Advancing Energy and Climate Planning Models

Optimization Methods, Variable Renewables, and Smart Grids

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February 27th 2019

Today's presentation

- Context and motivation
- Brief thoughts on structuring models
- Representing temporal variability in electric sector planning models
- Assessing the system value of optimal electricity load shifting

Trends for context and motivation

- Climate change
- Energy system changes (USDOE, 2016):

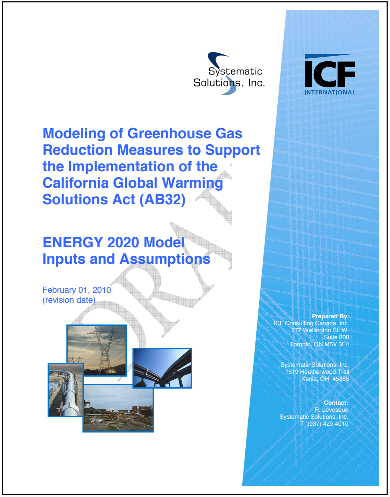
Technology	Cost decline 2008-2016
LED Lighting	94%
EV Battery	73%
PV ('utility scale')	64%
Wind (land based)	41%

- Cost per standard computation 1940-2012: 53%/**year** (Nordhaus, 2015)
- Algorithmic advances: factor of 580,000 device-independent speedup, 1990-2013, for mixed integer optimization problems (Bertsimas, 2014)

Energy and climate planning models

- Optimization based
- Often framed as finding a ‘good’ (e.g. least cost) way of meeting some goal, subject to constraints
- From planning a local utility investments to studying how the world can address climate change
- Increasing number of transportation applications
- Decision support tools

Use of energy and climate planning models


Systematic Solutions, Inc.

ICF INTERNATIONAL

Modeling of Greenhouse Gas Reduction Measures to Support the Implementation of the California Global Warming Solutions Act (AB32)

ENERGY 2020 Model Inputs and Assumptions

February 01, 2010
(revision date)

DRAFT

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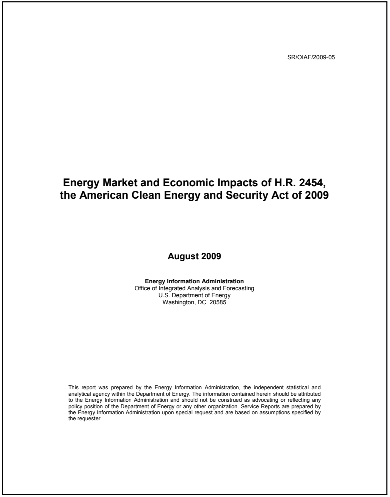
SR/OIAF/2009-05

Energy Market and Economic Impacts of H.R. 2454, the American Clean Energy and Security Act of 2009

August 2009

Energy Information Administration
Office of Integrated Analysis and Forecasting
U.S. Department of Energy
Washington, DC 20585

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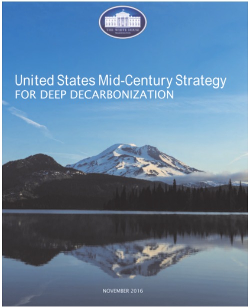
Use of energy and climate planning models

Models played a large role in mid century climate strategies submitted as part of Paris Agreement



Also, and importantly, used to understand fundamental value of different technologies and options

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- Context and motivation
- Brief thoughts on structuring models[1]
- Representing temporal variability in electric sector planning models
- Assessing the system value of optimal electricity load shifting

[1] Merrick & Weyant 2019

What is a ‘good’ model?

- Provide useful information for question asked
- Minimize detail

Turns out there is an Information Theory framework that can be applied to reason about this

Roadmap to building a 'good' model

Still resolving the map.. but it includes

- Use of available data
- Incorporation of structural constraints (economic/physical)
- Alignment between model and question
- The lightest model that can provide the most relevant information

So, what can we say about some topics important to RAEL: renewables and smart grid including storage?

