Developing Forecasts – Load Expansion

Christine Holland (PNNL), Sean Murphy(LBNL), and JP Carvallo (LBNL).

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Webinar Series Overview

1) Overview of Webinar Series and Connections to State Planning Efforts
    - October 14, 2:30-3:30 p.m. Eastern
    - Juliet Homer and Eran Schweitzer from PNNL
2) Developing Forecasts - General Overview
    - October 23, 4-5 p.m. Eastern
    - Brittany Tarufelli and Allison Campbell from PNNL and J.P. Carvallo from LBNL
3) Developing Forecasts – Load Expansion
    - October 29, 4-5 p.m. Eastern
    - Sean Murphy and J.P. Carvallo from LBNL and Christine Holland from PNNL
4) Developing Forecasts – Distributed Energy Resources
    - November 6, 2-3 p.m. Eastern
    - Sean Murphy, Margaret Pigman, and Natalie Frick (LBNL) and Shibani Ghosh (NREL)

Webinar Series Overview

5) Resource Adequacy Analysis – Basics
- November 10, 3-4 p.m. Eastern
- Jose Lara and Rafael Monge (NREL) and Allison Campbell and Eran Schweitzer (PNNL)

6) Transmission and Distribution System Planning – Basics
- November 13, 3-4 p.m. Eastern
- Jose Lara and Rafael Monge (NREL)

7) The Evolution of Resource Accreditation
- December 2, 3-4 p.m. Eastern
- Travis Douville (PNNL)

Topics – Load expansion

- Electric vehicle forecasts – Christine Holland
- Building electrification – Sean Murphy
- Large load forecast – JP Carvallo

Electric Vehicle Forecast

Christine Holland (PNNL)

Content

- Motivations
- Methods
- Insights and relevant questions for planners
- Key takeaways

Motivation

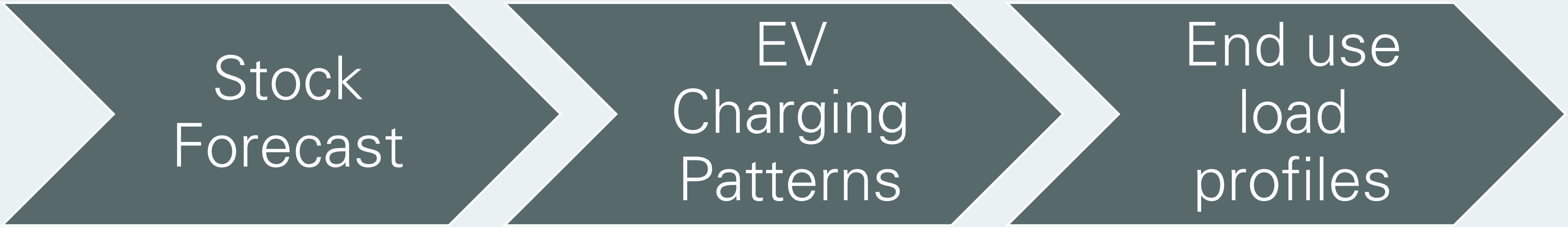
Utilities are planning for electric vehicle (EV) electricity consumption which could reach 283 – 319 TWh by 2030 (Hoyos 2025)

- As of 2023, California had highest EV saturation at 3% and lowest at 0.1% in Mississippi (US DOE and Census Bureau 2024)
- Potentially require new supply resources or stationary storage
- System wide and at the circuit-level, impacting distribution and transmission systems
- One size does not fit all
    - Residential – (primarily light-duty), higher levels of existing adoptions means more data to draw on
    - Commercial and Industrial (more medium- and heavy-duty), less market saturation of electric vehicles, more uncertainty

Uncertainty in the:

