Scalable Power System Economic Expansion and Dispatch

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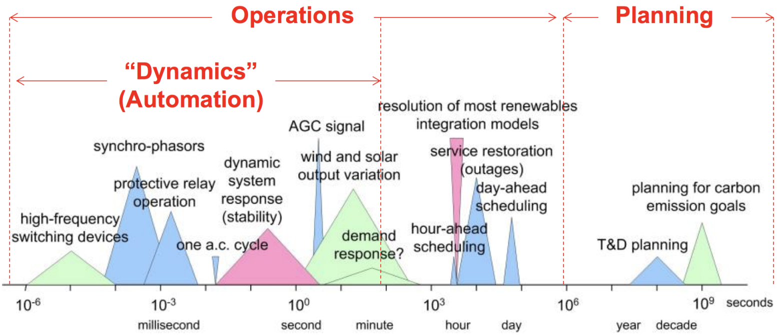
June 27, 2018

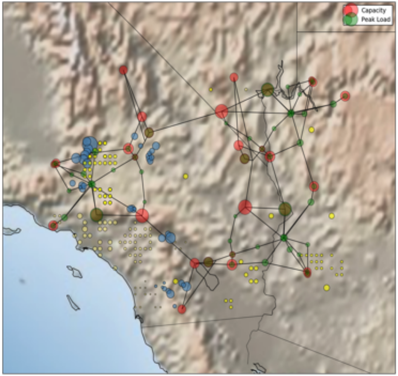
Power Grid Problems



source: Alexandra von Meier

Modeling Goal

Capacity Expansion: We seek to determine the optimal expansion of generation resources to be built to meet future load requirements on the power grid while ensuring that the grid operates economically and reliably for a suite of possible future scenarios.



General Problem Formulation

$$\begin{array}{ll} \text{minimize} & C(x) + O(x) \\ \text{subject to} & x \in \mathcal{X} \end{array}$$

- Where $x \in \mathcal{X}$ represents the build decisions made subject to constraints
- $C(x)$ represents annual payment on assets x built
- $O(x)$ represents the annual cost of operations given assets x are built

Established Models

- IPM: Environmental Protection Agency
- NEMS: U.S. Energy Information Administration
- ReEDS: National Renewable Energy Laboratory
- US-REGEN: Electrical Power Research Institute
- SWITCH: open source model original developed by Matthias Fripp [1]
- All are either linear or mixed integer linear programs in their base configuration [2]

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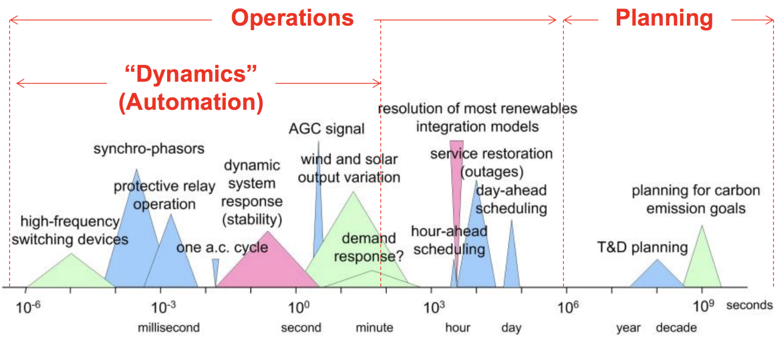
[1] https://github.com/switch-model/switch.git

[2] Variable Renewable Energy in Long-Term Planning Models: A Multi-Model Perspective (https://www.nrel.gov/docs/fy18osti/70528.pdf)