Contributions

- An early attempt at systematic evaluation
- Increasing importance with greater data and greater computing power

Today's presentation

- Context and motivation
- Brief thoughts on structuring models
- Representing temporal variability in electric sector planning models[2]
- Assessing the system value of optimal electricity load shifting

[2] James H. Merrick. "On representation of temporal variability in electricity capacity planning models". In: *Energy Economics* 59 (2016), pp. 261–274.

The electricity capacity planning problem

$11 trillion projected investment 2014-2040 (IEA 2014)

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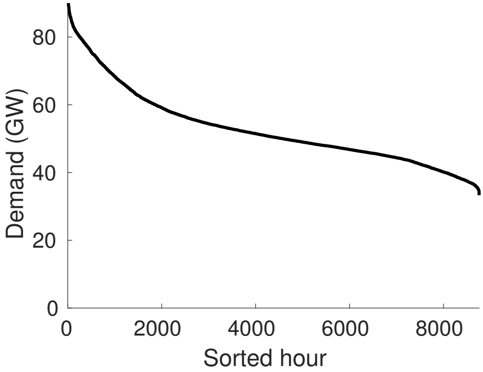
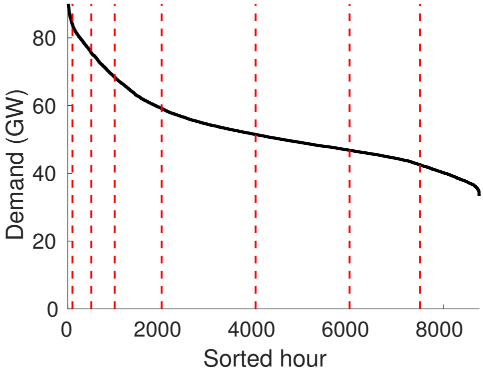


The electricity capacity planning problem

Before variable renewables, intuitive temporal representation, to significantly speed up computation.



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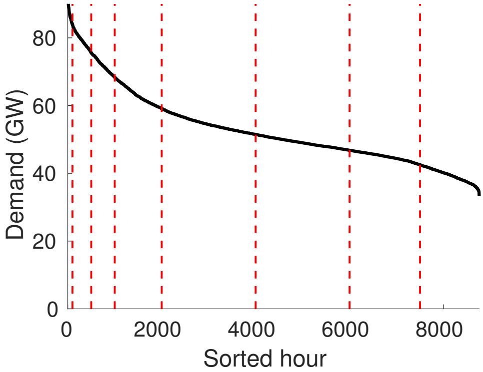

With renewables, now need to consider joint distribution of load, wind, and solar when aggregating temporal representation.

The computational motivation

Temporal resolution (number of periods)	Runtime for single run (s)
8760	15
144	0.09
1	<0.01

Influence of temporal resolution on small model runtime

Number of constraints: $|\mathcal{H}|(1+2|\mathcal{G}|) \rightarrow |\mathcal{P}|(1+2|\mathcal{G}|)$
Number of variables: $|\mathcal{G}|(1+|\mathcal{H}|) \rightarrow |\mathcal{G}|(1+|\mathcal{P}|)$

The mathematical structure

Detailed Form

Objective Function (minimise generation and investment costs):

$$\text{minimise } Z = \sum_{g\in\mathcal{G}}(I_g cc_g + \sum_{h\in\mathcal{H}} G_{g,h} vc_g)$$

Subject to:

Supply-demand balance:

$$\sum_{g\in\mathcal{G}} G_{g,h} \geq dmd_h : \lambda_h \quad \forall h \in \mathcal{H}$$

Generation less than available capacity:

$$G_{g,h} \leq I_g a_{g,h} : \delta_h \quad \forall g \in \mathcal{G}, h \in \mathcal{H}$$

Non-negativity constraints:

$$I_g, G_{g,h} \geq 0 \quad \forall g \in \mathcal{G}, h \in \mathcal{H}$$

Plus desired policy constraints etc.

The mathematical structure

Aggregate Form ($|\mathcal{P}| < |\mathcal{H}|$, $\sum_{p \in \mathcal{P}} w_p = 8760$)

Objective Function (minimise generation and investment costs):

$$\text{minimise } Z = \sum_{g \in \mathcal{G}} (I_g cc_g + \sum_{p \in \mathcal{P}} G_{g,p} vc_g w_p)$$

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Plus desired policy constraints etc.