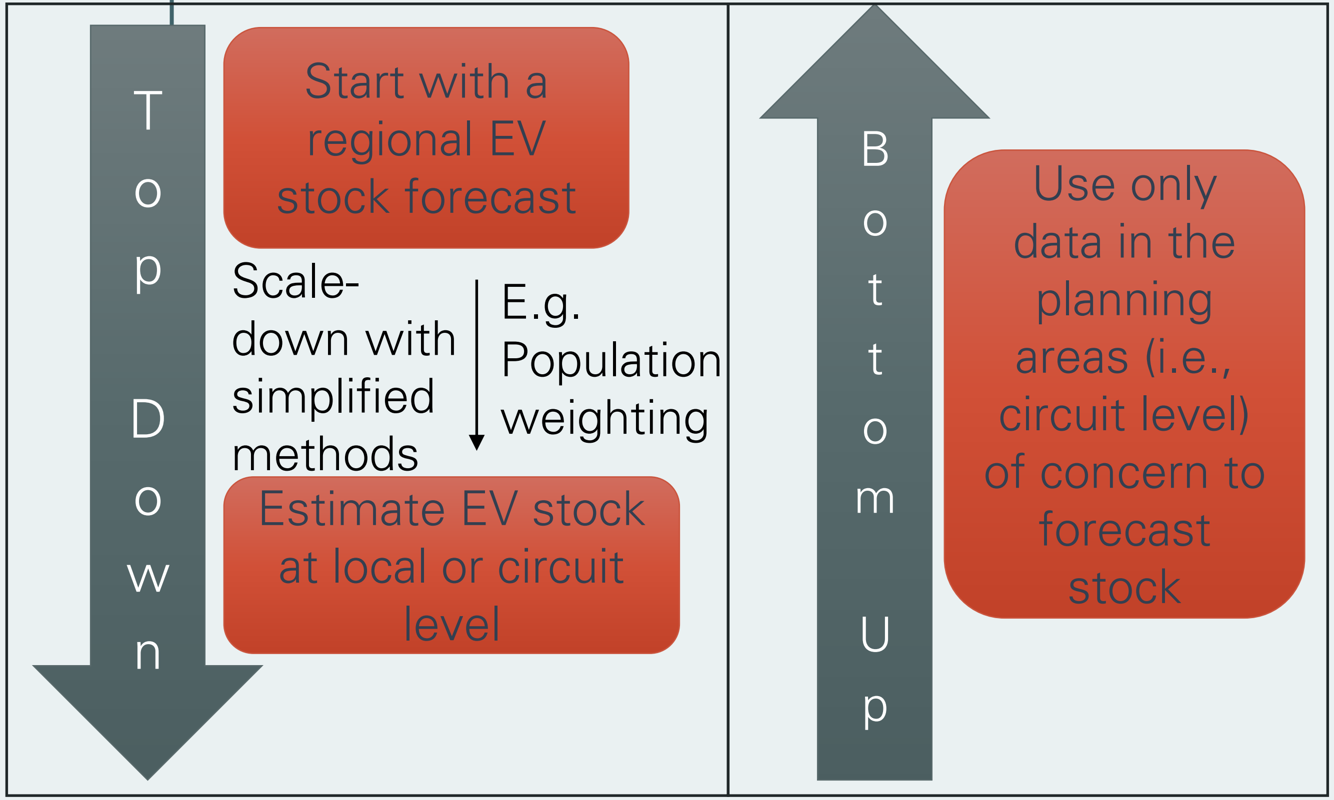
- Timing and magnitude of adoption
- Timing and magnitude of loads for each adopted technology
- Methods and data that utilities can use to incorporate load expansion into forecasts

Methods - overview



Methods – Stock forecast

- *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 at micro level are amplified at macro leve when scaling up

Blended approach – 1) Start with more aggregated registration or sales data to forecast more broadly, 2) Use more detailed customer-level data to distribute to homes or census regions.

Methods – Model Options

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, given consumer traits, i.e. income, education.
   - **Agent based models** – used to study interactions between people, things, places, and time; data intensive.
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).
   - Includes Bass, Gompertz, Weibull, and Logistic.

Practical Customer Segmentation (stock considerations)

Light Duty Vehicles

- Residential, commercial

Med- & Heavy-Duty Vehicles

- Commercial fleets, truck transportation

- Define distinct groups when different characteristics drive adoption
- Homogenous characteristics within each group

