





MILP FORMULATION AND NESTED DECOMPOSITION FOR PLANNING OF ELECTRIC POWER INFRASTRUCTURES

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EWO Meeting March 15th, 2017



Motivation

Electricity mix gradually shifts to lower-carbon options



High variability in the renewables capacity factor



 Increasing contribution of intermittent renewable power generation in the grid makes it important to include operational details at the hourly (or sub-hourly) level in long term planning models to capture their variability.



Problem Statement

Given a region with:

A set of **existing** and **potential generators** with the respective

generation technology*

if existing:

nuclear: steam turbine coal: steam turbine natural gas:

- steam turbine,
- gas-fired combustion turbine,
- and combined cycle solar: photo-voltaic wind turbines

if potential:

<u>nuclear</u>: steam turbine <u>coal</u>: IGCC w/ or w/o carbon capture <u>natural gas</u>:

- gas-fired combustion turbine,
- combined cycle w/ or w/o carbon capture solar:
- photo-voltaic
- concentrated solar panel wind turbines
- location, if applicable
- nameplate capacity
- age and expected lifetime
- CO₂ emission
- operating costs
- investment cost, if applicable
- operating data
 - if <u>thermal</u>: ramping rates, operating limits, spinning and quick-start maximum reserve
 - If renewable: capacity factor





Problem Statement

Given:

- Projected load demand over the time-horizon at each location
- Distance between locations
- Transmission loss per mile

Find:

- When, where, which type and in how many generators to invest
- When to **retire** the generators
- Whether or not to extend their lifetime
- Power flow between locations
- Detailed operating schedule

in order to minimize the overall operating, investment, and environmental costs





Modeling Strategies

To tackle the multi-scale aspect and reduce the size of the model

- Time scale approach:
 - 1 representative cycle per season (e.g., a day or a week) with hourly level information
- Region and cluster representation
 - Area represented by a few zones
 - Potential locations are the midpoint in each zone
 - Clustering of generators*
- Transmission representation
 - Flow in each line is determined by the energy balance between each region *r*.
 - This approximation ignores
 Kirchhoff's Circuit Law



*Palmintier, B.S., Webster, M.D., *Heterogeneous unit clustering for efficient operational flexibility modeling*, 2014



MILP Model

Summary of constraints:

Continuous variables:

- Power output at sub-period s
- Curtailment generation slack at s
- Power flow between regions at s
- Deficit from renewable quota at *t*
- Spinning reserve at s
- Quick-start reserve at s

Integer variables:

- no. of generators installed at period t
- no. of generators built at t
- no. of generators retired at t
- no. of generators with life extended at t
- no. of generators ON at sub-period s
- no. of generators starting up at s
- no. of generators shutting down at s
- Energy balance: ensures that the sum of instantaneous power generated at region *r* plus the net power flow being sent to this region equal the load demand plus a slack for curtailment.
- **Capacity factor:** limits the generation of renewable generators to be equal to a given fraction of the capacity in each hour.
- Unit commitment constraints: compute the startup and shutdown, operating limits and ramping rates for thermal generators.
- **Operating reserve constraints :** determine the maximum contribution per thermal generator for spinning and quick-start reserves, and the minimum total operating reserves.
- **Investment constraints :** ensure that the planning reserve and renewable energy contribution requirements are satisfied, and limit the yearly installation per generation type.
- **Constraints of number of generators:** define the number of generators that are operational, built, retired, and have their life extended at each time period *t*.



MILP Model

Objective function:

Continuous variables:

- Power output at sub-period s
- Curtailment generation slack at s
- Power flow between regions at s
- Deficit from renewable quota at *t*
- Spinning reserve at s
- Quick-start reserve at s

Integer variables:

- no. of generators installed at period t
- no. of generators built at t
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- no. of generators shutting down at s

Minimization of the **net present cost** over the planning horizon comprising:

- Variable operating cost
- Fixed operating cost
- Startup costs
- · Cost of investments in new generators
- · Cost to extend the life of generators that achieved their expected lifetime
- Fuel consumption
- Carbon tax for CO₂ emission
- Penalty for not meeting the minimum renewable annual energy production requirement

Even with the approximations adopted, this is still a very large MILP model. In order to allow longer representative cycles per season, we propose a decomposition algorithm based on **Nested Benders Decomposition*.**

*Birge, J.R., Decomposition and Partitioning Methods for Multistage Stochastic Linear Programs, 1985 Pereira, M.V.F., Pinto, L.M.V.G, Multi-stage stochastic optimization applied to energy planning, 1991 Sun & Ahmed, Nested Decomposition of Multistage Stochastic Integer Programs with Binary State Variables, 2016



Nested Decomposition for Mixed-Integer Multi-period Problems

Basic idea:

- This algorithm decomposes the problem by time period, which in this case is by year.
- It consists of Forward and Backward Passes.
- The Forward Pass solves the problem in myopic fashion (1 year time horizon).
- The **Backward Pass** projects the problem onto the subspace of the linking variables by adding cuts.



Nested Decomposition Algorithm

- 1. Set iteration k = 1, and tolerance ϵ_{1} .
- 2. Solve the Forward Pass for time periods t = 1, ..., T, and store the fixed values for $\hat{ngb}_{i,r,t,k}$ and $\hat{ngo}_{i,r,t,k}$.
- 3. Compute **upper bound**.
- 4. Solve the Backward Pass for time periods t = T, ..., 1, and generate the cuts (expected future cost).
- 5. Compute lower bound.
- 6. If $UB_k LB_k \le \epsilon_1$, STOP.
- 7. If not, set k = k+1, go back to step 2.





Case Study: ERCOT (Texas)

- **30 year** time horizon (1st year is 2015)
- Data from ERCOT database
- Cost information from NREL (Annual Technology Baseline (ATB) Spreadsheet 2016
- All costs in 2015 USD
- Regions:
 - Northeast (midpoint: Dallas)
 - West (midpoint : Glasscock County)
 - Coastal (midpoint: Houston)
 - South (midpoint : San Antonio)
 - Panhandle (midpoint : Amarillo)
- Fuel price data from EIA Annual Energy Outlook
 2016 Reference case
- No imposed carbon tax
- No renewable generation quota requirement
- Maximum transmission line capacity





Algorithm Performance

1 representative day per season

Full-space MILP Model
Integer variables: 413,644
Continuous variables:
594,147
Equations: 1,201,761

Solver: CPLEX 12.6.3 optcr: 1% CPU Time: 2.1 hours Optimality gap: 0.55%

Optimality gap over solution time



1 representative week per season

Full-space MILP Model	Solver: CPLEX 12.6.3
Integer variables: 2,901,96	<u>optcr</u> : 1%
Continuous variables:	CPU Time: Out of memory!
4,136,547	(Does not solve)
Equations: 8,476,641	

Optimality gap over solution time





Results

1 representative week per season



- Fixed operating cost
- Variable operating cost
- Startup cost
- Investment cost
- Life extension cost
- Fuel cost (not including startup)

Total cost: \$198.0 billions



61-fold increase in PVsolar capacity 31% increase in natural gas combined-cycle capacity 6% decrease in wind capacity 30% decrease in natural gas steam turbine



Conclusions

- Time scale, region and clustering approaches reduce considerably the size of the MILP planning model.
- Decomposition algorithm greatly speeds up the solution, and allows longer representative cycles per season.
- For ERCOT region, future growth in generation capacity will be met by a portfolio of different generation technologies.

Acknowledgments



Carnegie Mellon University Scott Institute for Energy Innovation





Thank you!