Aggregation of temporal resolution in literature

A wide variety of existing methods:

Method	Model examples
Model every hour	EMMA (Hirth, 2013), SMART (Powell, 2012)
13 selected weeks	Aboumahboub, 2012
500 hours chosen from 10,000 sample combinations	Van der Weijde, 2012
Peak and median load day for each month	Berkeley SWITCH
86 representative hours chosen through combination of clustering and finding extreme hours	EPRI REGEN (2014)
6 representative days with 8 time slices each	PIK LIMES-EU (2014)
Representative day for each season, 4 time slices each	NREL ReEDS (2011)
3 time slices from each of 3 seasons	EIA NEMS (2014)
4 representative hours (in USA)	JGCRI GCAM (2013)
1 average segment	Implicit in an LCOE comparison

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Research questions:

- What are mechanisms through which representation can alter model insights?
- A representation with a guarantee of no error? How to find it?
- Further improvements?

Temporal variability and the economics of variable renewables

Lamont (2008)[3]: Marginal value of a renewable generator:

$$\text{Marginal Value}_g = \quad |\mathcal{H}|[(\text{Average price}).(\text{Capacity factor}) \\ \qquad +Cov(\text{price}, \text{availability})]$$

$$\text{Marginal Value}_g = 8760[E(\boldsymbol{\lambda}).CF_g + Cov(\boldsymbol{\lambda}, \boldsymbol{a}_g)]$$

[3] Alan D. Lamont. "Assessing the long-term system value of intermittent electric generation technologies". In: *Energy Economics* 30.3 (2008), pp. 1208–1231.

[4] Let $\Lambda_p = \lambda_p / w_p$

Temporal variability and the economics of variable renewables

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$$\text{Marginal Value}_g = 8760[E(\boldsymbol{\lambda}).CF_g + Cov(\boldsymbol{\lambda}, \boldsymbol{a}_g)]$$

After aggregation[4]:

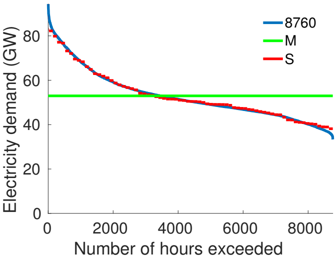
$$\text{Marginal Value}_g = 8760[E(\boldsymbol{\Lambda}).\overline{CF}_g + Cov(\boldsymbol{\Lambda}, \overline{\boldsymbol{a}}_g)]$$

[3] Alan D. Lamont. "Assessing the long-term system value of intermittent electric generation technologies". In: *Energy Economics* 30.3 (2008), pp. 1208–1231.

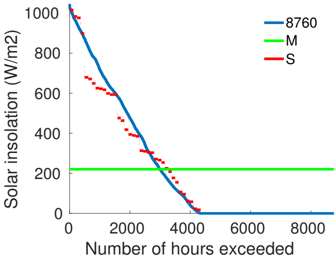
[4] Let $\Lambda_p = \lambda_p / w_p$

Illustrative example with two aggregate resolutions

- S Resolution: 144 periods. 2 days chosen per month, sampled at 4 hour periods
- M Resolution: Average demand and wind/solar availability



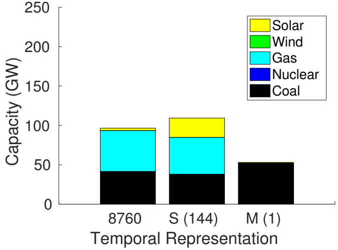
(a) Load duration curve



(b) Solar duration curve

Illustrative example with two aggregated resolutions

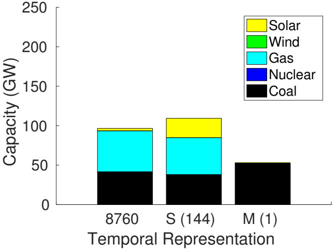
Computer implementation of mathematical formulation, using ERCOT (Texas) system data.



