GMLC 4.2.2 – TA to State PUCs

Forecasting Cohort

Developing Forecasts: Basics & Best Practices

January 30, 2023

Workshop Agenda

GRID MODERNIZATION INITIATIVE
U.S. Department of Energy

1:00-1:15 Introductions & Overview

1:15-1:45 Intro to Electricity Forecasting

1:45-2:15 Load Forecasting

2:15-2:30 Break

2:30-3:00 Energy Efficiency and Demand Flexibility Forecasting

3:00-3:35 Building Electrification & Electric Vehicle Forecasting

3:35-3:50 Break

3:50-4:20 Distributed Solar & Battery Storage Forecasting

4:20-4:50 Cost Forecasting

4:50-5:00 Final Thoughts

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Overview of Workshop #2

- **Objective: Provide an overview of and best practices associated with developing forecasts generally and specifically for utility load, DERs, beneficial electrification, and utility costs**
- Each topic will generally cover:
  - Commonly Applied Methods
  - Best Practices
  - Popular Tools
  - Potential Scenarios
  - Worked Examples
- Presenters will leave roughly one-third of the allotted time on each topic for Q&A
- Feel free to use the Chat feature to submit your questions during the presentation or raise your hand during Q&A

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Intro to Electricity Forecasting

ALLISON CAMPBELL

Pacific Northwest National Laboratory

January 30, 2023

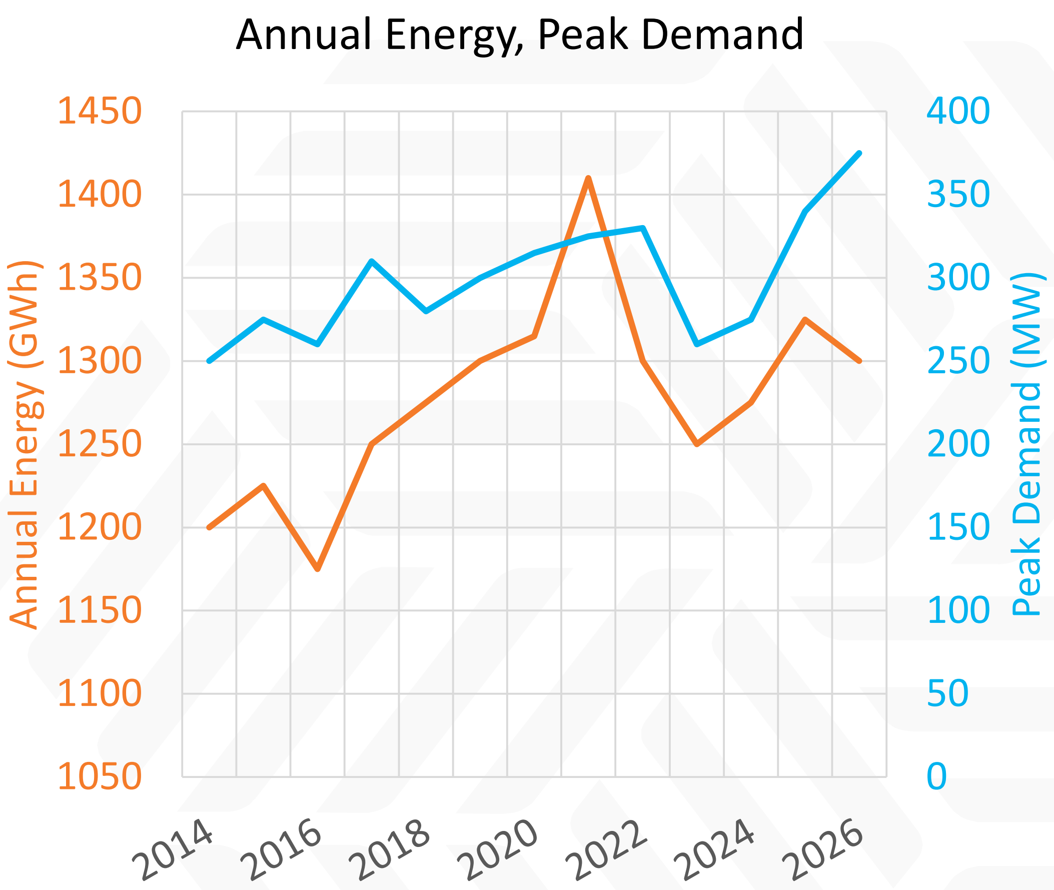
Factors That Impact Forecast Development

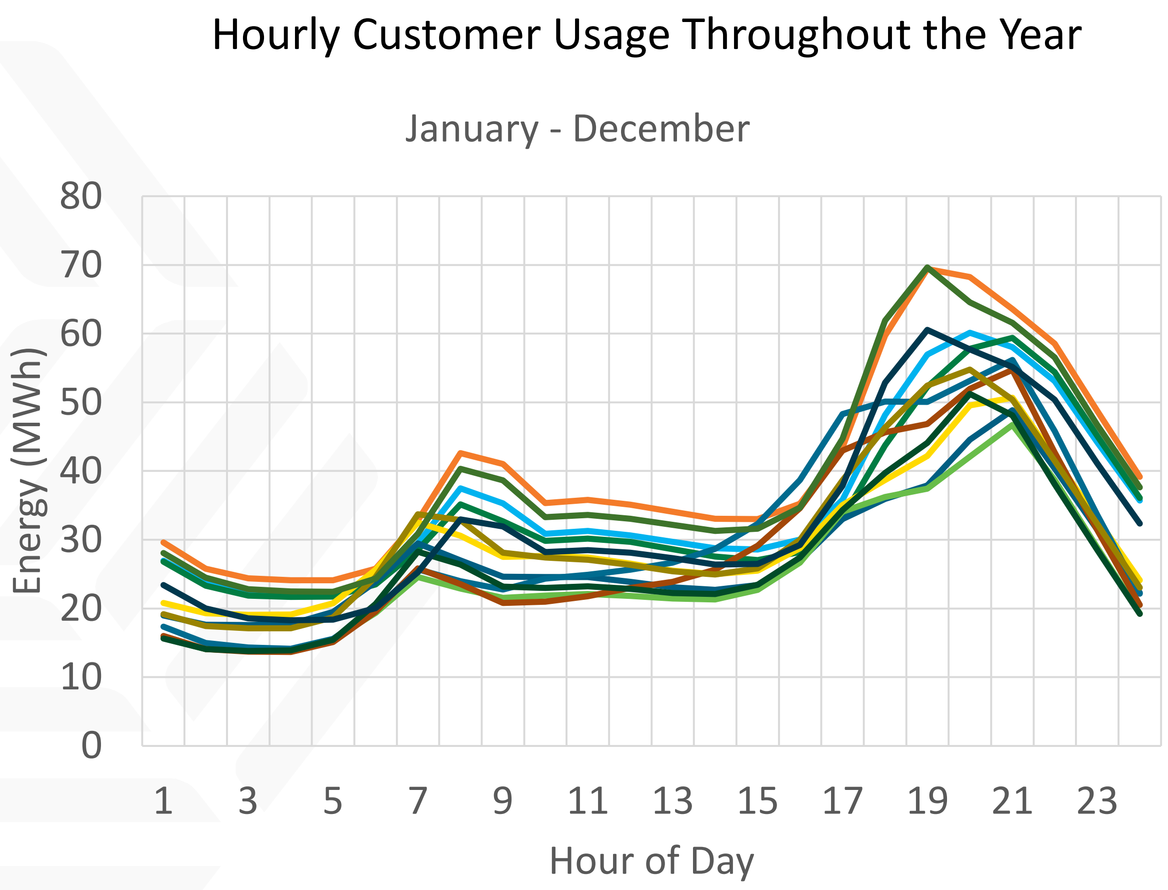
- Factors that utilities consider when developing a forecast:
  - Spatial Aggregation
  - Time Frame
  - Variables
  - Forecast Purpose
  - Algorithm/Method
- Forecasts provided to regulators
  - Annual Energy (kWh)
  - Peak Demand (MW)
  - Hourly Load Profiles
- Forecast Algorithms/Methods
  - Time Series (Econometric)
  - Multiple linear regression
  - Bottom-up engineering/physics based
  - Adjustments to forecast for specific end uses
  - Probabilistic/Scenario-based

Factors That Impact Forecast Development

- What is the **spatial aggregation**?
  - Balancing Authority
  - Customer Class
    - Residential & Commercial
    - Industrial
    - All of the above
  - Feeder
  - Building
- What **time frame** is the forecast for?
  - Operational – tomorrow
  - Planning – 1 to 10 years from now
- What **variables** should go into the forecast?
- How complex do we need to make the forecast **method**?
  - What capacity does the utility have to build a more complex forecast?
  - Does the forecast require an advanced approach, or is a traditional approach sufficient?
- What is the **purpose** of the forecast?
  - Does the utility need to upgrade a feeder? (need to forecast peak loads below the feeder)
  - Does the utility need more baseload power?
  - Are customers adopting more EVs?

Forecasts Provided to Regulators





National Renewable Energy Laboratory. (2014). Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States [data set]. Retrieved from https://dx.doi.org/10.25984/1788456.

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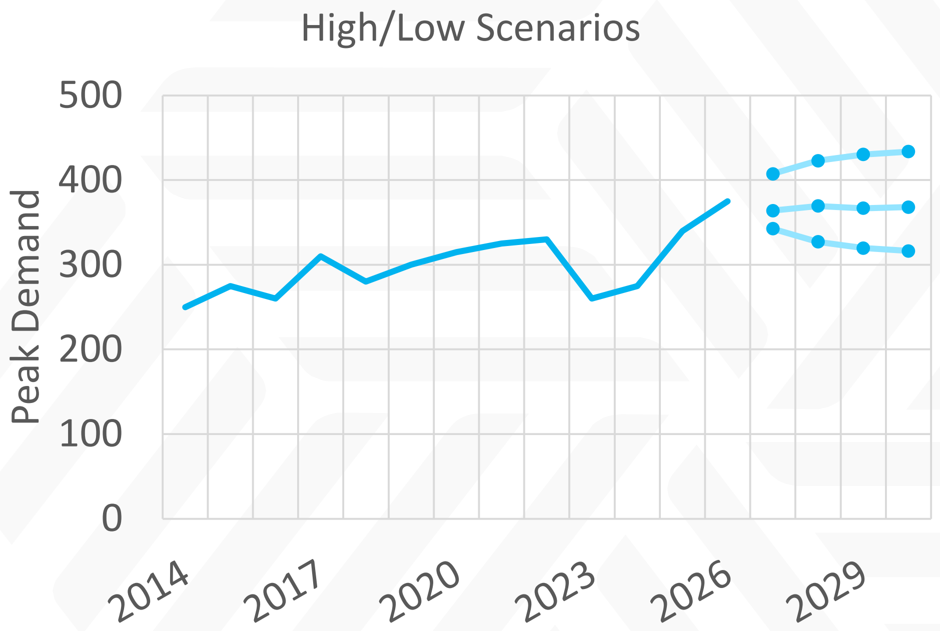

Probabilistic forecast
High and Low Scenarios for Peak Demand Growth

Time Frame: Short Term

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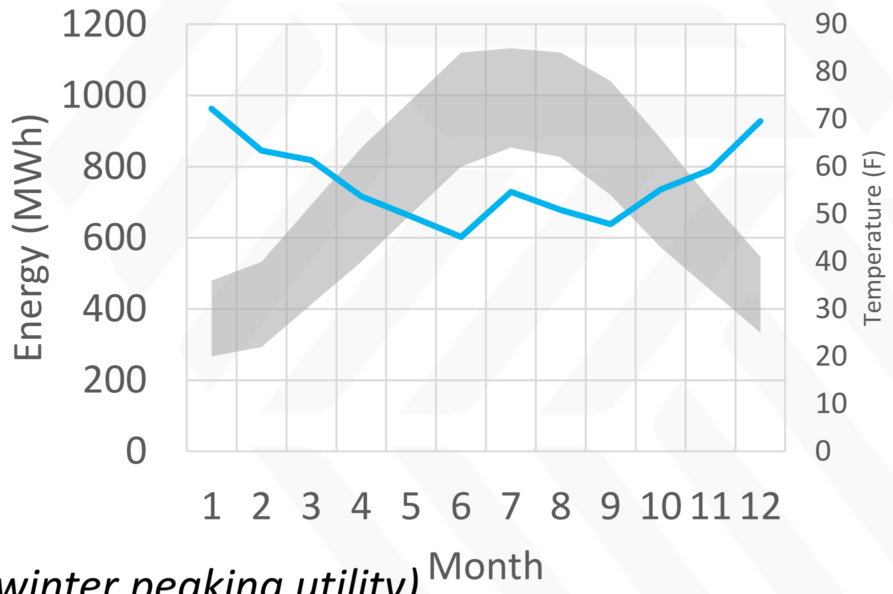
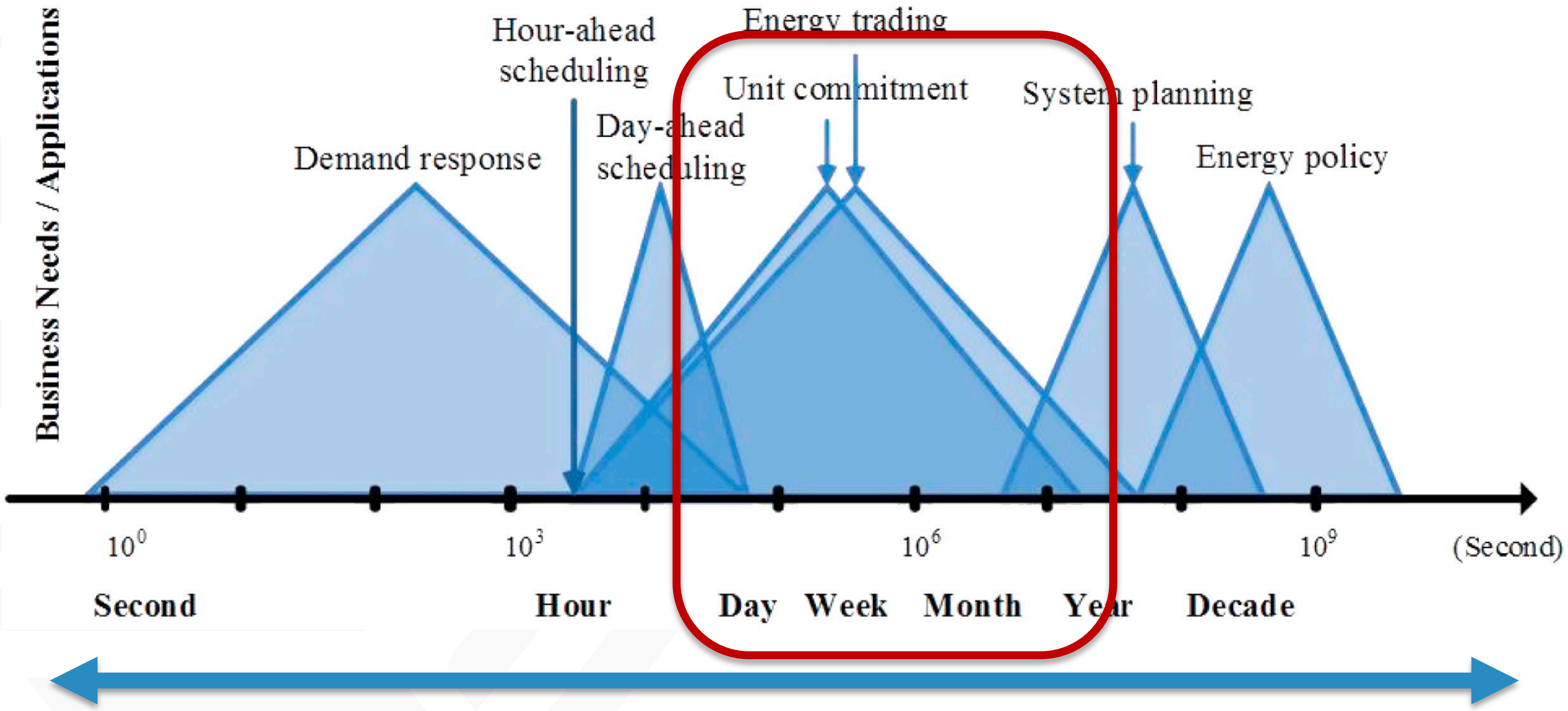
On the energy trading time scale, forecasts can incorporate greater detail about month of year and ranges of temperature for specific customer classes.



(winter peaking utility)



- bottom-up
- stochastic
- physics-based

- top-down
- overall trend
- economics-based

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Forecasts Provided to Regulators

Type of forecast:	Spatial Agg	Time Frame	Purpose	Variables	Method
Peak Load	Balancing Authority, Feeder	1-10 years	Transmission, distribution upgrades	Population Growth, GDP	Time Series Regression, Physics-based
Energy Demand	Customer Class	1-3 years	Area reliability, Multi-Year Rate Plan	*Each customer class may see different variables*	Multiple Linear Regression
Hourly Profiles	Customer Class, Building	1-3 years	Identify customer adoption of distributed resources & impacts	Temperature, Population, saturation of new appliances	Engineering- & Physics-based, end-use adjustments
Low/High Scenarios (probabilistic)	all	all	Sensitivity of analysis to input variables	*all of the above: identify possible deviations*	all

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Longer time frames must manage less information – this results in aggregating to larger areas and using methods that depend on fewer external variables

Forecasts Provided to Regulators

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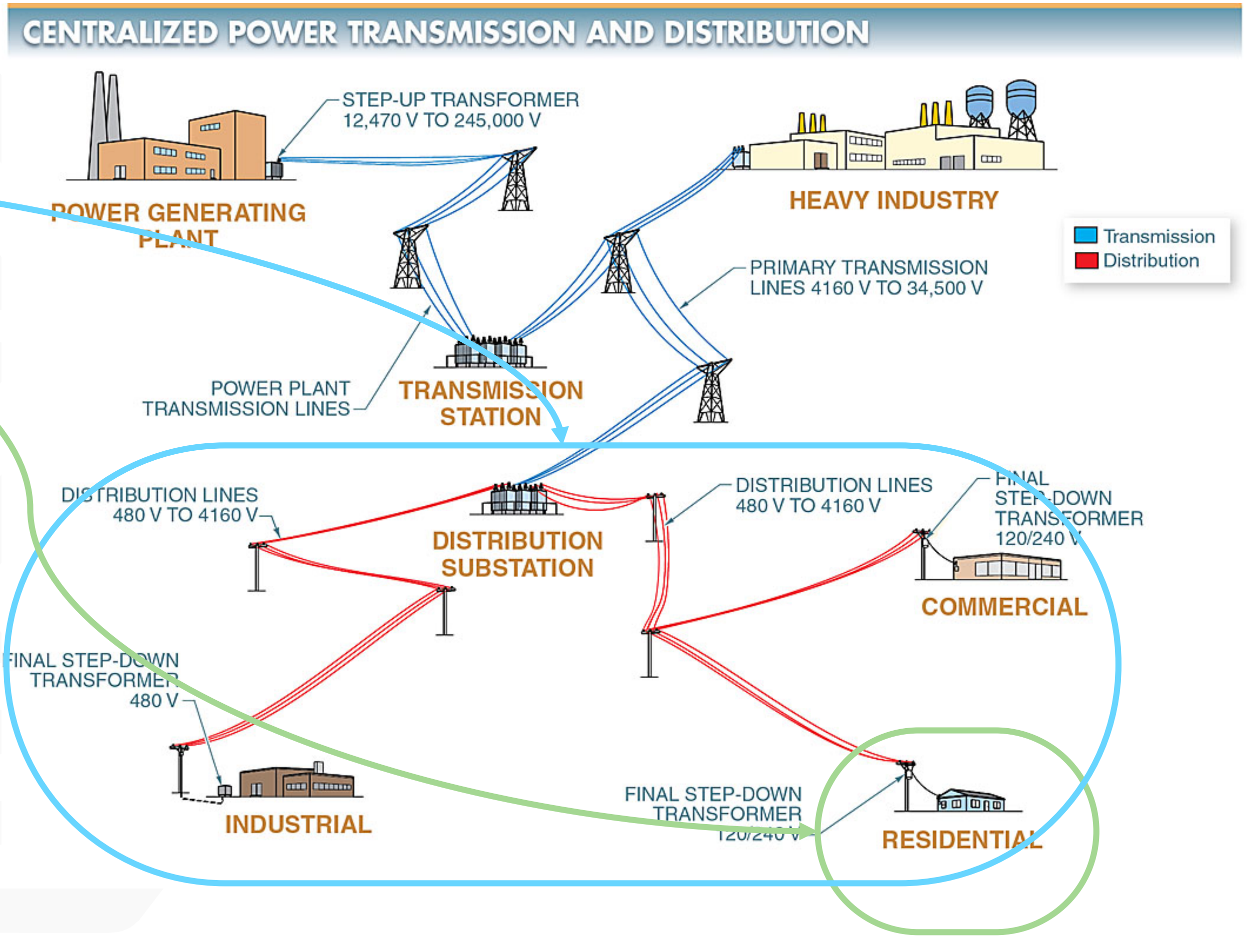
Shorter time frames can take advantage of richer datasets – this allows utilities to build models for each customer class and even buildings at a very detailed level

Spatial Aggregation

- Types of aggregation:
  - Balancing Authority
  - Distribution Feeder
  - Customer Class
    - Residential & Commercial
    - Industrial
    - All of the above
  - Building
- **Residential** & **Commercial:** components are forecasted separately
  - Number of customers in each class
  - Usage per customer
- **Industrial**: specific to each customer
  - Need to consult each customer – usage typically follows set schedules defined by the type of industrial user
  - Schedules change infrequently
  - Important to forecast entry/exit of large customers (follow market trends)
- **Disaggregated forecasts** can be done separately and then aggregated to necessary level:
  - Monthly customer class forecasts aggregated to annual by customer class
  - Monthly customer class forecasts aggregated to monthly at Balancing Authority level



https://electricala2z.com/electrical-power/electrical-power-transmission-distribution-distribution-substation-components/

Time Frame: Long Term

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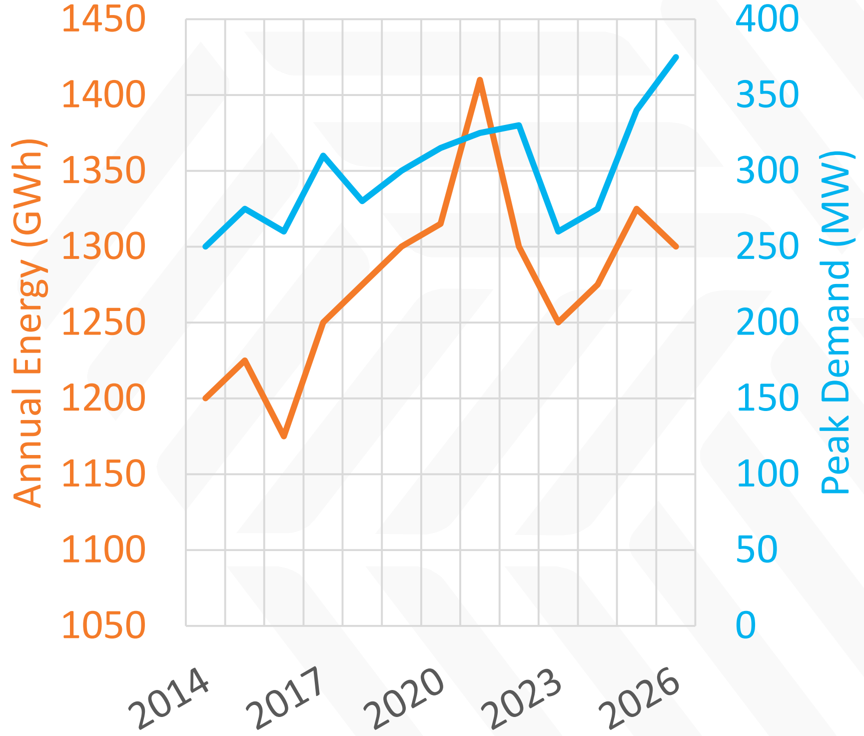
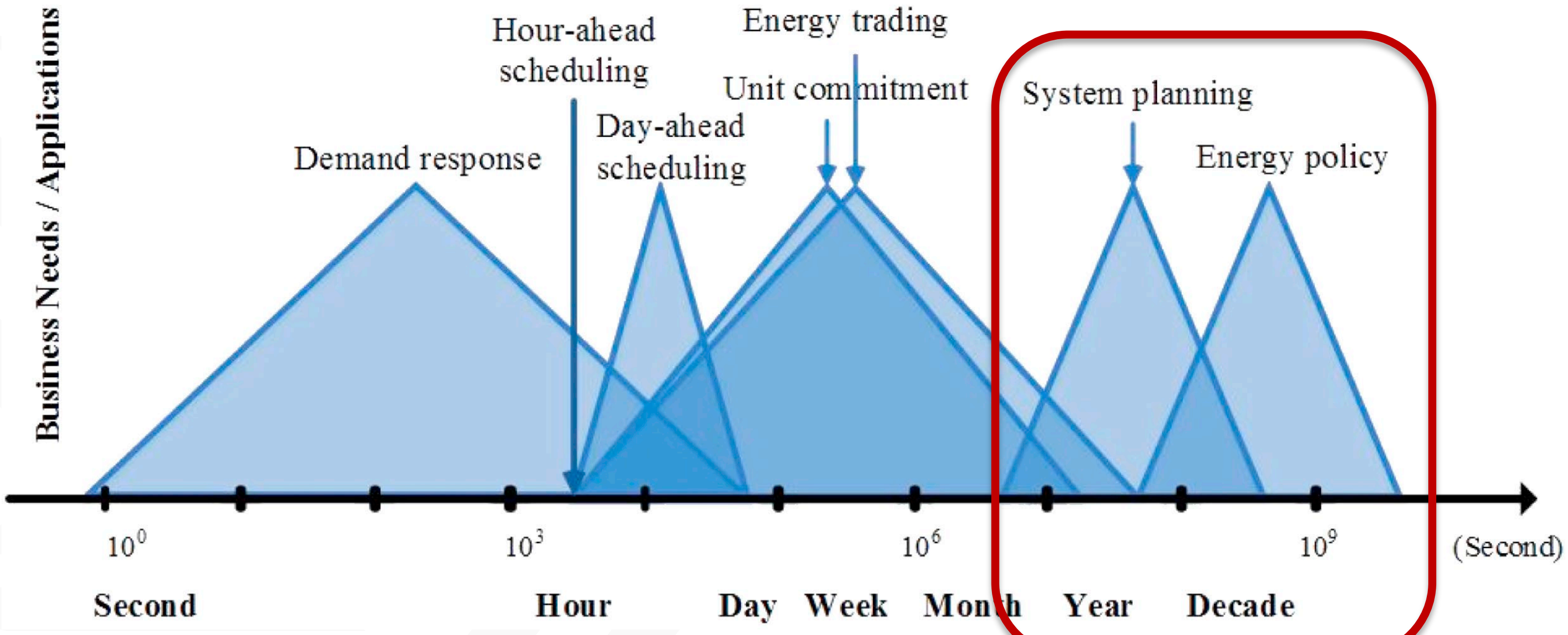
On the regulatory time scale, forecasts are largely built from **load growth** and **overall trend** of system peak.





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- stochastic
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Source: T. Hong and S. Fan, "Probabilistic Electric Load Forecasting: A Tutorial Review," International Journal of Forecasting 32 (3): 914–938, July–September 2016.

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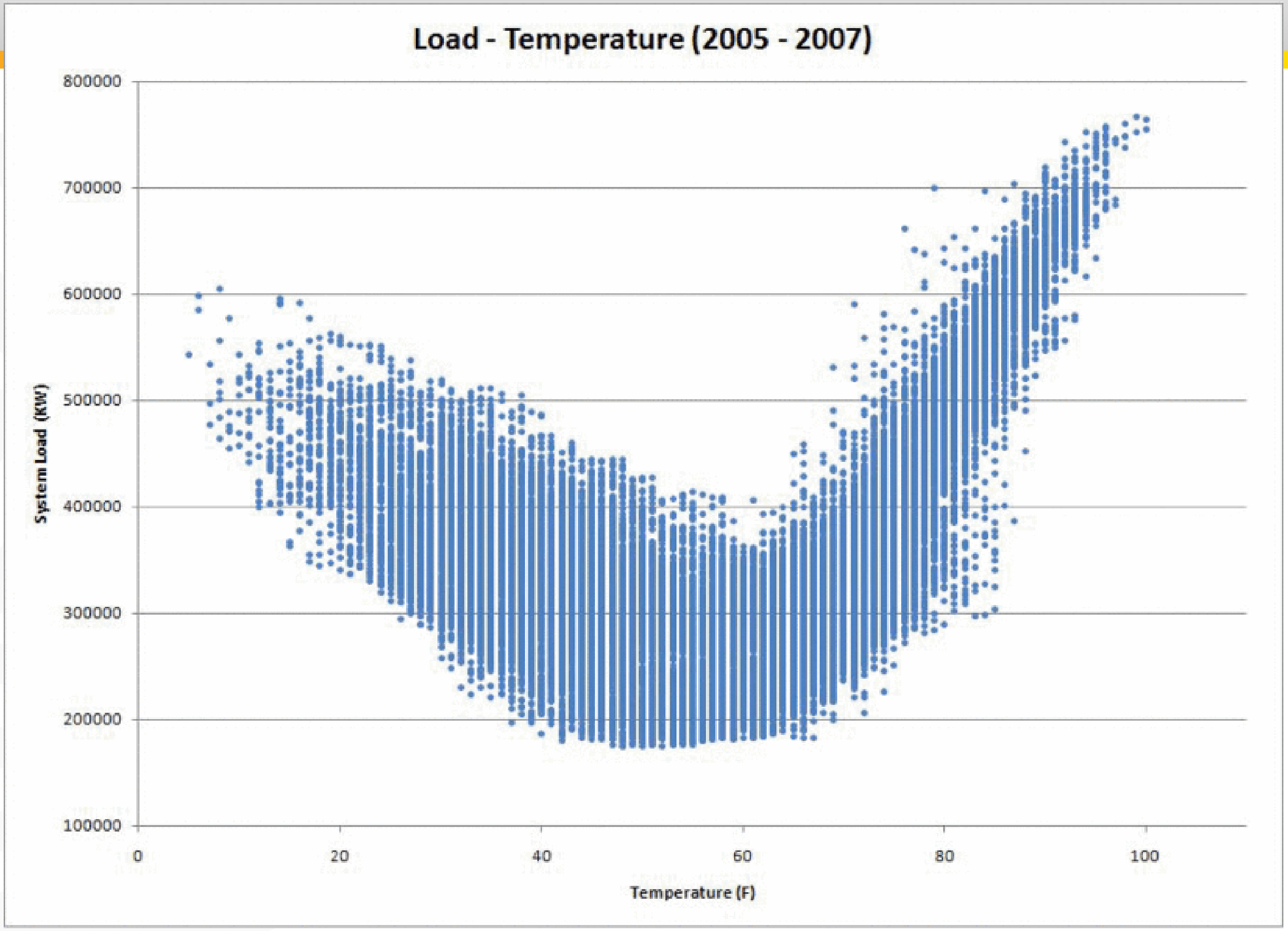
Variables

- Temperature
  - Heating Degree Days
  - Cooling Degree Days
- Cyclic Factors
  - Weekday/Weekend, Holidays
  - Hour of Day
  - Month of Year
- Demographic Factors
  - Population Growth
  - Household Size
- Economic Factors
  - Employment
  - Energy Efficiency Trends
  - GDP
  - Adoption of Appliances
  - Price Elasticity
    - Typical values range between 0 and -0.2, meaning customers will switch to using other types of energy if prices increase



T. Hong, P. Wang and H. L. Willis, "A Naïve multiple linear regression benchmark for short term load forecasting," 2011 IEEE Power and Energy Society General Meeting, Detroit, MI, USA, 2011, pp. 1-6, doi: 10.1109/PES.2011.6038881.

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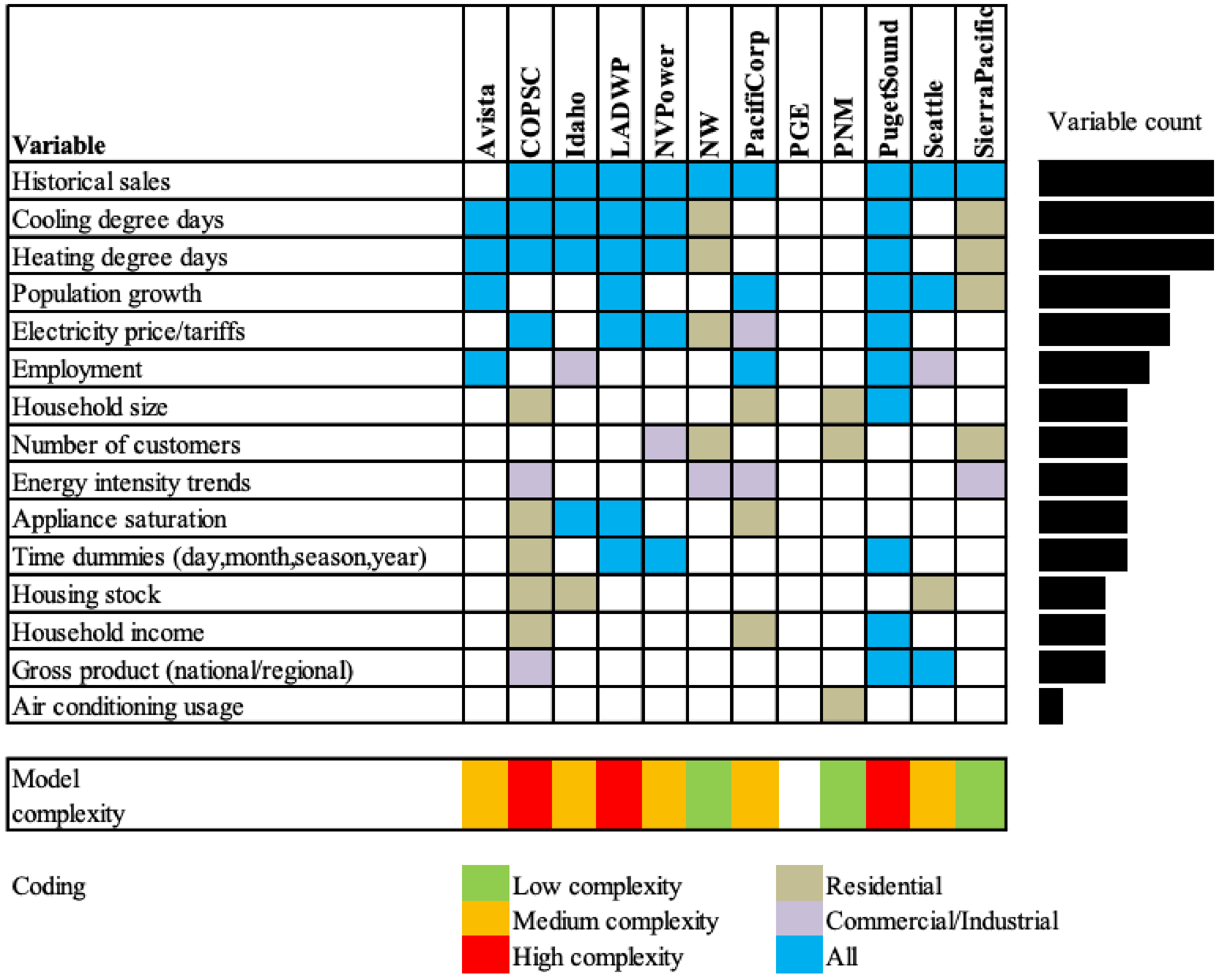


Carvallo, Juan Pablo, Larsen, Peter H., Sanstad, Alan H, and Goldman, Charles A.. *Load Forecasting in Electric Utility Integrated Resource Planning*. United States: N. p., 2017. Web. doi:10.2172/1371722.

Algorithms / Methods

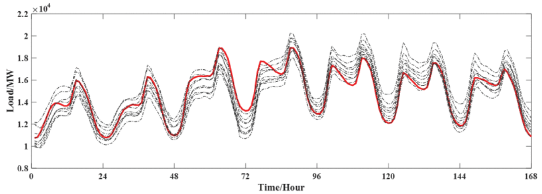
- Time series regression (Econometric)
  - Primarily relies on past observations – “auto regressive”, “moving average”
  - Can incorporate “exogenous” non-linear variables influenced by the economy, such as GDP, household income, S-curve for energy efficiency or appliance adoption
- Multiple linear regression
  - Primarily relies on cross sectional variables – number of customers, GDP, day of week
- Bottom-up engineering/physics based
- Adjustments to forecast for specific end uses
- Ensemble / Combined Forecasts

	Time series regression (AR*, MA**)	Multiple linear regression	Engineering model	End-Use Adjustment
Avista		RC		
COPSC				RC
Idaho				RC
LADWP		RC		
NVPower	RC	RC		
NW	C	R		
PacifiCorp				
PGE				
PNM			RC	
PugetSound		RC		
Seattle		RC		
SierraPacific				

*AR: Auto-regressive; **MA: Moving Average
R: Residential; C: Commercial

Carvallo, Juan Pablo, Larsen, Peter H., Sanstad, Alan H, and Goldman, Charles A.. *Load Forecasting in Electric Utility Integrated Resource Planning*. United States: N. p., 2017. Web. doi:10.2172/1371722.

Who uses the methods?

	Who uses it, when?	Approach
Time Series/ Econometric	All types of utilities, by customer class	Fit an auto-regressive or moving average model to annual peak Economic variables incorporated with S-curve: (2) $(class\ kWh)_{year} = a \bullet (income\ per\ capita)^{b}_{year} \bullet (population)^{c}_{year} \bullet (price)^{d}_{year}$
Multiple Linear Regression	All types of utilities, 1 day to 1 year hourly	(1) $E(Load) = \beta_0 + \beta_1 \times Trend + \beta_2 \times Day \times Hour + \beta_3 \times Month + \beta_4 \times Month \times TMP + \beta_5 \times Month \times TMP^2 + \beta_6 \times Month \times TMP^3 + \beta_7 \times Hour \times TMP + \beta_8 \times Hour \times TMP^2 + \beta_9 \times Hour \times TMP^3$ Trend Day, Month Temperature
End-Use	Mid to large utilities; to model building-level equipment (solar, EV, other DER)	Regression for each type of customer and equipment: (2) $(kWh)_i = (customers) \bullet \left(\frac{units\ of\ equipment}{customer}\right) \bullet \left(\frac{kWh}{units\ of\ equipment}\right)$
Ensemble (Combined)	Large utilities; improves the resulting forecast by taking advantage of multiple approaches	Simple average of multiple different forecasts (3) 

(1) T. Hong, P. Wang and H. L. Willis, "A Naïve multiple linear regression benchmark for short term load forecasting," *2011 IEEE Power and Energy Society General Meeting*, Detroit, MI, USA, 2011, pp. 1-6, doi: 10.1109/PES.2011.6038881.