Build Decisions Informed by Operations



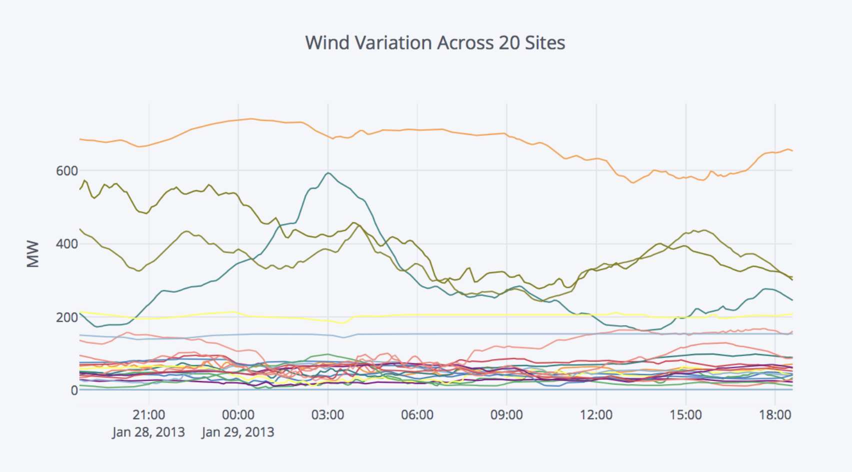
source: Alexandra von Meier

Traditional Approaches for Handling Operations

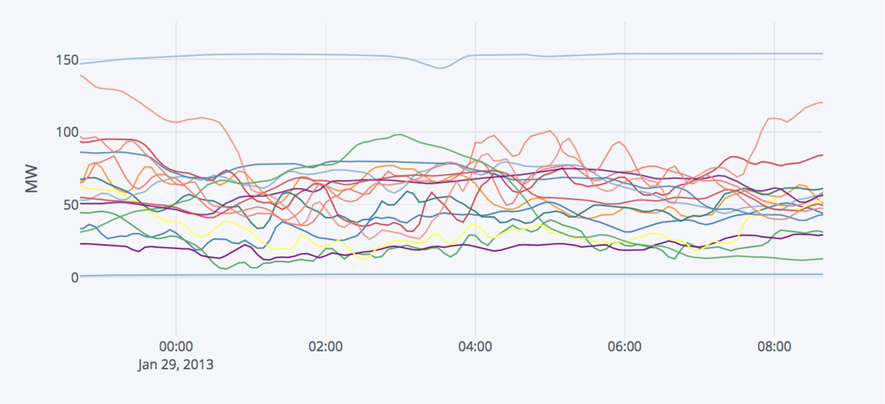
- Choose a representative set of time points from various points in the year, and weight them according to their frequency
- Choose a small set of representative days using clustering methods
- Observation: common methods use a set of operational scenarios to inform build decisions
- Question: are the existing methods sufficient for making expansion decisions where there is high penetration or renewable energy?

Variable Generation

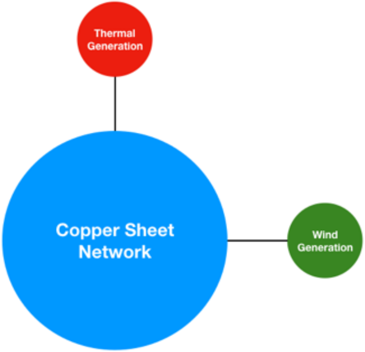
source: NREL Wind Tool Kit



source: NREL Wind Tool Kit

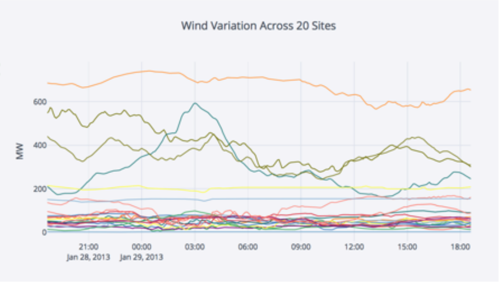

MW
150
100
50
0
00:00
Jan 29, 2013
02:00
04:00
06:00
08:00

Variable Generation on a Simple Network



One can think through the problematic cases.