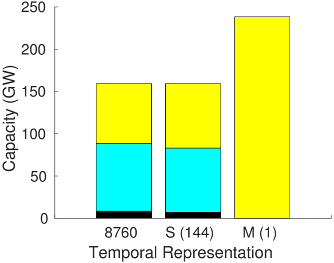
(c) $1/W PV Case

Illustrative example with two aggregated resolutions

Computer implementation of mathematical formulation, using ERCOT (Texas) system data.



(e) \$1/W PV Case



(f) \$0.5/W PV Case

How many representative periods?

Zipkin (1980)[5]: error in objective introduced by aggregation proportional to similarity of elements within each block

[5] P. H. Zipkin. "Bounds for Row-Aggregation in Linear Programming". In: *Operations Research* 28.4 (1980), pp. 903–916.

How many representative periods?

Zipkin (1980)[5]: error in objective introduced by aggregation proportional to similarity of elements within each block

Sample of temporal data (normalised) used in numerical analysis

	Load	Wind	Solar
H1	0.4480	0.4186	0
⋮	⋮	⋮	⋮
H8	0.5615	0.3810	0
H9	0.5588	0.3867	0.0130
⋮	⋮	⋮	⋮
h5225	1.0000	0.1207	0.2550
⋮	⋮	⋮	⋮
h8759	0.5285	0.5339	0
h8760	0.5025	0.4721	0

[5] P. H. Zipkin. "Bounds for Row-Aggregation in Linear Programming". In: *Operations Research* 28.4 (1980), pp. 903–916.

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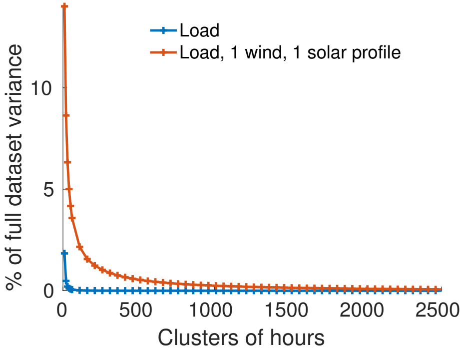
⋮	⋮	⋮	⋮
h5225	1.0000	0.1207	0.2550
⋮	⋮	⋮	⋮
h8759	0.5285	0.5339	0
h8760	0.5025	0.4721	0

Hierarchical clustering algorithm as a means of finding similar hours systematically

[5] P. H. Zipkin. "Bounds for Row-Aggregation in Linear Programming". In: *Operations Research* 28.4 (1980), pp. 903–916.

Similarity of hours

$$\text{y-axis metric: } 100.\frac{\text{Sum across clusters of within-cluster variance}}{\text{Variance across all hours}}$$



Relative variance by clustered resolution. When zero, each cluster consists only of duplicate hours.

Reducing resolution further

- Problem structure and prior information
- Operating conditions
- Further statistical development

Contributions

Introduction of variable renewables implies an increase in the number of electricity goods from the order of 10 to the order of 1000.

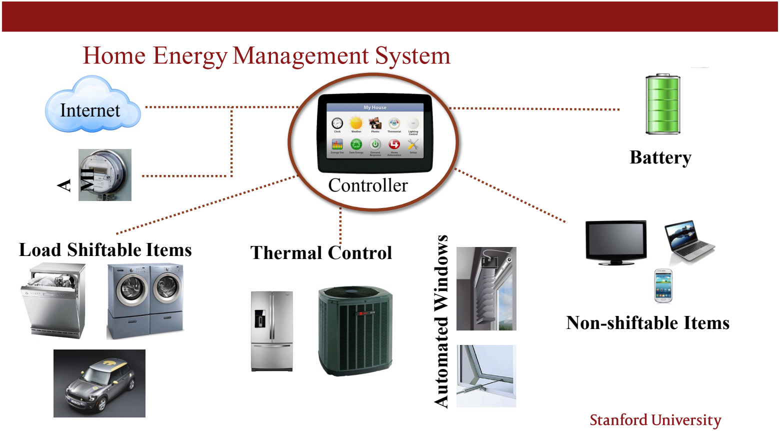
- Illustration of the mechanisms by which aggregation can produce error
- Pointing out of conditions that guarantee such errors are not introduced
- An assessment of clustering as a method for aggregation in this context
- Base on which to appropriately reduce resolution further if necessary