(2) https://www.rand.org/content/dam/rand/pubs/reports/2006/R3315.pdf

(3) Y. Wang, N. Zhang, Y. Tan, T. Hong, D. S. Kirschen and C. Kang, "Combining Probabilistic Load Forecasts," in *IEEE Transactions on Smart Grid*, vol. 10, no. 4, pp. 3664-3674, July 2019, doi: 10.1109/TSG.2018.2833869.

Time Series / Econometric

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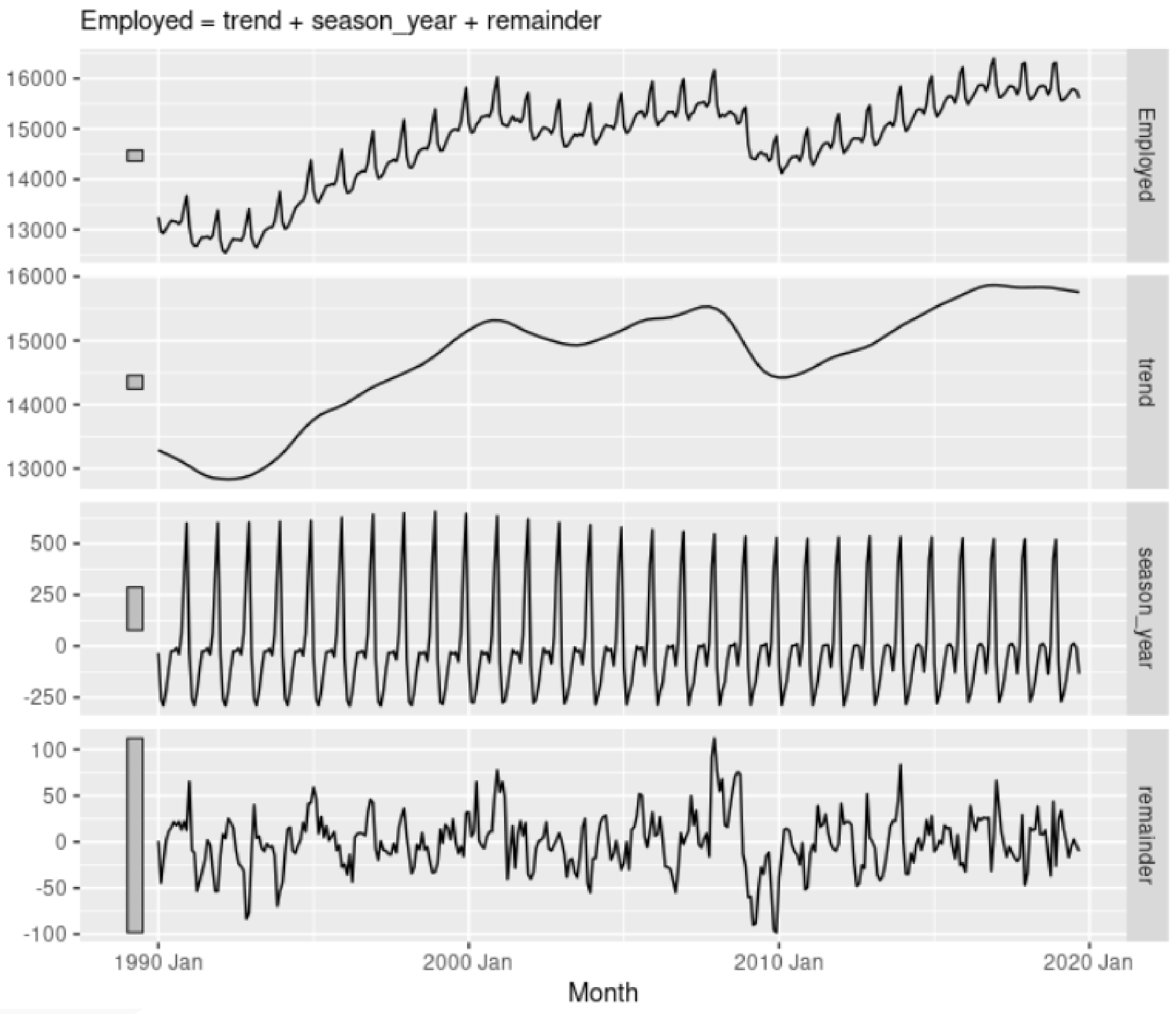
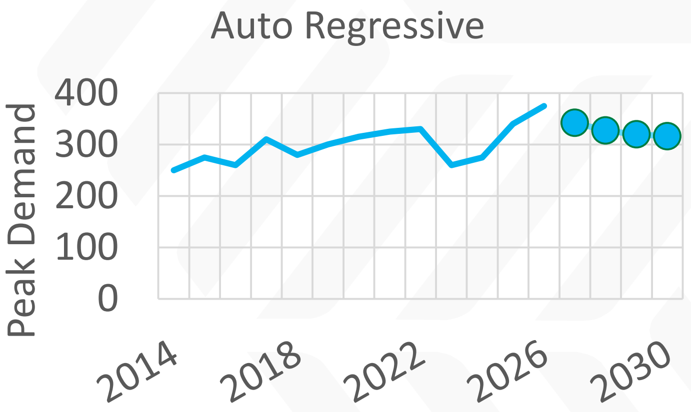
- Time series can be decomposed into **cyclic** trends and **overall** trends
- Cycles can account for weekly, monthly, yearly repetition
- ARIMA typically used to model overall trend
- Exogenous econometric variables can be incorporated into ARIMA model as additional variables (ARIMA**X**):
  - customer growth with econometric growth model using per capita incomes
  - employment levels
  - electricity prices



Hyndman, R.J., & Athanasopoulos, G. (2021) *Forecasting: principles and practice*, 3rd edition, OTexts: Melbourne, Australia. OTexts.com/fpp3. Accessed on 1/24/23

Auto-Regressive Integrated Moving Average

"Auto-Regressive": Use information from past observations to predict the future
"Moving Average": The next value will be an average of the previous several values
ARIMAX: All of the above, plus additional variables



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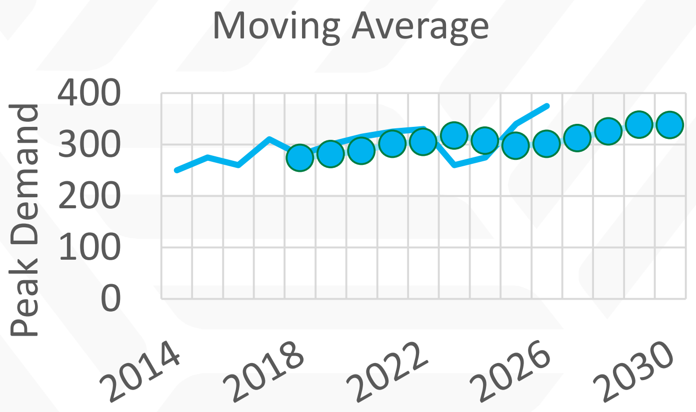

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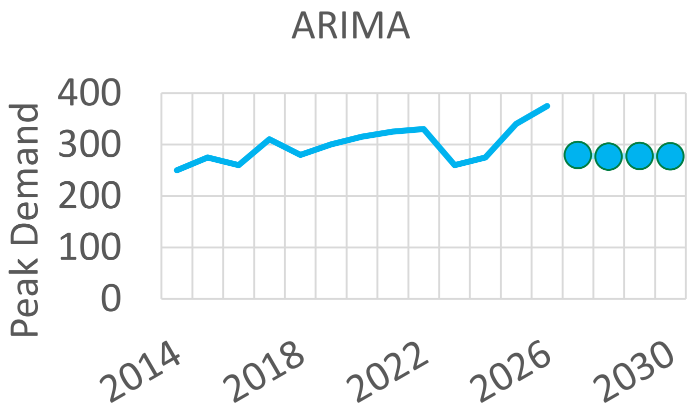
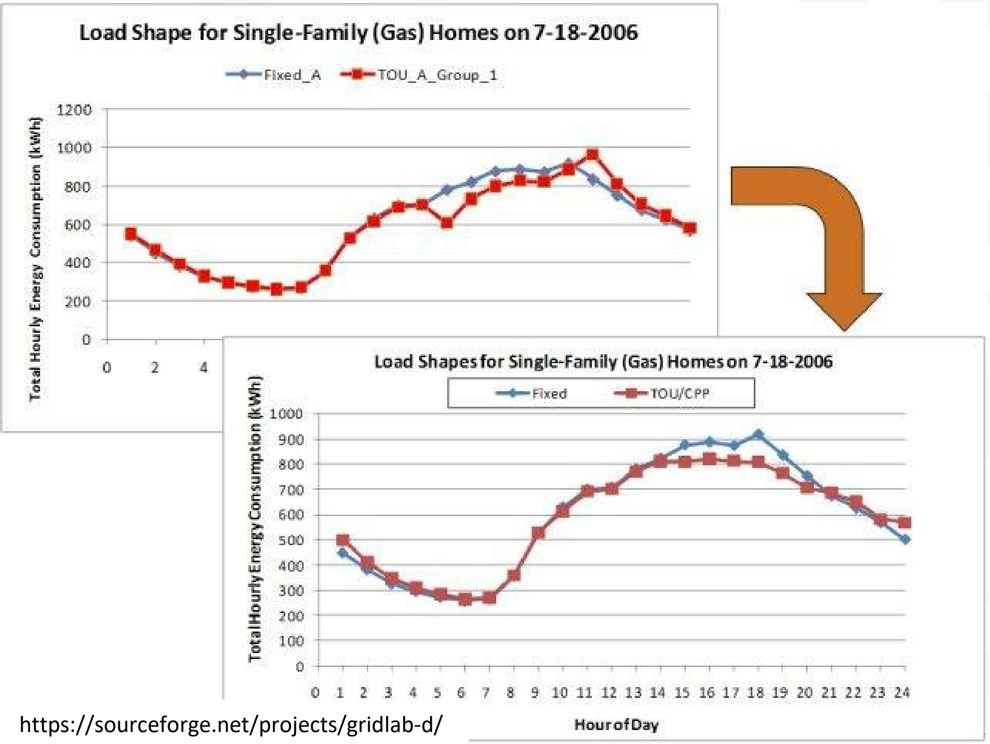
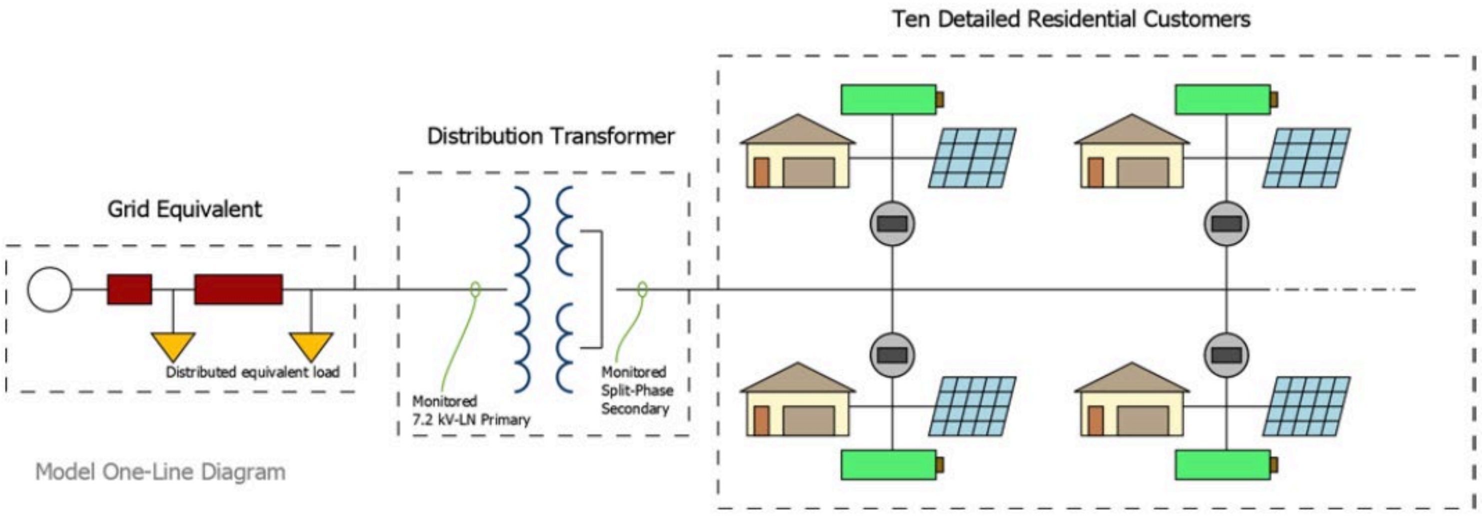


Bottom-Up Engineering/Physics Based

- GridLAB-D (PNNL), OpenDSS (EPRI):
  - Models physics of feeder, household, to get load shape as a function of usage patterns based on specific appliances
  - Can incorporate impacts of price-sensitive appliances on hourly energy usage
  - Models system losses and electrical engineering to simulate power flow
  - Can model PVs and batteries at the household level



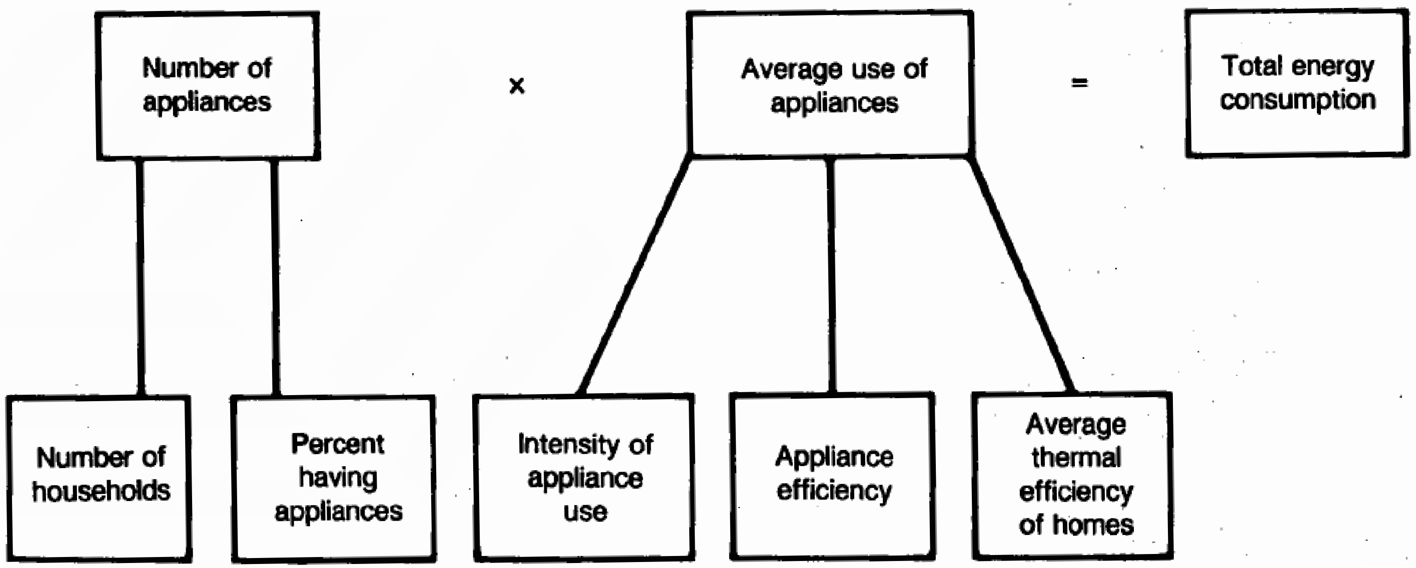
https://sourceforge.net/projects/gridlab-d/



Reiman, Andrew P., Singhal, Ankit, and Campbell, Allison M.. *American-Made Challenges Round 2 Voucher: Orison Enables Solar*. United States: N. p., 2020. Web. doi:10.2172/1755441.

End-Use Models

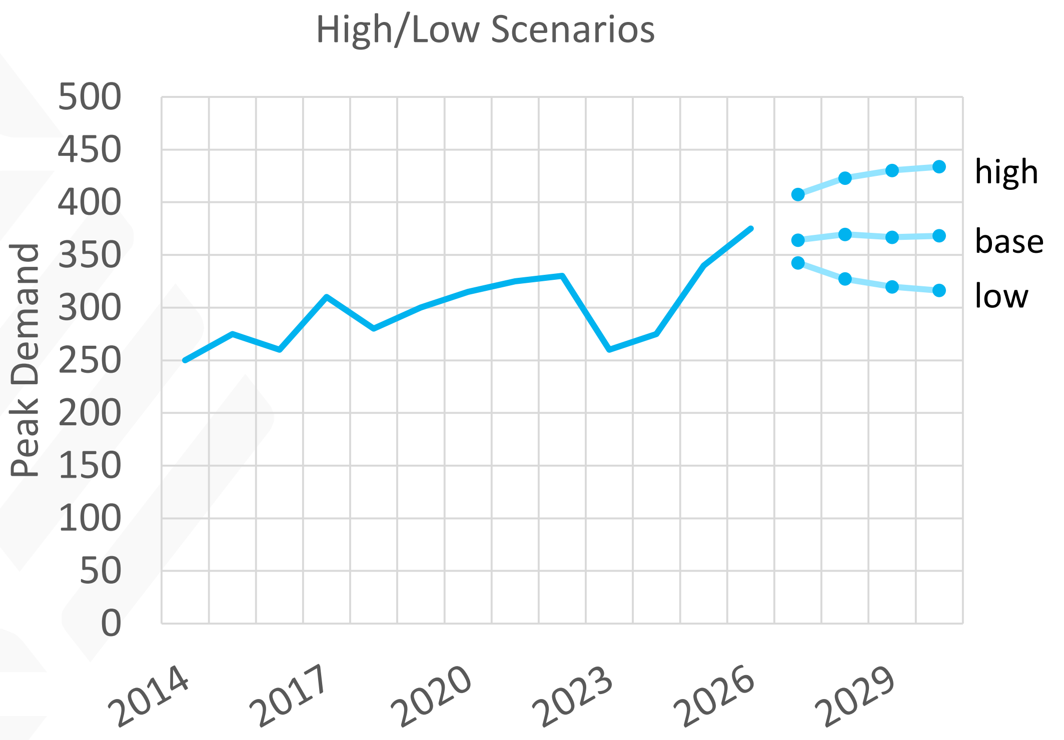
- Directly estimate energy consumption by using extensive information on end use and end users
- Information used: weather, appliances, size of houses, age of equipment, technology changes, customer behavior, and population dynamics
- Require less historical data but more information about customers and their equipment
- Cons: sensitive to the amount and quality of end-use data



Mitchell, Ross, and Park. (1985) *A Short Guide to Electric Utility Load* Forecasting. The Rand Corporation. https://www.rand.org/content/dam/rand/pubs/reports/2006/R3315.pdf

Probabilistic/Scenario Based

- Probabilistic Forecasts are created by changing the input variable.
- Example:
  Utility needs to project peak demand by customer class, starting with Residential, which is highly sensitive to temperature
  1. Use TMY (typical meteorological year) temperatures to project load – this is the base case
  2. Use a representative “cold” weather year to project load – this is the “low” scenario
  3. Use a representative “hot” weather year to project load – this is the “high” scenario
- The scenario outcomes provide a range of possible futures



Questions regulators can ask (1)

- What type of model(s) is/are being used?
  - How does the utility forecast DER adoption?
  - Are models derived from peer-reviewed publications?
  - How does the utility select their input variables?
- What are the modeling inputs?
  - What forecasts are utilities using as inputs to other forecasting models and how were those developed?
  - Are potential climate change impacts to forecasts being considered and, if so, how?
  - Are the assumptions reasonable?
    - Are the assumptions objective (based on objective data, for example) or subjective (based on expert opinion, for example)?
    - Are assumptions valid (do parameter estimates align with those found in existing research, for example)?
  - Are proper methods and data used?
    - Are methods disclosed?
    - Are they understandable?
    - Is the data reliable and valid? What kind of data limitations exist?
    - Is the data readily accessible?

Source material from *Load forecasting with climate variability for transmission and distribution system planning*, https://eta-publications.lbl.gov/sites/default/files/combined_pnnl_and_nrel_load_and_der_forecasting_ncep_fin.pdf

Questions regulators can ask (2)

- What are the outputs?
  - Are results replicable?
  - How well does the model fit the data?
  - How accurately does the model predict past outcomes compared to actual outcomes in historical data?
  - Is the model updated based on performance? How frequently?
  - How sensitive is the model to assumptions?
- What is the tradeoff between the cost to implement a more granular, accurate forecast vs. the benefits?
  - How granular are the utility's current forecasts?
  - Should consultants vs. in-house modeling be used to achieve forecasting goals?

Resources

- Excel-based statistics: https://real-statistics.com/
- Online textbook Forecasting Principles and Practice: https://otexts.com/fpp3/
- Data for hourly load shapes used in this presentation:
  - National Renewable Energy Laboratory. (2014). Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States [data set]. Retrieved from https://dx.doi.org/10.25984/1788456.
- Physics-based open-source models:
  - GridLAB-D: https://sourceforge.net/projects/gridlab-d/
  - OpenDSS: https://www.epri.com/pages/sa/opendss
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Load Forecasting

ELAINE HALE[1], BRITTANY TARUFELLI[2], AND ALLISON CAMPBELL[2]

CONTENT CREDIT: RUI YANG[1], JULIET HOMER[2], PAUL DE MARTINI[3], ALAN COOKE[2]

[1]National Renewable Energy Laboratory, [2]Pacific Northwest National Laboratory, [3]Newport Consulting Group

Forecasting horizons and applications

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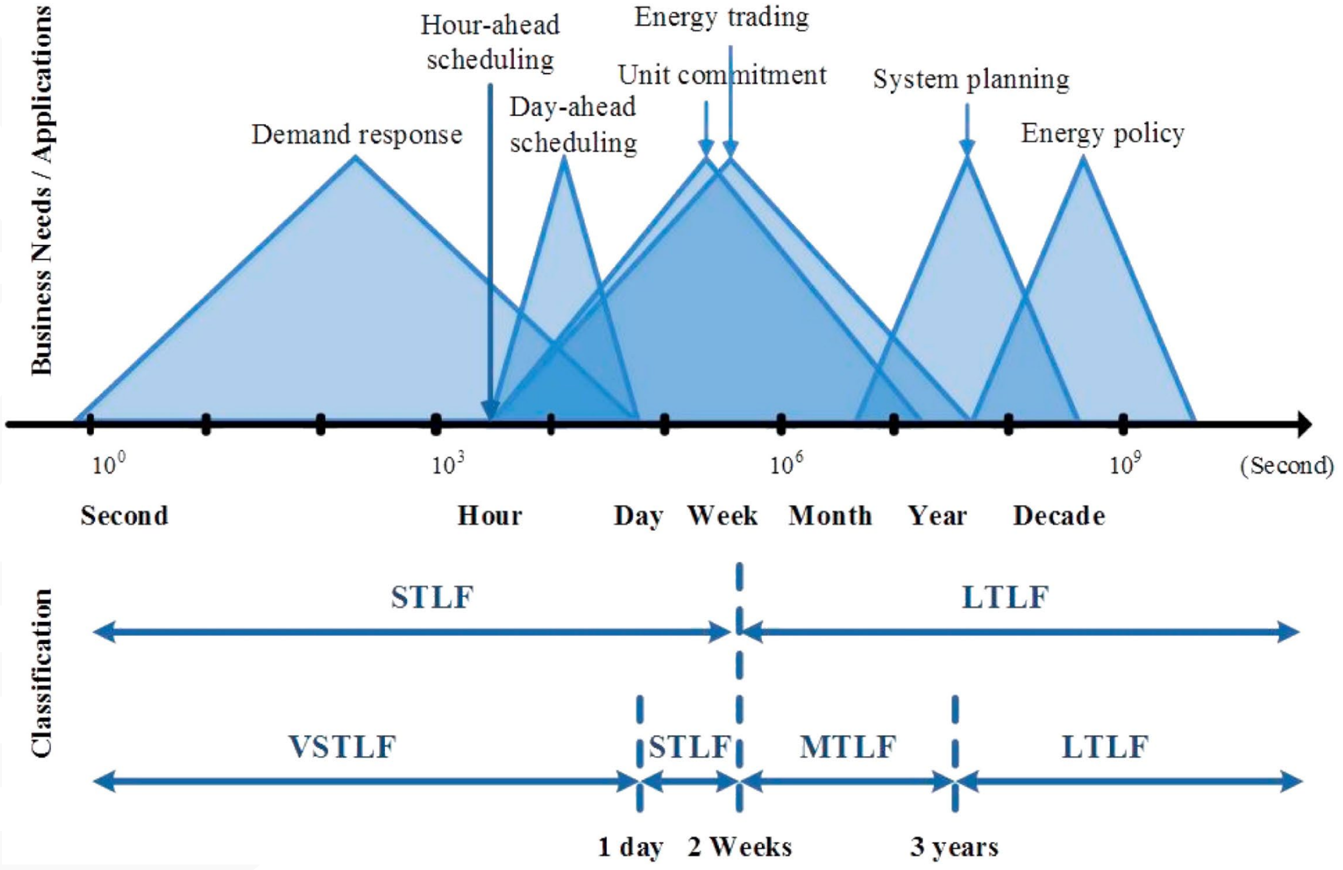
Most relevant for Public Utility Commissions

- Long term
  - Power system planning
  - Energy policy analysis
- Medium term
  - Maintenance and fuel planning
  - Energy trading
- Short term
  - Generation scheduling
  - Economic dispatch and reliability
  - Power system security



Source: T. Hong and S. Fan, "Probabilistic Electric Load Forecasting: A Tutorial Review," *International Journal of Forecasting* 32 (3): 914–938, July–September 2016.

Long-term load forecasting methods

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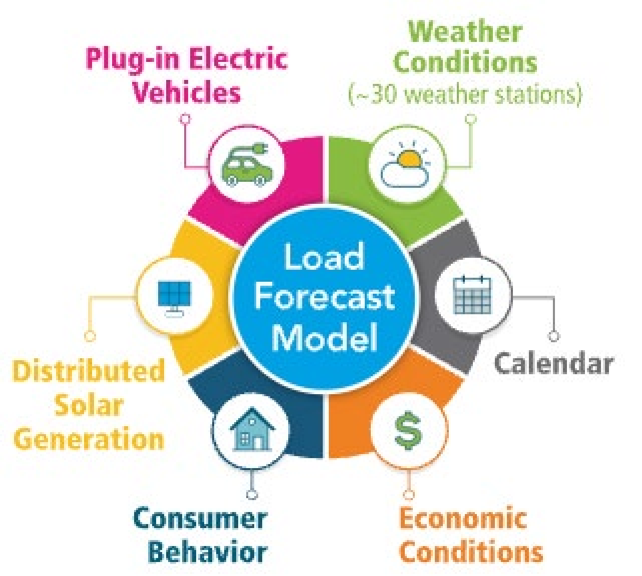
- Econometric models
  - Combine economic theory and statistical techniques
  - Estimate the relationships between energy consumption and factors influencing consumption
  - Factors considered: weather, per capita incomes, employment levels, and electricity prices

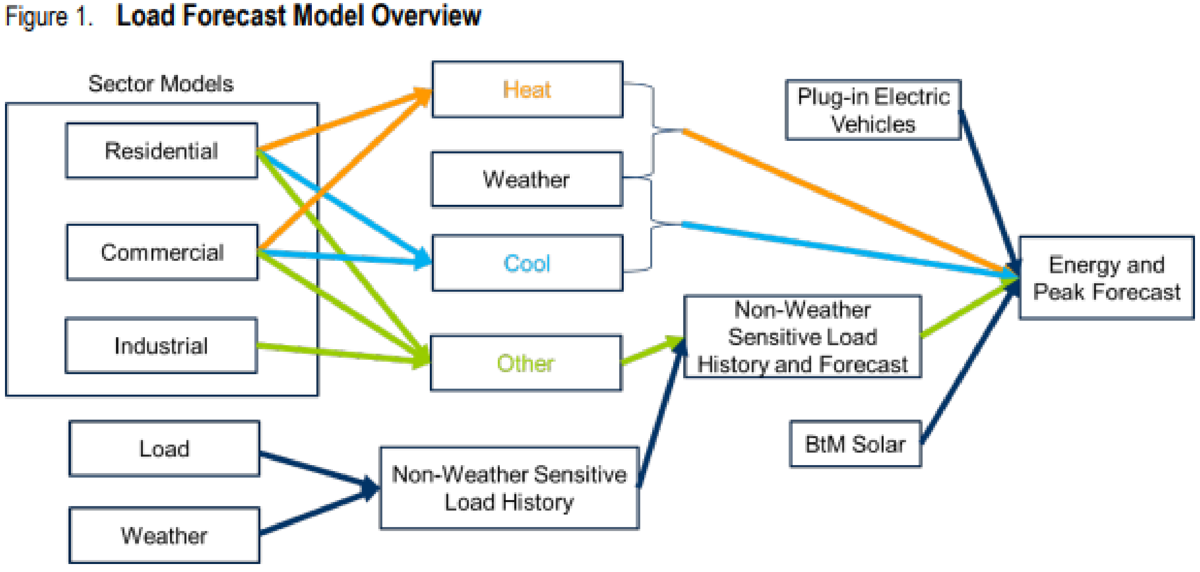
- Combination / Extensions
  - Adjust econometric forecasts with technology-based projections not yet visible in historical data
  - Marshal additional data streams (e.g., AMI, SCADA) to develop more information about customer classes and end-uses
  - Downscale system-level long-term forecasts to create distribution feeder long-term forecasts and vice-versa

Transmission system forecasting

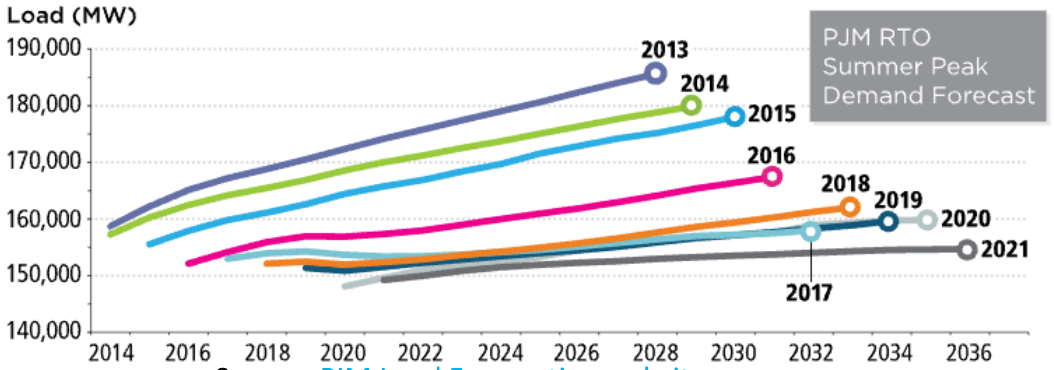
- Transmission system forecasting includes:
  - Long-term forecasting – one to 20 years
  - Medium-term forecasting – one week to one year
  - Short-term forecasting – one hour to one week
- Long-term example: Yearly, PJM issues 15-year load forecasts that include peak usage, net energy consumption, load management, and data on distributed solar and plug-in electric vehicles.
  - Forecasts are provided for individual zones, load deliverability areas and for the RTO overall



Source: PJM Load Forecasting website



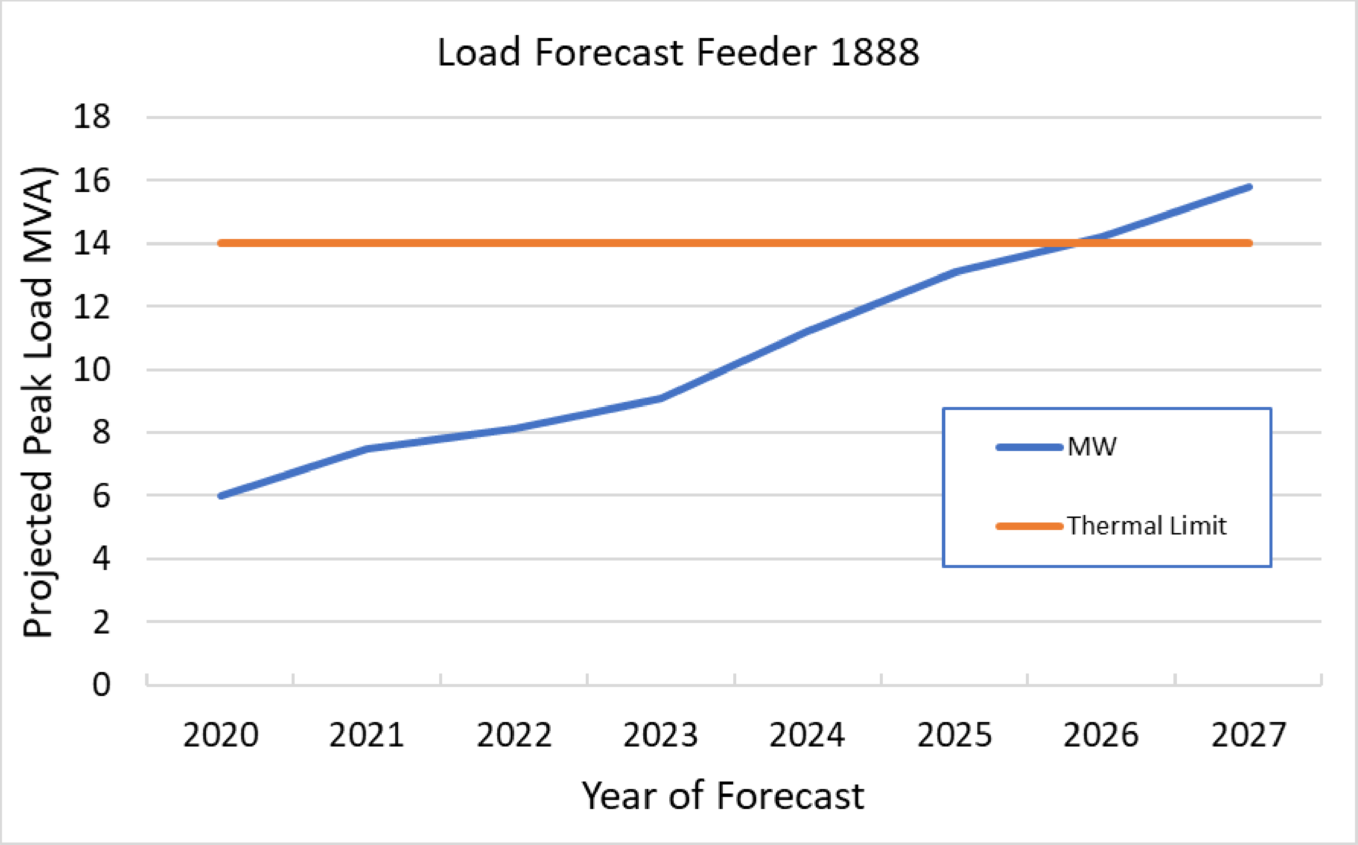
Source: PJM 2021 Load Forecast Supplement



Source: PJM Load Forecasting website

Traditional distribution load forecasting

- Track peak loads (using SCADA data)
- Evaluate each distribution feeder for annual growth and new loads
- Feeder load forecasts aggregated to show substation status, need for expansion
- Substations may require upgraded transformers, new transformer banks, transmission, distribution equipment
- Standard load growth projections are commonly included in traditional utility tools (e.g., CYME, Synergi, Milsoft)



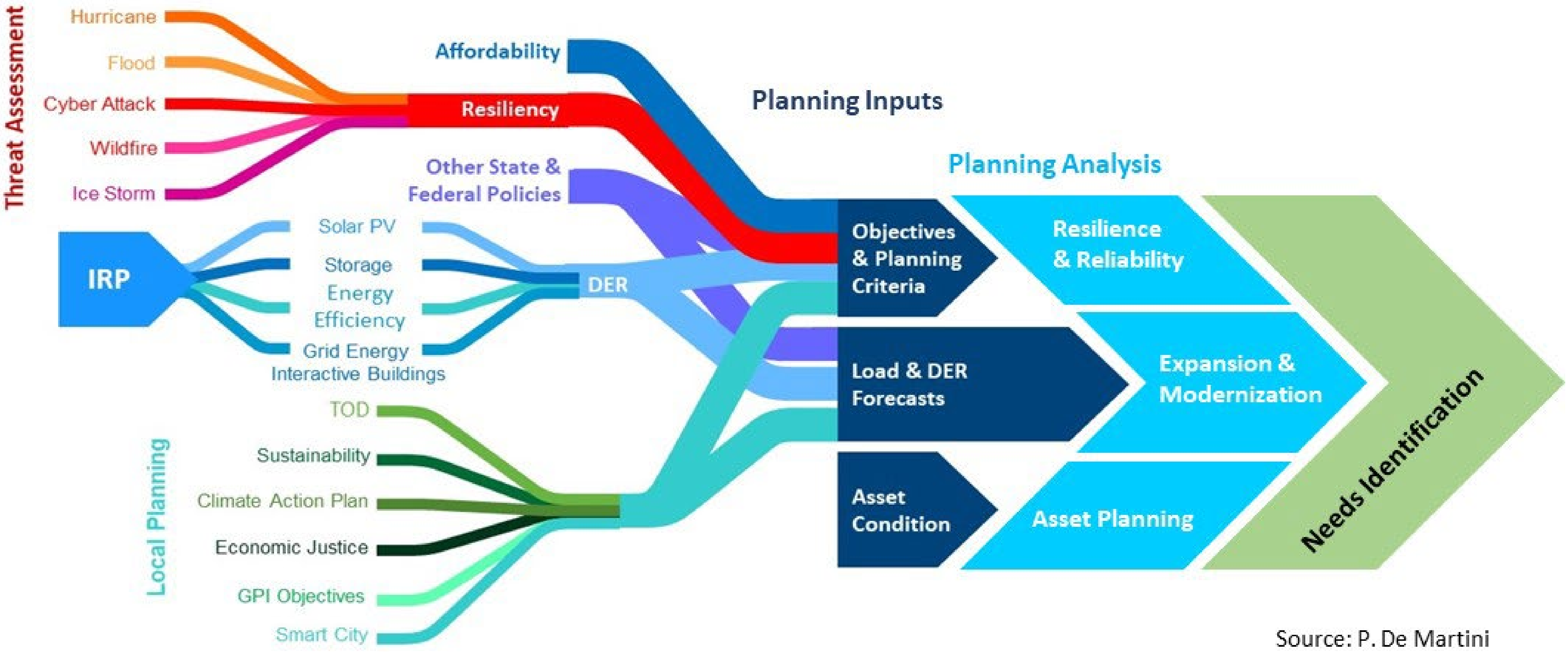
Long-term Load Forecasting Challenges

- Distributed energy resources (covered by other presentations)
- Impact of electrification on electricity load (covered by other presentations)
- Interactions between load forecasts and dynamic policy environments
- Impact of climate change on electricity load
- Preparing distribution systems for demand-side change
- Planning under deep uncertainty

Interactions between load and dynamic policy environments

Integrated System Planning

System planning is increasingly dependent upon Integrated Resource Planning (IRP)/bulk power use of distributed energy resources (DER) and local sustainability and resilience plans.