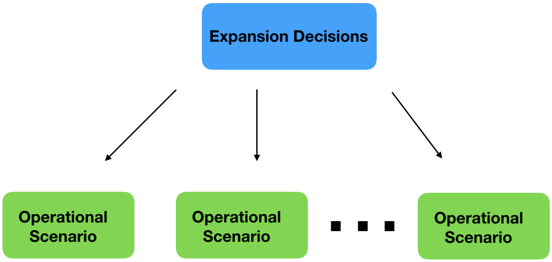
Variable Generation on a Complex Network



One can no longer think through the problematic cases, due to weakness that may exist in the network.

Big Picture Goal

A scalable modeling framework that gives us the flexibility pursue a more data driven approach that takes into account all of the operational edge cases introduced by variable generation, especially when we don't know what they are.

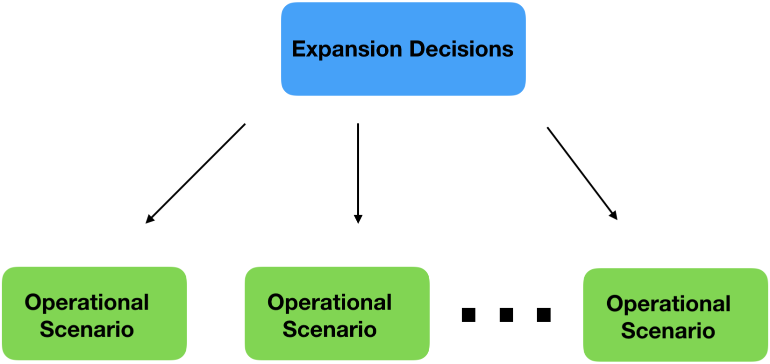


A Two-Stage View

- First Stage Decisions: What is going to be built to meet electrical power demand

- Second Stage Decisions: Grid Operations
  - Which generators to turn on
  - What levels to dispatch generators that are one
  - Which generators should hold reserves

Model Structure



We want a $O(x)$ to be a set of operational scenarios which capture the variability in renewable energy sources.

Resulting Sparsity Structure

$$
\begin{array}{lllllll}
\min\limits_{\boldsymbol{x},\boldsymbol{y}_i i=1,\dots,N} & \boldsymbol{c}^\mathsf{T}\boldsymbol{x} & + & \sum_{i=1}^{N} \boldsymbol{d}_{\xi_i}^\mathsf{T}\boldsymbol{y}_i & & & \\
\text{s. t.} & \boldsymbol{A}\boldsymbol{x} & & & & & = b \\
& \boldsymbol{T}_{\xi_1}\boldsymbol{x} & + & \boldsymbol{W}_{\xi_1}\boldsymbol{y}_1 & & & = b_{\xi_1} \\
& \boldsymbol{T}_{\xi_2}\boldsymbol{x} & + & & \boldsymbol{W}_{\xi_2}\boldsymbol{y}_2 & & = b_{\xi_2} \\
& \boldsymbol{T}_{\xi_3}\boldsymbol{x} & + & & & \ddots & = \vdots \\
& \boldsymbol{T}_{\xi_N}\boldsymbol{x} & + & & & \boldsymbol{W}_{\xi_N}\boldsymbol{y}_N & = b_{\xi_N} \\
& \boldsymbol{x} \geq \boldsymbol{0}, & & \boldsymbol{y}_1 \geq \boldsymbol{0}, & \boldsymbol{y}_2 \geq \boldsymbol{0}, & \dots, \boldsymbol{y}_N \geq \boldsymbol{0}\,. &
\end{array}
$$

Here $\boldsymbol{x}$ and $\boldsymbol{y_i}$ can have continuous and integer components

Progressive Hedging

- Horizontal technique for solving multi-stage scenario based stochastic programs
- Solves individual subproblems with penalty terms to force consensus over time amongst the first stage decision variables
- Converges linearly when subproblems are convex[3]
- Has been demonstrated to be an effective heuristic for solving stochastic mixed integer programs[4]

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[3] Rockafellar, and Wets, 1991

