periods of time (hours) $s \in S$, we also have a set of energy storage clusters $j \in J$.

The first modified constraint is the energy balance (1), which was Equation (1) in Lara et al. (2017). This constraint ensures that the sum of the instantaneous power $p_{i,r,t,d,s}$ by the generators in cluster *i*, regions *r*, plus the difference between the power flow from regions *r'* to region $r$, $p^{flow}_{r',r,t,d,s}$, and the power flow from region *r* to regions $r'$, $p^{flow}_{r,r',t,d,s}$, plus the power discharged from all the storage clusters $j$ in region $r$ $p^{discharge}_{j,r,t,d,s}$, equals the load demand $L_{r,t,d,s}$ at region *r*, plus the power being charged to the storage clusters *j* in region *r* $p^{charge}_{j,r,t,d,s}$, plus a slack for curtailment of renewable generation $cu_{r,t,d,s}$ at all times.

$$\begin{aligned}&\sum_i p_{i,r,t,d,s} + \sum_{r' \neq r} \left( p^{\text{flow}}_{r',r,t,d,s} \cdot (1 - T^{\text{loss}}_{r,r'} \cdot D_{r,r'}) - p^{\text{flow}}_{r,r',t,d,s} \right) + \sum_j p^{\text{discharge}}_{j,r,t,d,s} \\ &= L_{r,t,d,s} + \sum_j p^{\text{charge}}_{j,r,t,d,s} + cu_{r,t,d,s} \quad \forall\ r,t,d,s\end{aligned} \tag{1}$$

Constraints (2)-(24) from Lara et al. (2017) are also included in this formulation. The objective function (25) is modified to include a term for storage cost,

$$\min \quad \Phi = \sum_t \left( \Phi^{\text{opex}}_t + \Phi^{\text{capex}}_t + \Phi^{\text{PEN}}_t + \Phi^{\text{storage}}_t \right) \tag{25}$$

where the operating $\Phi^{opex}_t$ and investment cost $\Phi^{capex}_t$ of generators, and the penalties $\Phi^{PEN}_t$ are defined in equations (26)-(28) of Lara et al. (2017), respectively. The new term $\Phi^{storage}_t$ accounts for the costs associated with storage and is defined in (29).

$$\Phi^{\text{storage}}_t = If_t \cdot \sum_j \sum_r SIC_{j,t} \cdot Storage^{\max}_j \cdot nsb_{j,r,t} \qquad \forall\ t \tag{29}$$

Additionally, there are constraints related to the energy storage devices, which are assumed to be ideal and generic (Pozo et al., 2014). Constraints (30)-(31) compute the number of storage units that are ready to operate $nso_{j,r,t}$, taking into account the storage units already existing at the beginning of the planning horizon $Ns_{j,r}$, and the ones built $nsb_{j,r,t}$ and retired $nsr_{j,r,t}$ at year *t*. Due to the flexibility in sizes for storage units, $nso_{j,r,t}$, $nsb_{j,r,t}$, and $nsr_{j,r,t}$ are relaxed to be continuous.

$$nso_{j,r,t} = Ns_{j,r} + nsb_{j,r,t} - nsr_{j,r,t} \qquad \forall\ j,r,t=1 \tag{30}$$

$$nso_{j,r,t} = nso_{j,r,t-1} + nsb_{j,r,t} - nsr_{j,r,t} \quad \forall\ j,r,t>1 \tag{31}$$

Constraint (32) enforces the retirement of storage units that have reached the end of their lifetime $LT_j$.

$$\sum_{t'' \le t-LT_j} nsb_{j,r,t''} = \sum_{t' \le t} nsr_{j,r,t'} \qquad \forall\ j,r,t \tag{32}$$

Constraints (33) and (34) establish that the power charge $p_{j,r,t,d,s}^{charge}$ and discharge $p_{j,r,t,d,s}^{discharge}$ of the storage units in cluster $j$ $nso_{j,r,t}$ has to be within the operating limits $Charge_j^{min}$ and $Charge_j^{max}$, and $Discharge_j^{min}$ and $Discharge_j^{max}$, respectively.

$$Charge_j^{\min} \cdot nso_{j,r,t} \le p_{j,r,t,d,s}^{\text{charge}} \le Charge_j^{\max} \cdot nso_{j,r,t} \qquad \forall\ j,r,t,d,s \tag{33}$$

$$Discharge_j^{\min} \cdot nso_{j,r,t} \le p_{j,r,t,d,s}^{\text{discharge}} \le Discharge_j^{\max} \cdot nso_{j,r,t} \qquad \forall\ j,r,t,d,s \tag{34}$$