Source: P. De Martini

Vermont Example (c. 2019)

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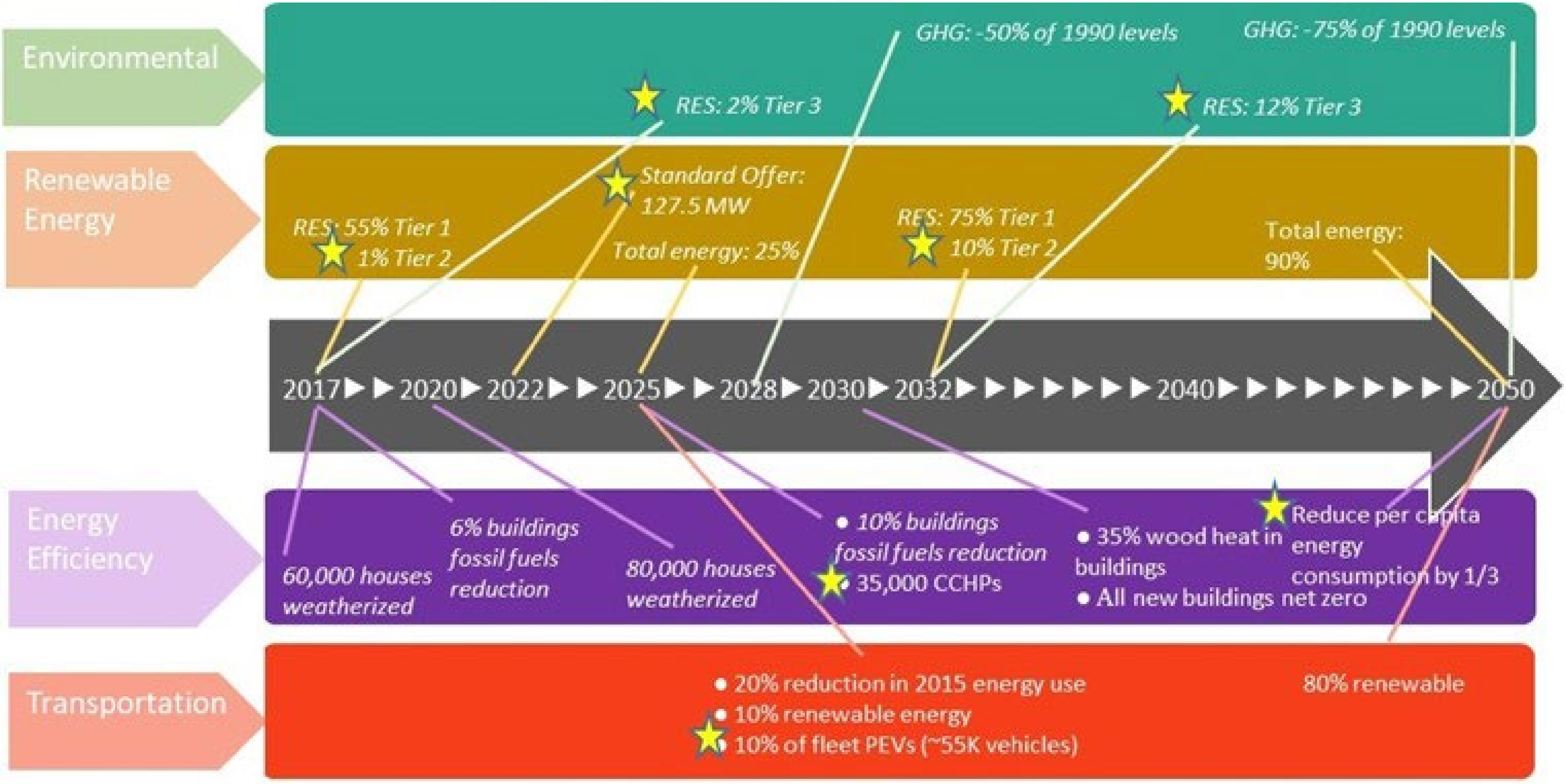
State policy goals inform system planning objectives.



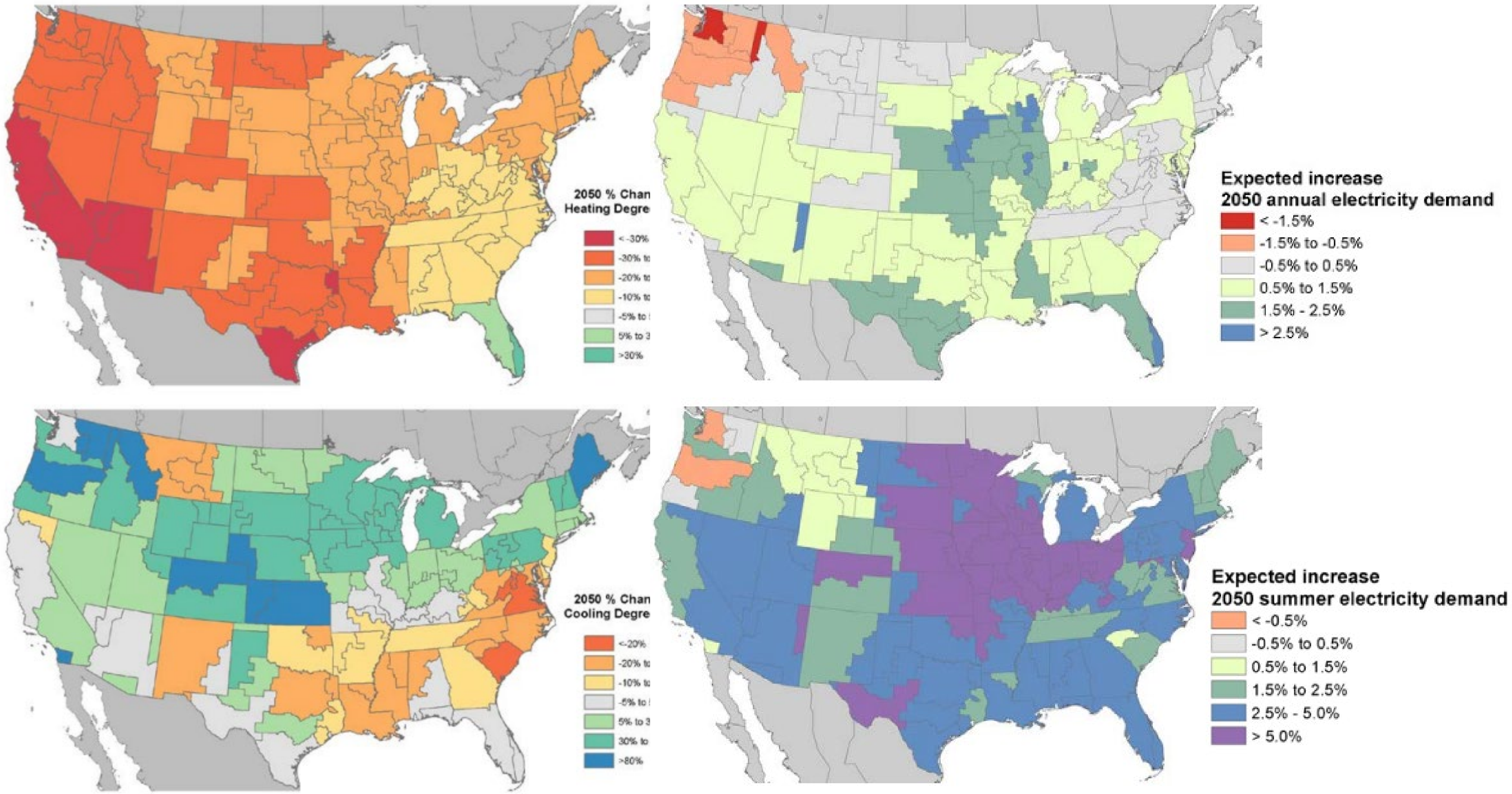
Italics indicate statutory requirements/goals

Impact of climate change on electricity load

New Challenges for Load Forecasting – Climate Change

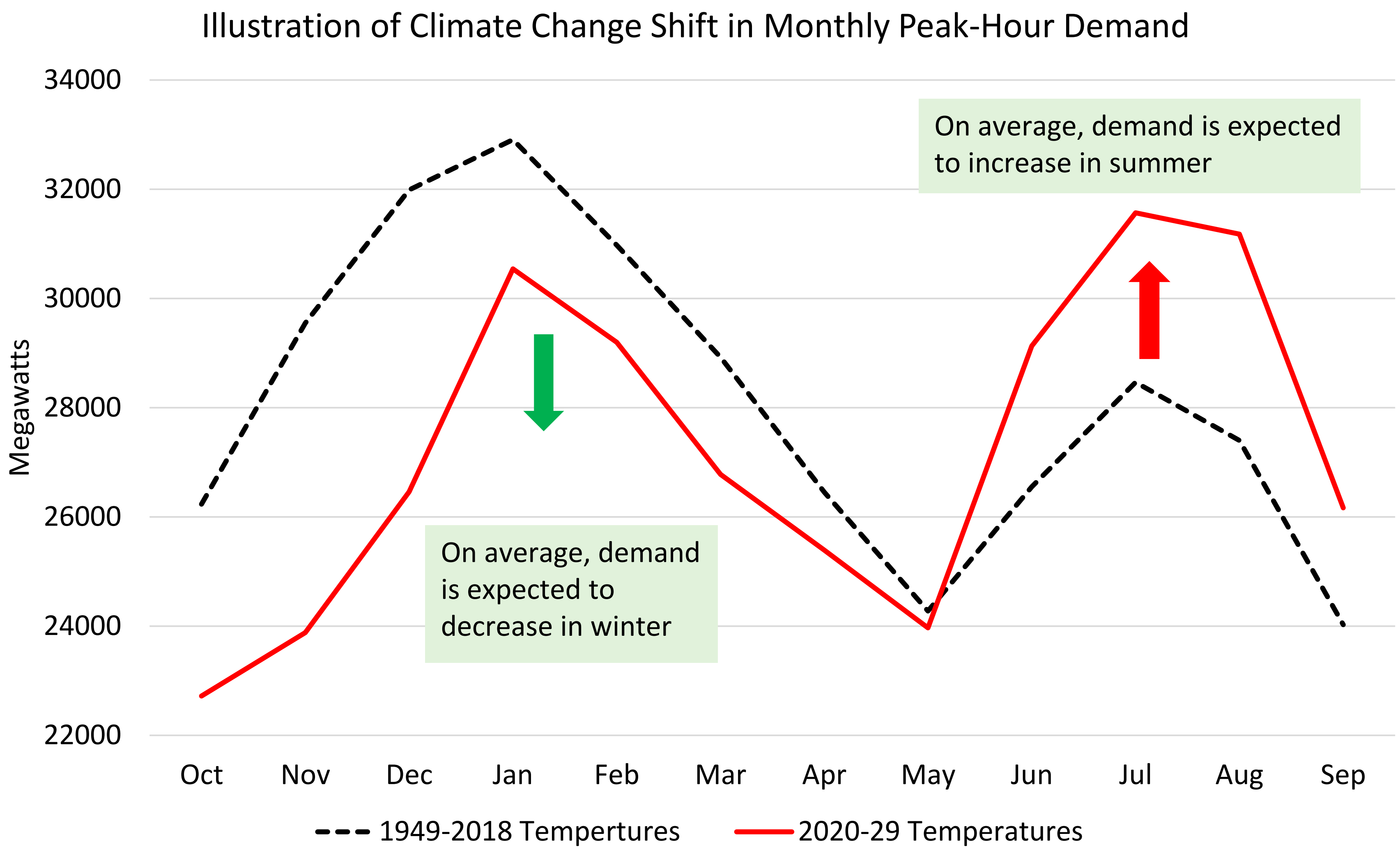
- Impact of climate change
  - Temperature increase
  - Precipitation, cloud, and wind speed patterns
  - River flows and hydro electric generation
- Load forecasting
  - Demand
  - Peak load
- Example studies
  - Demand projection [1]
  - Peak load forecasting [2]

Load Projection in 2050 [1]



[1] P. Sullivan, J. Colman, and E. Kalendra, *"Predicting the Response of Electricity Load to Climate Change,"* NREL Technical Report, NREL/TP-6A20-64297, 2015.
[2] D. Burilloa, M. V. Chester, S. Pincetl, E. D. Fournier, and J. Reyna, "Forecasting Peak Electricity Demand for Los Angeles Considering Higher Air Temperatures Due to Climate Change," *Applied Energy* 236 (15): Feb. 2019.

NW Power Plan Example – Downscaled Climate Data (Rather than Historic Data) Shifts System Peak



Dashed line represents monthly average peak-hour demand based on historic temperatures from 1949-2018.

Solid line represents monthly average peak-hour demand based on forecasted climate change temperatures for 2020-29.

[1] Because this chart was created in 2019, historic temperatures (and therefore demand forecasts) for that year were not available.

From John Fazio, Northwest Power and Conservation Council, November 2021, Presentation to the National Council on Electricity Policy.

Best practices for incorporating climate change impacts and evaluating resilience to extreme events are still evolving

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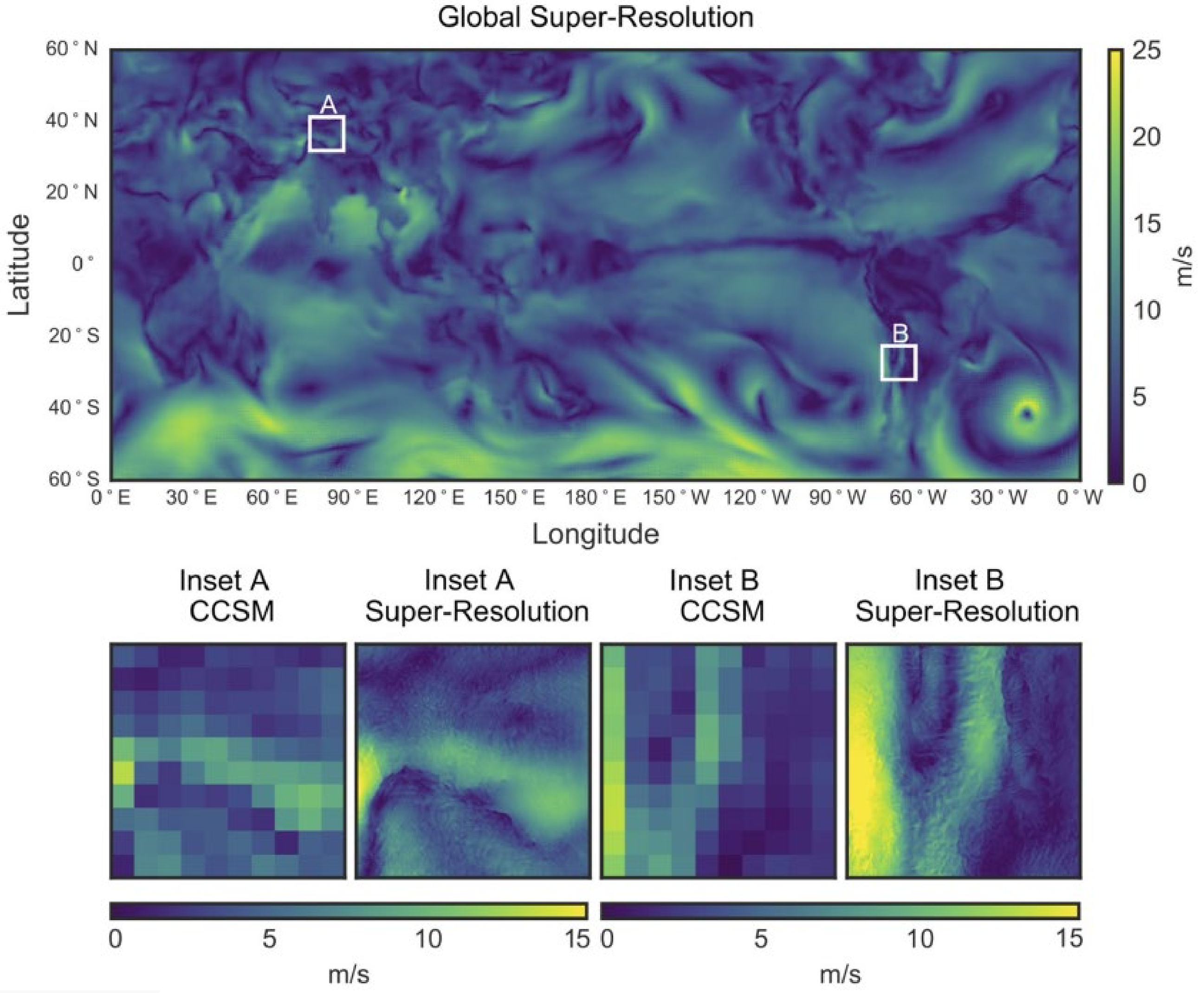
- **Climate Forecasts: Policymakers and planners need to understand changes in local weather to assess grid risks.**
  - Climate is a description of a long-run average over a large area, and weather is the realization of climate in a small geographic and time scale.
  - “Downscaling” is required to transform low-resolution environmental information into high-resolution spatial and temporal scales to assess grid infrastructure impacts.
- **Emerging practice: Researchers are starting to develop the data and techniques required to understand local climate and extreme event impacts.**
  - Directly downscale data from global climate models for different climate change scenarios (right)
  - Systematically high wind and solar grid performance during extreme events (Novacheck et al. 2021, https://www.osti.gov/biblio/1837959)



Wind speed downscaling as described in Stengel et al. (2020)
https://www.pnas.org/doi/abs/10.1073/pnas.1918964117

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Preparing distribution systems for demand-side change

System Level vs. Distribution Level Forecasts

Resource planning is usually at system level

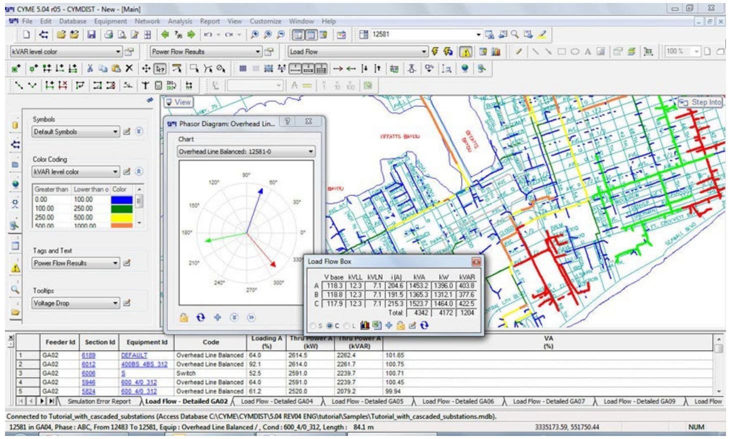
- Loads forecasted at a system level
- Generation meeting load at the system or other high aggregation level — e.g., state level
- BTM generation included in IRPs often at an aggregated system level
  - Distribution system and BTM generation tend to be areas of low visibility
  - Load forecasting models (listed earlier) can help with visibility

Integrated planning is at multiple levels

- A significant portion of new generation is connecting to the distribution system.
- To encourage more new generation to connect requires knowledge – where there is available capacity and where there are bottlenecks.
- Distribution-level data needed to assess:
  - What is happening BTM – PV, EV, and electrification
  - What is happening BTM is uneven for many reasons, but equity concerns are better addressed if spatial disaggregation is improved.
- Some of the load forecasting tools help provide spatial visibility.
- Ideally, the granular distribution forecasts in aggregate comport with the system-level forecasts.

Load Forecasting – Current Best Practices

- **Load Forecast** advanced practices are granular load forecasts
  - Granular in time – Forecasts for all 365 days x 24 hours = 8,760 hours per year
    - Feeds into advanced modeling of resources
  - Granular in space – Forecasts at the circuit and transformer level
- A diverse set of tools are used to create these forecasts
  - LoadSEER
  - CYMEDIST
  - SYNERGI
  - GridLab-D
  - Econometric models
  - Probabilistic forecasting techniques
  - End-use models
- Judgement and company projections can form basis of forecasts



Limitations

- **Data**
  - A main limitation to forecasting granular DER adoption is the need for granular data.
  - Some utilities that have not yet implemented these forecasts cite the need for enhanced capabilities to collect and monitor granular data (such as from Advanced Metering Infrastructure, which will provide greater temporal and geospatial granularity).
  - Other utilities note that data quality for substations and circuit locations has been a barrier to more granular load forecasting.
    - Example: “Historically, data quality for substations and circuit locations has been a barrier to their use for more granular load forecasting due to lack of metering, meter data gaps, and abnormal system operations or configurations. This step required extensive use of data analytics to identify and remove load transfers, outages, data gaps, and data recording errors. Load transfers were of particular importance since they can be confused with load decreases or growth.” Central Hudson Gas & Electric Corporation’s 2020 DSIP report
- **Need for enhanced probabilistic forecasting techniques**
  - Another often mentioned limitation to advancing forecasting practices is the need for enhanced probabilistic forecasting techniques for variabilities in weather, economic growth, proliferation of DER, etc.—which can all impact load.

Advanced forecasting example – National Grid

- Since 2018, National Grid has generated and published 8,760-hour feeder level forecasts
- Forecasts are used for local area planning assessments and non-wires alternative evaluations
- A Marginal Avoided Distribution Capacity study is used to quantify the value of DER in targeted locations
- In-house modeling combined with **GridLAB-D**™, an open-source, simulation-based modeling environment that enables detailed power flow solutions, is used to generate 8,760 load profiles for every feeder
- High-performance cloud computing, such as Amazon Web Services, is used to improve the overall computational process
- EV charging behaviors of both residential and non-residential customers are simulated using the **POLARIS** model
- Annual peak load forecasts incorporate projected economic and demographic impacts and anticipated technological advances and policy objectives
- Future enhancements will incorporate probabilistic forecasting techniques.

https://jointutilitiesofny.org/sites/default/files/NG_2020_DSIP.pdf

Planning under deep uncertainty

Long-term electricity planning is highly uncertain

Keying off the table to the right:

- ► Most utility planning for the late 20th century through to the last couple of decades could be characterized as Level 1 to Level 2
- ► The current energy transition and climate change uncertainties push planning farther to the right, into Levels 2 – 4
  - ■ What will future weather be?
  - ■ What will future (electrified?) loads be?
  - ■ How much generation, balancing, and other grid services will be provided by DERs and other devices at the edge of the grid?

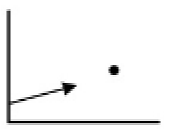
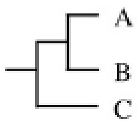
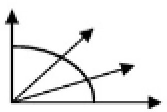
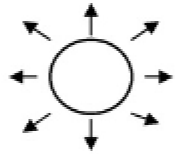
Determinism		Level 1	Level 2	Level 3	Level 4	Total ignorance
				Deep Uncertainty		
	Context	A clear enough future 	Alternate futures (with probabilities) 	A multiplicity of plausible futures 	Unknown future 	
	System model	A single system model	A single system model with a probabilistic parameterization	Several system models, with different structures	Unknown system model; know we don't know	
	System outcomes	A point estimate and confidence interval for each outcome	Several sets of point estimates and confidence intervals for the outcomes, with a probability attached to each set	A known range of outcomes	Unknown outcomes; know we don't know	
	Weights on outcomes	A single estimate of the weights	Several sets of weights, with a probability attached to each set	A known range of weights	Unknown weights; know we don't know	

Fig. 1. The progressive transition of levels of uncertainty from determinism to total ignorance.

Source: Walker, Warren E., Vincent AWJ Marchau, and Darren Swanson. "Addressing deep uncertainty using adaptive policies: Introduction to section 2." Technological forecasting and social change 77.6 (2010): 917-923.

Developing and using multiple load scenarios is a first step to understanding what different demand-side futures could mean for power systems

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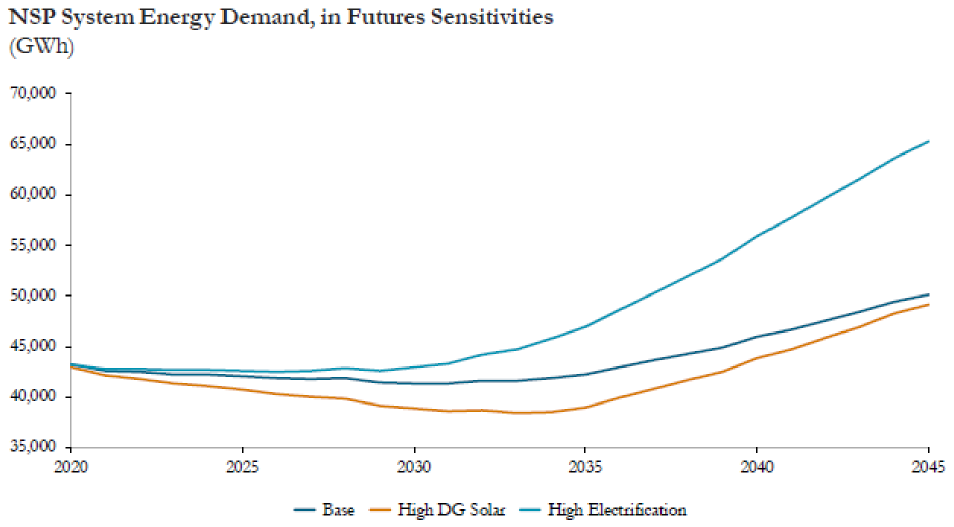
- Becoming commonplace for utilities to create multiple load scenarios
- For example, Xcel Energy in their 2020 IRP:

IRP Futures Scenarios, adapted from Table 2-3

Component	High Distributed Solar	High Electrification
Gas, Power, Coal Prices	-	+
New Resource Capital Costs	-	-
Native Load	Base	+
EE	+	Base
D-PV	+	Base
Overall	-	+



Source: Figure 2-12, 2020 IRP

- Additional scenarios might help to bracket demand-side possibilities, for example:

Component	Low Load	High Load	Low Change	High Change
Native Load	Base	+	Base	+
EE	+	-	Base	+
DR	+	-	Base	+
D-PV	+	-	Base	+
EV	-	+	Base	+
D-BESS	Base	Base	Base	+
Overall	--	++	Base	+

Robust decision-making frameworks could be used to plan for, track, and respond to demand-side change

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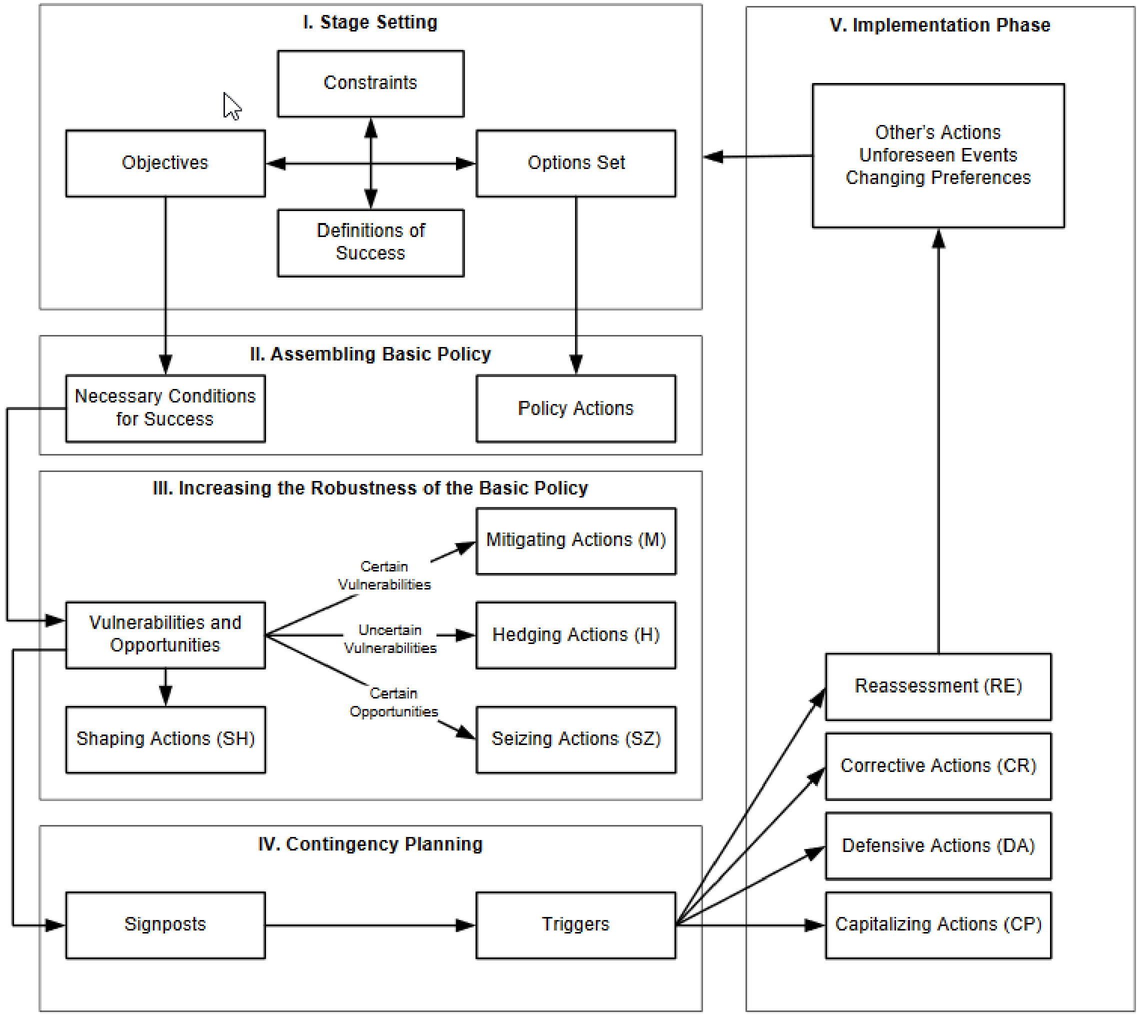
- The figure to the right concisely describes how one might plan and act in a highly dynamic environment
- In the Xcel Energy documents I reviewed, there was more discussion of monitoring and recourse/decision robustness related to plant retirements than to demand-side change
- As some jurisdictions pursue rapid decarbonization, utilities and PUCs will need to incorporate load, DERs and distribution assets, not just generation and transmission assets, into these types of robust and dynamic decision-making frameworks



Source: Kwakkel, Jan H., Warren E. Walker, and V. A. W. J. Marchau. "Adaptive airport strategic planning." *European Journal of Transport and Infrastructure Research* 10.3 (2010).

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Social science methods could help integrate insights from various stakeholders into energy modeling

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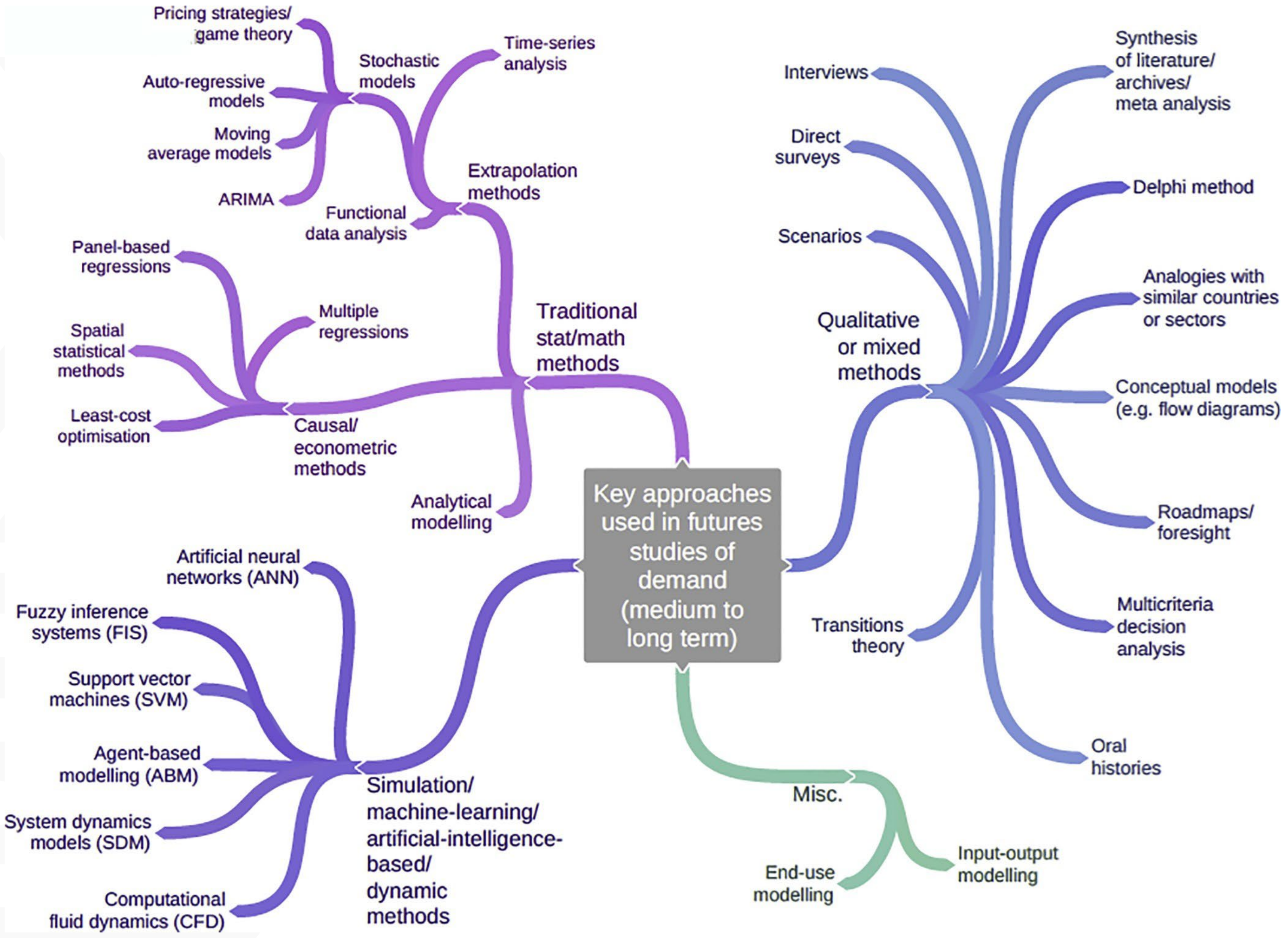
In the figure to the right:

- *Left-side:* Traditional and emerging numerical modeling methods
- *Right-side:* More qualitative methods
  - Some (e.g., direct surveys, interviews, oral histories) **aimed at gathering insights from stakeholders, who could be quite diverse**
  - Others (e.g., transitions theory, conceptual models, analogies, roadmaps) **aimed at understanding and planning for what large changes could look like**



Source: Sharmina, Maria, et al. "Envisioning surprises: How social sciences could help models represent 'deep uncertainty' in future energy and water demand." *Energy Research & Social Science* 50 (2019): 18-28.

Stakeholder processes can help raise, clarify, and validate the representation of key uncertainties

- Stakeholders generally asked for:
  - Additional details and visibility into the methodologies and data sources/inputs for DER and load forecasting. From Orange Rockland Utilities, Inc.'s 2020 DSIP report:
    - "Describe the forecasts provided separately for key areas including but not limited to photovoltaics, energy storage, electric vehicles, and energy efficiency"
    - "Identify where and how DER developers and other stakeholders can readily access, navigate, view, sort, filter, and download up-to-date load and supply forecasts"
  - Additional scenarios and sensitivity analysis. From Orange Rockland Utilities, Inc.'s 2020 DSIP report:
    - "Provide sensitivity analyses which explain how the accuracy of substation-level forecasts is affected by DG, energy storage, EVs, beneficial electrification, and EE measures"
- Designated and proactive forecasting stakeholder working groups can help support understanding and agreement
  - Hawaii – Forecast Assumptions Working Group
  - California – Distribution Forecasting Working Groups
  - New York – NYISO Electric System Planning Working Group

Questions?

Contact

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Grid Planning and Analysis Center
National Renewable Energy Laboratory
https://www.nrel.gov/

Workshop Agenda

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1:00-1:15 Introductions & Overview

1:15-1:45 Intro to Electricity Forecasting

1:45-2:15 Load Forecasting

2:15-2:30 Break

2:30-3:00 Energy Efficiency and Demand Flexibility Forecasting

3:00-3:35 Building Electrification & Electric Vehicle Forecasting

3:35-3:50 Break

3:50-4:20 Distributed Solar & Battery Storage Forecasting

4:20-4:50 Cost Forecasting

4:50-5:00 Final Thoughts

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4:20-4:50 Cost Forecasting
4:50-5:00 Final Thoughts

Forecasting Efficiency and Demand Flexibility

Natalie Mims Frick
Berkeley Lab

This presentation was funded by the U.S. Department of Energy's Office of Electricity and Building Technologies Office.