[4] Løkketangen, and Woodruff, 1996

Model Development

- Pyomo contains a framework PySP for modeling stochastic programs[5]
- PySP has an implementation of progressive hedging
- PySP's progressive hedging algorithm can be executed in serial or in parallel using Pyro
- A capacity expansion model was constructed using Pyomo in the PySP framework

[5]Hart, William E., et al, 2017

Core Model Features

- Objective: minimize annual costs
- First stage decisions: generators built
- First stage constraints: number of each generator type, level of generation capacity on the system
- Second stage decisions: generator hourly commitment, dispatch levels, holding reserves
- Second stage constraints: pipe and bubble network, generator commitment, min/max generation, minimum reserve levels, generator ramping

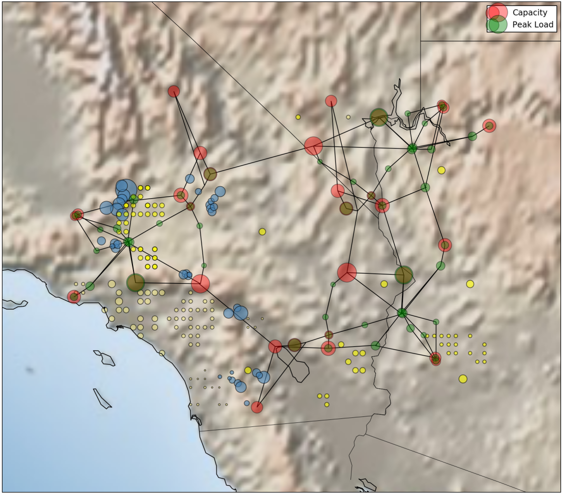
Test Case

RTS-GMLC [6] is a modernized version of the IEEE Reliability Test System-1996. It was developed to satisfy the need for a standardized data base to test and compare results from different power system reliability evaluation methodologies.

- Buses 73
- Lines 120
- Generators 158
- Three weakly connected regions

[6] https://github.com/GridMod/RTS-GMLC

RTS-GMLC



Green Field Formulation

We considered a modified version of the RTS-GMLC with the following components

- Buses 3
- Lines 3
- A pool of 279 generators divided spatially amongst the 3 buses

Our model was run to determine which of the 279 generators should be built

Performance Test Runs

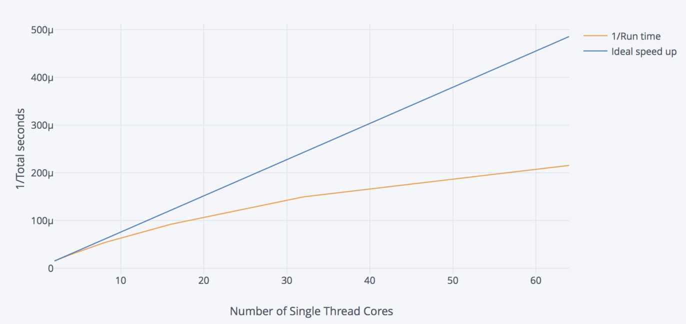
- Considered grid operations for every 3rd day of the year (122 day long scenarios)
- Each day long scenario was 24 temporally linked hourly operations decisions
- Solver used was Xpress
- Sub-problems for each scenario were solved to a 1% relative MIP gap
- Heuristics regarding cycle detection and variable fixing for acceleration convergence

Timing Results

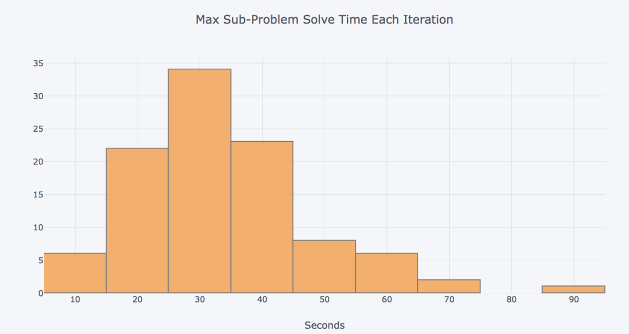
- Binary variables= 623934, continuous variables=2667408, total variables=3291342
- Iterations=100
- Relative MIP gap range=3.25% – 4.25%