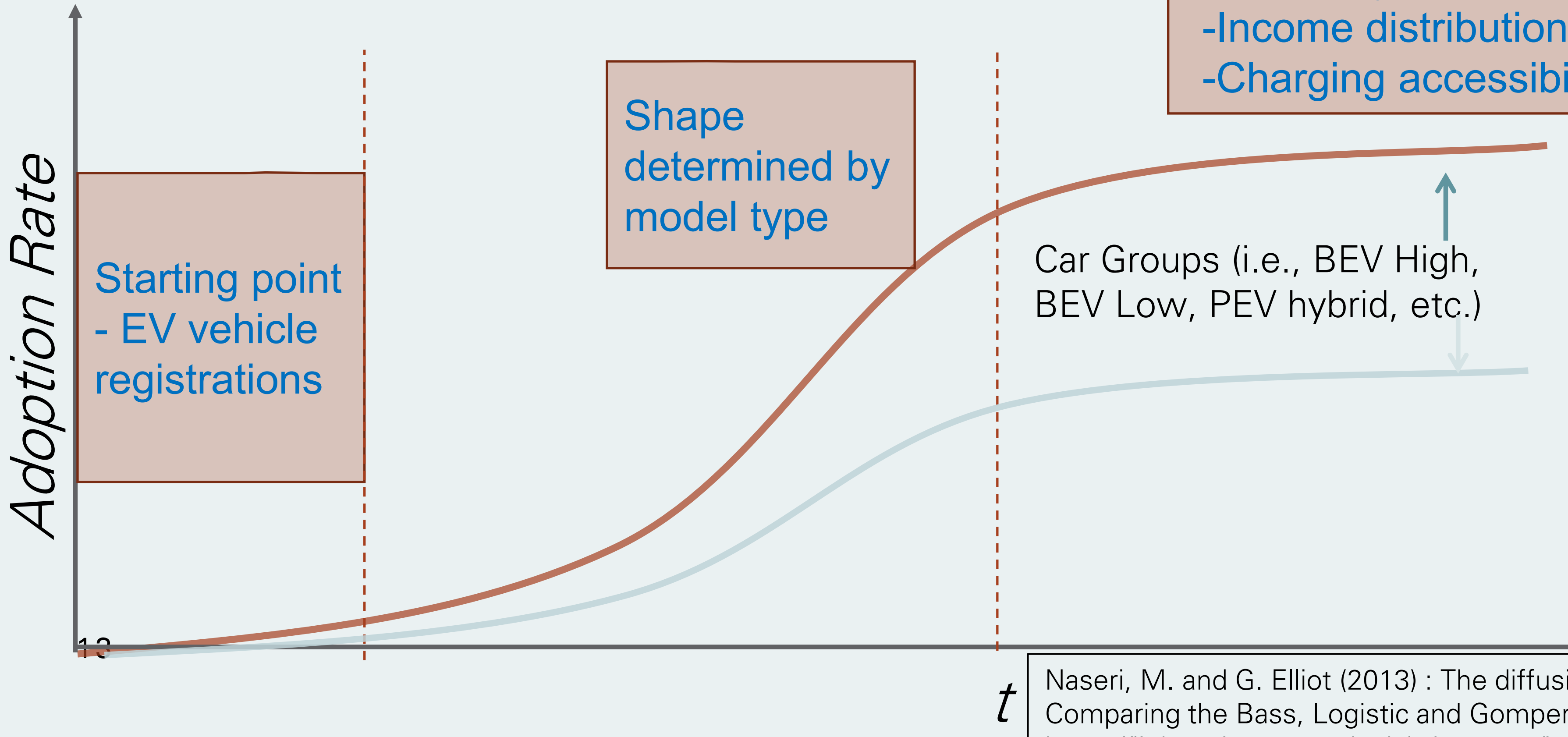
Method - Examples of Load Forecasts

Research Entity	EV Adoption Approach	Model Description
EPRI	eRoadMAP (meta-approach)	Uses historic registrations when available, along with forecasts from other reputable sources, proprietary data and market intelligence, and driving patterns to load forecasts
PG&E (in-house)	Propensity model	Uses a propensity model to drive the market potential component of an S-curve adoption model
SDG&E/EPRI	Blended approach : EPRI zip code-level forecasts, then disaggregates using their in-house model	Disaggregates zip code level forecasts based on socio-economic, demographic, education levels and time to work. Used internal EV load shapes to determine hourly forecasts
Hawaiian Electric/ Integral Analytics, Inc.	Blended approach: Bass aggregate modeling and agent-based modeling at customer-level	The EOT Roadmap, Appendix E states: "When past participation and locational information is available, these models can be trained to include socio-economic and peer-effects that contribute to adoption"; also examines utility incentives, rebates, tax credits, electric and gasoline prices
SCE/PNNL	Blended approach - aggregate Bass forecast with discrete choice disaggregation	Bass model driven by historic circuit level vehicle registrations. Discrete choice model disaggregation based on housing characteristics and socio-economic data

Methods – Ex. Diffusion Growth Models

- Also know as 'S' curve model
- Very simple or complex (multivariate)
- Start with the end-points
- Curve shape driven by the type of model – usually Bass, Logistic, Gompertz

Saturation points – somewhat deterministic
- Known no. of registrants and population growth rates
-Driven by state ZEV targets
-Income distributions
-Charging accessibility