Agenda

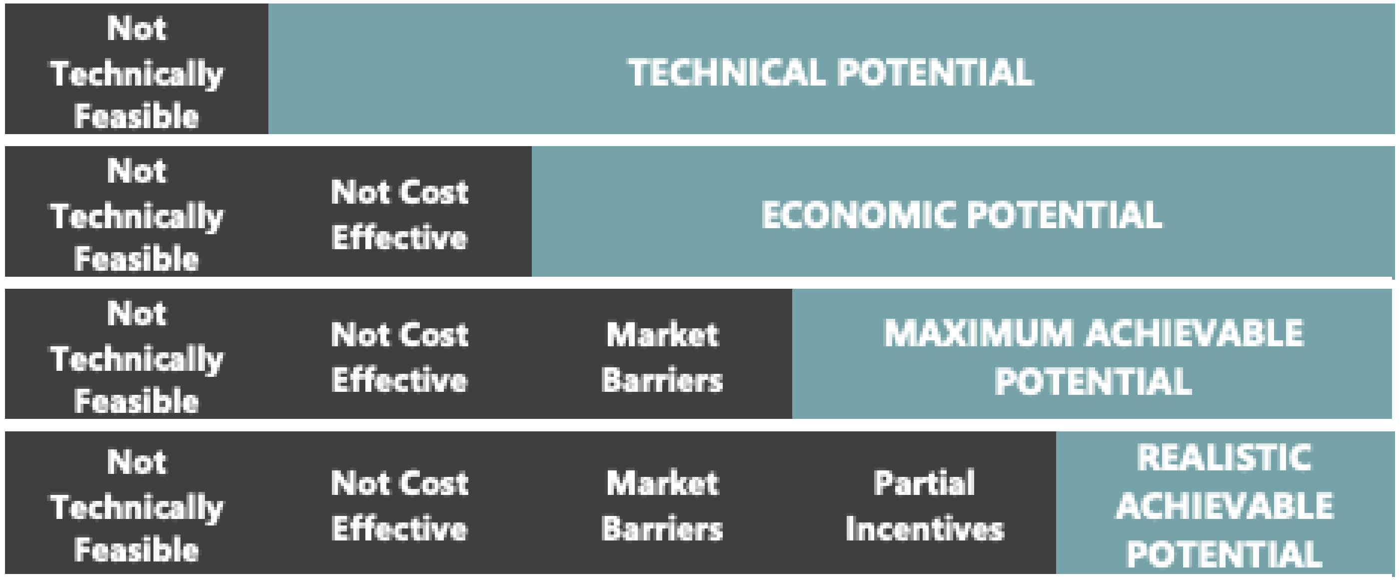
- Two approaches to forecast energy efficiency (EE), demand response (DR) and demand flexibility (DF)
  - Potential studies
  - Use EE and other distributed energy resources (DERs) as selectable resources
- Interactions between potential studies and load forecasts
- Questions states can ask

Resource potential assessments

- The objective of EE and DF potential assessments is to provide accurate and reliable information on:
  - Quantity of EE and DF available
  - Timing of availability (e.g., new construction, stock turnover)
  - EE and DF measure cost
  - Load or savings shape

NIPSCO estimated four types of potential in their 2021 Market Potential Study for electric and gas efficiency.

FIGURE 3-2 TYPE OF ENERGY EFFICIENCY POTENTIAL



Source: NIPSCO

Typically, an EE or DF forecast is developed in a 6-step process.

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- Step 1 – Estimate *technical potential* on a *per application* basis (i.e., savings per unit)
- Step 2 – Estimate *economic potential* on a *per application* basis (i.e., levelized cost per unit) based on "avoided cost" of a "proxy" resource or capacity expansion model marginal resource analysis
- Step 3 – Estimate *number of applicable units* (account for physical limits, retirements, new construction, etc.)
- Step 4 – Estimate *economic potential* for *all applicable* units
- Step 5 – Estimate *economically achievable* potential for *all realistically achievable* units
- Step 6 – **Reduce the load forecast provided to the capacity expansion model** by the amount of *economically achievable* savings (determined in Step 5) before the model is used to "optimize" supply side resources

An alternative to forecasting EE and DF from potential studies is to consider them as selectable resources

- Integrated Resource Planning (IRP) is intended to evaluate multiple resource portfolio options in an organized, holistic, and technology-neutral manner and normalize solution evaluation across generation, distribution, and transmission systems and demand-side resources.
- In this framework, DERs are a decision variable directly comparable to amounts and timing of generation options. This allows for consideration of relative cost and risk across the broadest array of potential solutions.
- Modeling energy efficiency and other DERs as resource options for bulk power systems can support many state objectives, including greater reliability and resilience, reduced electricity costs, achieving energy efficiency and renewable energy targets, and lower air pollutant emissions.

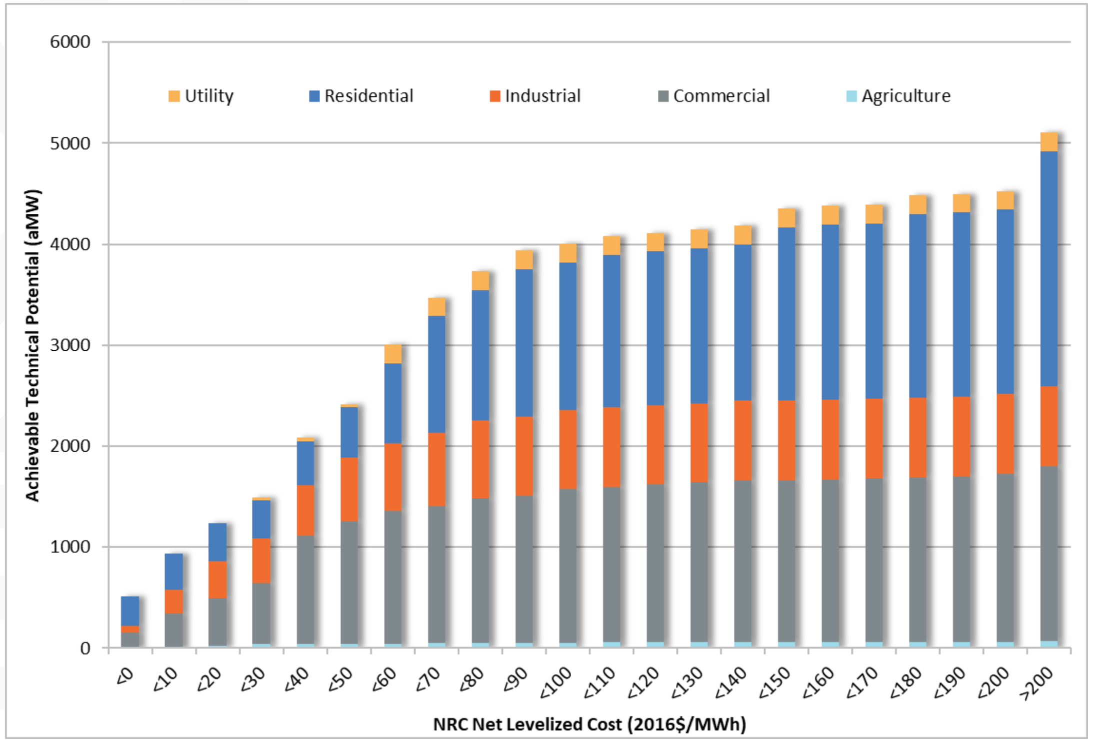
The process and order are different when considering EE and DF as selectable resources in IRPs.

- Step 1 – Estimate *technical potential* on a <u>*per application*</u> basis (i.e., savings per unit)
- Step 2 – Estimate <u>*number of applicable units*</u> (account for physical limits, retirements, new construction, etc.)
- Step 3 – Estimate *technical potential* for <u>*all applicable*</u> units
- Step 4 – Estimate *achievable potential* for <u>*all realistically achievable*</u> units
- Step 5 – Estimate *economic potential* for <u>*all realistically achievable*</u> units **by competing EE and DR against supply side resources in capacity expansion modeling***

*Any Energy Efficiency Resource Standard (EERS) requirements are typically modeled as "must build" resources. Only additional increments above EERS requirements compete against generating resources in capacity expansion modeling.

What is an efficiency supply curve?

- EE potential is comprised of hundreds of measures.
- IRP models cannot simulate individual efficiency measures, so they are grouped together.
- Supply curves for EE (and other DERs) are usually represented as the amount of resource potential available in discrete “bundles” or “bins.”



Source: NWPC Draft 8th Plan

[Methods to Incorporate Energy Efficiency in Electricity System Planning and Markets]

Example: Georgia Power EE bundling approaches

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Commercial Load Shape-Based Bundles

Bundle Number	Number of Measures	Total Potential (MWh)	Weighted Avg. Levelized Cost ($/MWh)	Mean Levelized Cost ($/MWh)	Range of Levelized Cost ($/MWh)
21	2	21	0	0	$0-$0
11	2	8	0	0	$0-$0
14	1	1	0	0	$0-$0
4	343	87,593	16	17	$0-$43
19	323	32,363	18	18	$0-$49
2	160	97,414	20	19	$0-$43
9	157	12,452	22	30	$0-$73
13	183	30,355	54	57	$36-$87
10	34	2,700	59	39	$18-$128
18	3	46	78	56	$0-$167
0	150	76,169	78	74	$48-$130
16	89	10,862	118	117	$75-$167
3	107	31,497	122	121	$89-$160
20	1	0	195	195	$195-$195
15	23	376	200	228	$142-$361
5	101	43,549	205	197	$159-$240
8	95	55,907	212	200	$139-$231
17	47	5,139	246	223	$173-$277
1	112	10,863	272	270	$243-$326
12	42	7,142	309	332	$286-$387
7	42	7,781	378	376	$330-$461
6	47	6,234	432	442	$387-$497

Commercial Value Based Bundles

Bundle Number	Number of Measures	Total Potential (MWh)	Weighted Avg. Levelized Cost ($/MWh)	Mean Levelized Cost ($/MWh)	Range of Levelized Cost ($/MWh)
12	3	22	$0	$0	$0-$0
6	2	8	$0	$0	$0-$0
13	340	56,611	$7	$6	$0-$14
1	446	148,971	$20	$21	$14-$29
15	231	32,718	$36	$37	$29-$45
10	146	33,509	$55	$54	$46-$62
4	139	14,604	$70	$71	$63-$80
19	82	56,404	$87	$90	$81-$101
14	85	20,333	$111	$112	$103-$122
0	52	12,239	$135	$135	$124-$146
11	53	11,535	$159	$159	$147-$173
8	109	13,847	$192	$192	$176-$202
3	78	78,154	$214	$212	$202-$222
18	49	5,731	$238	$236	$225-$250
7	93	9,620	$265	$264	$250-$277
17	35	7,287	$295	$297	$282-$315
2	25	3,364	$333	$334	$318-$350
16	44	6,102	$376	$372	$353-$388
9	17	3,697	$402	$407	$391-$430
5	35	3,716	$457	$459	$436-$497

Commercial Cost Based Bundles

Bundle Number	Number of Measures	Total Potential (MWh)	Weighted Avg. Levelized Cost ($/MWh)	Mean Levelized Cost ($/MWh)	Range of Levelized Cost ($/MWh)
8	344	56,631	7	6	$0-$13
2	453	149,882	20	21	$14-$29
14	225	31,817	36	37	$29-$45
5	146	33,509	55	54	$46-$62
6	139	14,604	70	71	$63-$80
13	89	58,291	87	91	$81-$104
0	110	25,676	117	118	$106-$136
10	73	16,545	153	154	$136-$173
4	128	17,543	194	194	$176-$207
11	93	78,377	215	220	$208-$240
1	110	11,631	263	262	$241-$283
9	46	8,854	301	305	$285-$331
3	52	5,956	365	364	$336-$383
12	20	5,358	396	402	$385-$422
7	36	3,799	456	458	$430-$497

Source: Georgia Power

Example: Northwest Power and Conservation Council DR supply curve

Source: [NWPCC]

Several states and utilities considering efficiency as a selectable resource in long-term electricity planning*

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- California
  - 2021 Energy Efficiency Potential and Goals Study
  - Staff Proposal for Incorporating Energy Efficiency into the SB 350 Integrated Resource Planning Process
- Georgia
  - Georgia Power - Supply-Side Representation of Energy Efficiency Resources in the Georgia Power IRP Model
- Hawaii
  - Hawaiian Electric Company Integrated Grid Plan
- Idaho
  - Idaho Power – 2nd Amended 2019 IRP
- Indiana
  - Duke Energy – 2020 IRP
  - Vectren
  - IPL/AES – 2019 IRP
  - NIPSCO
  - I&M
- Louisiana
  - Entergy New Orleans - 2018 IRP
- Missouri
  - Ameren 2020 IRP
- Minnesota
  - Xcel Energy /Northern States Power 2020 IRP
- Northwest Power and Conservation Council
  - Draft 8th Power Plan
- PacifiCorp (CA, OR, WA, WY, UT)
  - 2021 IRP
- Tennessee
  - Tennessee Valley Authority - 2019 IRP
- Washington
  - Puget Sound Energy – 2021 IRP
  - Avista – 2021 IRP

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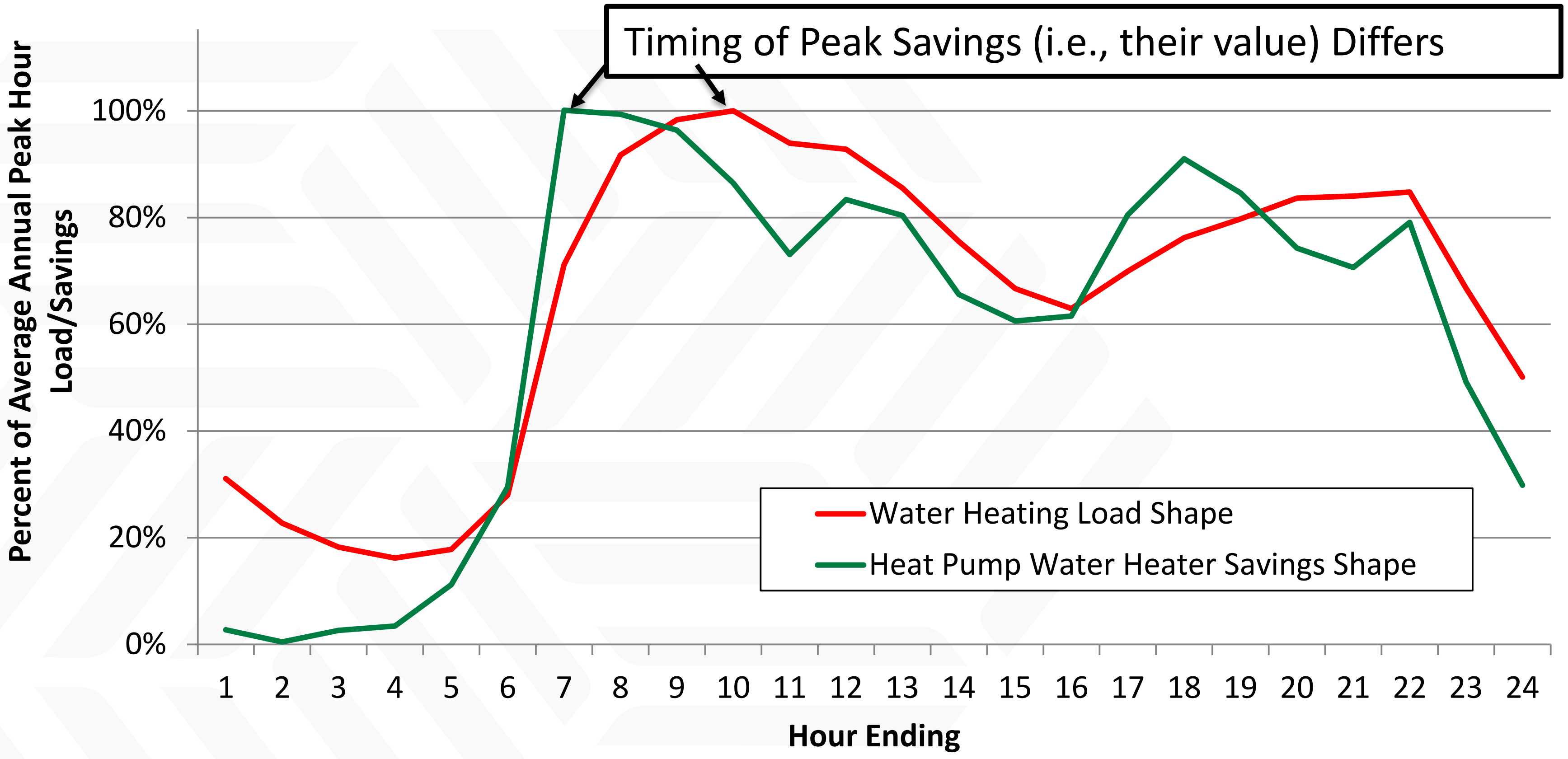
*These are the states/utilities that I am aware of - please let me know if you see an omission.

Challenges with potential studies

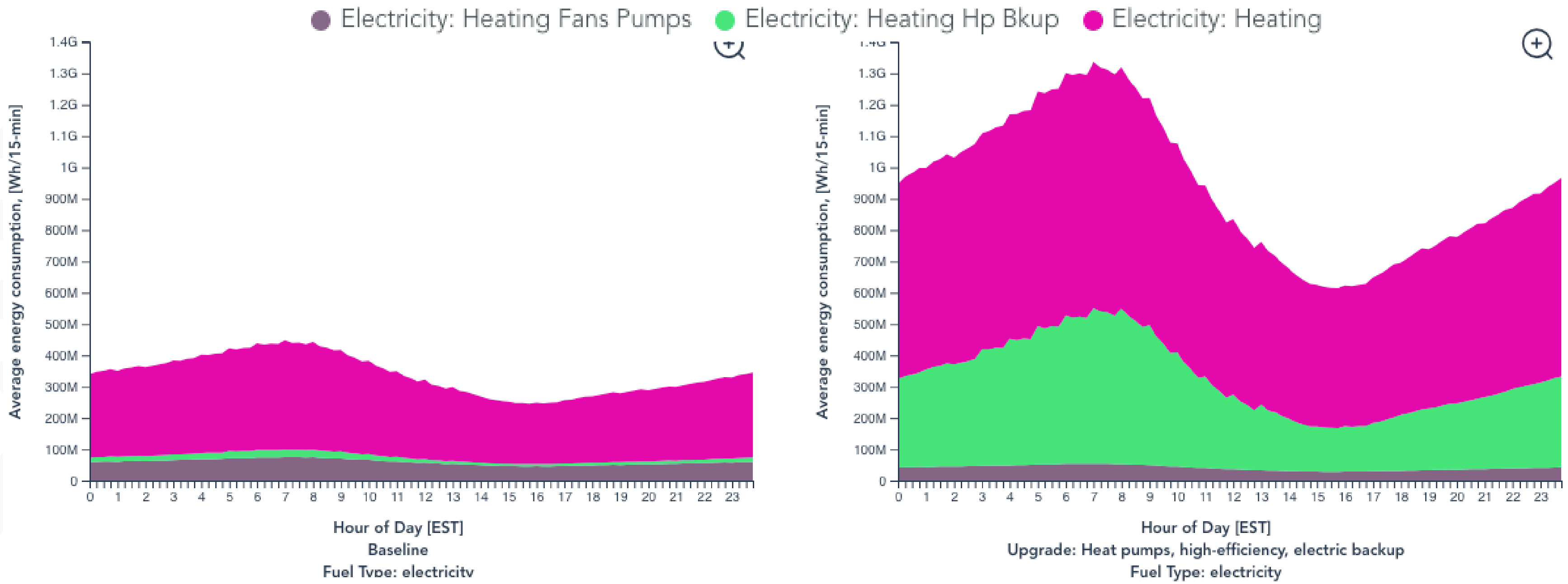
- Data inputs to the potential study must be robust. Common shortcomings with potential studies include:
  - Not using accurate load shapes
  - Not accounting for variations in interactions between DERs
  - Not accounting for variations in interactions between DERs and existing and future utility system resources
  - Not accounting for all benefits, including distribution and transmission system capacity impacts

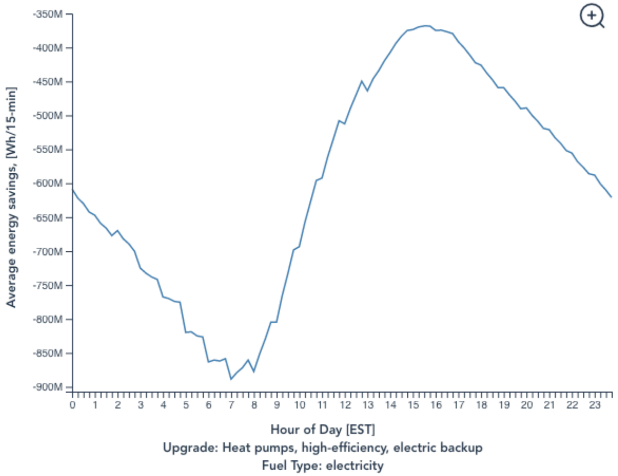
- Using efficiency and other DERs as selectable resource overcomes some of these shortcomings.

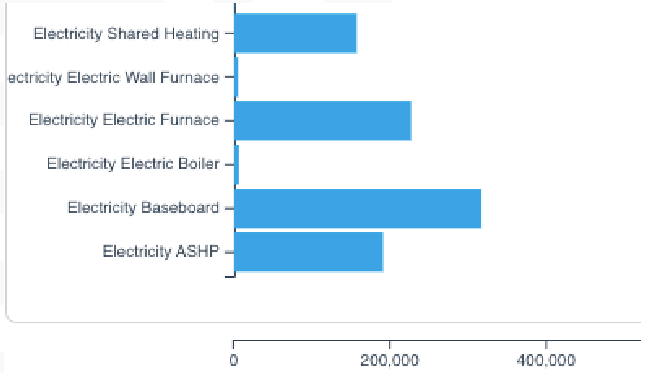
Each measure assigned the applicable energy savings load shape or end use load shape



Example: Illinois end-use load profiles







Source: ResStock

Treating EE and DR as selectable resources in a capacity expansion model permits optimization *between these resources*

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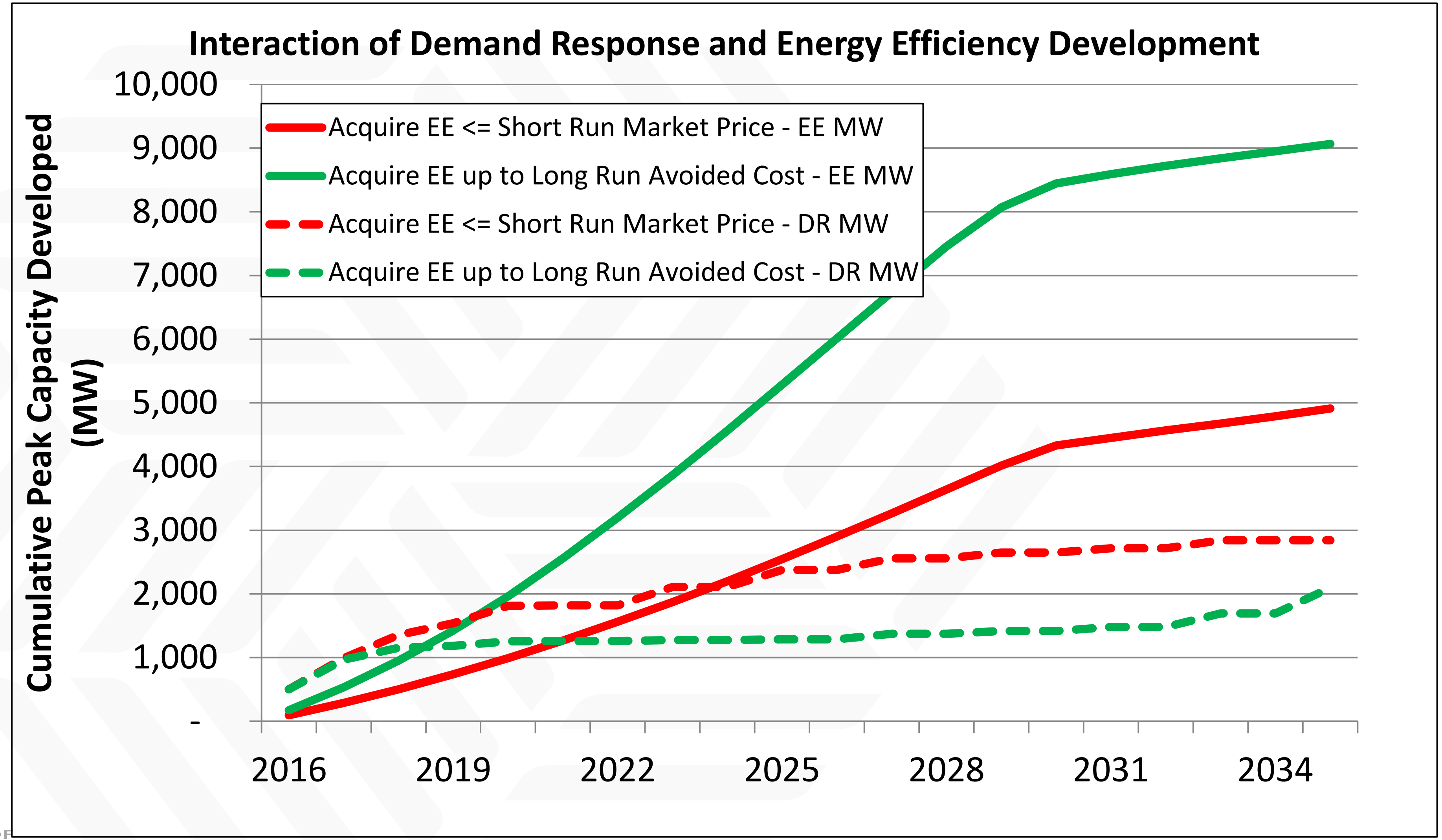

Source: Northwest Power and Conservation Council, 7th Power Plan

Treating EE and DR as selectable resource options in a capacity expansion model permits optimization *across supply side and demand side resources*

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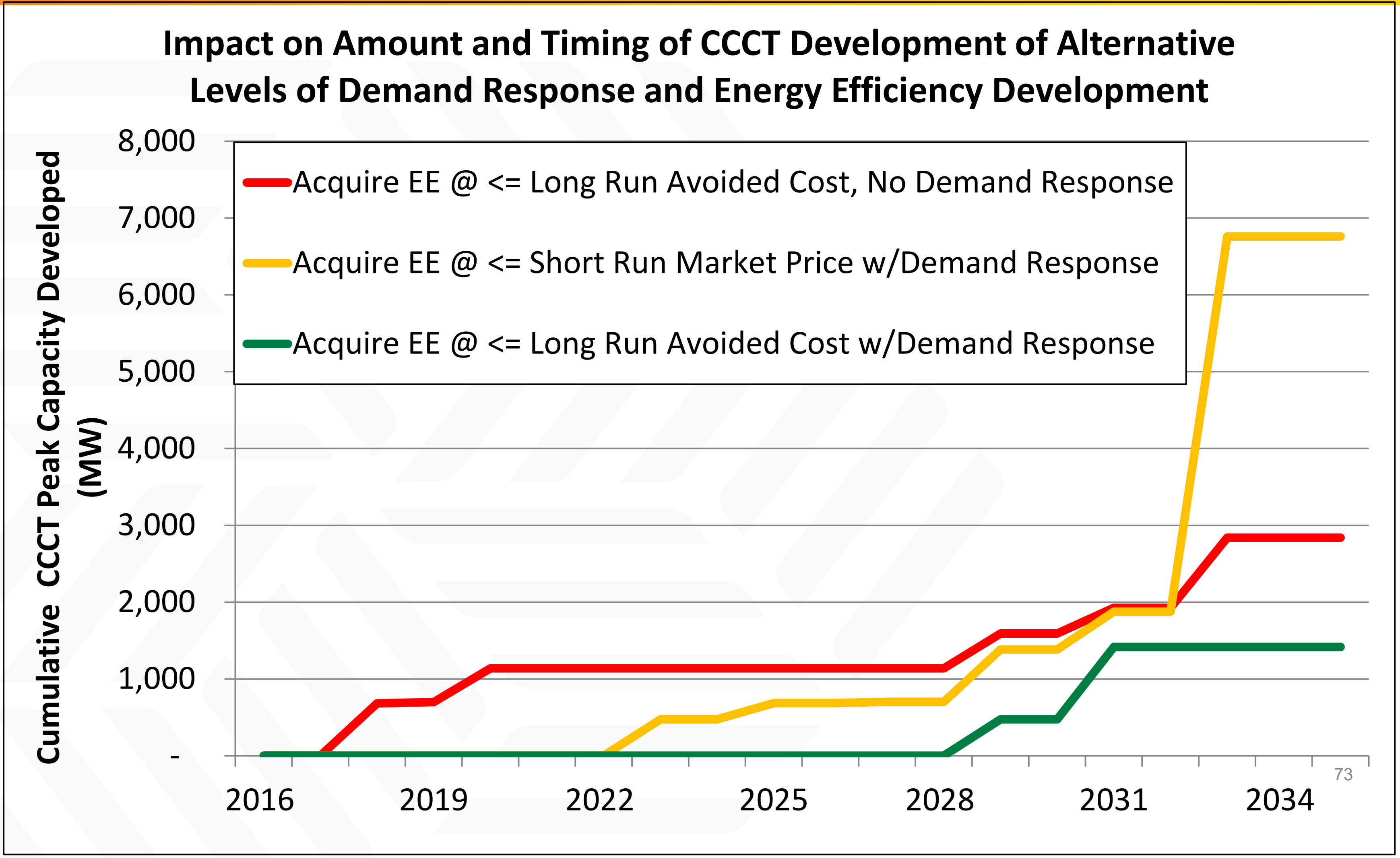
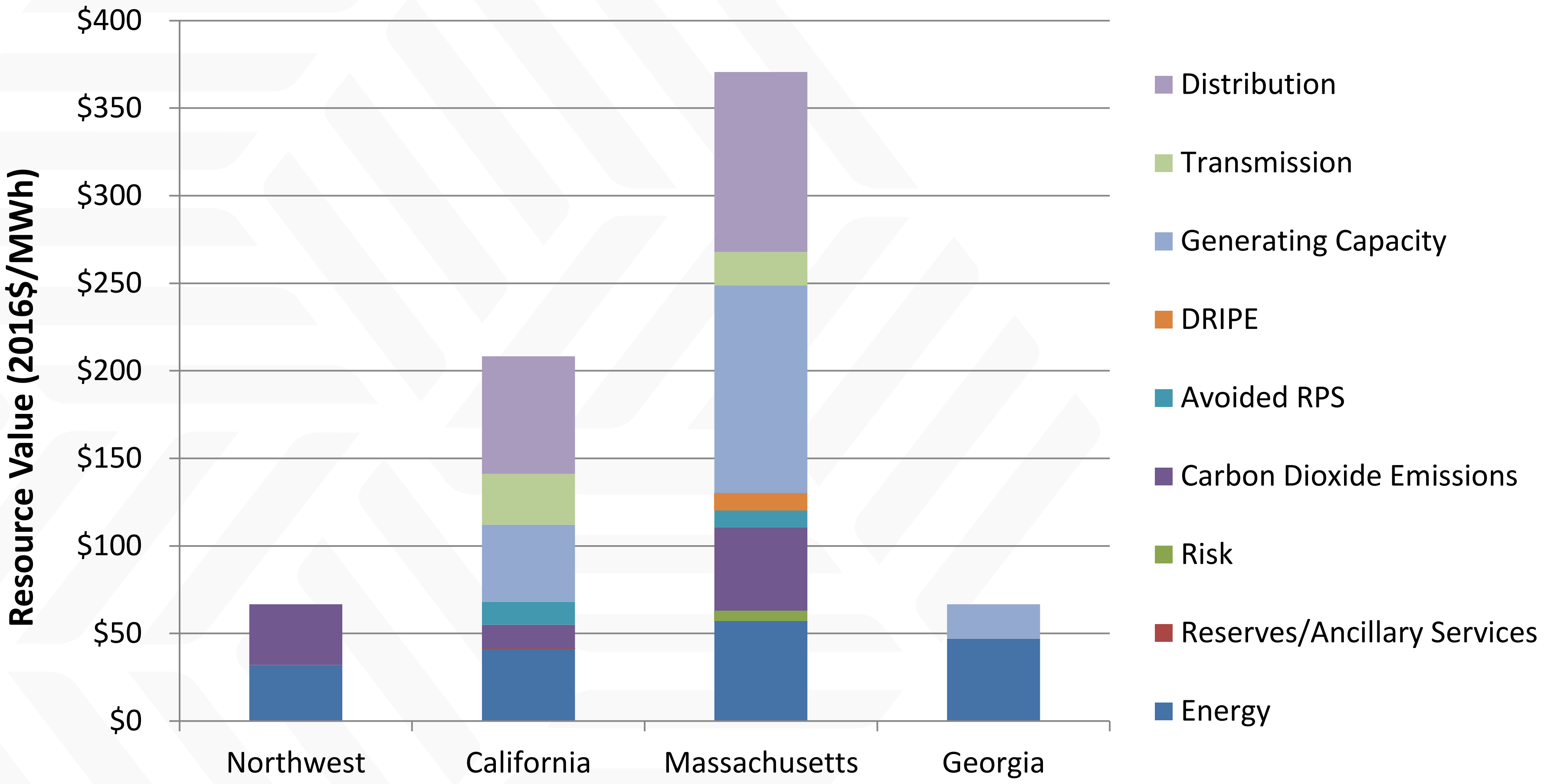


Source: Northwest Power and Conservation Council, 7th Power Plan

Example: Value of residential air-conditioning measure varies based on avoided costs included in analysis



Source: LBNL

EE and DF potential interact with the load forecast

- EE and DF forecast interact with the load forecast in both approaches.
  - The more common approach uses the EE or DF potential to reduce the load forecast.
  - Considering EE or DF as a selectable resource requires planners to know the quantity of the resource in the load forecast and the quantity the model can select.
- Internal consistency between the load forecast and EE and DF potential assessments is necessary to avoid the potential for *over* or *under* estimating remaining EE and DF potential.
  - Baseline use and efficiency assumptions should be equivalent.
  - "Units" (e.g., houses, commercial floor space, appliance counts) should be identical.
- Emerging issues such as electrification impact the load forecast.
  - Replacing an electric resistance heater with an air source heat pump that is more efficient will reduce electricity consumption.
  - Replacing a gas heater with an air source heat pump will increase electricity consumption.
  - It is important to understand where this data is used in the analysis (e.g., load forecast, potential study, both, neither) for consistency.

Example: NIPSCO includes building electrification in their load forecast, but not their potential study.

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- NIPSCO considers the impact of efficient HVAC in their potential study for electric and gas customers, but there is no consideration of fuel switching.
- NIPSCO considers the impact of building electrification in their Economy Wide Decarbonization load forecast scenario.

Figure 3-20: Total Net Energy for Load Forecast across Scenarios

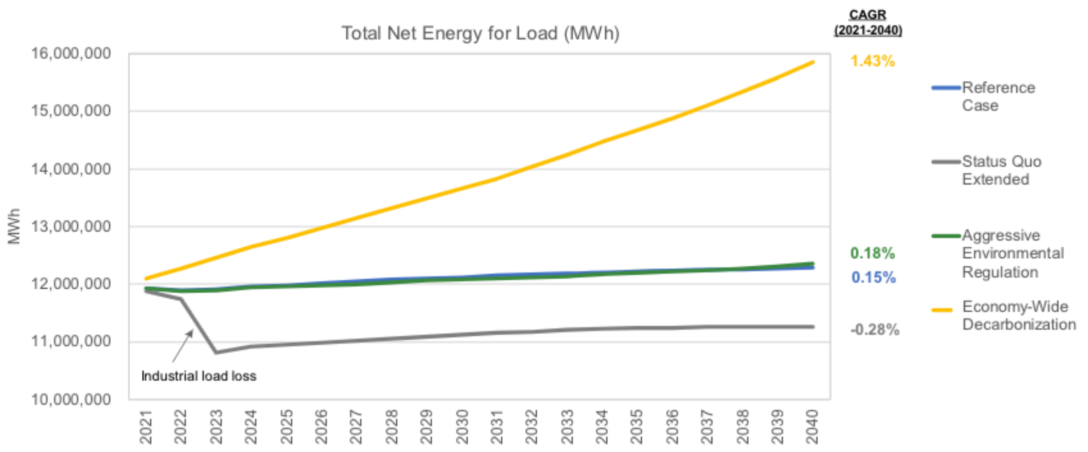
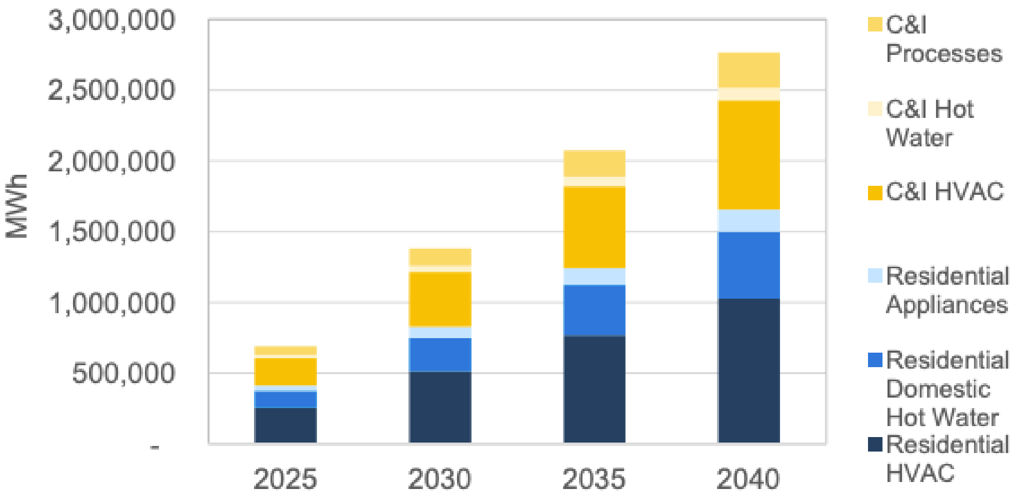


Figure 3-19: Electrification Impact on NIPSCO Energy Sales



Source: NIPSCO [IRP]

Example: National Grid includes building electrification in their EE and DR potential study

Table ES- 1. Summary Energy Efficiency BAU Achievable Potential, 2022-2024

Incremental Annual Net BAU Scenario	Electricity MWh	Summer Peak Electric Demand MW	Natural Gas Therms	Propane MMBtu	Fuel Oil MMBtu
Residential Sector					
2022	125,601	20.73	11,793,655	260,779	19,318
2023	132,705	21.78	12,726,842	301,036	23,410
2024	139,718	22.93	13,695,535	335,592	27,611
Total	398,024	65.44	38,216,032	897,408	70,339
Commercial & Industrial Sector					
2022	241,758	40.84	5,784,105	433	627
2023	219,670	36.18	5,556,680	484	771
2024	200,553	32.22	5,261,190	508	927
Total	661,981	109.25	16,601,976	1,425	2,324
Portfolio Total					
2022	367,359	61.57	17,577,760	261,213	19,944
2023	352,375	57.96	18,283,523	301,520	24,181
2024	340,271	55.15	18,956,725	336,100	28,538
Total	1,060,005	174.68	54,818,008	898,833	72,663

Source: Guidehouse analysis

Table ES- 4. Summary Energy Optimization BAU Achievable Potential, 2022-2024

Incremental Annual Net BAU Scenario	Electricity MWh	Summer Peak Electric Demand MW	Natural Gas Therms	Propane MMBtu	Fuel Oil MMBtu
Residential Sector					
2022	-26,327	1.05	20,303	281,015	83,773
2023	-35,246	1.29	21,759	344,496	146,878
2024	-44,135	0.60	27,055	395,896	223,205
Total	-105,708	2.94	69,117	1,021,406	453,856
Commercial & Industrial Sector					
2022	-3	0.00	0	32,442	20,658
2023	-3	0.00	0	34,171	22,204
2024	-3	0.00	0	35,173	22,902
Total	-8	0.00	0	101,785	65,764
Portfolio Total					
2022	-26,329	1.05	20,303	313,457	104,431
2023	-35,249	1.29	21,759	378,667	169,082
2024	-44,138	0.60	27,055	431,068	246,108
Total	-105,716	2.94	69,117	1,123,192	519,620

Source: Guidehouse analysis

Source: [MA EEAC]

Questions states can ask

- How are utilities in your state modeling EE, DR and other DERs today?
- Are the EE and other DER potential studies assumptions clearly provided? Are the load forecast and EE and other DER forecasts aligned?
- What state policy or regulatory changes are needed to facilitate consideration of EE, DR and other DERs as selectable resources in electricity planning?