	Total execution time(s)	Total PH execution time(s)	Ideal speed up(s)	Sum of max subproblem times(s)
1 Cores	128379	118829	128379.3	3267.5
2 Cores	65838.4	60928.6	64189.7	3267.5
4 Cores	34507.1	31991.5	32094.8	3279.2
8 Cores	18638.9	17358.8	16047.4	3291.8
16 Cores	10852.5	10168.1	8023.7	3328
32 Cores	6678.5	6315.2	4011.9	3350.6
64 Cores	4636.3	4450.7	2005.9	3402.3

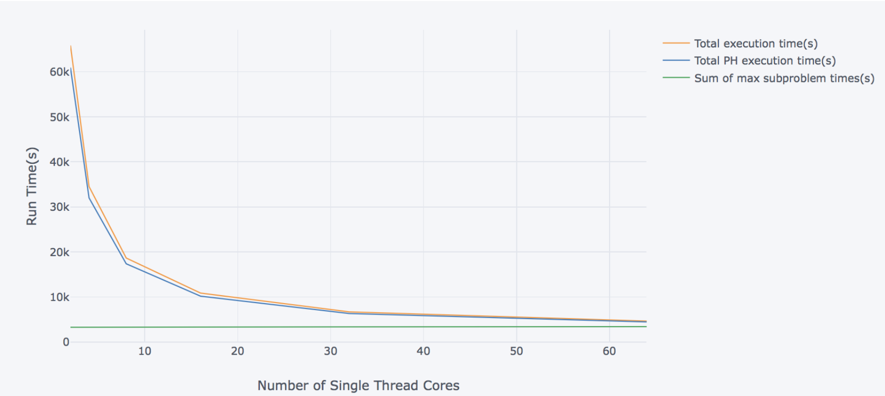
Speed Up


1/Run time
Ideal speed up
500μ
400μ
300μ
200μ
100μ
0
10
20
30
40
50
60
1/Total seconds
Number of Single Thread Cores

Sub-problems in the 64 Core Case

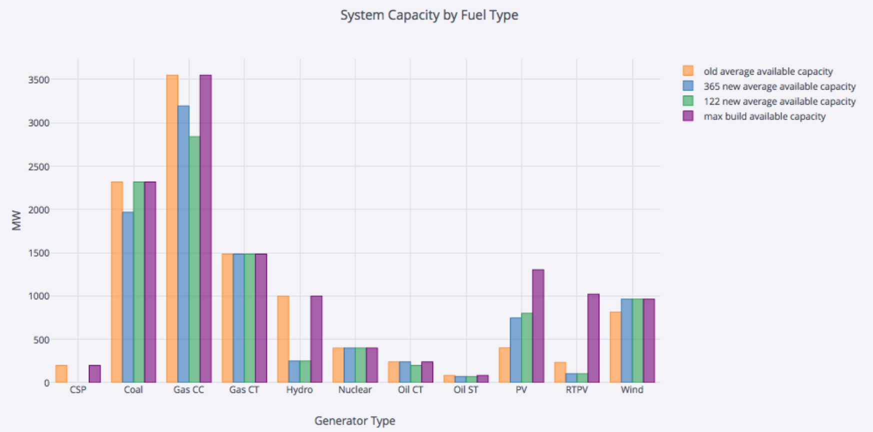


Sub-Problem Barrier



Capacity Build Out

Note: 365 days ran 100 iterations and achieved 2.1-3.1% Relative MIP gap



Summary

- We have developed a scalable capacity expansion model with respect to the number of operational scenarios in can consider
- We have done this using the stochastic programming framework PySP within Pyomo and by leveraging Pyomo's implementation of the PH algorithm

Future Work

- Refine underlying operational model, Include full RTS-GMLC network, Test on larger systems
- Close relative mip gap
- Run model with various numbers of scenario and test the resulting build decisions in a high fidelity production cost model