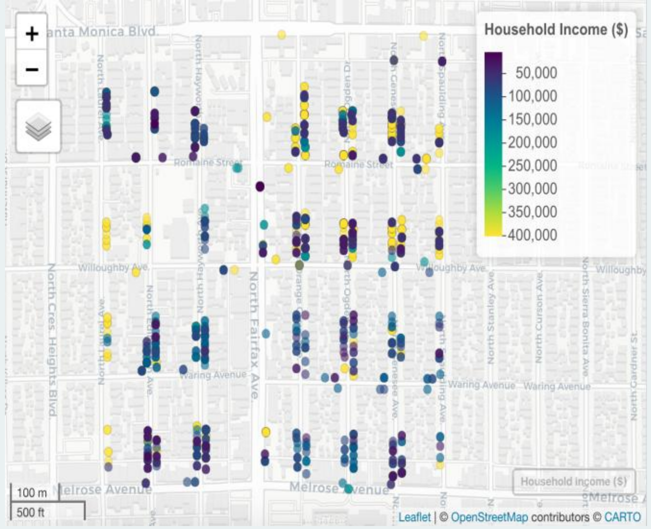


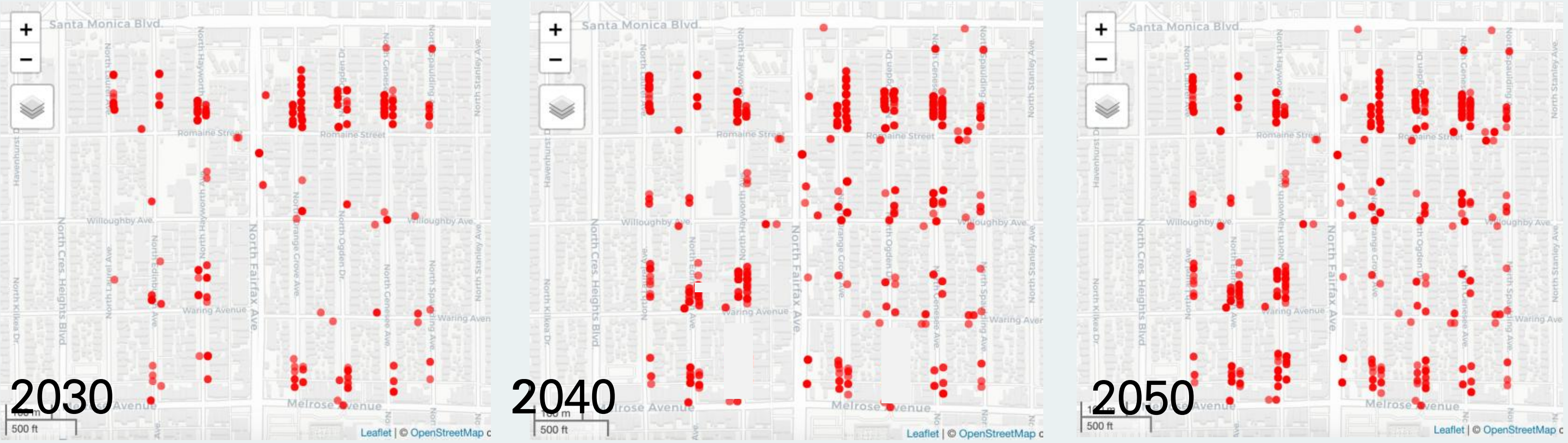
Scenarios:
Low – Bass model solves endogenously ("Normal" market activities)
Medium/High – ZEV goals according to state targets; high incentives; large investment in EVSE, etc.

Naseri, M. and G. Elliot (2013) : The diffusion of online shopping in Australia: Comparing the Bass, Logistic and Gompertz growth models." https://link.springer.com/article/10.1057/jma.2013.2

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

- Creates a household probability of adoption based on housing type and income. Then 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