Today's presentation

- Context and motivation
- Brief thoughts on structuring models
- Representing temporal variability in electric sector planning models
- Assessing the system value of optimal electricity load shifting[6]

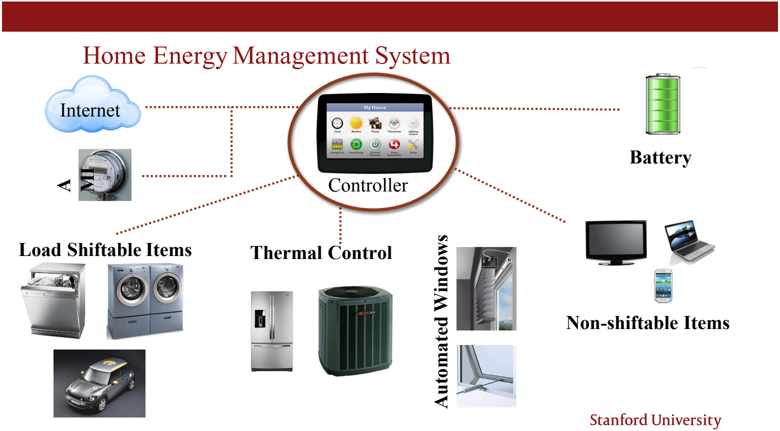
[6]Merrick, J., Y. Ye, and R. Entriken (2018). Assessing the System Value of Optimal Load Shifting, *IEEE Transactions on Smart Grid*, 9:6 (2018), pp.5943-5952

Context



Home Energy Management System
Internet
AMI
Controller
My House
Battery
Load Shiftable Items
Thermal Control
Automated Windows
Non-shiftable Items
Stanford University

Context



Research goals:

- Development of associated modeling methods
- Principles of the valuation of these technologies

Consumer model formulation

Consumer j problem (from Hu et al., 2016[7]):

$$\begin{array}{lll} \text{maximize} & u^j(D^j) - \boldsymbol{p}^T \boldsymbol{u}^j & \\ \text{subject to} & \boldsymbol{u}^j & \geq \boldsymbol{d}^j, \\ & (\boldsymbol{e}^j)^T \boldsymbol{u}^j & \geq D^j, \\ & \boldsymbol{u}^j & \leq C\boldsymbol{e}, \\ & \boldsymbol{u}^j, D^j & \geq \boldsymbol{0}; \end{array}$$

- $\boldsymbol{u}^i \in \mathbf{R}_+^T$ electricity consumption [decision variable]
- $u^j(D^j)$ utility of total demand D^j, a concave function
- $\boldsymbol{p} \in \mathbf{R}_+^T$ electricity price
- $\boldsymbol{d}^j \in \mathbf{R}_+^T$ Non-shiftable demand

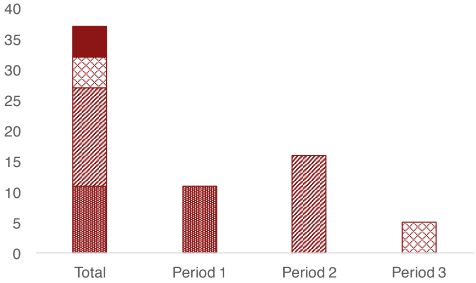
Maximize utility given constraints

[7] R Lily Hu et al. "A Mathematical Formulation for Optimal Load Shifting of Electricity Demand for the Smart Grid". In: *IEEE Transactions on Big Data* PP.99 (Early Access Article) (2016).