Two Stage Stochastic Structure

$$\begin{aligned} \min_{\boldsymbol{x}\in\mathbb{R}^n} \quad & \boldsymbol{c}^{\mathsf{T}}\boldsymbol{x} \quad + \quad \mathbb{E}_{\xi}\left[L\left(\boldsymbol{x},\xi\right)\right] \\ \text{s. t.} \quad & \boldsymbol{A}\boldsymbol{x} = \boldsymbol{b} \\ & \boldsymbol{x} \geq \boldsymbol{0} \end{aligned}$$

where the recourse function is defined as the solution to,

$$\begin{aligned} L\left(\boldsymbol{x},\xi\right) = \min_{\boldsymbol{y}\in\mathbb{R}^m} \quad & \boldsymbol{d}_{\xi}^{\mathsf{T}}\boldsymbol{y} \\ \text{s. t.} \quad & \boldsymbol{T}_{\xi}\boldsymbol{x} + \boldsymbol{W}_{\xi}\boldsymbol{y} = \boldsymbol{b}_{\xi} \\ & \boldsymbol{y} \geq \boldsymbol{0}\,. \end{aligned} \tag{1}$$

Sample Average Two Stage Stochastic Sparsity Structure

$$
\begin{array}{lllllll}
\min\limits_{\boldsymbol{x},\boldsymbol{y}_i i=1,\ldots,N} & \boldsymbol{c}^{\mathsf{T}}\boldsymbol{x} & + & \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{d}_{\xi_i}^{\mathsf{T}}\boldsymbol{y}_i & & & \\
\text{s. t.} & \boldsymbol{A}\boldsymbol{x} & & & & & = b \\
& \boldsymbol{T}_{\xi_1}\boldsymbol{x} & + & \boldsymbol{W}_{\xi_1}\boldsymbol{y}_1 & & & = b_{\xi_1} \\
& \boldsymbol{T}_{\xi_2}\boldsymbol{x} & + & & \boldsymbol{W}_{\xi_2}\boldsymbol{y}_2 & & = b_{\xi_2} \\
& \boldsymbol{T}_{\xi_3}\boldsymbol{x} & + & & & \ddots & = \vdots \\
& \boldsymbol{T}_{\xi_N}\boldsymbol{x} & + & & & \boldsymbol{W}_{\xi_N}\boldsymbol{y}_N & = b_{\xi_N} \\
& \boldsymbol{x} \geq \mathbf{0}, & & \boldsymbol{y}_1 \geq \mathbf{0}, & \boldsymbol{y}_2 \geq \mathbf{0}, & \ldots, \boldsymbol{y}_N \geq \mathbf{0}\,. &
\end{array}
$$

Weighted Sample Average Sparsity Structure

$$
\begin{array}{lllllllll}
\min\limits_{\boldsymbol{x},\boldsymbol{y}_i i=1,\ldots,N} & \boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} & + & \frac{1}{N}\sum_{i=1}^{N} N\left(\boldsymbol{d}_{\xi_i}^{\mathrm{T}}\boldsymbol{y}_i\right) & & & & & \\
\text{s. t.} & \boldsymbol{A}\boldsymbol{x} & & & & & & = b \\
& \boldsymbol{T}_{\xi_1}\boldsymbol{x} & + & \boldsymbol{W}_{\xi_1}\boldsymbol{y}_1 & & & & = b_{\xi_1} \\
& \boldsymbol{T}_{\xi_2}\boldsymbol{x} & + & & \boldsymbol{W}_{\xi_2}\boldsymbol{y}_2 & & & = b_{\xi_2} \\
& \boldsymbol{T}_{\xi_3}\boldsymbol{x} & + & & & \ddots & & = \vdots \\
& \boldsymbol{T}_{\xi_N}\boldsymbol{x} & + & & & & \boldsymbol{W}_{\xi_N}\boldsymbol{y}_N & = b_{\xi_N} \\
& \boldsymbol{x} \geq \boldsymbol{0}, & & \boldsymbol{y}_1 \geq \boldsymbol{0}, & \boldsymbol{y}_2 \geq \boldsymbol{0}, & \ldots, & \boldsymbol{y}_N \geq \boldsymbol{0}\,. &
\end{array}
$$