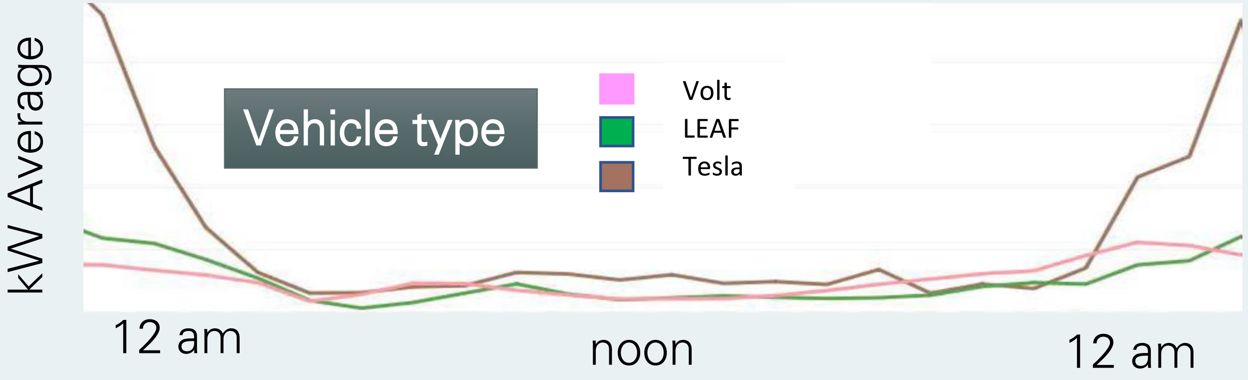


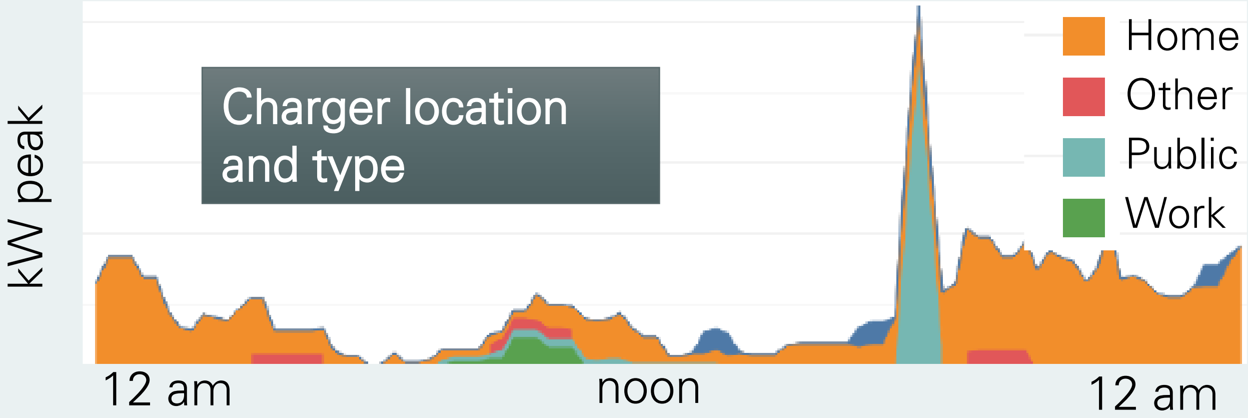
Kajanova, M. and P. Bracinik. (2021) "Definition of Discrete Choice Models of EV Owners Based on Difference Socio-Demographic Aspects." https://doi.org/10.3390/app11083679

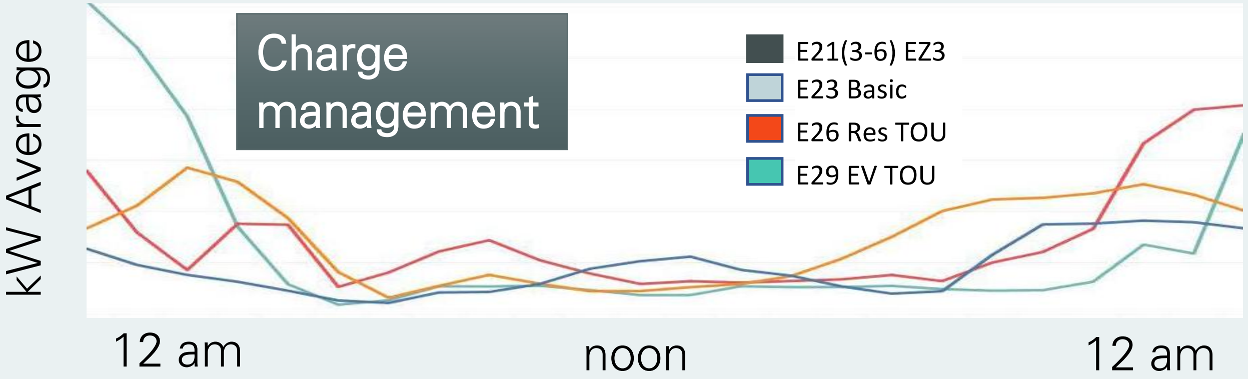
- **Indicates EV vehicle**

***simulation based on PNNL's work for SCE**

Methods – EV Charging







	kWh	kW
Volt	60-66	55 (max)
LEAF	24-62	50-100
Tesla S	75-100	100-250

Complex and evolving (Green car reports '24):
85% of EV drivers charge at home the majority of the time
- **56% still use public a few times a week**