Consumer model formulation

Consumer j problem (toy version)

$$\begin{aligned} \text{minimize} \quad & \boldsymbol{p}^T \boldsymbol{u} \\ \text{subject to} \quad & u_1 \geq 11, \\ & u_2 \geq 16, \\ & u_3 \geq 5, \\ & u_1 + u_2 + u_3 \geq 37, \end{aligned}$$



Expanding model to system

- An economy with T goods, electricity in each time period
- Price taking consumers demand electricity to maximise utility given load-shifting ability
- Price taking producers supply electricity to maximise profit

Producer model formulation

Producer i problem:

$$\begin{array}{rll} \text{maximize} & \boldsymbol{p}^T \boldsymbol{x}^i - c^i(\boldsymbol{x}^i) & \\ \text{subject to} & A^i \boldsymbol{x}^i & \leq \boldsymbol{b}^i, \\ & \boldsymbol{x}^i & \geq \boldsymbol{0}, \end{array}$$

- $\boldsymbol{x}^i \in \mathbf{R}_+^T$ electricity generation [decision variable]
- $c^i(.) : \mathbf{R}_+^T \rightarrow \mathbf{R}$ production cost function
- $\boldsymbol{p} \in \mathbf{R}_+^T$ electricity price
- $\boldsymbol{b} \in \mathbf{R}_+^T$ vector of physical constraints

Essentially: maximize profit given capacity constraints

Model formulation

Market-clearing condition:

$$\sum_{i=1}^{m} \boldsymbol{x}^i = \sum_{j=1}^{n} \boldsymbol{u}^j.$$

Supply equal demand in each period

Equivalence to a convex program

Equivalence to a convex program

Each supplier i and consumer j solving their individual problems simultaneously is equivalent to the following social problem:

$$
\begin{array}{rcl}
\text{maximize} & \sum_{j=1}^{n} u^j(D^j) & -\sum_{i=1}^{m} c^i(\boldsymbol{x}^i) \\
\text{subject to} & A^i \boldsymbol{x}^i & \leq \boldsymbol{b}^i, \ \forall i, \\
 & \boldsymbol{u}^j & \geq \boldsymbol{d}^j, \ \forall j, \\
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\end{array}
$$

maximize	Societal surplus
subject to	Constraints of each generator
	Constraints of each consumer
	Market clearing constraint

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\end{array}
$$

maximize	Societal surplus
subject to	Constraints of each generator
	Constraints of each consumer
	Market clearing constraint

A convex optimization problem, useful for policy analysis or potentially market design

A numerical application

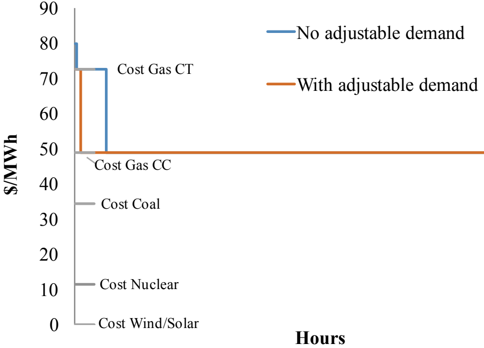
- Data from 'Current Trends' scenario of ERCOT Long Term System Assessment, 2031 scenario year.

Capacity mix in example

Technology	Capacity (GW)	Short-Run Marginal Cost ($/MWh)
Solar	21.7	0
Wind	21.5	0
Nuclear	5.2	11
Gas CC	37.3	49
Gas CT	12.1	73
Gas Steam	8.7	80
Coal	10.2	34.3

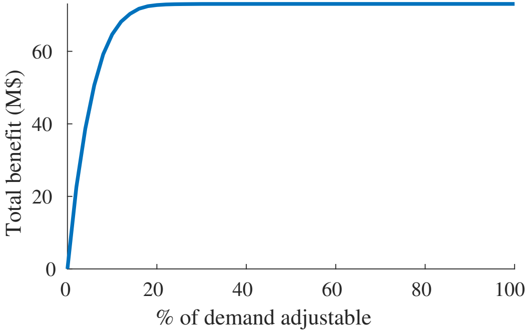
- Abstract representation of optimal load shifting capabilities

A numerical application



Price Duration Curve. In adjustable demand case, 15% of reference demand is shiftable within each 24 hour window

Value



Sensitivity of the value of load shifting to the fraction of demand that can shift within each hour (assuming 24 hour window).