The Progressive Hedging Algorithm

1. $k \longleftarrow 0$, $w_i^0 \longleftarrow 0$, for $i = 1, \ldots, N$ where $w_i^0 \in \mathbb{R}^n$
2. Solve sub-problems corresponding to $\xi_1, \ldots, \xi_N$

$$\begin{aligned} \min_{\boldsymbol{x_i} \in \mathbb{R}^n, \boldsymbol{y_i} \in \mathbb{R}^m} \quad & \boldsymbol{c}^{\mathrm{T}} \boldsymbol{x_i} \quad + \quad \boldsymbol{d}_{\boldsymbol{\xi_i}}^{\mathrm{T}} \boldsymbol{y}_i \\ \text{s. t.} \quad & \boldsymbol{A x_i} = \boldsymbol{b} \\ & \boldsymbol{T}_{\boldsymbol{\xi_i}} \boldsymbol{x_i} + \boldsymbol{W}_{\boldsymbol{\xi_i}} \boldsymbol{y_i} = \boldsymbol{b}_{\boldsymbol{\xi_i}} \\ & \boldsymbol{x_i} \geq \boldsymbol{0}, \boldsymbol{y_i} \geq \boldsymbol{0}. \end{aligned}$$

$\boldsymbol{x_i}^k \longleftarrow \boldsymbol{x_i}$ for $i = 1, \ldots, N$

3. $k \longleftarrow k + 1$
4. $\bar{\boldsymbol{x}}^{k-1} \longleftarrow \sum_{i=1}^{N} \frac{1}{N} \boldsymbol{x_i}^{k-1}$
5. $w_i^k \longleftarrow w_i^{k-1} + \rho \left(\boldsymbol{x_i}^{k-1} - \bar{\boldsymbol{x}}^{k-1} \right)$ for $i = 1, \ldots, N$

The Progressive Hedging Algorithm Cont.

6. Solve penalized sub-problems corresponding to $\xi_1, \ldots, \xi_N$

$$\begin{aligned} \min_{\boldsymbol{x_i} \in \mathbb{R}^n, \boldsymbol{y_i} \in \mathbb{R}^m} \quad & \boldsymbol{c}^{\mathrm{T}} \boldsymbol{x_i} + \boldsymbol{d}_{\boldsymbol{\xi_i}}^{\mathrm{T}} \boldsymbol{y}_i + w_i^{kT} \boldsymbol{x_i} + \frac{\rho}{2} \left\| \boldsymbol{x_i} - \bar{\boldsymbol{x}}^{k-1} \right\|^2 \\ \text{s. t.} \quad & \boldsymbol{A x_i} = \boldsymbol{b} \\ & \boldsymbol{T}_{\xi_i} \boldsymbol{x_i} + \boldsymbol{W}_{\xi_i} \boldsymbol{y_i} = \boldsymbol{b}_{\xi_i} \\ & \boldsymbol{x_i} \geq \mathbf{0}, \boldsymbol{y_i} \geq \mathbf{0}\,. \end{aligned}$$

$\boldsymbol{x_i^k} \longleftarrow \boldsymbol{x_i}$ for $i = 1, \ldots, N$

7. Check to see if $\boldsymbol{x_i^k}$ are identical for $i = 1, \ldots, N$, if not return to step 3

Model

$$\text{minimize} \quad \sum_{g \in G_{new}} c_g p_g^{max} n_g + \sum_{r \in R_{new}} c_r p_r^{max} n_r \quad +$$

$$\sum_{s \in S} \lambda_s \sum_{t \in T} \sum_{g \in G \cup G_{new}} \left(c_g^{dis} p_{g,t}^s + c_g^{su} SU_{g,t}^s + c_g^{sd} SD_{g,t}^s \right) +$$