Resources for more information

Berkeley Lab's research on time- and locational-sensitive value of DERs

U.S. Department of Energy. 2021. A Roadmap for Grid-interactive Efficient Buildings. Prepared by Andrew Satchwell, Ryan Hledik, Mary Ann Piette, Aditya Khandekar, Jessica Granderson, Natalie Mims Frick, Ahmad Faruqui, Long Lam, Stephanie Ross, Jesse Cohen, Kitty Wang, Daniela Urigwe, Dan Delurey, Monica Neukomm and David Nemtzow

Natalie Mims Frick, Tom Eckman, Greg Leventis, and Alan Sanstad. Methods to Incorporate Energy Efficiency in Electricity System Planning and Markets. January 2021

State and Local Energy Efficiency Action Network. 2020. Determining Utility System Value of Demand Flexibility from Grid-Interactive Efficient Buildings. Prepared by: Tom Eckman, Lisa Schwartz, and Greg Leventis, Lawrence Berkeley National Laboratory. https://emp.lbl.gov/publications/determining-utility-system-value

Natalie Mims Frick, Snuller Price, Lisa Schwartz, Nichole Hanus, and Ben Shapiro. Locational Value of Distributed Energy Resources

Natalie Mims Frick, Juan Pablo Carvallo and Lisa Schwartz. Quantifying reliability and resilience impacts of energy efficiency: Examples and opportunities

Natalie Mims Frick, Juan Pablo Carvallo and Margaret Pigman. Time-sensitive Value of Efficiency Calculator

Fredrich Kahrl, Andrew D Mills, Luke Lavin, Nancy Ryan, Arne Olsen, and Lisa Schwartz (ed.). The Future of Electricity Resource Planning. 2016. Berkeley Lab's Future Electric Utility Regulation report series.

Berkeley Lab and NREL's End Use Load Profiles for the U.S. Building Stock project

Workshop Agenda

1:00-1:15 Introductions & Overview
1:15-1:45 Intro to Electricity Forecasting
1:45-2:15 Load Forecasting
2:15-2:30 Break
2:30-3:00 Energy Efficiency and Demand Flexibility Forecasting
3:00-3:35 Building Electrification & Electric Vehicle Forecasting
3:35-3:50 Break
3:50-4:20 Distributed Solar & Battery Storage Forecasting
4:20-4:50 Cost Forecasting
4:50-5:00 Final Thoughts

Building Electrification Forecasting: Best Practices and Case Studies

AVEN SATRE-MELOY, PHD

Lawrence Berkeley National Laboratory

Agenda

- Current state of building electrification forecasting
- Methodological approaches for forecasting building electrification
  - Scenario analysis-based approaches
  - Adoption model-based approaches
- Scenario analysis case study
  - Guidehouse scenarios developed for U.S. DOE's Energy Emissions, and Equity (E3) Initiative
- Adoption model case study
  - ISO-NE ASHP adoption forecast
- Future research needs

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Current state of building electrification forecasting

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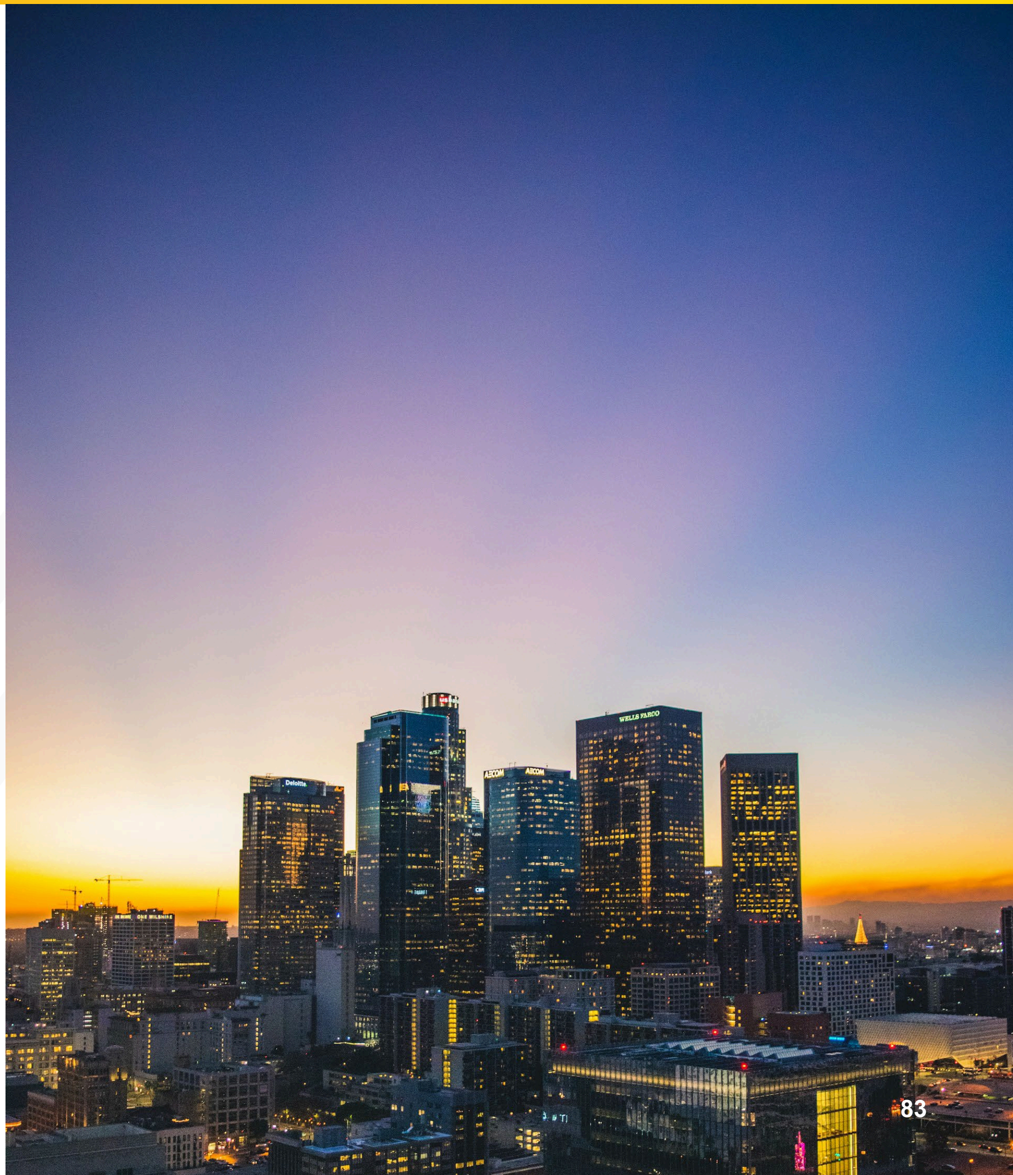
- Methods and approaches for forecasting building electrification are less well developed than for other DERs (e.g., EVs, PV)
- Challenge of lack of data/evidence regarding consumer decision-making for building electrification
- Primary approaches include scenario-based analyses with varying assumptions and statistical-based analyses (diffusion models, regressions)
- Most approaches rely on expert judgment of how broader economic/policy environment will influence consumer choice
- In many cases, forecasts rely on published scenarios from research for different regions/states



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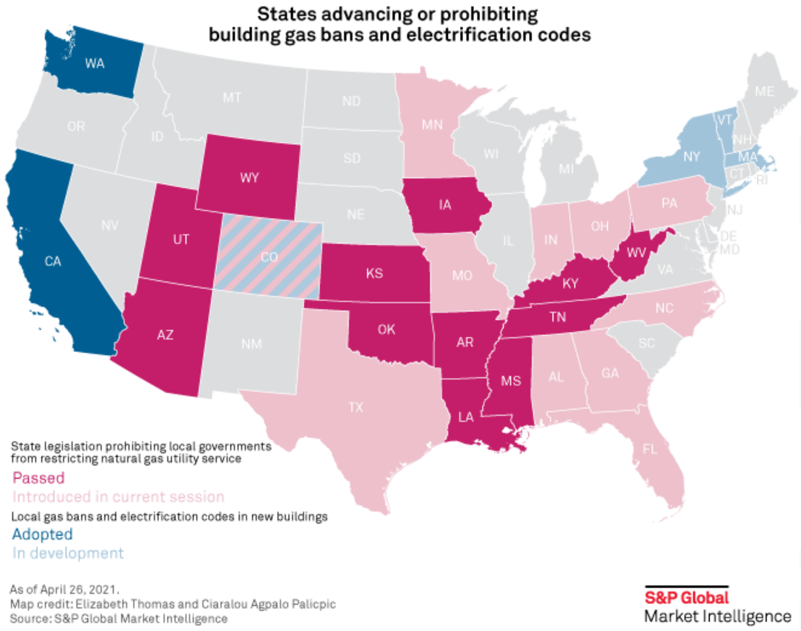
Methodological approaches: Scenario Analyses



Source: S&P Global Market Intelligence

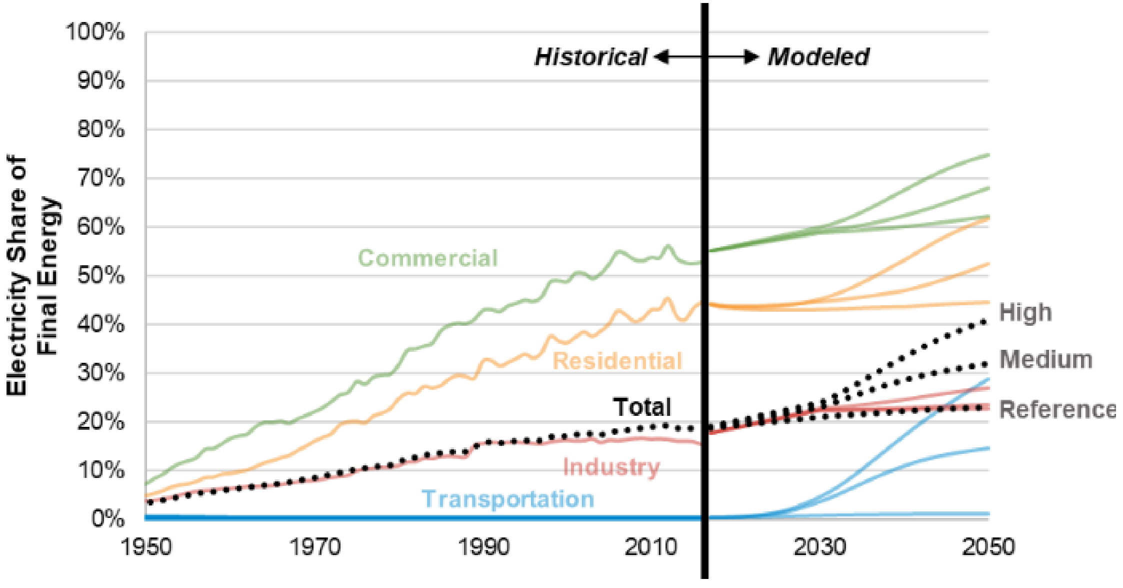
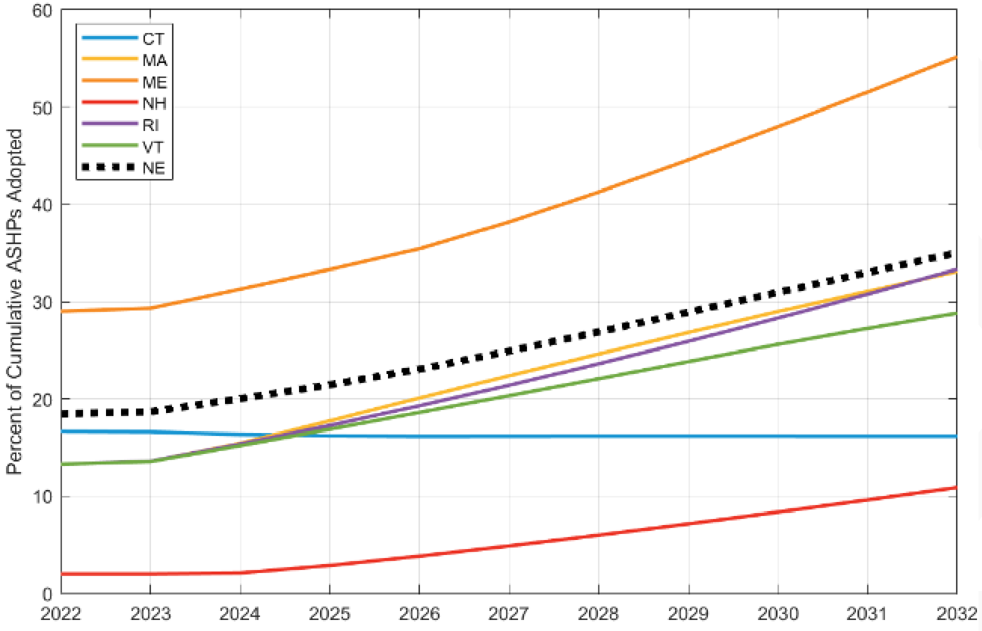


Figure ES-5. Electricity share of final energy consumption

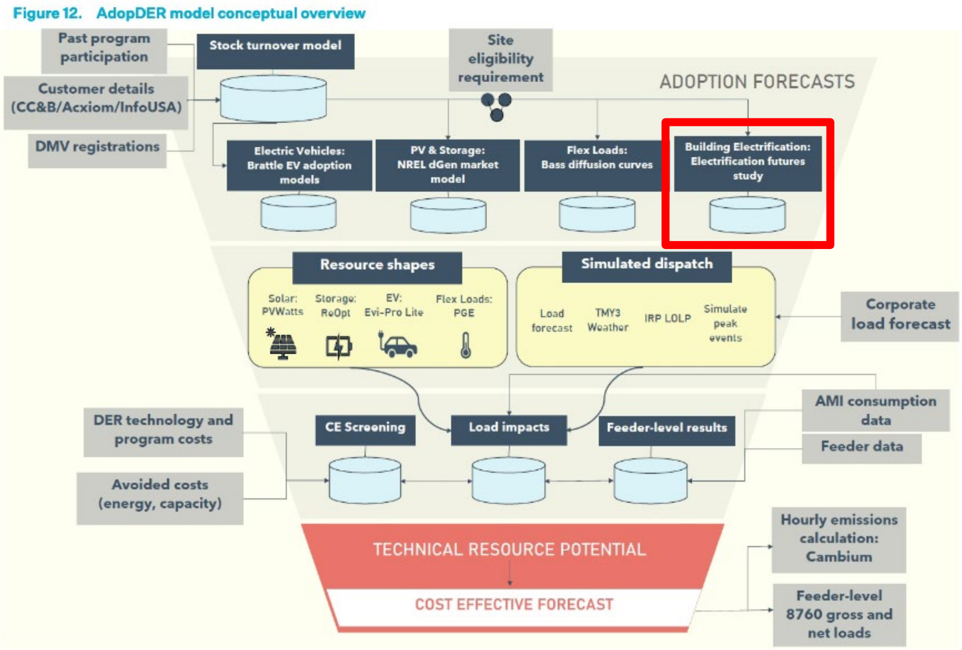
Source: NREL Electrification Futures Study (Mai et al., 2018)

- Granular/technology-rich estimates of baseline stock characteristics
- Prescriptive scenarios developed based on combination of expert judgment and current trends (economic/regulatory)
- Bottom-up accounting and multi-sectoral representation
- Geographical resolution: national/regional

Methodological approaches: Adoption Models



Source: Final 2022 Heating Electrification Forecast (ISO-NE, 2022)



Source: PGE 2022 Distribution System Plan

- ► Granular/technology-rich estimates of baseline stock characteristics
- ► Statistical/modeling approach based on select input parameters (e.g., Bass diffusion model)
- ► Often rely on expert judgment to determine modeling parameters
- ► Geographical resolution: utility/municipal service territory

Scenarios case study: Guidehouse E3 Initiative Scenarios of Heat Pump Adoption

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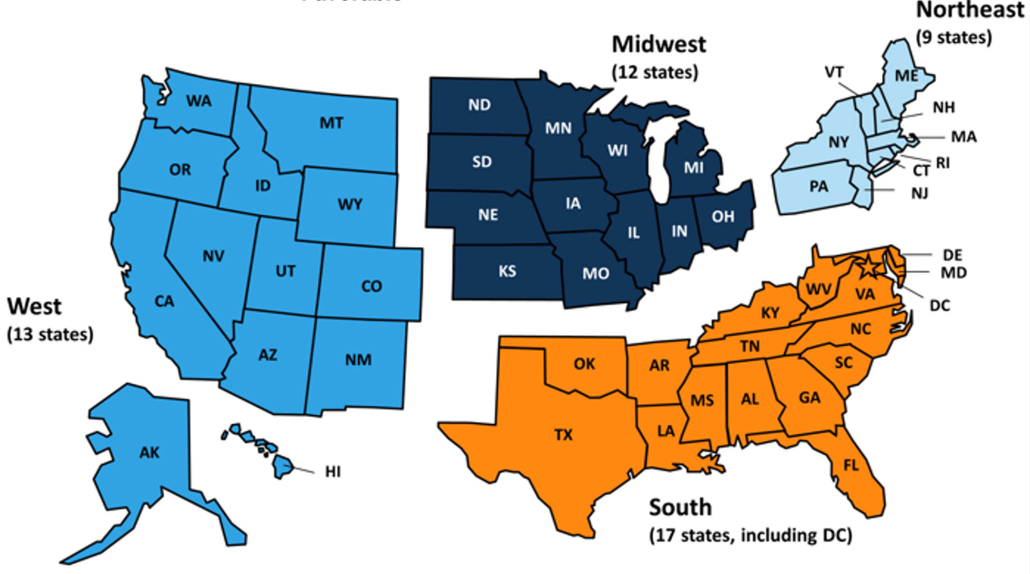
🟢 Favorable 🟡 Neutral 🔴 Unfavorable

Midwest

HP Saturation	4%	
HPWH Saturation	~1%	
Policy Support	🟡	
Utility Rates	🔴	🟢 (Electric resistance)
Climate	🔴	
Fuel Mix	🔴	🟡 (2050)

West

HP Saturation	10%	
HPWH Saturation	~ 1%	
Policy Support	🟢	
Utility Rates	🔴	🟢 (Electric resistance)
Climate	🟢	
Fuel Mix	🟡	🟢 (2050)



Northeast

HP Saturation	4%	
HPWH Saturation	~1%	
Policy Support	🟢	
Utility Rates	🔴	🟢 (Fuel oil/Propane)
Climate	🔴	
Fuel Mix	🟡	🟢 (2050)

South

HP Saturation	24%	
HPWH Saturation	~1%	
Policy Support	🔴	
Utility Rates	🟢	🟢 (Electric resistance)
Climate	🟢	
Fuel Mix	🔴	🔴 (2050)

Source: Guidehouse analysis based on EIA RECS 2015

Guidehouse

Explanation of Key Metrics (see regional slides for more details)	
HP Saturation	The region's existing residential home stock (as a %) that currently uses HP for primary heating
HPWH Saturation	The region's existing residential home stock (as a %) that currently uses HPWH for primary heating
Policy Support	The region's policy outlook toward heating electrification
Utility Rates	The region's electricity: gas price ratio + electricity: 2nd choice energy source ratio - and how they compare to the national average
Climate	The region's climate and its compatibility with current HP solutions
Fuel Mix	The region's 2020 electricity generation fuel mix and its ability to provide a GHG benefit if rapid electrification takes place (see slides **34/35),** as well as anticipated changes in electricity fuel mix by 2050 due to state commitments **(see slide 28).** *State population within a region is considered.*

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Scenarios case study: Guidehouse E3 Initiative Scenarios of Heat Pump Adoption

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Scenario (2030 Target)	Federal / Utility Incentives	State / Local Restrictions*	Product Innovations	Drivers (Key Differences Highlighted in BOLD)
Conservative Scenario (45%)	**Modest federal, few utilities**	**Few for NC, none for Existing**	**Low GWP refrigerants, grid interactive**	• Moderate market transformation expansion by BTO, utility, and industry groups • Few utilities offer substantial incentives for electrification • Modest federal incentive for heat pump conversions (targets customers that already have attractive lifecycle cost savings, such as electric resistance, propane, and fuel oil) • Few state and local governments restrict natural gas for new construction
Optimistic Scenario (50%)	**Moderate, federal, more utilities**	**Some for NC, none for Existing**	**Affordable CCHPs**	• **Large market transformation expansion** by BTO, utility, and industry groups • **More utilities offer substantial incentives for electrification** • **Moderate federal incentive** for heat pump conversions (targets customers that already have attractive lifecycle cost savings, such as electric resistance, propane, and fuel oil) • **Some state and local governments** restrict natural gas for new construction
Aggressive Scenario (60%)	**Large federal, more utilities**	**More for NC, some for Existing**	**Affordable CCHPs**	• Large market transformation expansion by BTO, utility, and industry groups • More utilities offer substantial incentives for electrification • **Large federal incentive for heat pump conversions (targets customers with more challenging conversions, as well as some environmentally focused gas customers)** • **More state and local governments restrict natural gas for new construction, and some provide significant incentives and/or restrictions for existing homes**
Most Aggressive Scenario (75%)	**Large federal, most utilities**	**Most for NC, most for Existing**	**Affordable CCHPs**	• Large market transformation expansion by BTO, utility, and industry groups • **Most utilities offer substantial incentives for electrification** • Large federal incentive for heat pump conversions (targets customers with more challenging conversions, as well as some environmentally focused gas customers) • **Most state and local governments restrict natural gas for new construction, and provide significant incentives and/or restrictions for existing homes**

Increasing levels of :

- Federal / utility incentives
- State / local policy support
- Marketing support
- Certification development
- Product innovations

Scenarios case study: Guidehouse E3 Initiative Scenarios of Heat Pump Adoption

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Segment	Representative Equipment	2019 HP Sales Market Share (US)	2019 Shipments	Segment Share of Total Shipments 2019 (All Categories)	Conservative Scenario		Optimistic Scenario		Aggressive Scenario		Most Aggressive Scenario	
					2030 Sales Market Share	2050 Sales Market Share	2030 Sales Market Share	2050 Sales Market Share	2030 Sales Market Share	2050 Sales Market Share	2030 Sales Market Share	2050 Sales Market Share
Residential Space Heating	Central ducted furnace+AC / HP	37%	7,500,000	47%	45%	61%	50%	76%	63%*	85%	75%	90%
Residential Water Heating	Storage water heater	1%	7,880,000	50%	10%	30%	20%	60%	40%*	75%	50%	85%
Commercial Space Heating	Rooftop unit	9%	220,000	1%	15%	27%	20%	42%	25%	66%	30%	85%
Commercial Water Heating	Storage water heater	0.10%	240,000	2%	3%	20%	5%	30%	7%	45%	10%	50%
U.S. Total Sales Shares (Weighted Average of Unit Shipments)					**27%**	**44%**	**34%**	**67%**	**50%**	**79%**	**61%**	**87%**

Guidehouse

Quantitative case study #2: ISO-NE ASHP adoption

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- Approach considers potential pathways to space and water heating electrification based on existing building stock characteristics as well as state policy and economic considerations
- Adoption forecasts based on a Bass diffusion model with following input parameters:
  – Return on Investment (ROI)
  – State-level policy
  – Barrier indicator
  – Current levels of technology saturation
- Uncertainty in the evolution of ROI and policy impacts over the forecast horizon is reflected via a Monte Carlo simulation

Year	Annual ASHP Installs (Thousands)						
	CT	MA	ME	NH	RI	VT	ISO-NE
2022	2.9	17.7	20.6	3.6	2.0	10.1	57.0
2023	3.3	20.4	21.3	4.7	2.4	10.4	62.5
2024	3.8	35.3	21.6	5.1	2.9	10.7	79.7
2025	4.3	50.0	22.6	5.6	3.5	11.0	97.1
2026	5.0	63.4	23.3	6.2	4.2	11.3	113.4
2027	5.8	75.0	23.9	6.8	5.1	11.6	128.2
2028	6.6	87.0	24.6	7.5	6.1	11.9	143.7
2029	7.6	96.0	25.4	8.2	7.3	12.3	156.8
2030	8.8	102.4	26.1	9.1	8.7	11..4	166.5
2031	10.1	107.5	27.0	10.0	10.5	10.8	175.6
Cumulative Total	**58.2**	**654.7**	**236.4**	**66.8**	**52.7**	**100.1**	**1,180.5**

Source: Final 2022 Heating Electrification Forecast (ISO-NE, 2022)

Future Research Needs

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- Assess what is currently understood about the various drivers of and impact on customer adoption of electrification technologies (heating, water heating, cooking)
- Develop analytical frameworks to improve the representation of adoption
  - Include the identification of key drivers of adoption of electrification technologies
  - Develop quantitative assessment of these drivers' impacts on adoption
- Assess how the key drivers of adoption of electrification technologies affect the adoption of other technologies (e.g., EVs, PV)
- U.S. DOE's DECARB research project – scoping study for building electrification adoption

Photo by Shea Rouda on Unsplash

EV Forecasting: Best Practices and Case Studies

CHRISTINE HOLLAND

Pacific Northwest National Laboratory

EV Load Forecasting Agenda

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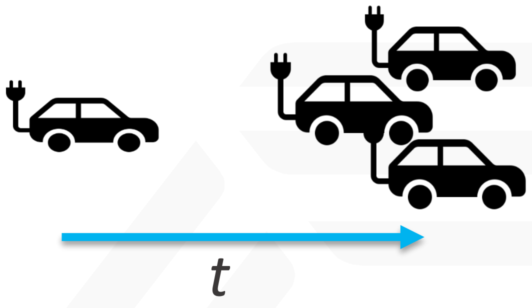
- Major components of EV load
- Load shape considerations
- Major modeling approaches
- Commonly used models
- Model examples

Electric Vehicle Load Forecasting Overview

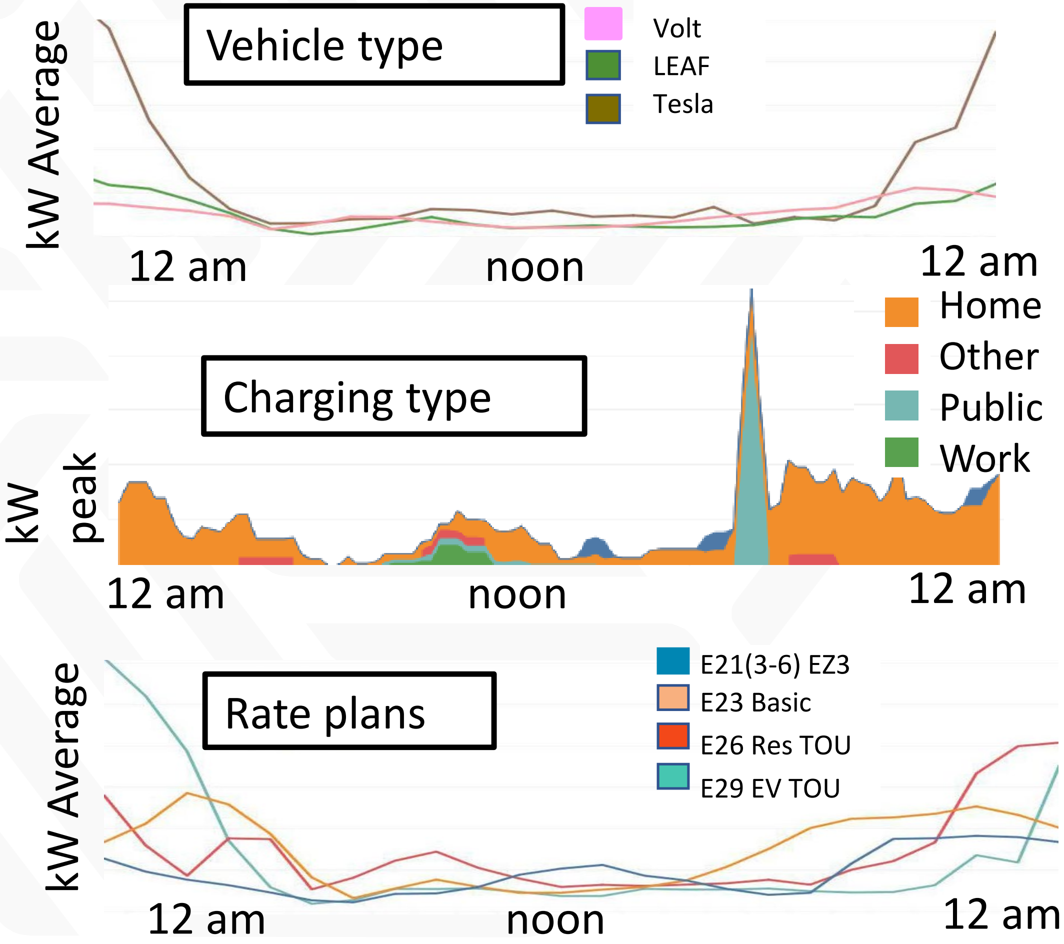
Stock Forecast



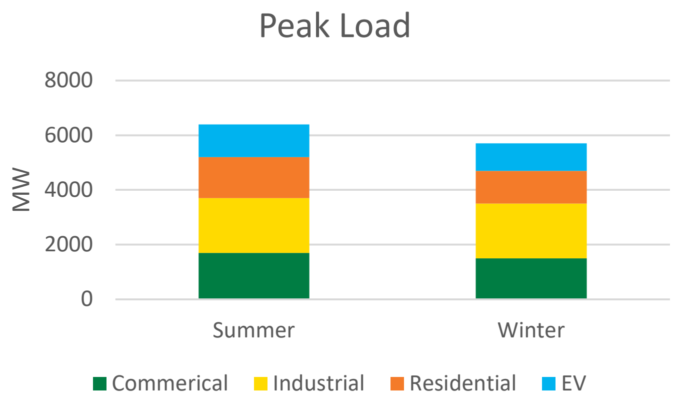
- **Number of Vehicles** – price, income, access to charging, incentives (state, federal)
- **Type of Vehicles** – consumer preferences (size, range), what they can afford

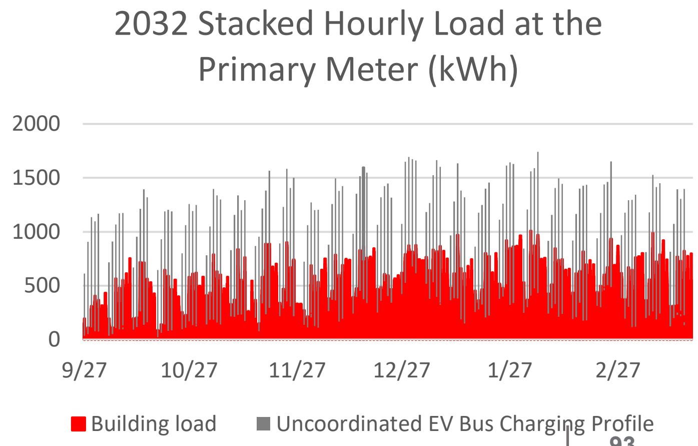
\- *impact* - differing charging rates, energy consumption, ranges

EV Charging Patterns



EV Charging Load Profile





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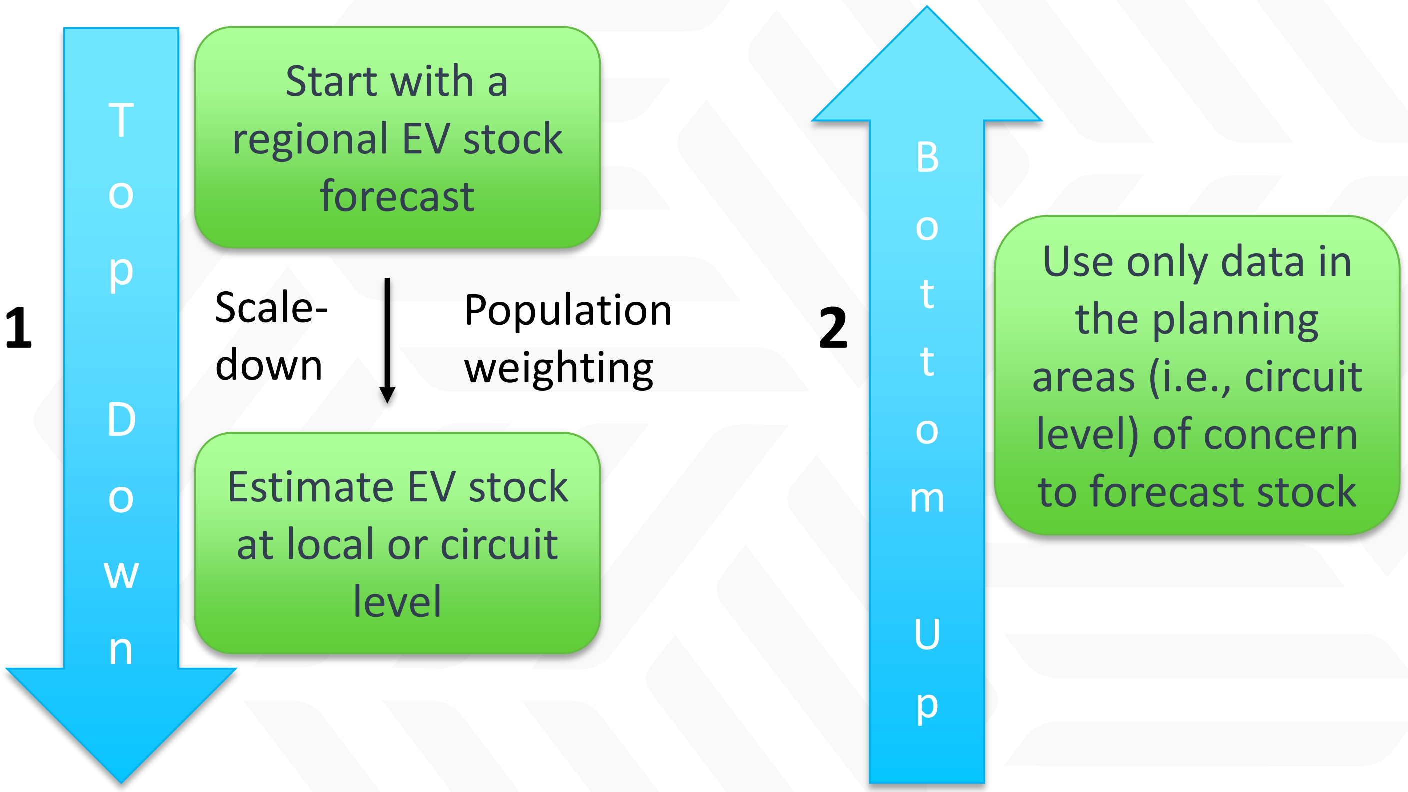
EV Stock Forecasting Modeling Approaches

- *Two major approaches:*



Approach	Pros	Cons
Top Down	• Easier because of data availability • More robust • Good for generalizations and overall movement of the market	• Often difficult to scale-down when average system characteristics are not the same as the circuit • Difficult to evaluate policy impacts on load
Bottom Up	• Potentially more accurate because you are basing the forecast on actual customer characteristics and preferences.	• Data for new technologies may not be available • Errors as micro level are amplified at macro level when scaling up

Types of Models Used for Either Approach

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Three categories of commonly used adoption models relevant to EVs:

1. **Consumer preference models -** Describe behaviors regarding consumer choice based on known or discovered consumer preferences
   - **Discrete choice models** – predict choices between two or more discrete alternatives, i.e., deciding to purchase an EV or internal combustion engine (Top-down approach)
   - **Agent based models** – used to study interactions between people, things, places, and time. Data intensive (Bottom-up approach).
2. **Propensity models –** a set of approaches to building predictive models based on past behavior, e.g., identify the characteristics of customers who purchased a hybrid vehicle
   - **Random forest** – machine learning algorithm; based on multiple decision trees built over a random extraction of observations from the dataset
3. **Diffusion models -** All use the common ‘S’ shaped adoption curve based on diffusion of innovation (Rogers)
   - Include Bass, Gompertz, Weibull, and Logistic

Practical Customer Segmentation (stock considerations)

Light Duty Vehicles

- Residential, commercial

Med- & Heavy-Duty Vehicles

- Commercial fleets, truck transportation

How some major labs and utilities forecast EV stock

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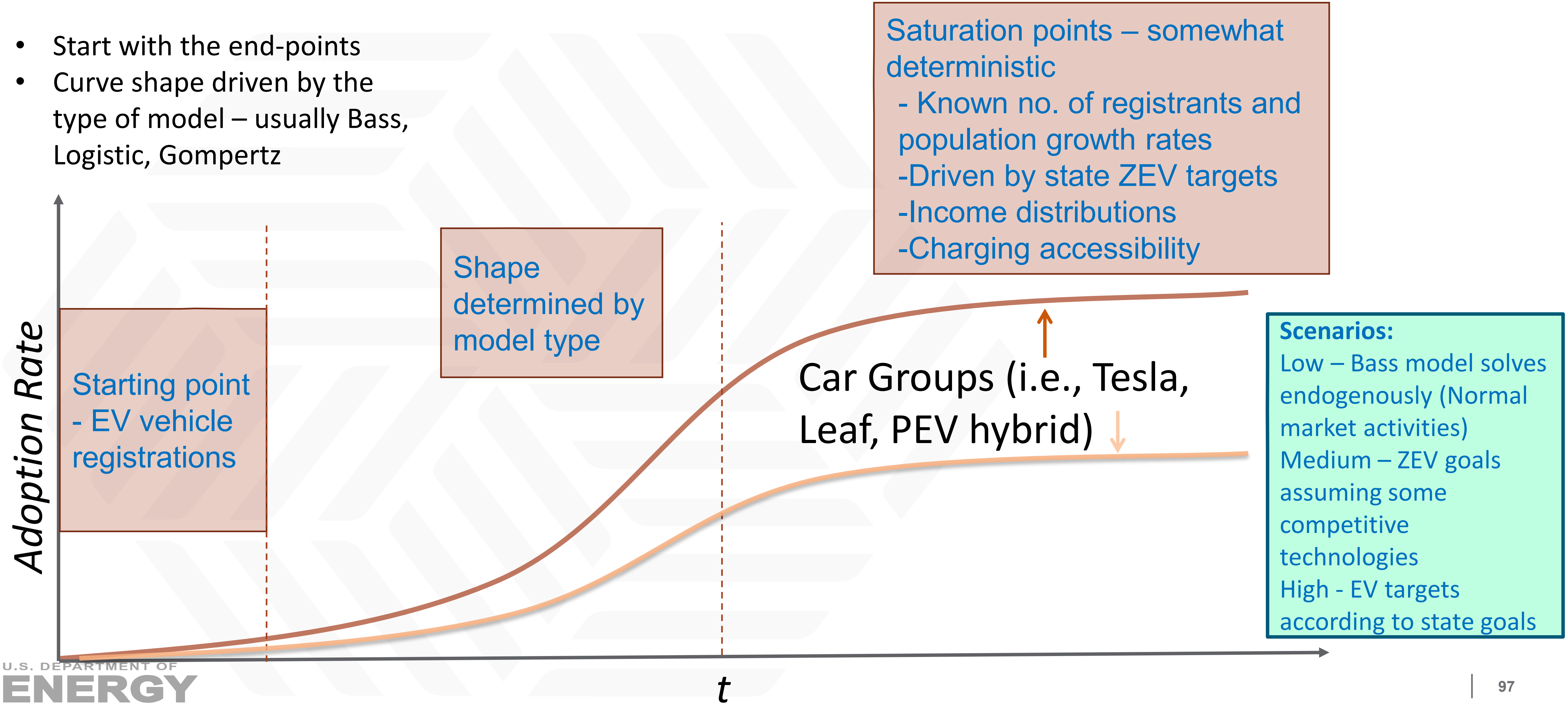
Utility or Research Entity	EV Adoption Approach	Model Description
EPRI	Metadata approach	Uses several forecasts from University's and other data sources, along with market intelligence to arrive at zip code, county, state, and national forecasts.
NREL	ADOPT consumer choice model	Based on the relative attractiveness of vehicles given technological development scenarios
SCE	Dual approach Bass aggregate with discrete choice model dissagregate. (External - PNNL).	Bass model driven by actual circuit level adoption based on vehicle registration data. Discrete choice model disaggregation based on existing adoption, housing characteristics, and socio-economic data.
PG&E	Propensity model. (Internal)	Use propensity model results to drive the market potential component of an S-curve adoption model.
SDG&E	EPRI zip code-level forecasts then disaggregates. (Internal)	Disaggregate based on their own propensity model. Score each zip code based on historic EV purchases and demographic and socio-economic data, education levels, and time to work. Used internal EV load shapes to determine hourly forecasts.
Hawaiian Electric	Dual approach: Bass modeling for the aggregate and agent-based modeling for geospatial customer-level. (External - Integral Analytics, Inc.)	The EOT Roadmap, Appendix E states: "When past participation and locational information is available, these models can be trained to include the socio-economic and peer-effects that contribute to adoption, as well as but not limited to time-sensitive utility incentive, rebates, tax credits, electric and gasoline prices etc."