Constraint (35) specifies that the energy storage level for the storage units in cluster $j$ $nso_{j,r,t}$ has to be within the storage capacity limits $Storage_j^{min}$ and $Storage_j^{max}$.

$$Storage_j^{\min} \cdot nso_{j,r,t} \le p_{j,r,t,d,s}^{\text{level}} \le Storage_j^{\max} \cdot nso_{j,r,t} \qquad \forall\ j,r,t,d,s \tag{35}$$

Constraints (36) and (37) show the power balance in the storage units. The state of charge $p_{j,r,t,d,s}^{level}$ at the end of hour *s* depends on the previous state of charge $p_{j,r,t,d,s-1}^{level}$, and the power charged $p_{j,r,t,d,s}^{charge}$ and discharged $p_{j,r,t,d,s}^{discharge}$ at hour *s*. The symbols $\eta_j^c$ and $\eta_j^d$ represent the charging and discharging efficiencies, respectively. For the first hour of the day, the previous state of charge (i.e., $s=0$) is the variable $p_{j,r,t,d}^{level,0}$.

$$p_{j,r,t,d,s}^{\text{level}} = p_{j,r,t,d,s-1}^{\text{level}} + \eta_j^{\text{c}} \cdot p_{j,r,t,d,s}^{\text{charge}} + \frac{1}{\eta_j^{\text{d}}} \cdot p_{j,r,t,d,s}^{\text{charge}} \qquad \forall\ j,r,t,d,s>1 \tag{36}$$

$$p_{j,r,t,d,s}^{\text{level}} = p_{j,r,t,d}^{\text{level,0}} + \eta_j^{\text{c}} \cdot p_{j,r,t,d,s}^{\text{charge}} + \frac{1}{\eta_j^{\text{d}}} \cdot p_{j,r,t,d,s}^{\text{charge}} \qquad \forall\ j,r,t,d,s=1 \tag{37}$$

Constraints (38) and (39) force the storage units to begin $p_{j,r,t,d}^{level,0}$ and end $p_{j,r,t,d,s=S}^{level}$ each day with 50% of their maximum storage $Storage_j^{max}$. This is a heuristic to attach carryover storage level form one representative day to the next (Liu et al., 2017).

$$p_{j,r,t,d}^{\text{level,0}} = 0.5 \cdot Storage_j^{\max} \cdot nso_{j,r,t} \qquad \forall\ j,r,t,d \tag{38}$$

$$p_{j,r,t,d,s}^{\text{level}} = 0.5 \cdot Storage_j^{\max} \cdot nso_{j,r,t} \qquad \forall\ j,r,t,d,s=S \tag{39}$$

The integrated planning and operations model for the generation expansion planning is then given by the multi-period MILP model defined by equations (1)-(39).

Even though this formulation incorporates the modelling strategies aforementioned, it can still be very computationally expensive to solve it depending on the size of the area, the length of the planning horizon, and the time resolution of the representative days. Therefore, we use the Nested Decomposition algorithm for deterministic multi-period problems proposed by Lara et al. (2017). This algorithm consists of decomposing the problem per time period (year) and solving Forward and Backward Passes iteratively. The Forward Pass solves the problem for each time period sequentially, in a myopic fashion, and yields a feasible solution (upper bound). The Backward Pass solves a relaxed version of the subproblems from the last to the first time period, projecting the problem onto the subspace of the linking variables by adding cuts. These cuts provide approximations to predict the cost-to-go functions within the planning horizon, yielding a lower bound to the problem. The only difference between the algorithm framework presented by Lara et al. (2017) and the one used in this paper is that there are two additional state (i.e., linking) variables, $nso_{j,r,t}$ and $nsb_{j,r,t}$. For a detailed description of the algorithm, please refer to Lara et al. (2017).

## 4. Case study

We applied this formulation to a case study approximating the Texas Interconnection, managed by the Electric Reliability Council of Texas (ERCOT). Within the ERCOT covered area, we considered four geographical regions: Northeast, West, Coastal, and South, and also include a fifth region, Panhandle, which is outside the ERCOT limits but supplies electricity to ERCOT due to its renewable generation potential. Most of the data source information can be found in Lara et al. (2017), Section 6. In this case study we consider 3 types of utility batteries: lithium-ion, lead-acid and flow batteries, for which we use the capital cost forecast provided by Schmidt et al. (2017) and the technical information provided by Luo et al. (2015). We also consider two types of advanced fossil fuel energy systems: integrated gasification fuel cell (IGFC) (Iyengar et al. 2014) and natural gas fuel cell (NGFC) (Newby and Keairns, 2013). We assumed a carbon tax starting at \$10/tonne in year 5, and increasing linearly to \$100/tonne in year 14. The problem is solved for a 30-year planning horizon and 4 representative days per year. We implemented the monolithic formulation and the Nested Decomposition algorithm with Benders cut in Pyomo, and solved the LPs and MILPs using Gurobi version 7.0.1.