Average of $\approx \$3$ per customer

Marginal value

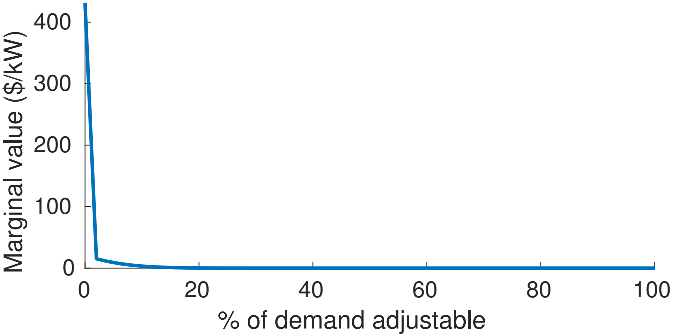
The marginal value of adjustable demand turns out to be:[8]

$$\texttt{marginal value} = \sum_t |p_t - \text{median}(\boldsymbol{p})|$$

- The sum of the differences in absolute values around the median
- A measure of distribution of electricity prices
- In absence of other constraints, model will keep building until price spread reduces to capital cost of installing
- System value driven by spread of prices

[8] Derived from optimality conditions. This is the simplest version for clarity

Marginal value



Marginal Value of an additional kW of adjustable electricity demand in ERCOT 2031 Current Trends example

More on value

- Caveats to numerical value
- Relationship to value of renewables

$$\begin{aligned} \text{M.V. load shifting} &\propto \text{dispersion of prices} \\ \text{M.V. variable renewables} &\propto \text{correlation(availability,price)} \end{aligned}$$

The challenge of modeling storage

Modeling storage, particularly tracking storage balance, requires something different, maintaining chronological information when aggregating.

A sample of approaches:

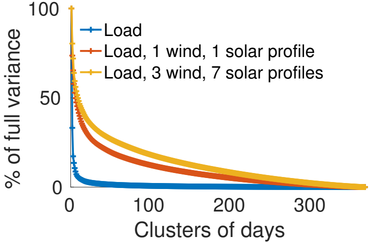
- No temporal aggregation (computationally prohibitive, will come back to this)
- Representative days/weeks (how know which days/weeks representative?[9])
- System states[10]

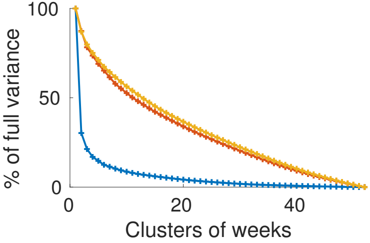
[9] James H. Merrick. "On representation of temporal variability in electricity capacity planning models". In: *Energy Economics* 59 (2016), pp. 261–274.

[10] Sonja Wogrin et al. "A New Approach to Model Load Levels in Electric Power Systems With High Renewable Penetration". In: *IEEE Transactions on Power Systems* 29.5 (2014), pp. 2210–2218.

Challenge of finding representative days/weeks

Days / weeks tend not to be very similar,[11] so how aggregate?





[11] James H. Merrick. "On representation of temporal variability in electricity capacity planning models". In: *Energy Economics* 59 (2016), pp. 261–274.

A step back: the mathematical structure

Minimize generation and investment and storage costs
$(\boldsymbol{x} \in \mathbf{R}_+^{|h|}, \boldsymbol{z}, t \in \mathbf{R}_+)$

$$\text{minimize} \ \sum_g c_g^x \boldsymbol{x}_g + \boldsymbol{c}^z \boldsymbol{z} + c^t t$$

Subject to: supply equal demand $(\boldsymbol{r} \in \mathbf{R}^{|h|})$

$$\sum_g \boldsymbol{x}_g - \boldsymbol{r} = \boldsymbol{d}$$

Generation less than available capacity

$$\boldsymbol{x}_g \leq \boldsymbol{a}_g z_g \quad \forall g$$

Storage balance tracking $(\boldsymbol{s} \in \mathbf{R}_+^{|h|})$

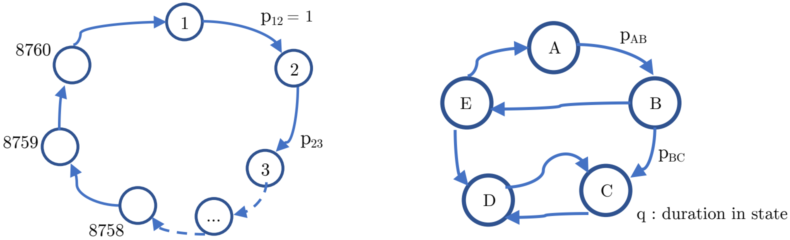
$$s_h = s_{h-1} + r_h \quad \forall h$$

Stored energy (discharge) less than 'room' ('door') capacity'