Aggregate EV adoption illustration using diffusion models

- Start with the end-points
- Curve shape driven by the type of model – usually Bass, Logistic, Gompertz



Customer EV distribution at the circuit-level produced from a discrete choice model

GRID MODERNIZATION INITIATIVE
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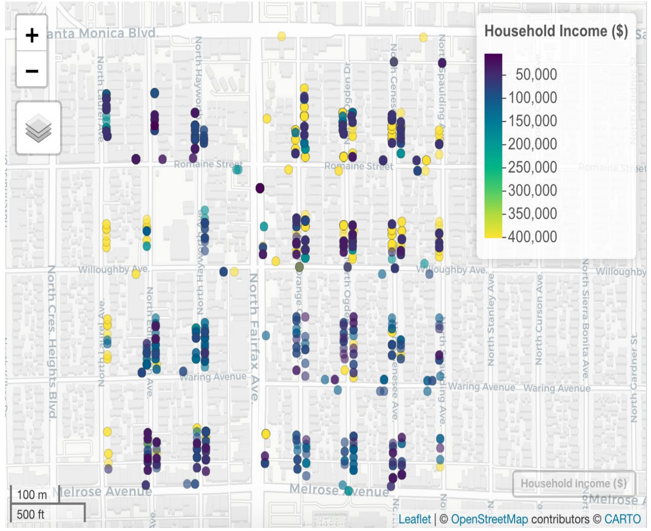
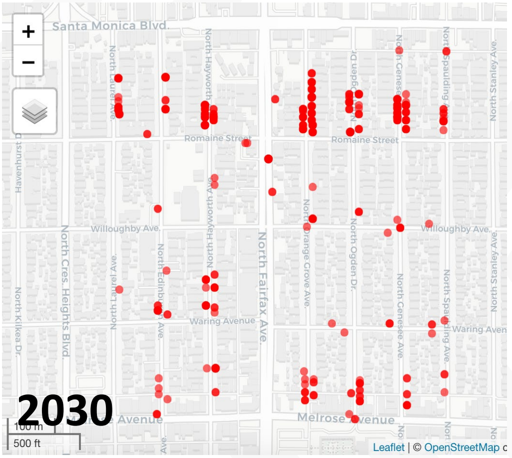
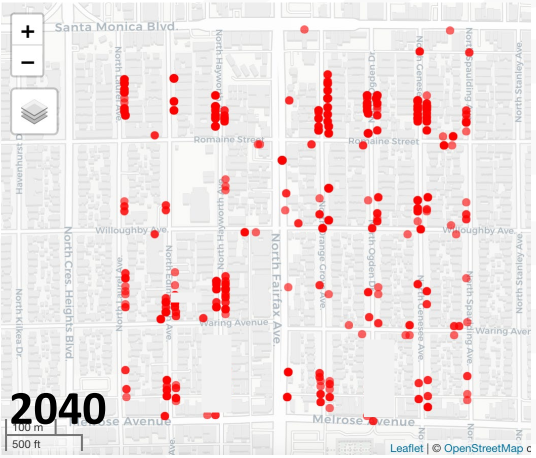
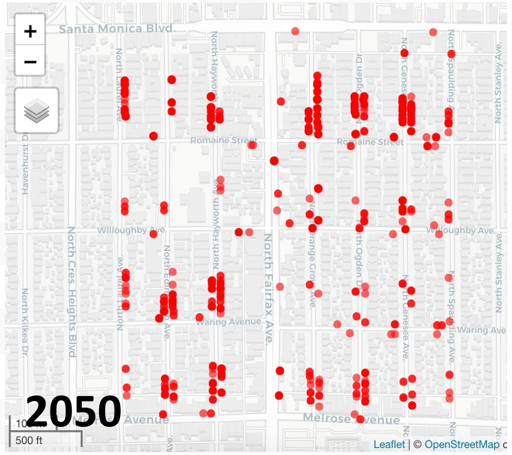
- Creates a household probability of adoption based on housing type or income. Uses Monte Carlo simulation to distribute EVs to remaining households
- Projections of EV adoption by households that can be located on the map for distribution planning
- Adoption model can be calibrated to local, regional, state EV goals









• Indicates EV vehicle

*simulation based on PNNL's work for SCE

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Electric Vehicle Infrastructure Projection Tool: EVI-Pro

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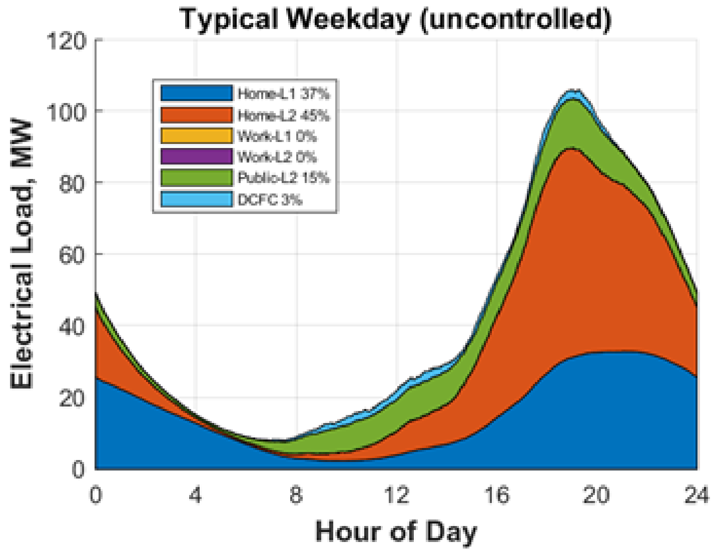
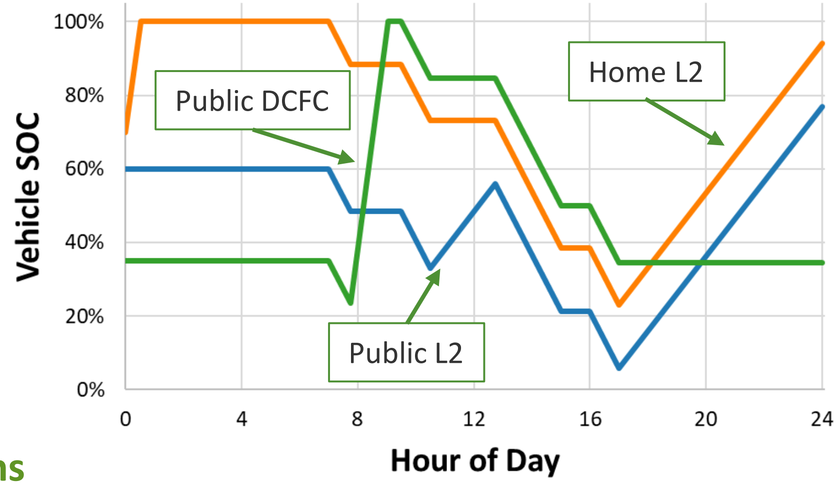
- The full model uses trip data and varying EV adoption levels to estimate charging demand, infrastructure requirements, and the resulting impact on the grid
- EVI-Pro Lite is a simplified web interface that can be used to get reasonable estimates of charging infrastructure needs for different US cities or states
  - https://afdc.energy.gov/evi-pro-lite
- Learn more about EVI-Pro here:
  - https://www.nrel.gov/transportation/evi-pro.html

Sample Aggregated EVSE Load Profile



Travel Data			Simulated Charge Events		
Departure	Arrival	Destination	Driver A	Driver B	Driver C
7:00 AM	7:45 AM	Public	None	None	Public DCFC
9:30 AM	10:30 AM	Public	None	Public L2	None
12:45 PM	3:00 PM	Public	None	None	None
4:00 PM	5:00 PM	Home	Home L2	Home L2	None

Driving, Charging Simulations



Grid load smoothing potential with V2X

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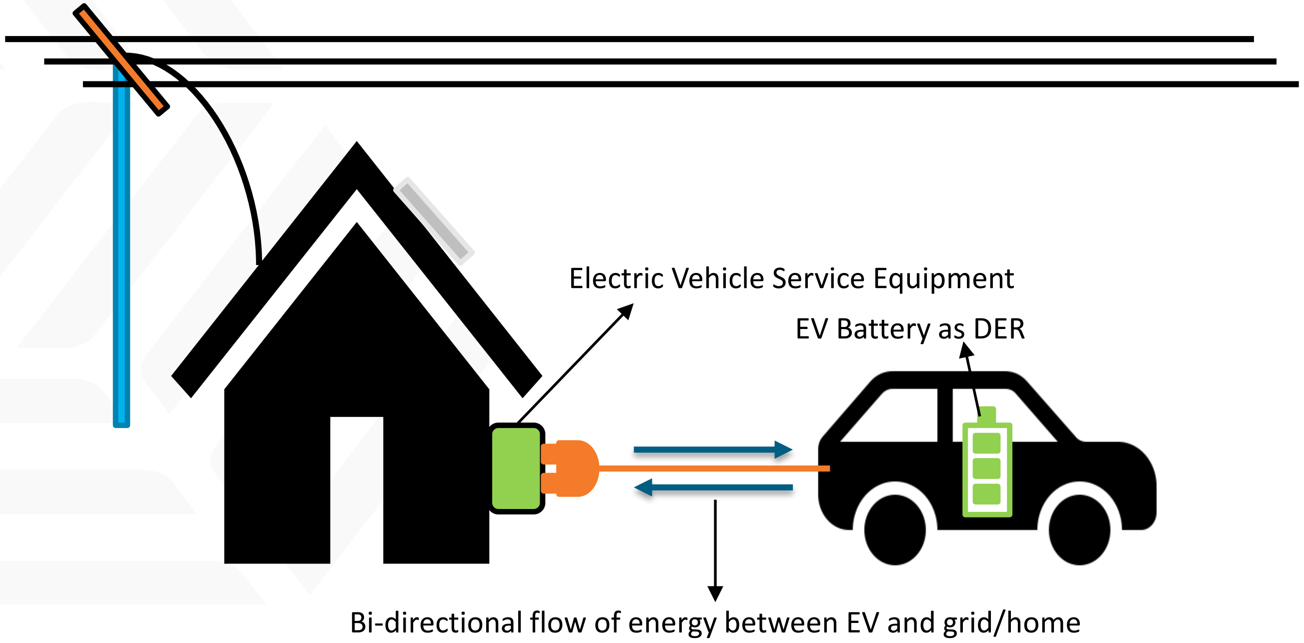
Utilities, such as **PNM** are starting to plan for V2G, V2H, V2X capability in buildings, to use batteries as a grid resource.

Utilities are performing V2G pilots:

- **Snohomish PUD** - testing V2G with two Nissan Leafs [SnoPUD V2G microgrid]
- **Duke** – testing five Ford f-150 Lightning trucks [Duke eTrucks as grid resource]
- **ConEdison** – V2G pilot with five Lion electric school buses [ConEd Bus V2G Demonstration]



Relevant questions for EV charging load forecasting

- What does the future of EV ownership in the region look? How might this be informed by historical adoption or other regional trends?
- How far are EV owners driving? How much do they need to charge?
- Where and when are they charging? How powerful are the chargers (level 1, 2, or 3)?
- What is the concentration of EV ownership? How will this impact grid for those areas?
- Are workplaces providing charging?
- Are there EV fleets with high VMT that would require frequent charging?

Questions?

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Additional Examples, Resources, and Links

- EVs
  - Electric Power Research Institute (EPRI)
    - Identifying Likely Electric Vehicle Adopters
    - The Impact of Incentives on Electric Vehicle Adoption
  - EVI-Pro Lite
    - https://afdc.energy.gov/evi-pro-lite
  - EV Sales data (global) from IEA
    - https://www.iea.org/reports/electric-vehicles
  - EV Station utilization estimates
    - https://www.sciencedirect.com/science/article/pii/S136192092200390X

- Building Electrification
  - NREL Electrification Futures Study
    - Scenarios of Electric Technology Adoption and Power Consumption for the United States
  - Portland General Electric (PGE) Distribution System Plan
    - Chapter 6. Plug and play: enabling DER adoption
  - Cadmus Group
    - The Building Electrification Primer for City-Utility Coordination
  - E3
    - Residential Building Electrification in California: Consumer economics, greenhouse gases, and grid impacts
  - NPCC
    - https://www.nwcouncil.org/sites/default/files/7thplanfinal_chap07_demandforecast_1.pdf
    - https://www.nwcouncil.org/sites/default/files/7thplanfinal_appdixj_demrspnse_1.pdf

Workshop Agenda

1:00-1:15 Introductions & Overview
1:15-1:45 Intro to Electricity Forecasting
1:45-2:15 Load Forecasting
2:15-2:30 Break
2:30-3:00 Energy Efficiency and Demand Flexibility Forecasting
3:00-3:35 Building Electrification & Electric Vehicle Forecasting
3:35-3:50 Break
3:50-4:20 Distributed Solar & Battery Storage Forecasting
4:20-4:50 Cost Forecasting
4:50-5:00 Final Thoughts

Workshop Agenda

GRID MODERNIZATION INITIATIVE
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Distributed Solar Photovoltaics and Storage Forecasting

ASHOK SEKAR

National Renewable Energy Lab

January 30, 2023

Why DERs adoption forecasting?

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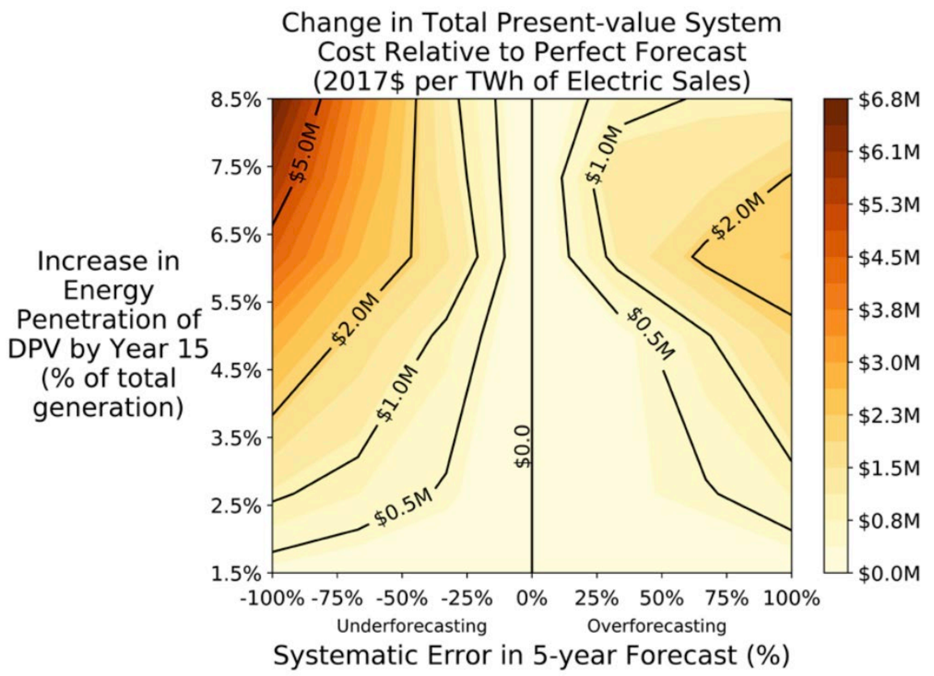
U.S. Department of Energy

- To inform utilities' investments in other energy-system infrastructure such as transmission and distribution infrastructure.

- To better understand supply requirements and thus to *manage associated financial risks* by quantifying the net change in electricity consumption offset by DER generation

- To optimally integrate DERs into the grid to maintain system functionality generally and especially during extreme grid conditions

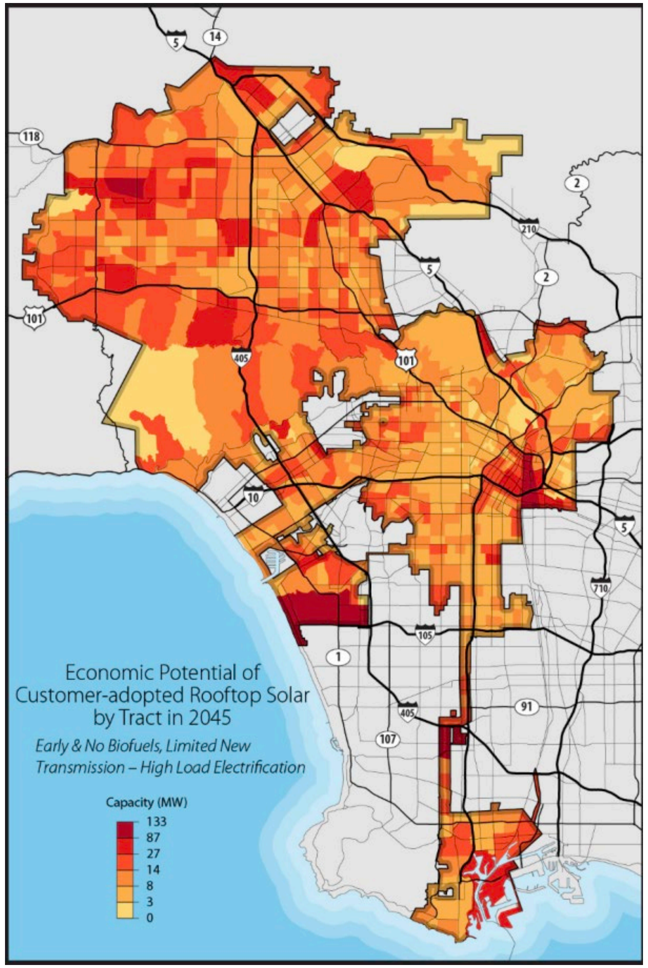
- To develop and drive policies to achieve decarbonization and climate goals



systematically mis-forecasting DPV adoption over multiple successive planning cycles increases the present value of utility system costs by up to $7 million per terawatt-hour (TWh) of electricity sales, relative to utility system costs under a perfect forecast

What are we forecasting?

- ► System size / capacity
- ► Total number of systems
- ► Location of adoption (Feeder, Tract-level, County, Utility territory, County, and etc.)
- ► Time horizon of the adoption
- ► Generation profile
- ► Consumption pattern and user behavior



Sigrin, Ben, Paritosh Das, Meghan Mooney, Ashreeta Prasanna, Dylan Harrison-Atlas, Jane Lockshin, Katy Waechter, Brady Cowiestoll, Paul Denholm, and Sam Koebrich. 2021. "Chapter 4: Customer-Adopted Rooftop Solar and Storage." In The Los Angeles 100% Renewable Energy Study, edited by Jaquelin Cochran and Paul Denholm. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-79444-4. https://www.nrel.gov/docs/fy21osti/79444-4.pdf.

Different approaches to understand a model

- There are numerous methods to forecast adoption in the academic literature and in use

- These methods can be studied using three different lenses.

  - *The approach used for building the model*, i.e., a top-down approach or a bottom-up approach.

  - *The model specification*: the relationship between the indicators and the outcome. Theory driven vs. Data Driven

  - *Assessing the capability of the model.* E.g., adaptability of the model. Can the model for PG&E customers be adapted for Xcel customers?

Modeling Approach: Top-down Models

- Uses macro-level indicators to model market forecasts
- Aggregated- historical data is sufficient to develop these models.
- Two classes of top-down models are popularly used to forecast DER deployment—time series, and Bass diffusion.
  - Time-series models extrapolate from historical data to infer future outcomes. They are the simplest specification to use because they only require past observations, though typically are only useful in near-term forecasting.
  - Bass models are among the most widely used specifications because they are simple to parameterize and are intended to simulate diffusion of new technologies. ([Dong et al., 2017](#))

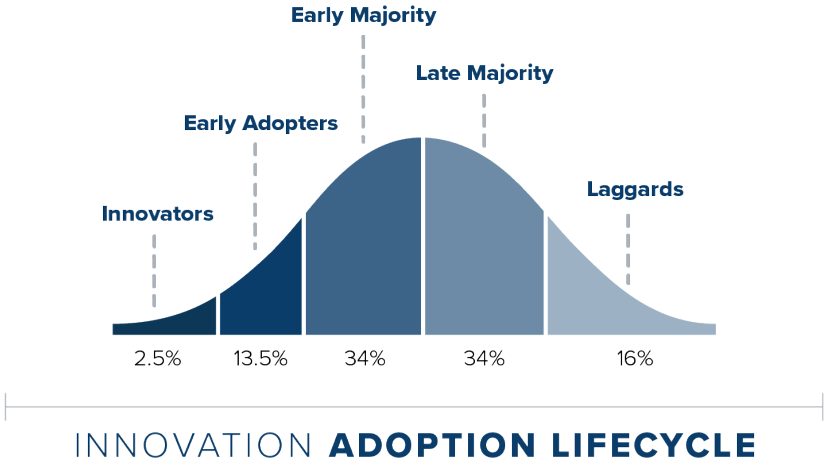
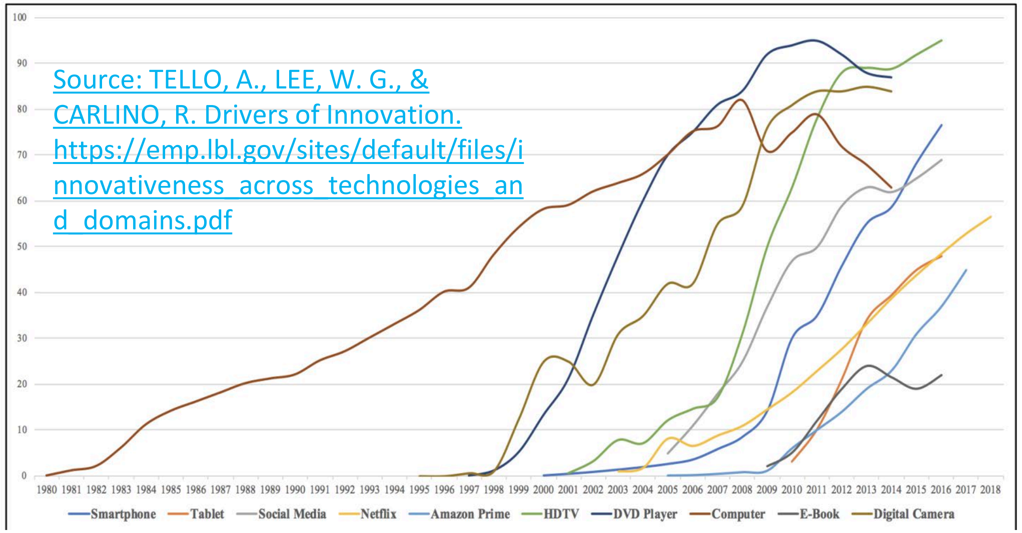


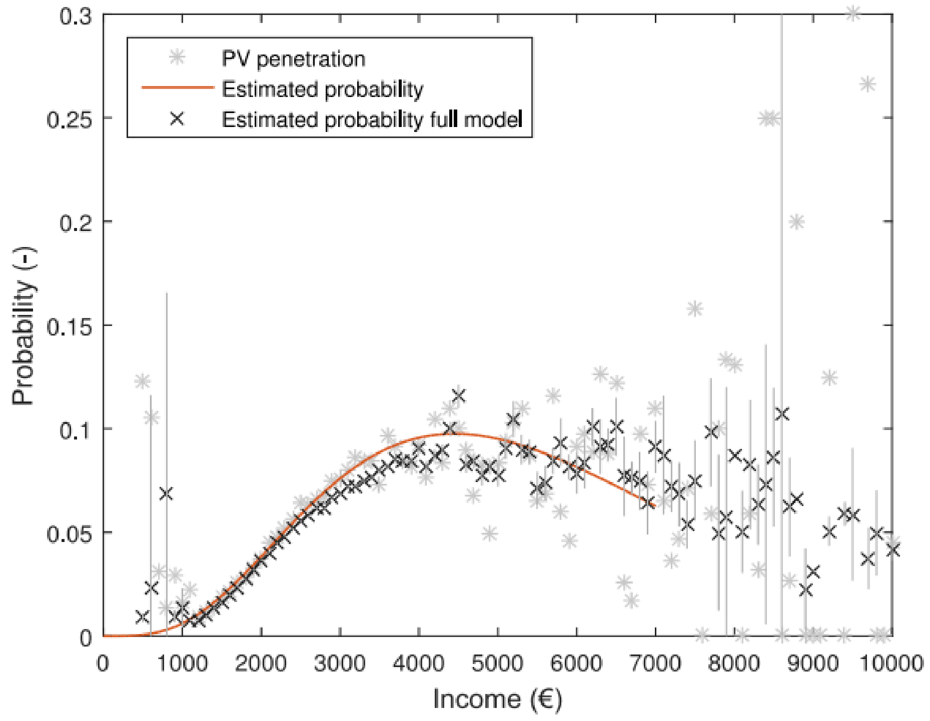
Image credit: https://www.qad.com/blog/2022/08/diffusion-of-innovation-how-adoption-of-new-ideas-spreads



Source: TELLO, A., LEE, W. G., & CARLINO, R. Drivers of Innovation. https://emp.lbl.gov/sites/default/files/innovativeness_across_technologies_and_domains.pdf

Modeling Approach: Bottom-up Models

- Bottom-up approach uses micro-level indicators to model individual forecasts, which are then aggregated into a market forecast.
- Micro-level indicators represent the traits of a fairly granular unit—typically an individual or a household, but it can also be a small spatial area such as a block—within the marke
- Common bottom-up approaches include:
  - Econometric models (Bernards et al., 2018; Davidson et al., 2014; Dharshing, 2017)
  - Agent-based models (Rai and Henry, 2016; Rai and Robinson, 2015; Sigrin et al., 2016;)
  - Machine learning models (Zhang et al., 2016)



R. Bernards, J. Morren and H. Slootweg, "Development and Implementation of Statistical Models for Estimating Diversified Adoption of Energy Transition Technologies," in *IEEE Transactions on Sustainable Energy*, vol. 9, no. 4, pp. 1540-1554, Oct. 2018, doi: 10.1109/TSTE.2018.2794579.

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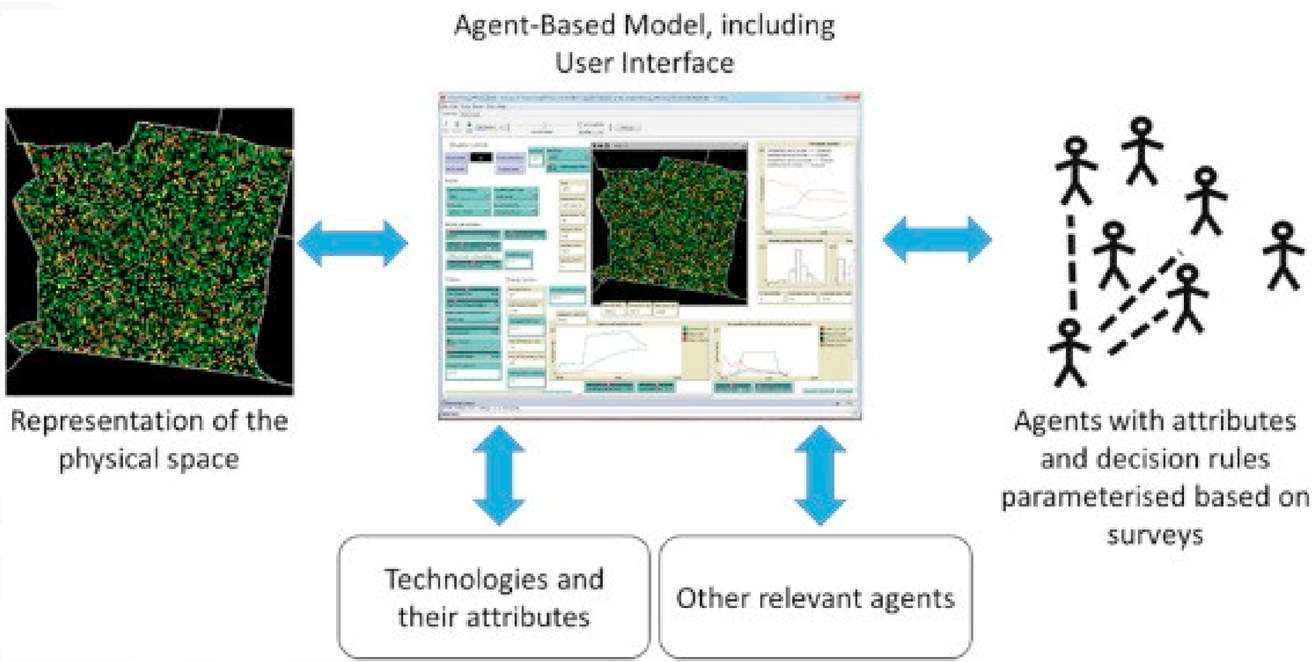


Moglia, M., Cook, S., & McGregor, J. (2017). A review of Agent-Based Modelling of technology diffusion with special reference to residential energy efficiency. Sustainable Cities and Society, 31, 173-182.

Relationship between indicators and outcomes

Theory-driven Models

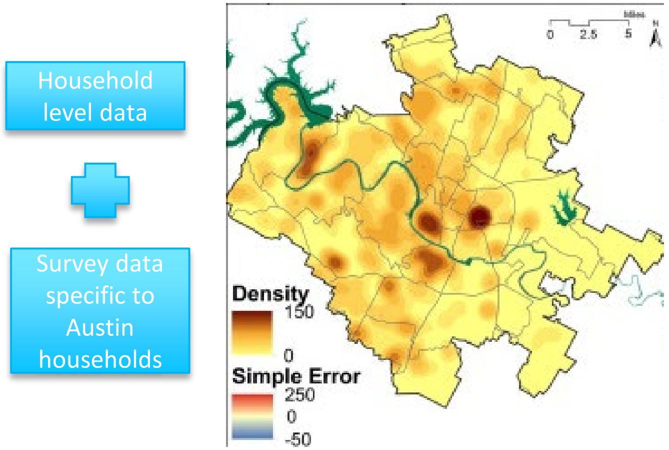
- Theory-driven models impose a relationship between the indicators and the outcome based on a theory of individual or market behavior.
- Theory-driven models are diagnostic in nature and can help decision makers understand the drivers and barriers of DER adoption/non-adoption while also serving as a tool for evaluating the impact of different policy interventions.
- The drawback wit theory driven model include the need to establish the theoretical linkage and collecting necessary data concerning the indicators variables

Data-driven Models

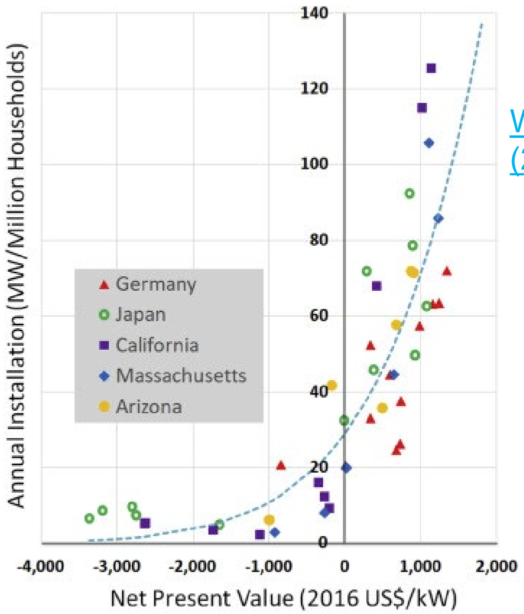
- Data-driven models, on the other hand, are agnostic and ideally expose hidden relationships in the data that explain outcomes better than theory.
- This is the foundation of machine learning, which has demonstrated superior predictive accuracy compared with theory-driven approaches
- Data-driven models have several drawbacks including: requiring large amounts of data, susceptibility to overfitting, and decreased interpretability.

Capability of the model

- It is also important that models are adaptable, scalable, and have sufficient spatial resolution, all while remaining sensitive to changing policy contexts, incentives, and techno-economic conditions.
- Rai and Robinson (2015) present a highly granular agent-based model of residential solar PV adoption at the scale of a utility service territory (Austin, Texas). Their model incorporates not only economic but also physical and social household-level determinants of residential PV adoption. While the model is calibrated and validated across multiple outcomes, computational cost and data requirements make this model difficult to scale and adapt to different geographies.
- Williams et al. (2020) models annual PV installations as a function of net present value for five different international regions (three U.S. states and two countries). Given regional economics, the model is adaptable and highly scalable; however, spatial resolution of the model is quite coarse.



Rai and Robinson (2015)



Williams et al. (2020)

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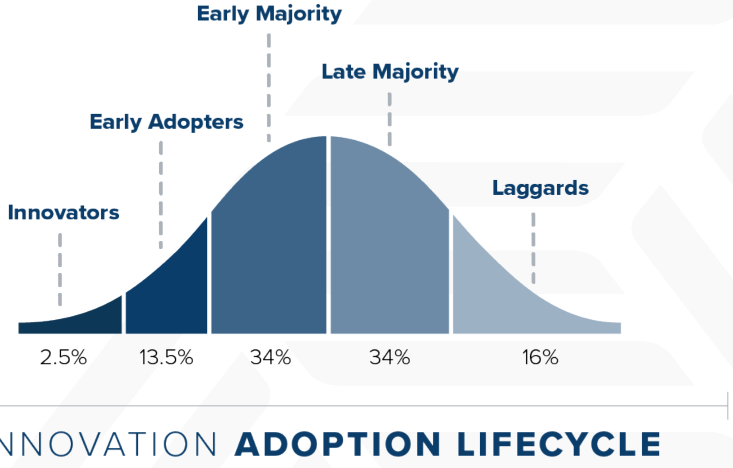
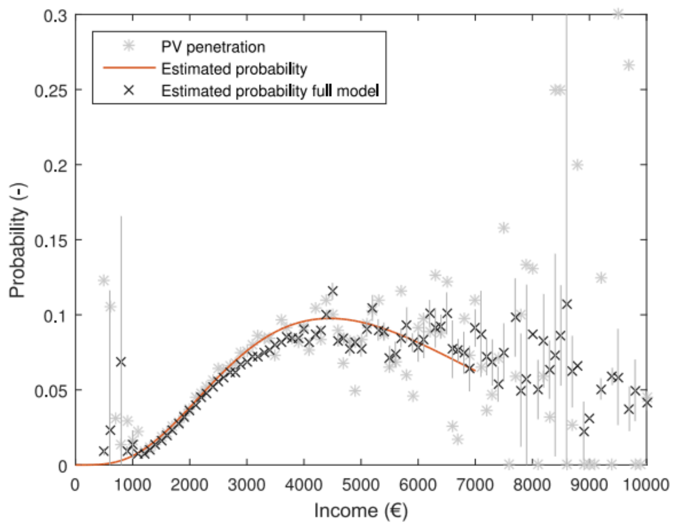
What category would the models fit?