$$\sum_{s \in S} \lambda_s \sum_{t \in T} \sum_{r \in R \cup R_{new}} c_r^{dis} p_{r,t}^s$$

$$\sum_{s \in S} \lambda_s \sum_{t \in T} \sum_{q \in D} \left(c^{oload} OL_{q,t}^s + c^{loss} L_{q,t}^s \right)$$

subject to

$$(1 + R^{cap})E^{cap} \leq \sum_{g \in G} p_g^{max} n_g^{old} l_g^{dis} +$$

$$\sum_{g \in G_{new}} p_g^{max} n_g l_g^{dis} + \sum_{r \in R} p_r^{max} n_r^{old} l_r^{dis} + \sum_{r \in R_{new}} p_r^{max} n_r l_r^{dis}$$

$$n_g^{therm,min} \leq n_g \leq n_g^{therm,max} \qquad \forall g \in G_{new}$$

$$n_r^{renew,min} \leq n_r \leq n_r^{renew,max} \qquad \forall r \in R_{new}$$

$$0 \leq N^s_{g,t} \leq n^{old}_g \qquad \forall s, t, g$$
$$(g \in G \setminus G_{new})$$

$$0 \leq N^s_{g,t} \leq n_g \qquad \forall s, t, g$$
$$(g \in G_{new} \setminus G)$$

$$0 \leq N^s_{g,t} \leq n_g + n^{old}_g \qquad \forall s, t, g$$
$$(g \in G \cap G_{new})$$

$$
\begin{aligned}
&p_g^{min} N_{g,t}^s \leq p_{g,t}^s && \forall s, t, g \\
&p_{g,t}^s + y_{g,t}^s \leq p_g^{max} N_{g,t}^s && \forall s, t, g \\
&R_g^{min} N_{g,t}^s(I_g) \leq y_{g,t}^s \leq \left(p_g^{max} - p_g^{min}\right) N_{g,t}^s(I_g) && \forall s, t, g \\
&y_{g,t}^s \leq R_g^{up} && \forall s, t, g
\end{aligned}
$$

$$
N_{g,t-1}^s - N_{g,t}^s + SU_{g,t}^s - SD_{g,t}^s = 0 \qquad \forall s, t, g
$$

(some initial condition on $N_{g,0}^s$)

$$R^{sys} \leq \sum_{g \in G \cup G_{new}} y^{s}_{g,t} \qquad \forall s, t$$

$$0 \leq p^{s}_{r,t} \leq \gamma^{s}_{r,t} p^{max}_{r} n^{old}_{r} \qquad \forall s, t, r$$
$$(r \in R \setminus R_{new})$$

$$0 \leq p^{s}_{r,t} \leq \gamma^{s}_{r,t} p^{max}_{r} n_{r} \qquad \forall s, t, r$$
$$(r \in R_{new} \setminus R)$$

$$0 \leq p^{s}_{r,t} \leq \gamma^{s}_{r,t} p^{max}_{r} \left(n_{r} + n^{old}_{r}\right) \qquad \forall s, t, r$$
$$(r \in R \cap R_{new})$$

$$R_g^{down} N_{g,t}^s \le p_{g,t}^s - p_{g,t-1}^s \le R_g^{up} N_{g,t}^s \qquad \forall s,t,g$$

(some initial condition on $p_{g,0}^s$)

$$-f_l^{max} \le f_{l,t}^s \le f_l^{max} \qquad \forall s,t,l$$

$$\sum_{g \in G_{[q]} \cup G_{new[q]}} p_{g,t}^s + \sum_{r \in R_{[q]} \cup R_{new[q]}} p_{r,t}^s + \sum_{l \in K} A_{q,l} f_{l,t}^s =$$
$$= d_{q,t}^s + OL_{q,t}^s - L_{q,t}^s \qquad \forall s,t,q$$

$$N_{g,t}^s, SU_{g,t}^s, SD_{g,t}^s \in \mathbb{N} \qquad \forall s,t,g$$