$$\boldsymbol{s} \leq bt, \quad |\boldsymbol{r}| \leq t$$

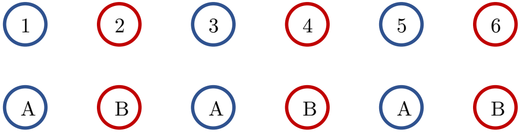
System states ideas

Inspired by Wogrin (2014), we investigate the representation of a (any given) temporal aggregation as the transformation from left to right below:



To explain: a thought experiment

Consider a world with 6 sequential periods, with periods 1, 3, and 5, and periods 2, 4, 6, respectively identical in terms of load/wind/solar:



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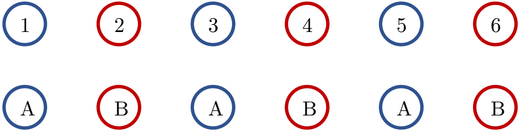
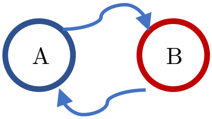


Now aggregate, and represent in context of generalized structure

w_A=3, w_B=3

q_A=1, q_B=1



Probability transition matrix:

	A	B
A	0	1
B	1	0

ADMM decomposition to scale model

ADMM: Alternating Direction Method of Multipliers
Initialise prices, then repeat until convergence:

- Producers (in parallel):
  $\boldsymbol{x}_k^i \leftarrow \arg\max_{\boldsymbol{x}^i} f^i(\boldsymbol{x}^i, \boldsymbol{p}_k) + \frac{\beta}{2}||\boldsymbol{x}^i - \boldsymbol{x}_{k-1}^i + \frac{\Delta_k}{|i|+|j|}||^2$
  Maximize profit subject to aggregate mismatch penalty
- Consumers (in parallel):
  $\boldsymbol{u}_k^j \leftarrow \arg\max_{\boldsymbol{u}^j} g^j(\boldsymbol{u}^j, \boldsymbol{p}_k) + \frac{\beta}{2}||\boldsymbol{u}^j - \boldsymbol{u}_{k-1}^j - \frac{\Delta_k}{|i|+|j|}||^2$
  Maximize utility subject to aggregate mismatch penalty
- System operator:
  $\Delta_{k+1} \leftarrow \sum_i \boldsymbol{x}_k^i - \sum_j \boldsymbol{u}_k^j$
  $\boldsymbol{p}_{k+1} \leftarrow \boldsymbol{p}_k - \beta(\Delta_{k+1})$
  Update aggregate mismatch and prices

[12] Dimitri P Bertsekas. "Incremental Aggregated Proximal and Augmented Lagrangian Algorithms". In: *arXiv:1509.09257v2 [cs.SY]* (2015). arXiv: 1509.09257.

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Guaranteed convergence[12], and unlocks an ability to solve larger problems

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Contributions

- A simple illustration of equilibrium effects, saturation effects
- Optimal load shifting, including storage, not hugely valuable in every case
- In valuing storage, the challenges of the representative day / week approach
- A model structure that can scale
- Reduced order methods for modeling batteries

Today's presentation

- Context and motivation
- Brief thoughts on structuring models
- Representing temporal variability in electric sector planning models
- Assessing the system value of optimal electricity load shifting

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A lot can be done before code is written and computers are run.
The mathematical structure can tell a lot.

Acknowledgements

- Rose M. Chappelear Memorial Fellowship
- US Department of Energy, Office of Science PIAMDDI Grant (`DE-SC0005171`) to the Energy Modeling Forum at Stanford University
- Electric Power Research Institute (EPRI)

Go raiḃ maiṫ agaiḃ

Thank You