Bass Model

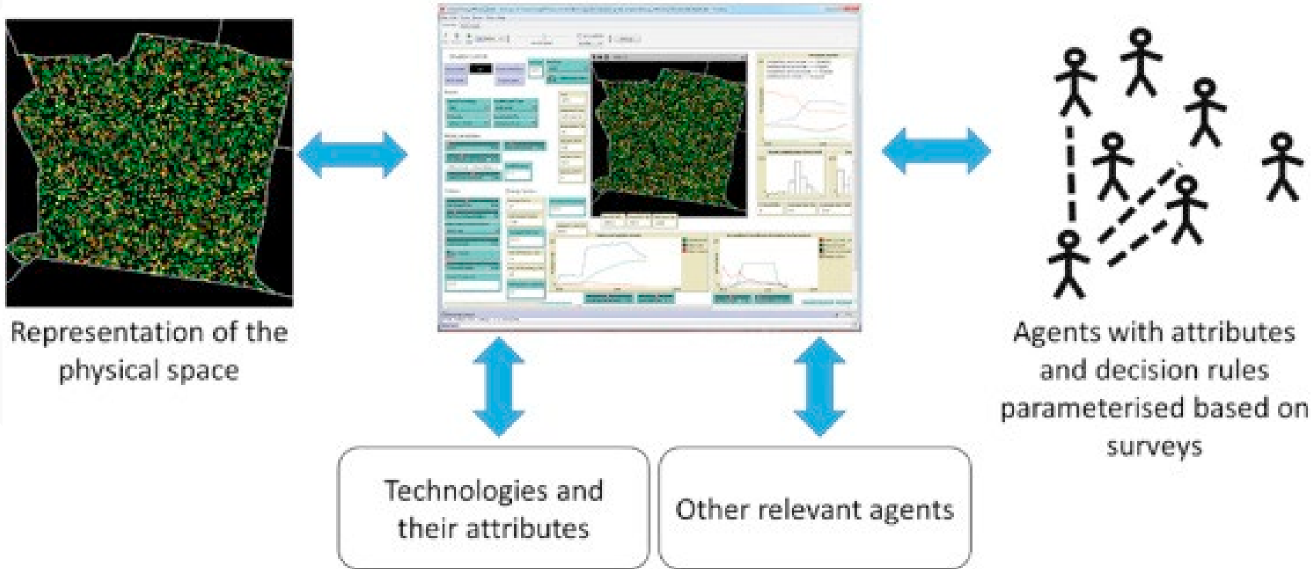


- Approach
- Theory vs. Data driven
- Capability

Econometric Model



Agent Based Model



Summary

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Models	Bottom-up vs. Top-Down	Theory-Driven vs. Data-Driven	Model scalability and Robustness
Bass Model	Top-down	Theory-driven	Yes
Econometric Model	Bottom-up / Top-down	Theory Driven/ Data-Driven	Depends – data requirement
Agent Based Model	Bottom-up	Theory Driven	No – data and computational requirement

Models	Data Requirement	Policy Analysis
Bass Model	Low: Historic adoption	Minimal
Econometric Model	Moderate: Historic adoption + Independent variables	Moderate – can test the effect of the independent variables on adoption (e.g., price of solar panels)
Agent Based Model	High: Historic adoption + Independent variables (open sourced and surveys)	Maximum – not only test independent variable effect but also understand impact of attitudes, behavior and informational aspects e.g., peer effects.

Other salient aspects to consider

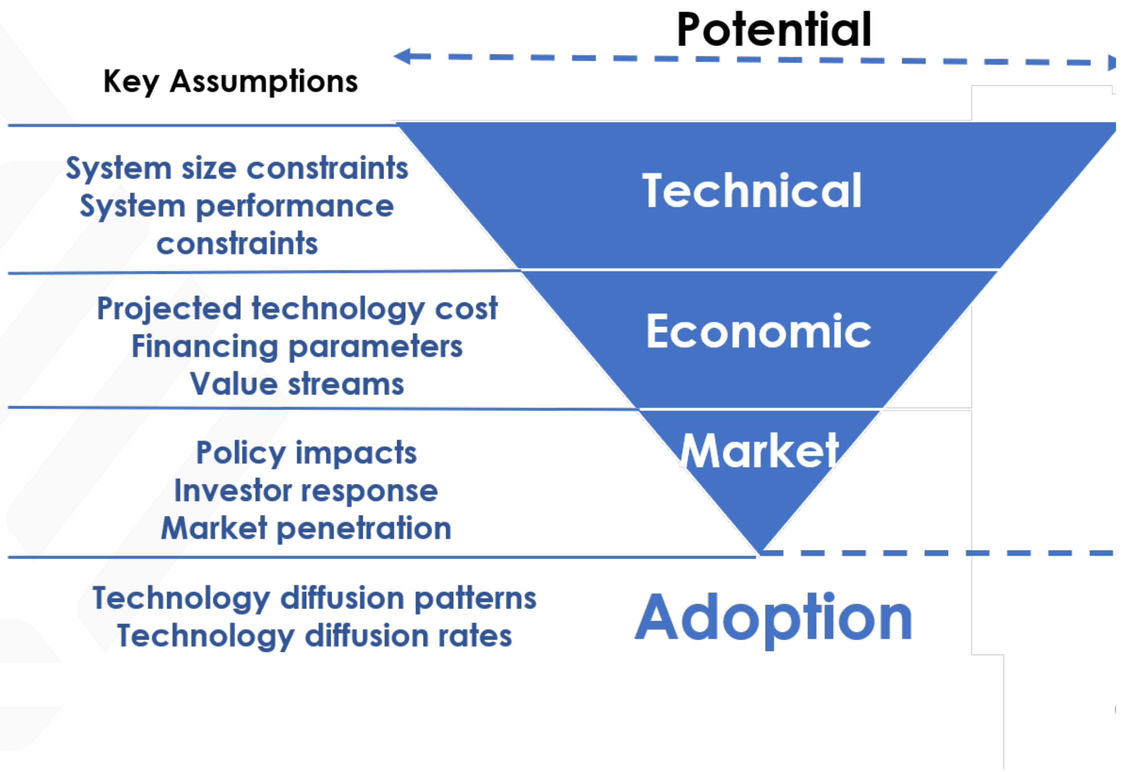
- The motivations for commercial or industrial consumers to adopt solar and storage are very different from residential consumers. Particularly, the attitudinal, emotional, and social and person norms-based motivations are prevalent among residential consumers.

- Models that forecasts solar-only adoption will be different to solar and storage co-adoption. The motivations for co-adoptions are currently being explored.

- Researchers use hybrid methods to solve the shortcomings from each modeling type described in the presentation.

Other salient aspects to consider

- Knowing the difference between technical potential, economic potential and market potential.
- Understanding the difference helps constrain the model and perform sanity checks.
- For rooftop residential solar
  - Technical potential – calculated as the total suitable roof available via Lidar
  - Economic potential – of the technical potential what percentage of the population has a positive NPV
  - Market potential – include policy impacts e.g., tax credits when calculating NPV
  - Adoption – consider what % of the population with market potential that would adopt.



Relevant questions for Solar and Storage adoption Forecasts

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- These three questions help deduce the capability of the model using the summary table presented in the slide above.
  - What is the modeling approach top-down or bottom-up?
  - Is the model theory-driven or data-driven
  - Is the model scalable/adaptable to other regions?
- Other detailed questions include:
  - What is the geographic resolution of the model?
  - What is the temporal resolution of the model?
  - Has the model been validated using historic data? How was the validation performed?
  - What policy intervention can one test with the model? (e.g., effect of tariff design, incentives)
  - If the model developed is using a bottom-up approach, identify the capability of the model
    - Can the model use complex utility rate design
    - How is solar system size calculated for each household? Is it constrained based on roof availability
    - Has current and expected future incentives and rebates captured?
    - What scenarios for storage dispatch assumptions?

Questions?

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- V. Rai, A.D. Henry. **Agent-based modelling of consumer energy choices**. Nat. Clim. Change, 6 (2016), pp. 556-562, 10.1038/nclimate2967
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Overview of dGen Model

The Distributed Generation Market Demand (dGen™) model simulates customer adoption of distributed energy resources for residential, commercial, and industrial entities in the United States or other countries through 2050.

- Consumer decision-making based on cost-effectiveness of technology
- Identification of drivers of adoption by analysis of multiple scenarios
- Hybrid model that combines agent-based methodological framework and bass model.

Methodology Steps

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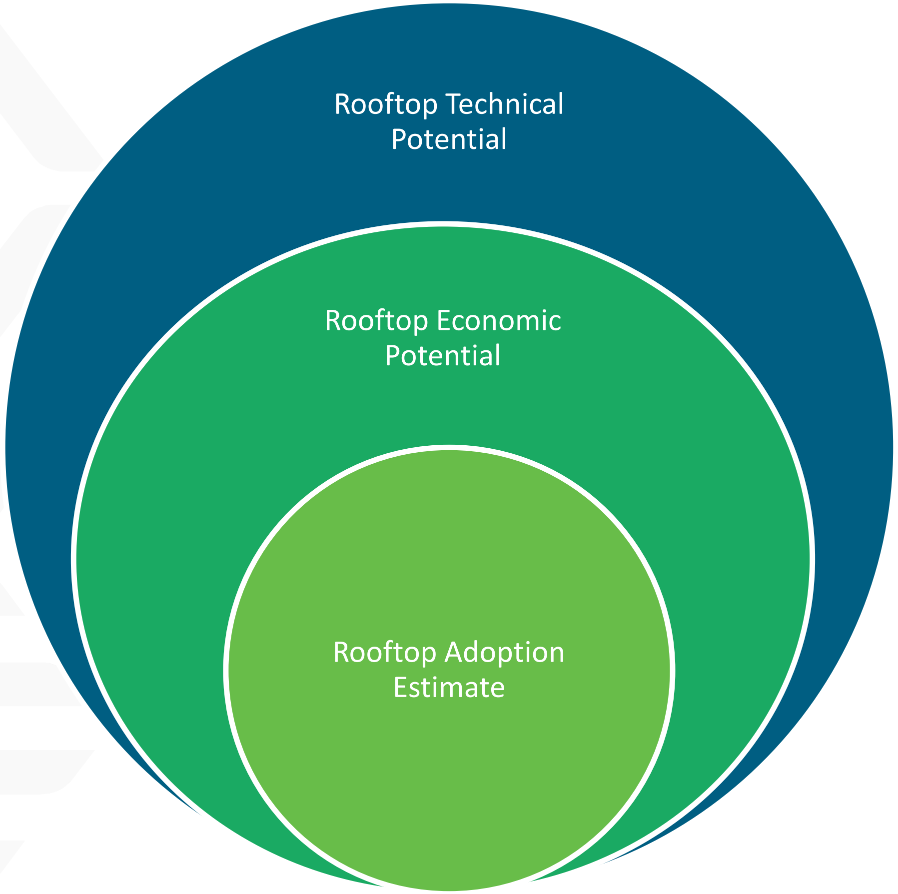
Data Preparation

1. **Develop a database of potential solar adopters ("agents")**
2. **Estimate Technical Potential**: Assess rooftop solar feasibility for each agent using LiDAR data.

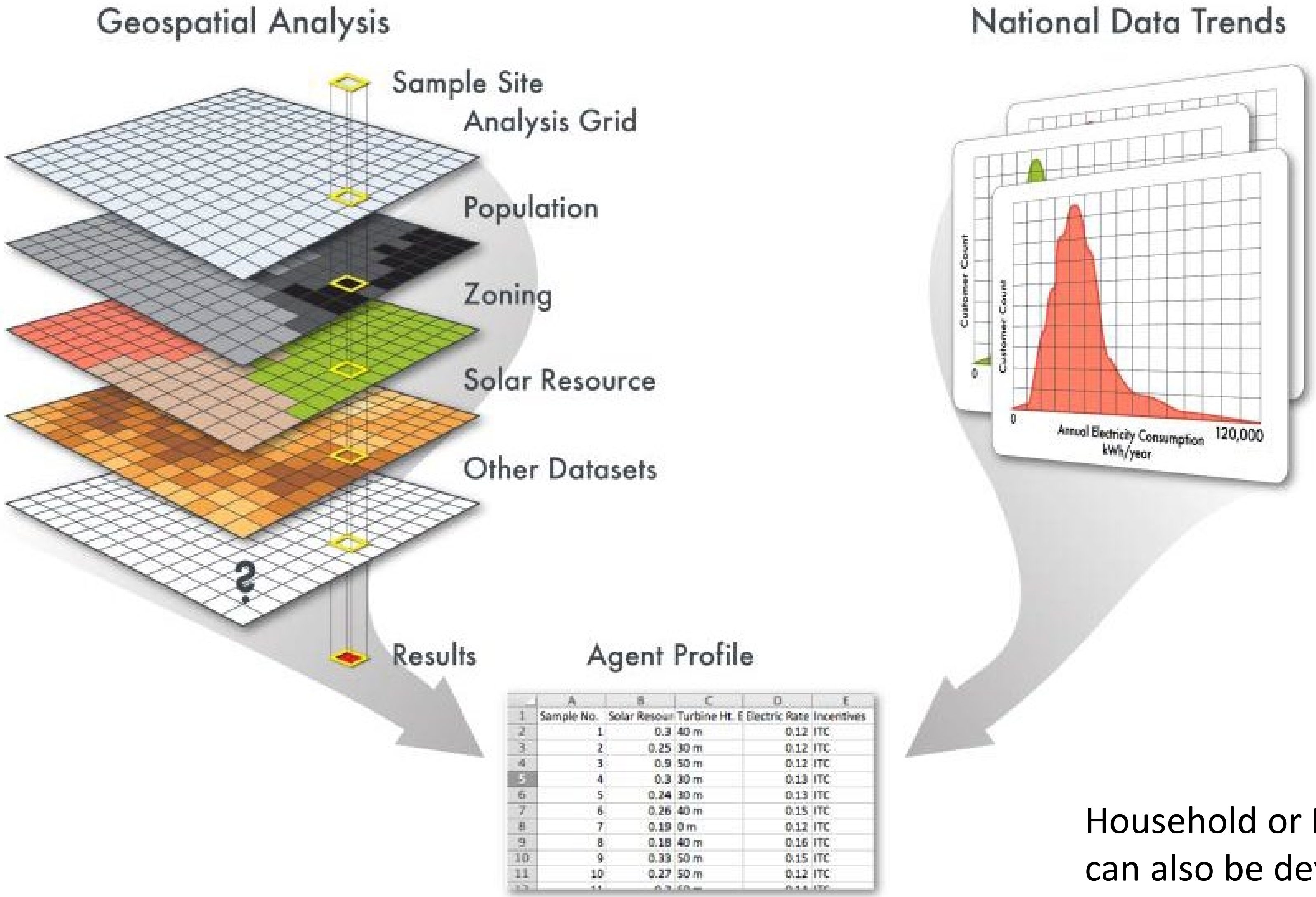
Adoption Modeling

For each agent, year, and scenario:

3. **Estimate Economic Potential**: Determine solar capacity that maximizes agent net present value using 5.3% weighted average cost of capital. Scenarios varied PV cost projections and tariff structures.
4. **Estimate Adoption Probability**: Assess adoption probability using a Bass Diffusion model and household propensity modeling.



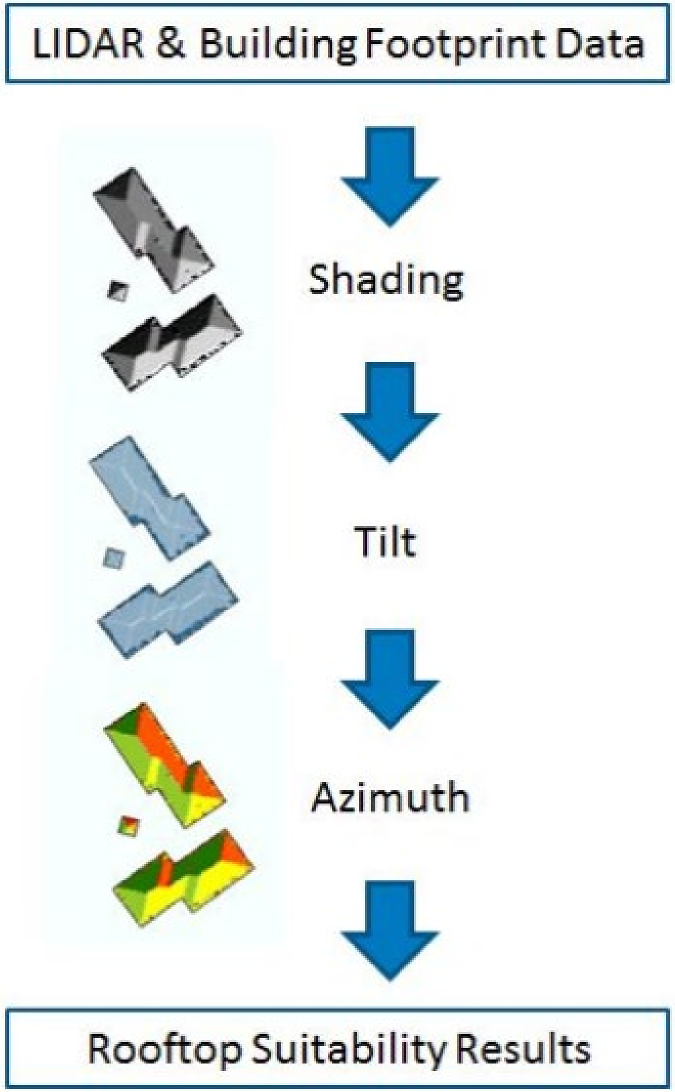
Statistical-based agent generation

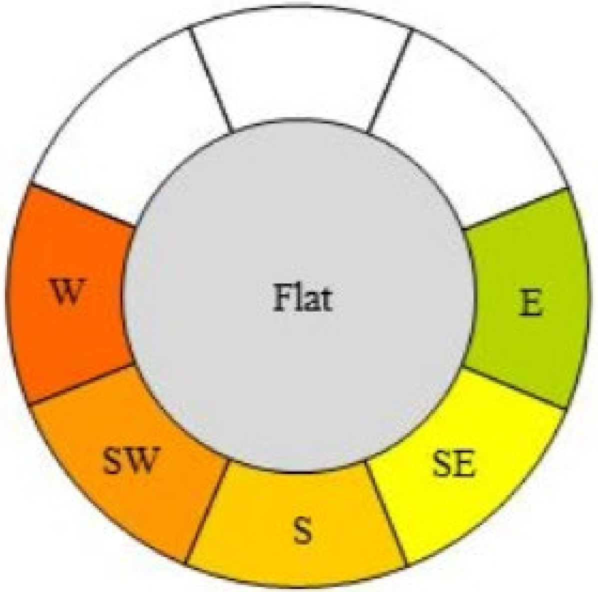


	A	B	C	D	E
1	Sample No.	Solar Resour	Turbine Ht. E	Electric Rate	Incentives
2	1	0.3	40 m	0.12	ITC
3	2	0.25	30 m	0.12	ITC
4	3	0.9	50 m	0.12	ITC
5	4	0.3	30 m	0.13	ITC
6	5	0.24	30 m	0.13	ITC
7	6	0.26	40 m	0.15	ITC
8	7	0.19	0 m	0.12	ITC
9	8	0.18	40 m	0.16	ITC
10	9	0.33	50 m	0.15	ITC
11	10	0.27	50 m	0.12	ITC

Household or Parcel-level agents can also be developed

Assessing Rooftop Solar Technical Potential





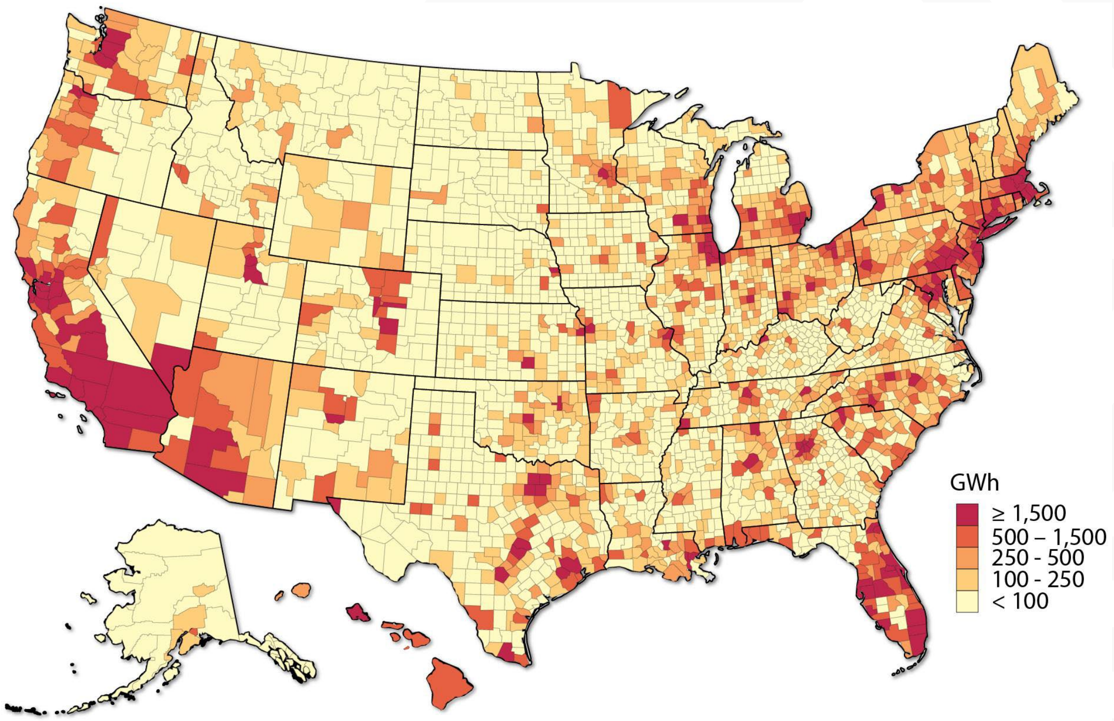
Clockwise:

(1) Raw LiDAR imagery of buildings

(2) Developable area estimated for each building in dataset, then aggregated at regional level

(3) Suitability based on roof plane orientations, tilt, size, and shading

Solar Technical Potential



County-level technical potential for low and moderate income households

- REPLICA data set provides tract-level estimates of residential rooftop solar potential by income, tenure, and building type
- Annual U.S. residential solar potential is 1000 TWh (roughly 75% of residential electricity consumption) (794 GW)
- LMI opportunity is 416 TWh, nearly half (42%) of total annual residential solar potential
- Average household potential is 8,553 kWh nationally

Load Profiles

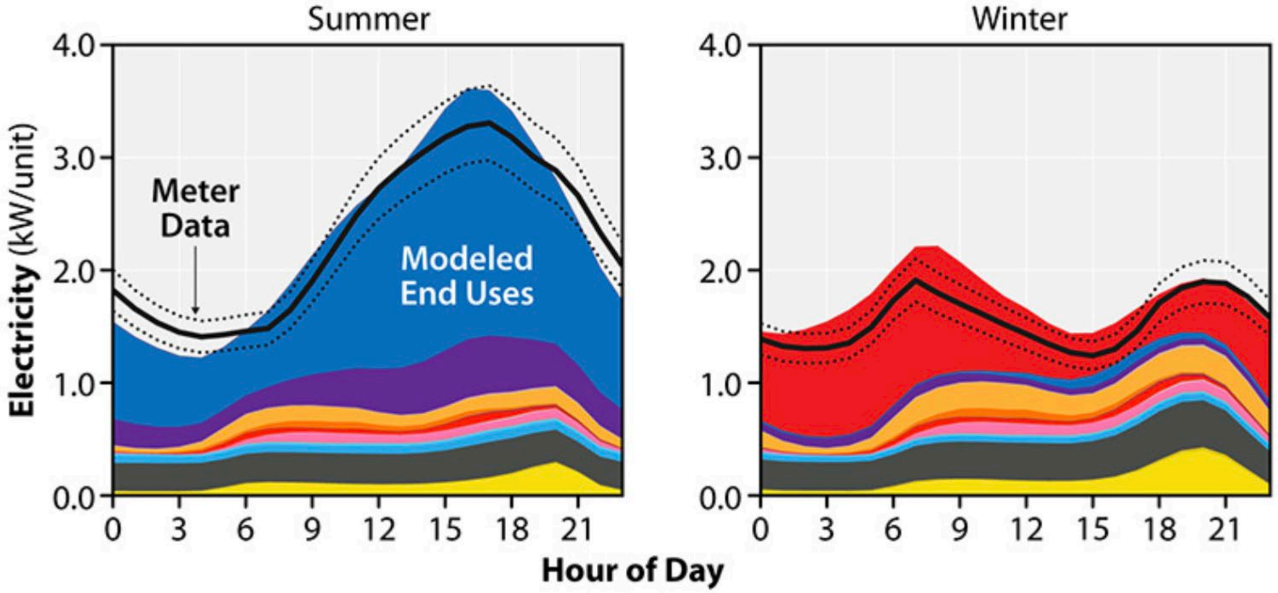
Foundational Dataset of ~1 Million End-Use Load Profiles for the U.S. Residential and Commercial Building Stock

ComStock ResStock

Building stock models calibrated through 70+ model updates, supported by data:

- Electric load data from 11 utilities and 2.3 million meters
- 15 end-use metering datasets

Example: Texas Residential Load (modeled end-uses)



Retail Tariff

1) Utility rate database (or)
2) Custom rates

Example rate from URDB

Energy Charge components are shown in table below, the schedule is shown in the figure (right).

Period	Tier	Max Usage ?	Max Usage Units ?	Rate $/kWh ?
1	1	13.5	kWh daily	0.39848
	2		kWh daily	0.48902
2	1	13.5	kWh daily	0.33504
	2		kWh daily	0.42558
3	1	11	kWh daily	0.30139
	2		kWh daily	0.39193
4	1	11	kWh daily	0.28406
	2		kWh daily	0.3746

https://apps.openei.org/IURDB/rate/view/62d06f573f6b437e6929e75a#2__Demand

Weekday Schedule

	12 am	1 am	2 am	3 am	4 am	5 am	6 am	7 am	8 am	9 am	10 am	11 am	12 pm	1 pm	2 pm	3 pm	4 pm	5 pm	6 pm	7 pm	8 pm	9 pm	10pm	11 pm
Jan	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4
Feb	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4
Mar	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4
Apr	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4
May	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4
Jun	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	2	2	2
Jul	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	2	2	2
Aug	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	2	2	2
Sep	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	2	2	2
Oct	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4
Nov	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4
Dec	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4

Weekend Schedule

	12 am	1 am	2 am	3 am	4 am	5 am	6 am	7 am	8 am	9 am	10 am	11 am	12 pm	1 pm	2 pm	3 pm	4 pm	5 pm	6 pm	7 pm	8 pm	9 pm	10pm	11 pm
Jan	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4
Feb	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4
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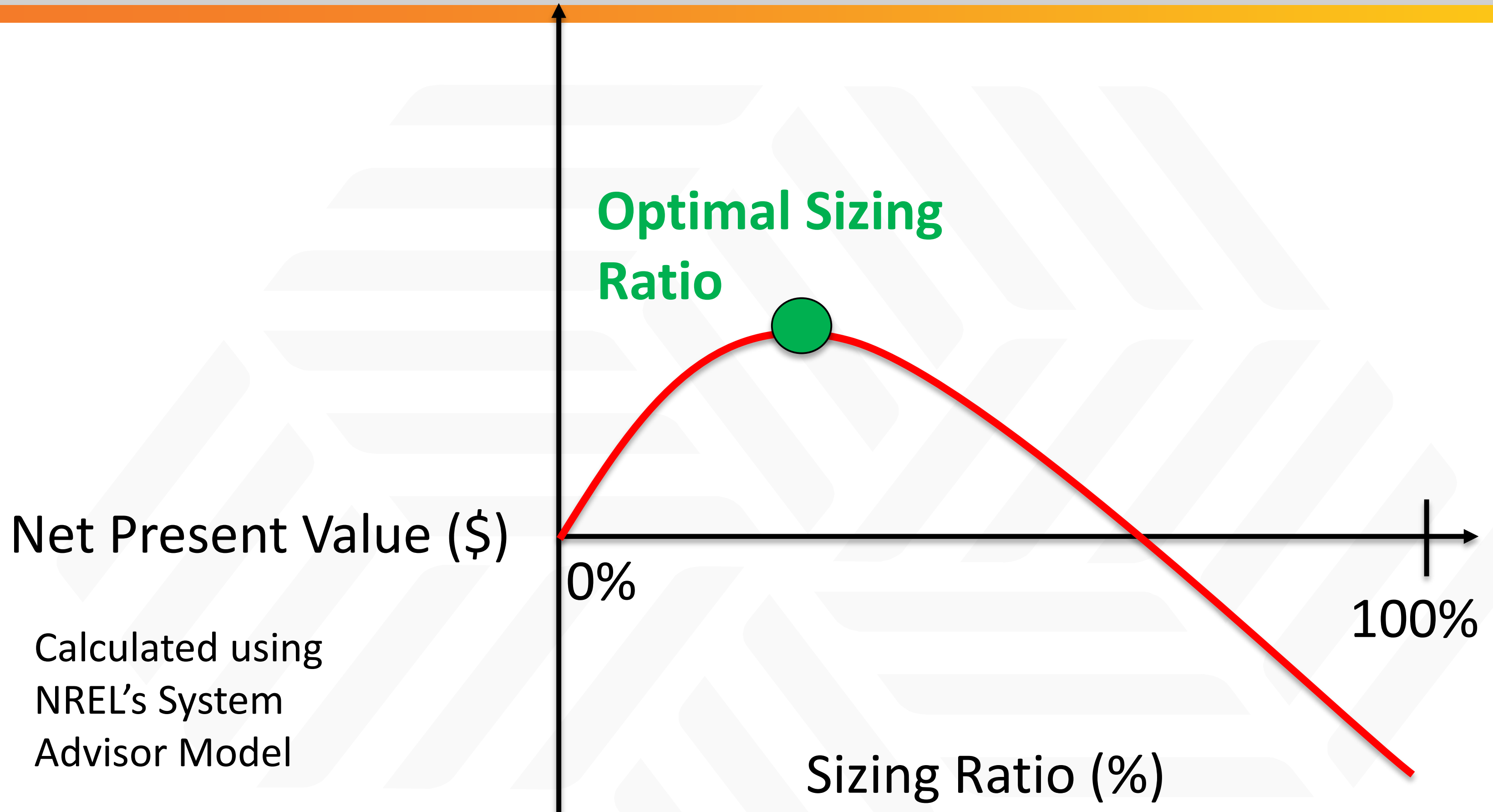
Nov	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4
Dec	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4

Five Variants of Sizing Decisions



Calculated using NREL's System Advisor Model

$$\text{Sizing Ratio} = \frac{\text{Annual system generation(kWh)}}{\text{Annual end-user consumption (kWh)}}$$

Size = 100%; Tariff-constrained
1) "I want more PV"

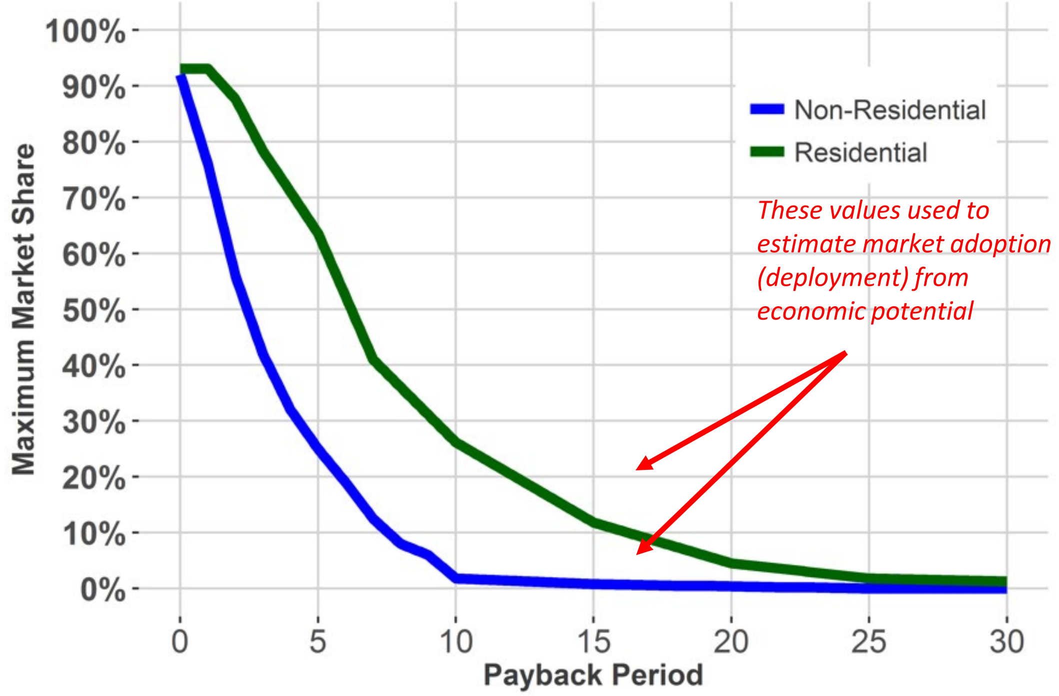
Size = 0%; Tariff-constrained
2) "PV is uneconomic for me"

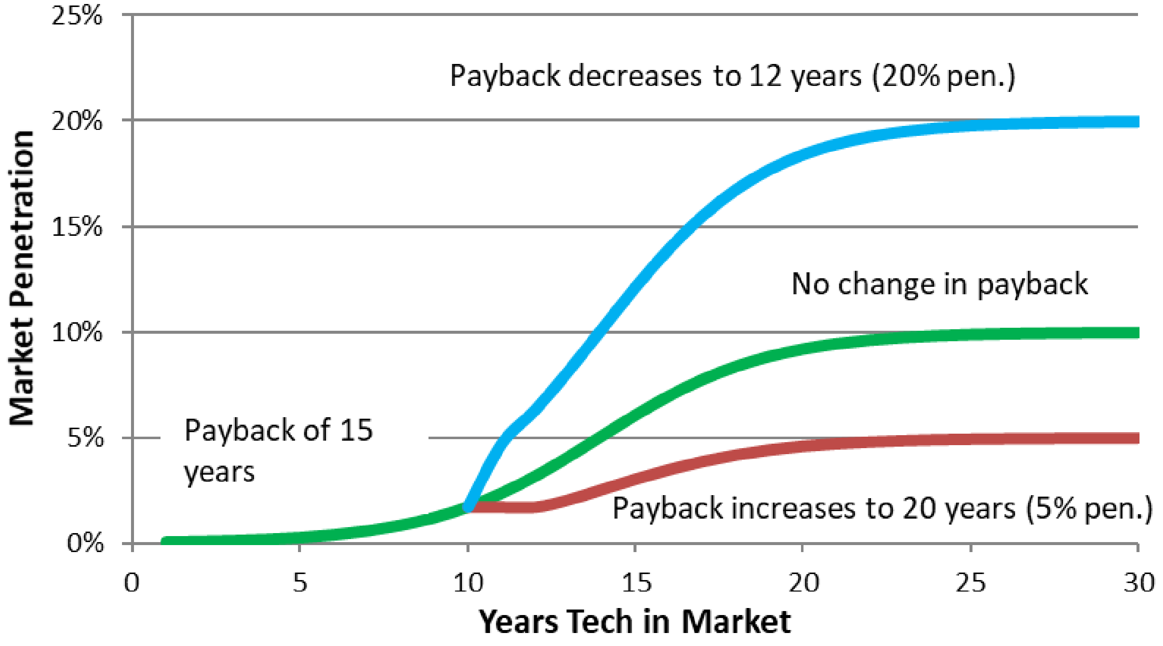
Size = 0%; Roof-constrained
3) "My roof is unsuitable"

Size = 0-100%; Roof-constrained
4) "I want a bigger roof"

Size = 0-100%; Tariff-constrained
5) "I'm getting the best I can"

Market Potential



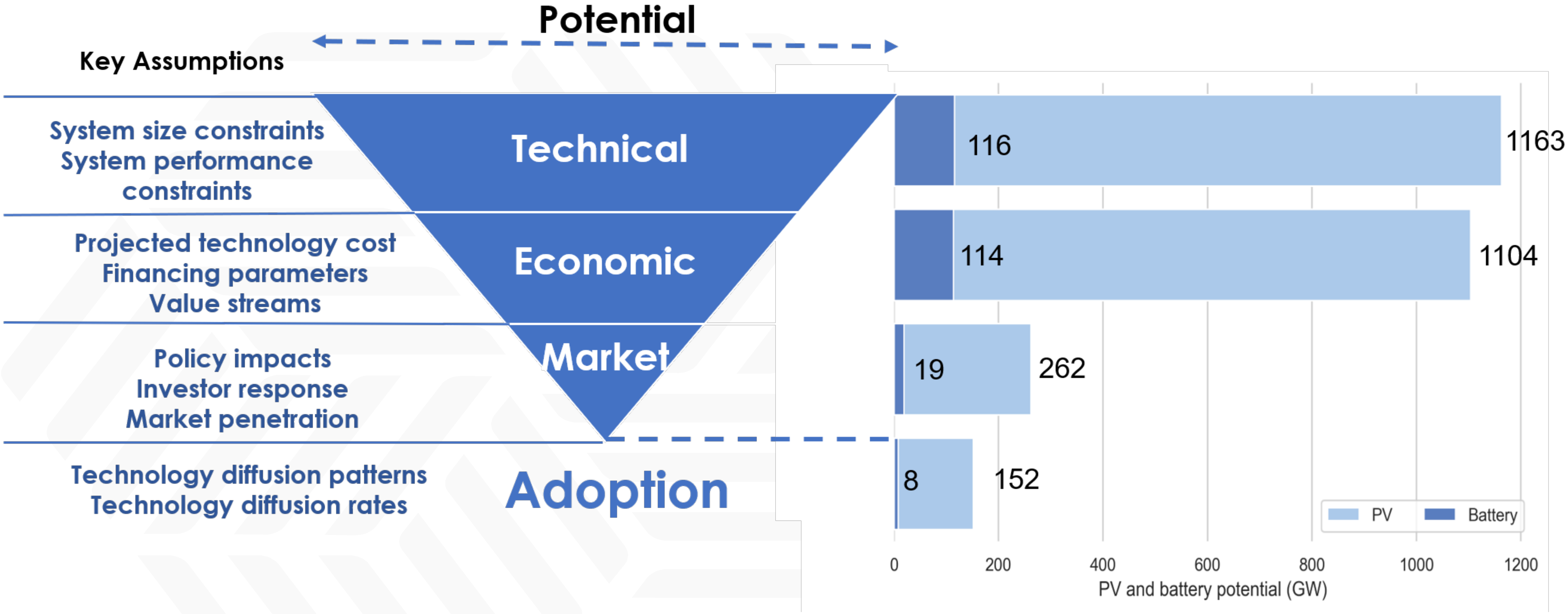


Using consumer surveys, relate the system payback to the fraction of consumers that would adopt solar[1,2].