The full-space MILP model has 1,730,491 constraints, and 1,310,681 variables (810,181 continuous, and 500,500 integer variables). It takes 4.0 hours for Gurobi to solve the full-space MILP within 1% gap, while it takes 2.8 hours to solve the same problem within 1% gap using the Nested Decomposition algorithm with Benders cuts, which is a reduction of 30% in solution time.

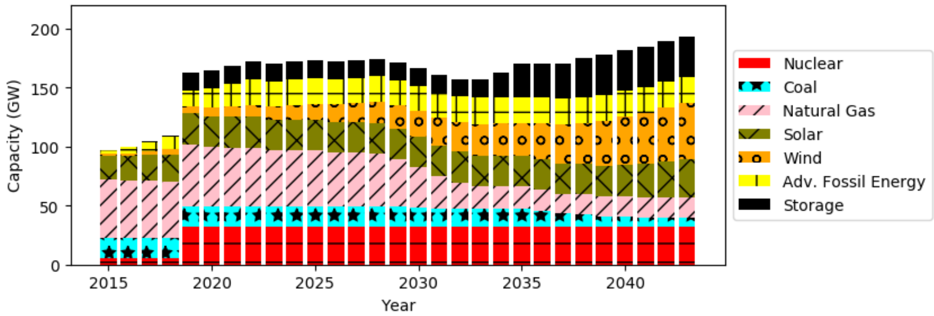


Figure 1: Generation and Storage Capacity: total ERCOT

The results displayed in Figure 1 show that most of the demand growth will be met by an increase in nuclear, solar photo-voltaic and wind capacity. It also shows that in the last year of the planning horizon there are 34.3 GW of lithium-ion batteries, and 22.0 GW of NGFC in the ERCOT region.

## 5. Conclusions

In this paper we propose an MILP model to solve power systems planning models considering increasing share of renewables and possibility of adding energy storage units. This deterministic formulation is applied to a case study in the ERCOT region. We show that by using the Nested Decomposition algorithm proposed by Lara et. al (2017) we are able to solve the problem more efficiently and predict which technologies show the highest likelihood of deployment and retirement under a variety of scenarios.

## Acknowledgements

The authors gratefully acknowledge financial support from the Department of Energy as part of the IDAES Project.



## References

A. Flores-Quiroz, R. Palma-Behnke, G. Zakeri, and R. Moreno, 2016, A column generation approach for solving generation expansion planning problems with high renewable penetration, Electric Power Systems Research, 136, 232-241.

C. F. Heuberger, E. S. Rubin, I. Staffell, N. Shah, N. M. Dowell, 2017, Power capacity expansion planning considering endogenous technology cost learning, Applied Energy, 204, 831-845.

A.K.S. Iyengar, R.A. Newby, D.L. Keairns, 2014, Techno-Economic Analysis of Integrated Gasification Fuel Cell Systems, DOE/NETL- 341/112613.

C. L. Lara, D. Mallapragada, D. Papageorgiou, A. Venkatesh, I. E. Grossmann, 2017, Electric Power Infrastructure Planning: Mixed-Integer Programming Model and Nested Decomposition Algorithm, Submitted for publication, 1-36.

Y. Liu, R. Sioshansi and A. Conejo, 2017, Multistage Stochastic Investment Planning with Multiscale Representation of Uncertainties and Decisions, IEEE Transactions on Power Systems, 99, 1-1.

X. Luo, J. Wang, M. Dooner, J. Clarke, 2015, Overview of current development in electrical energy storage technologies and the application potential in power system operation, Applied Energy, 137, 511-536.

R. Newby, D. Keairns, 2013, Analysis of Natural Gas Fuel Cell Plant Configurations – Revision 1, DOE/NETL-2013/1593.

B. Palmintier, and M. Webster, 2014, Heterogeneous unit clustering for efficient operational flexibility modeling, 2014 IEEE PES General Meeting | Conference & Exposition, National Harbor, MD, 2014, 1-1.

D. Pozo, J. Contreras and E. Sauma, Unit commitment with ideal and generic energy storage units, 2016 IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, 1-1.

O. Schmidt, A. Hawkes, A. Gambhir, I. Staffell, 2017, The future cost of electrical energy storage based on experience rates, Nature Energy, 2, 1-8.