[1] Dong & Sigrin 2019; [2] Paidipati et al. 2008

Maximum market share is paired with a Bass Diffusion model to simulate aggregate adoption over time. The aggregate adoption is then disaggregated to individual agents based on their predicted probability

Results from Solar Future Study

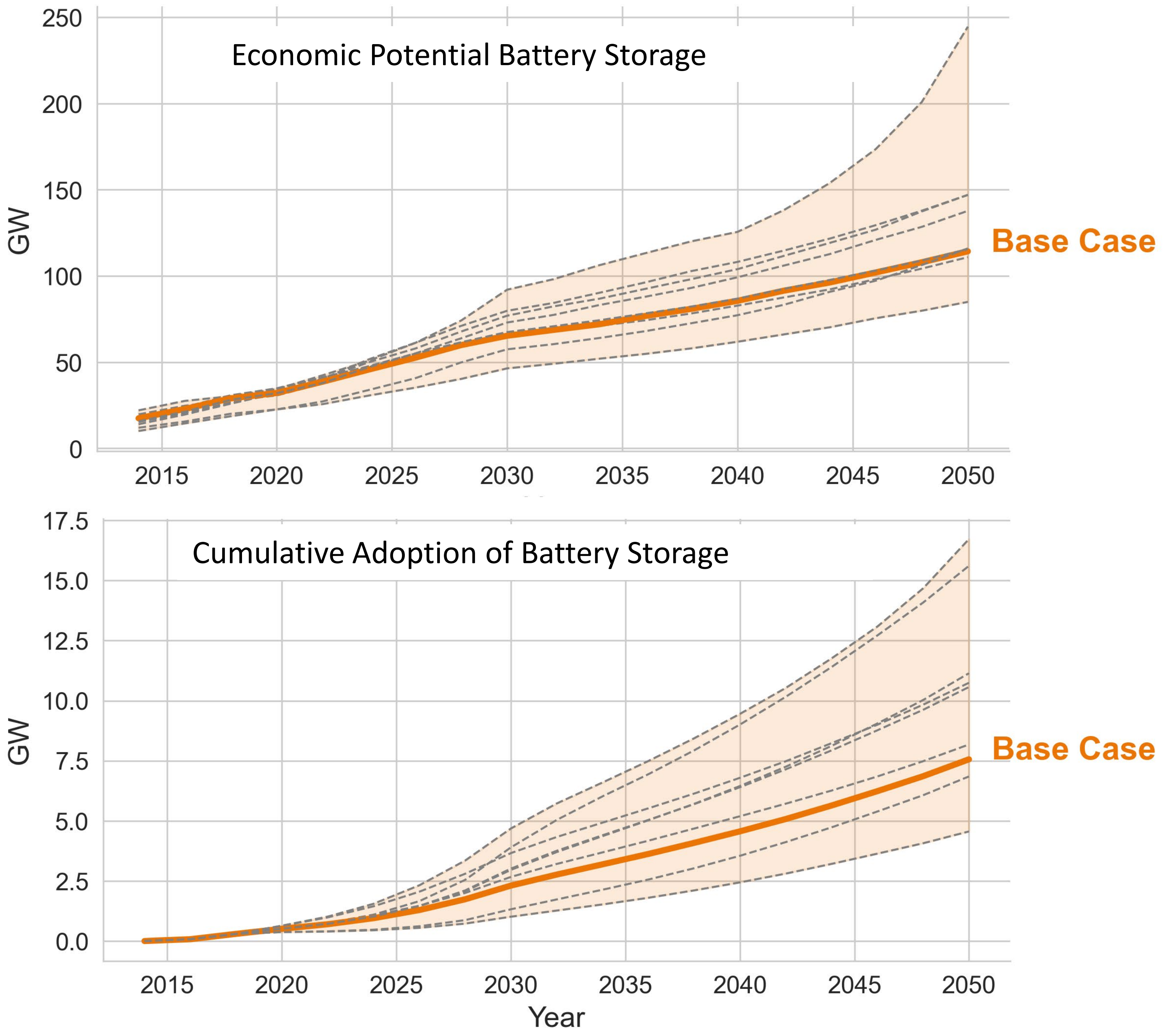


Economic Potential and Adoption

Economic potential is the total capacity in a given year that could return a positive NPV. A discounted cash flow analysis determines the NPV.

DER value is created through the sum of three value streams:

1. Value created by reducing electricity bills
2. Value of backup power
3. Revenue from selling excess PV generation.



Workshop Agenda

GRID MODERNIZATION INITIATIVE
U.S. Department of Energy

1:00-1:15 Introductions & Overview
1:15-1:45 Intro to Electricity Forecasting
1:45-2:15 Load Forecasting
2:15-2:30 Break
2:30-3:00 Energy Efficiency and Demand Flexibility Forecasting
3:00-3:35 Building Electrification & Electric Vehicle Forecasting
3:35-3:50 Break
3:50-4:20 Distributed Solar & Battery Storage Forecasting
4:20-4:50 Cost Forecasting
4:50-5:00 Final Thoughts

Cost Forecasting Methodologies and Best Practices

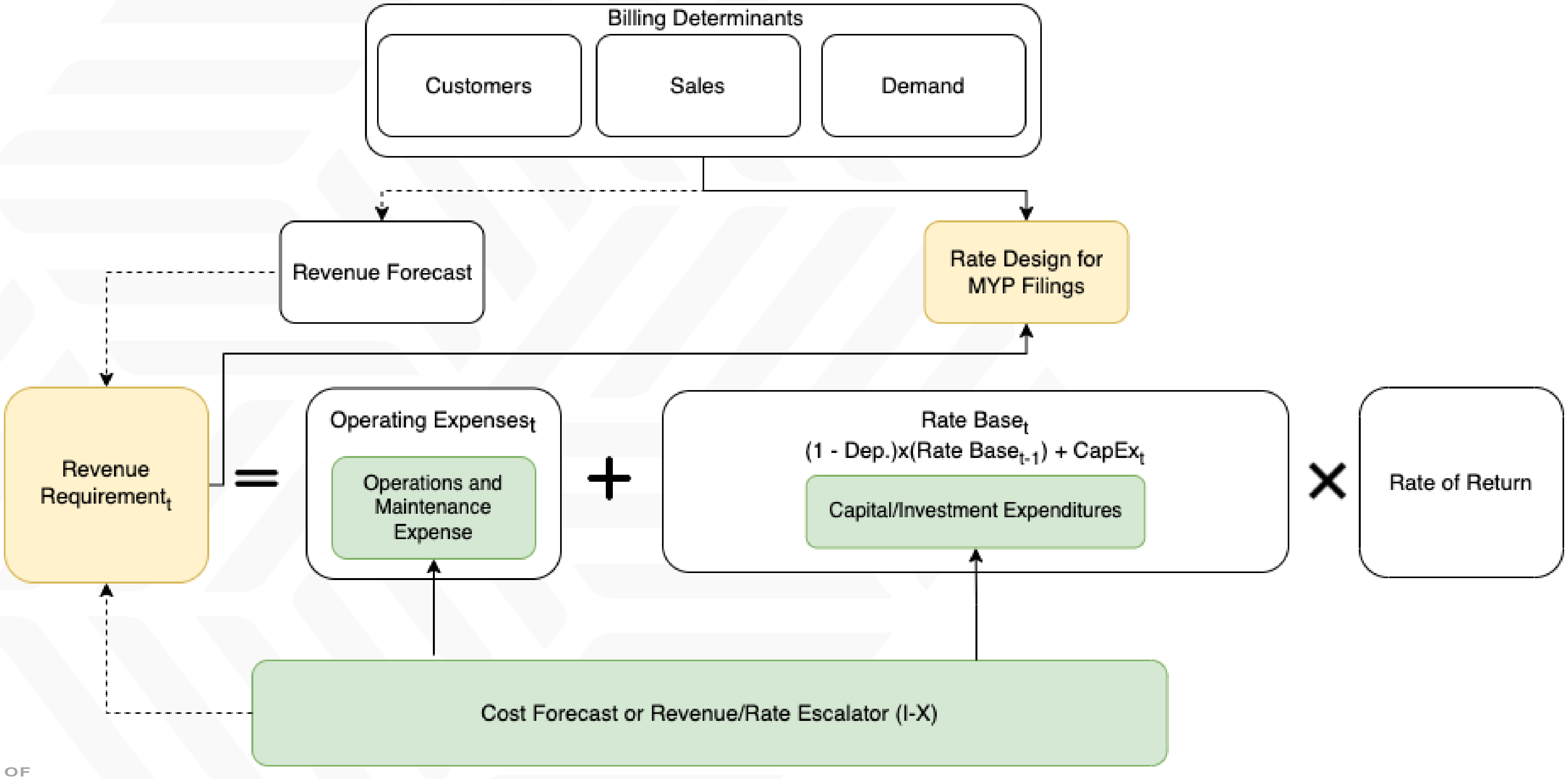
BRITTANY TARUFELLI

Pacific Northwest National Laboratory

Overview of Cost Forecasting Workshop

- Scope of cost forecasting in this workshop
  - Approaches applicable to O&M and capital investments for distribution systems
- Methods for cost forecasting
  - Range of approaches
  - Top-down approaches
  - Bottom-up approaches
- Best practices in cost forecasting
  - Best practices for I-X approaches
  - Challenges and best practices for bottom-up approaches
    - O&M
    - Capital Additions
  - Examples from New York Reforming Our Energy Vision
- Worked example: Benefit Cost Analysis of a Non-Wires Alternative

Scope of Cost Forecasting in this Workshop



Bottom-up Approaches to Cost Forecasts

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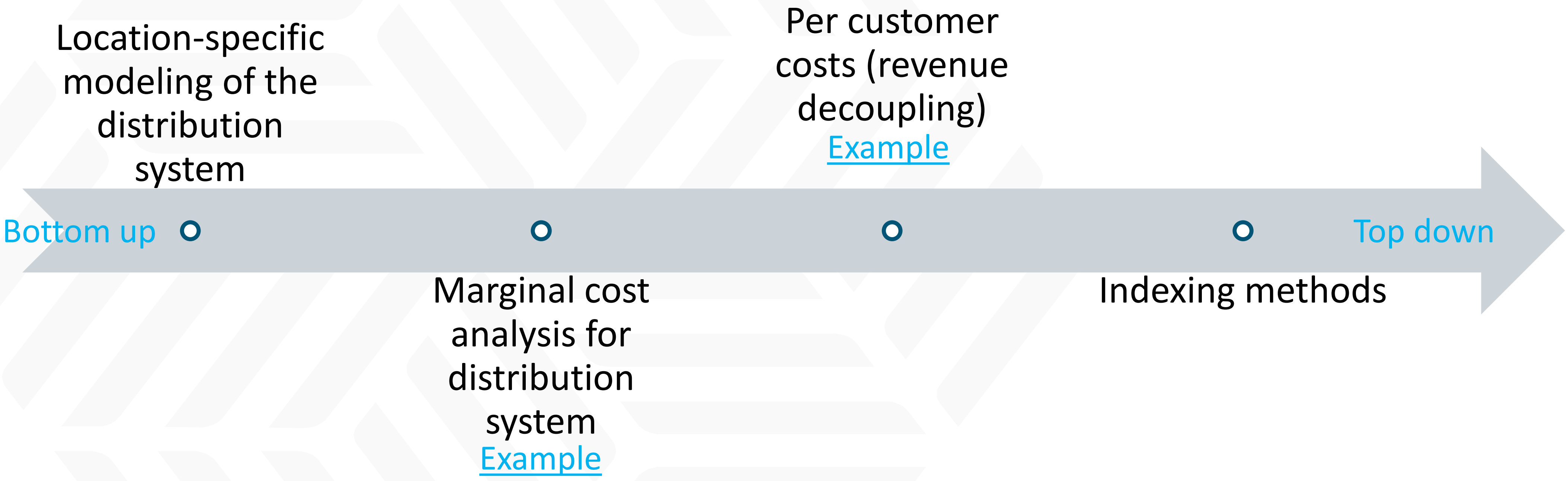
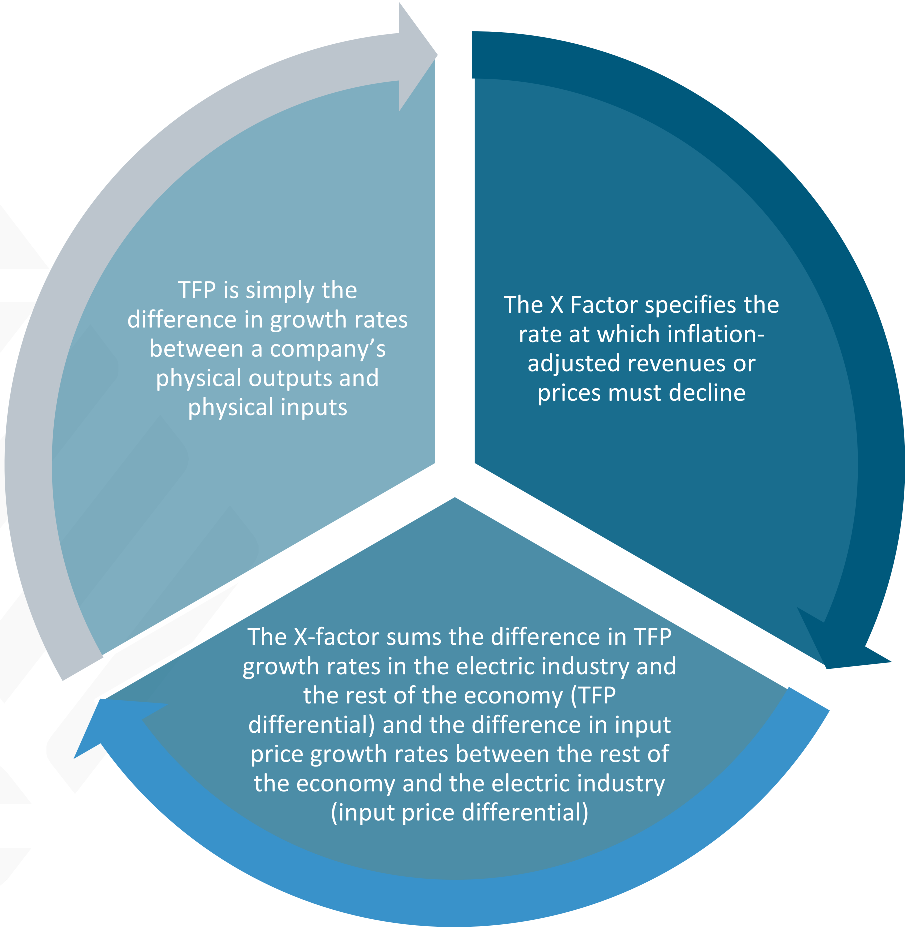
U.S. Department of Energy

- There are a range of approaches to estimate distribution system costs
  - Methods vary in the granularity of the approach



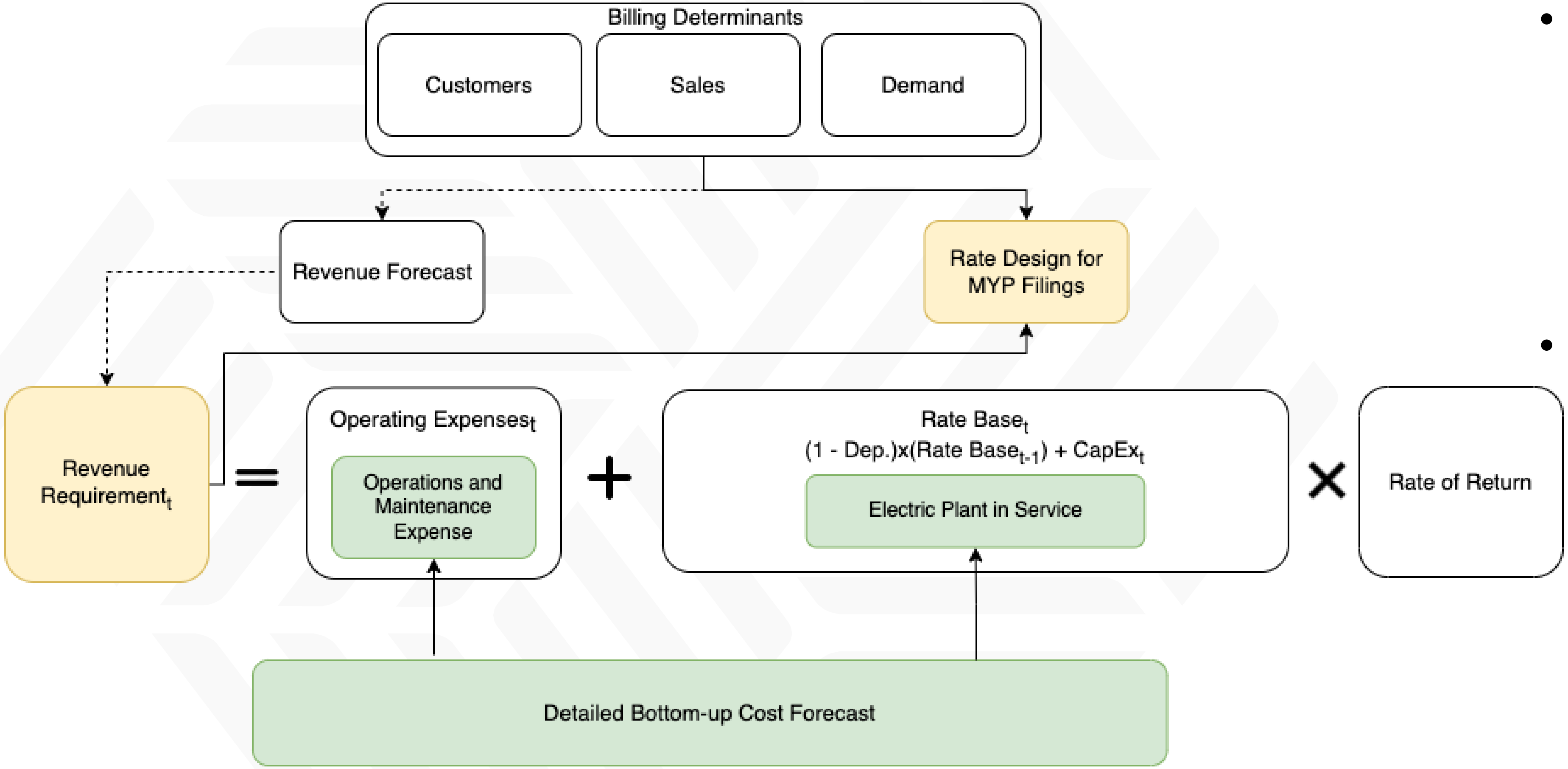
Top-Down Approaches: I-X

- Rates or revenues are escalated between rate cases with an index based on utility cost trends
- Growth in Revenue = Inflation – X
  - Inflation is usually a macroeconomic indicator: GDPPI
  - X Factor is a productivity offset, reflecting average historical productivity trends for a peer group of utilities
  - Assessed with total factor productivity studies
- Utilities are compensated for important cost drivers such as inflation and customer growth
- Best practices include that methodologies and assumptions should be transparent enough that the study could be reproduced, and sensitivity analysis of key assumptions can be undertaken to show the sensitivity of TFP to changing those key assumptions
- See Lowry et al. (2017) for further reading



X Factor Explanation

Bottom-up Approaches: Detailed Cost Forecast



- Detailed forecasting approach which builds up from customers/meters/ modeling of the distribution system
- Used to inform necessary investments and operations and maintenance expenditures

Best Practices for Bottom-up Approaches: O&M

Utilities can provide:

- Description of current O&M budgeting process
- Five-year historical and budgeted O&M spending amounts
- Forecasts for O&M budgets for the multiyear rate plan or forecast period
- Identification and documentation of driving factors when there are large changes between historic, current, and future spending amounts

Best Practices for Bottom-up Approaches: O&M Sample Questions

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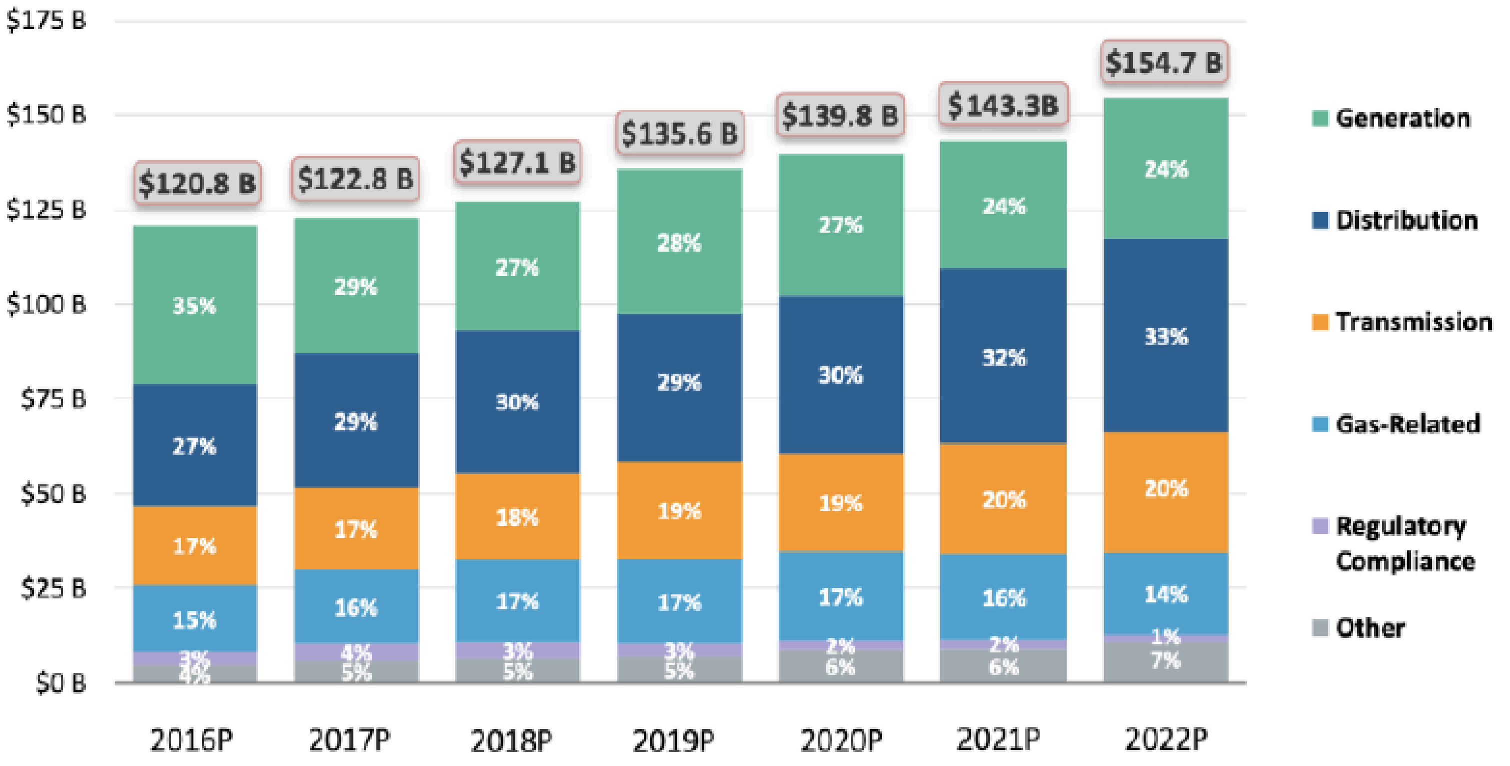
- Do forecasts reflect historical costs?
- Are deviations explained?
- Are test year costs unusually high?
- How are sporadic costs represented?
- For Covid-19 costs, are costs or efficiencies one-time or recurring?
- Are increases in cost adequately explained?

Challenges in Evaluating Bottom-up Cost Forecasts

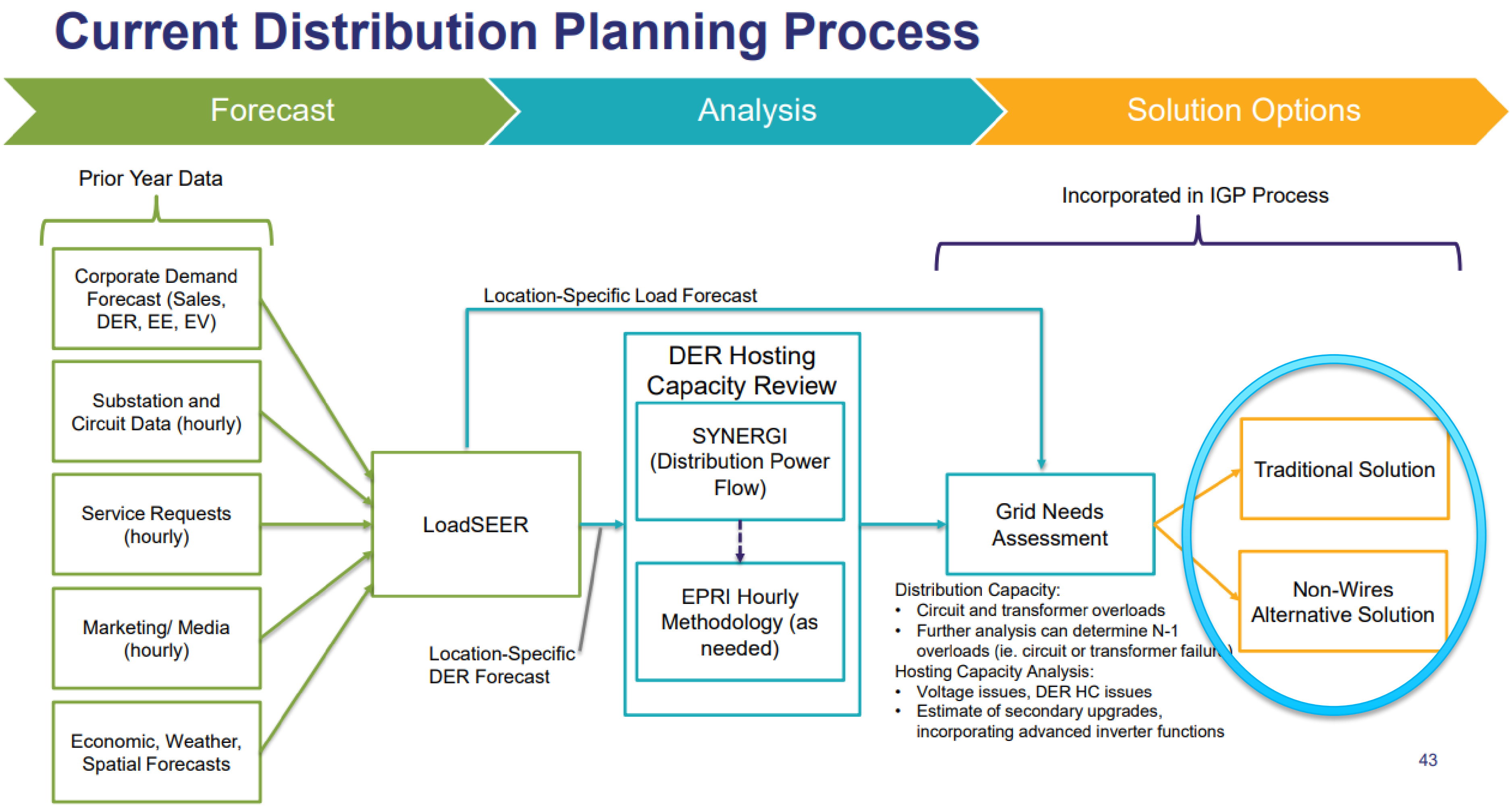


Projected Functional CapEx
Source: Edison Electric Institute (2022), reproduced from Shenot et al. (2022)

- Distribution system spending (as a share of total utility capital investment) is increasing
- Rapid growth in DER investment
- New investments are needed to modernize the grid
  - Need for smart investment in expensive, new technologies
- Best practices to evaluate distribution system investments are still emerging

Challenges in Evaluating Bottom-up Cost Forecasts

- Typically, trying to evaluate solution options (capital investments) from a larger distribution planning process



[Hawaii Integrated Grid Planning (IGP) Technical Conference June 2021]

Best Practices for Bottom-up Approaches: Capital Additions

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- **While best practices, or a single best approach for bottom-up cost forecasts are still emerging, there are two common approaches for regulators evaluating *future* year utility investments (Woolf et al., 2021; Shenot et al., 2022)**

Least Cost/Best Fit	Benefit Cost Analysis
• Compare **total costs** of investment alternatives, including capital costs and O&M costs, over a defined period of time • Identify options that **minimize the net present value** of the revenue requirement • Often used to select the **least cost alternative**, but best fit may be selected • Used for **investments deemed necessary** • Does not require the benefits associated with each investment alternative to be quantified	• Compare the **benefits and costs** of investment alternatives • Used to select the option that **maximizes net benefits** (benefits minus costs) • Considers benefits beyond reducing the revenue requirement • Often used to **determine if investment will be cost-effective** • Often used to evaluate investments **in new technologies**

- **Requires utilities to provide enough data to perform this type of analysis**

NY REV: DSIP Framework

- Some states are starting to implement useful frameworks to guide cost forecasting approaches
  - New York Reforming Our Energy Vision
  - Intended to provide greater transparency and visibility of electric system planning and operations
    - Benefit/Cost Analysis Framework
    - Distributed System Implementation Plan Framework

Delivery Infrastructure Capital Investment Plans	
	Identification of current **reliability planning criteria**
	Description of current **capital budgeting process**
	Five-year historical spending amounts for transmission, substation, and distribution infrastructure, as well as information technologies, communications, and shared services
	Five-year forecast capital budgets for the same categories above, as well as details on upgrades required … and projects where DER has the potential to impact project needs
	Identification of the **driving factors and mitigating technologies considered**, or rejected (and an explanation of why such techniques were rejected) for areas where there are **large changes between the historic, current, and future spending amounts**

NY REV: Benefit Cost Analysis Framework

- Enables comparison of the value of benefits obtained against the costs incurred for a potential project, quantifying the net present value of the project

Foundational Principles

Based on transparent assumptions and methods; list all benefits and costs	Avoid combining or conflating different benefits and costs	Assess portfolios rather than individual measures or investments	Address the full lifetime of the investment while reflecting sensitivities on key assumptions	Compare benefits and costs to traditional alternatives instead of valuing them in isolation

Methodological Approaches

- Societal Cost Test (SCT)
- Utility Cost Test (UCT)
- Rate Impact Measure (RIM)

See the California Standard Practice Manual for detail on how to perform these tests and the National Standard Practice Manual for Benefit-Cost Analysis of Distributed Energy Resources for additional information on implementing BCA for different resource types.

Source: NY REV Benefit/Cost Analysis Framework

Worked Example: Evaluating a non-wires alternative investment

Non-Wires Solution Case Study Assumptions

In this example, an electric utility is facing the need to upgrade its system infrastructure due to distribution capacity constraints identified in a densely populated geographic area within its service territory. The utility proposes to integrate DERs to serve as a non-wires solution in place of an infrastructure upgrade.

The NWS plan includes the following BTM DERs in residential and commercial buildings:

- Energy efficiency measures (e.g., lighting and controls)
- Demand response (e.g., Wi-Fi-enabled thermostats)
- Distributed photovoltaics
- Distributed storage systems

Jurisdiction-Specific Test: The hypothetical jurisdiction's primary BCA test accounts for utility system, host customer, and GHG emission impacts.

Key assumptions:

- *Non-Coincident Peak:* The distribution need is non-coincident with the overall system peak (e.g., the constrained distribution feeder peaks from 1:00–5:00pm, while system peaks from 5:00–9:00pm).
- *GHG Emissions Reduction:* The system-peak hours entail higher marginal emissions rates than the NWS, which allows the NWS to deliver GHG benefits.
- *DER Operating Profiles:* The NWS DERs operate in the following ways:
  - All DERs are operated to reduce the distribution peak, and some can reduce the system peak as well.
  - Storage charges during the distribution off-peak hours and discharges during the distribution peak hours.
  - DR reduces demand during distribution peak periods and/or shifts load from distribution peak periods to distribution off-peak periods.
  - Distributed PV resources generate during a portion of distribution peak period.
  - EE helps to reduce demand during distribution peak periods.

Source: National Standard Practice Manual for Benefit-Cost Analysis of Distributed Energy Resources

Worked Example: Evaluating a non-wires alternative investment

GRID MODERNIZATION INITIATIVE
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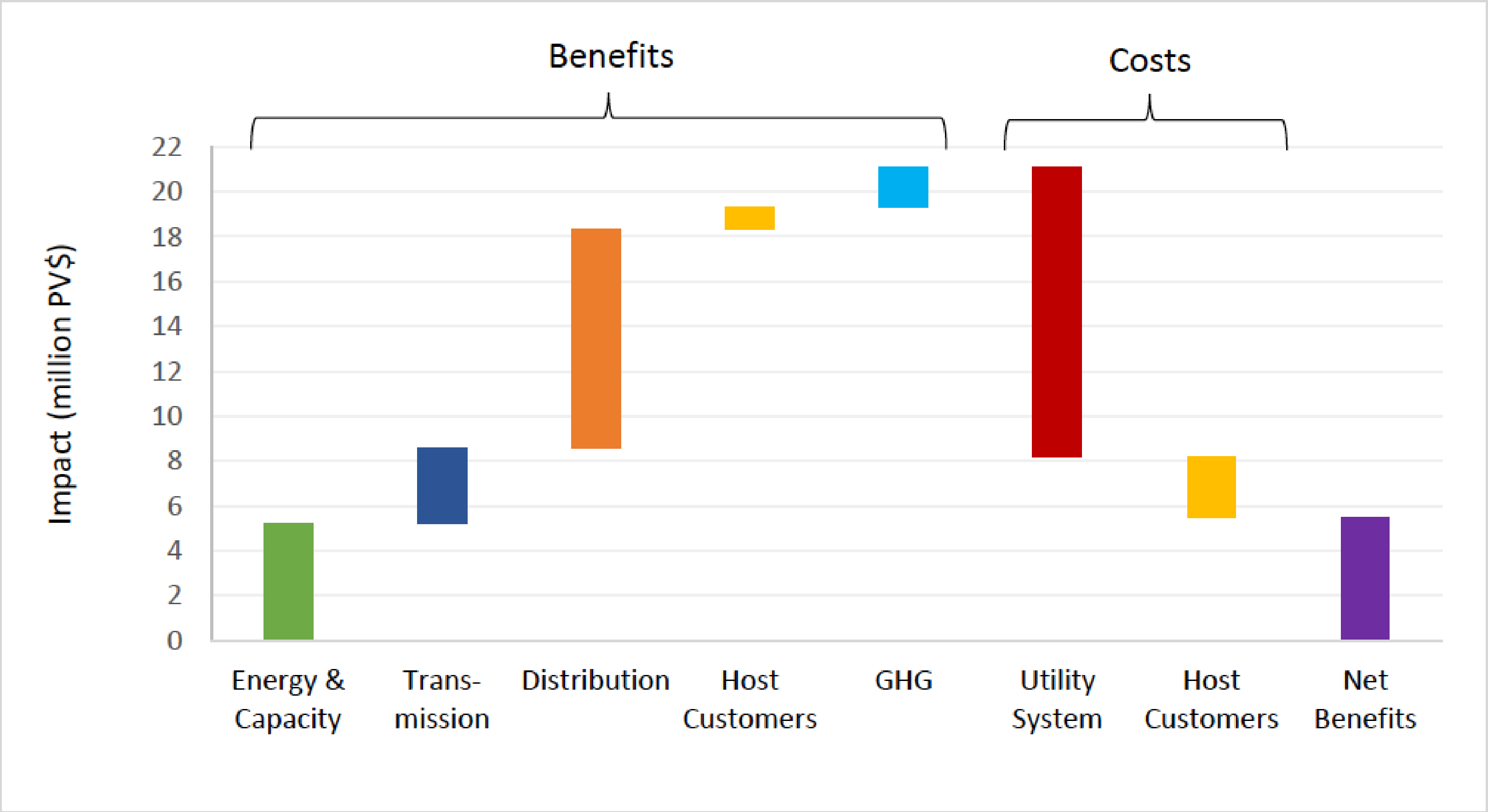
- Example benefits and costs:



Source:
[National Standard Practice Manual for Benefit-Cost Analysis of Distributed Energy Resources]

Conclusion

- There are a range of approaches to estimate distribution system costs which inform cost forecasts
  - Top-down: I-X
  - Bottom-up: Granular distribution system modeling resulting in detailed capital and O&M forecasts
- Although best practices exist for evaluating top-down methods, best practices for evaluating bottom-up methods are still emerging
  - Two dominant approaches exist for evaluating current or future year investments
    - Least cost/best fit
    - Benefit cost analysis
  - Further, states are implementing frameworks to guide the cost forecasting process and provide more rigorous requirements for data that must be provided with proposed investments

Questions?

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Energy and Environment Directorate
Economics, Policy & Institutional Support
https://www.pnnl.gov/sustainable-energy

References and Resources

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- Shenot, J., Prause, E., Shipley, J., 2022. Using Benefit-Cost Analysis to Improve Distribution System Investment Decisions: Reference Report. Available at: https://www.raponline.org/knowledge-center/using-benefit-cost-analysis-improve-distribution-system-investment-decisions-issue-brief/
- Woolf et al., 2021. Benefit-Cost Analysis for Utility-Facing Grid Modernization Investments: Trends, Challenges, and Considerations. Available at: https://www.synapse-energy.com/sites/default/files/GMLC-Grid-Mod-BCA-2021-02-02-18-094.pdf

Appendix: Best Practices for Top-Down (I-X) Approaches to MYP

- Total factor productivity, and the X-factor, is typically measured using index number methods
- Index number methods combine changes in diverse outputs and inputs into measures of change in total outputs and total inputs

$$\underbrace{lnA_{it} - lnA_{it-1}}_{Growth\ in\ TFP} = \underbrace{ln\frac{Q_{it}}{Q_{it-1}}}_{Growth\ in\ Output} \underbrace{- \underbrace{\left(\frac{s_{it}^{L} + s_{it-1}^{L}}{2}\right)}_{Labor\ Share} ln\frac{L_{it}}{L_{it-1}} - \underbrace{\left(\frac{s_{it}^{K} + s_{it-1}^{K}}{2}\right)}_{Capital\ Share} ln\frac{K_{it}}{K_{it-1}}}_{Growth\ in\ Input}$$

- Key challenges in TFP measurement include the measurement of output, the measurement of input—especially the concept of capital—missing or inappropriate data, and the weights used for indexes
- Best practices include that methodologies and assumptions should be transparent enough that the study could be reproduced, and sensitivity analysis of key assumptions can be undertaken to show the sensitivity of TFP to changing those key assumptions

Appendix: Benefit Cost Analysis

- Key Steps (Shenot et al., 2022)
  - Select the cost effectiveness test
    - See the California Standard Practices Manual and the National Standard Practice Manual for Benefit-Cost Analysis of Distributed Energy Resources
  - Identify incremental impacts of a proposed expenditure compared to a reference scenario without the expenditure
  - Examine costs or avoided costs of incremental impacts. Consider additional benefits or avoided costs as recommended by the cost-effectiveness test
  - If benefits > costs, the investment is cost effective

Test	Key Question Answered	Benefits/Costs Considered
Societal Cost Test	Will total costs to society be reduced?	Benefits and costs experienced by society
Utility Cost Test	Will utility system costs be reduced?	Benefits and costs experienced by the utility system
Ratepayer Impact Measure	Are rates likely to increase or decrease due to the investment?	Benefits and costs that affect utility rates

Cost-Effectiveness Tests
Source: Adapted from NSPM (2022)

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