45.4% - public or work charging frequency

Demand response (DR): compensation in exchange for voluntary energy consumption reduction in response to a request

Direct Charge Management (DCM) – technology-induced automatic energy reduction during peak events, again with compensation

Time-of-use (TOU): static but tranched by on/off-peaks; potentially seasonal

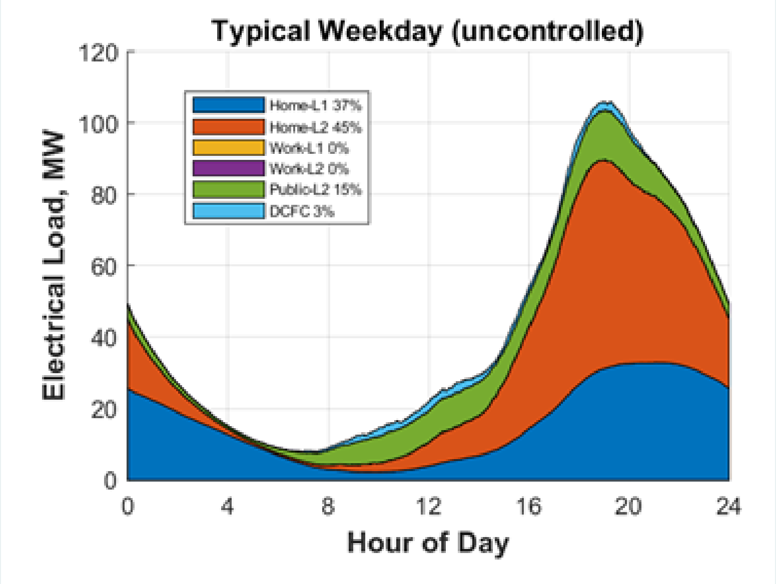
Dynamic pricing: Require more sophisticated systems that adjust based on real-time grid conditions

Images reproduced from EPRI http://mydocs.epri.com/docs/PublicMeetingMaterials/ee/000000003002013754.pdf

Method - Ex. Load Profile Estimation – Electric Vehicle Infrastructure Projection Tool (EVI-Pro)

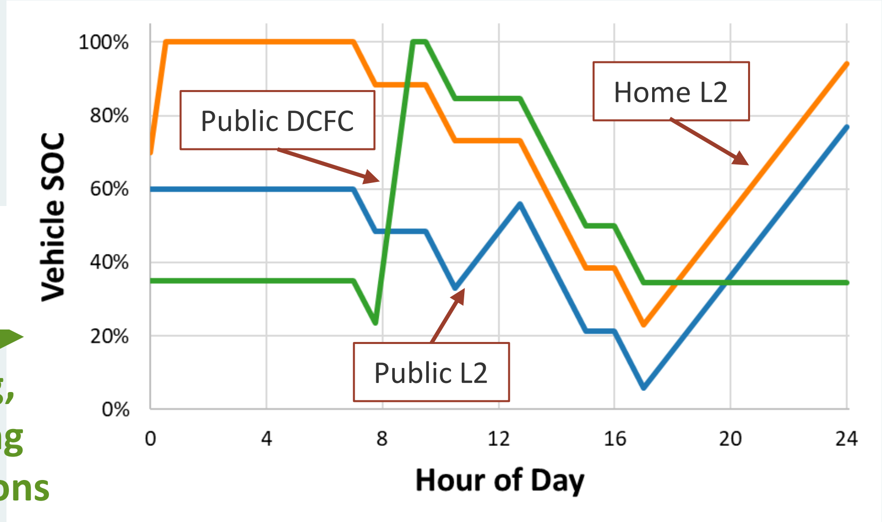
- The full model uses trip data and varying EV adoption levels to estimate charging demand, infrastructure requirements, and the resulting impact on the grid (user must enter # of vehicles)
- EVI-Pro Lite is a simplified web interface that can be used to get reasonable estimates of charging infrastructure 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



Insights and relevant questions for EV 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, i.e., adoption of hybrids and other DERs.
- For distribution level planning, socio-economics will impact adoption forecasts. Goal achievement may require specific incentives/rates.
- Segment commercial and residential to capture major differences, i.e., how far are EV owners driving? How much do they need to charge?
- Where and when are they charging: home, work, public? How powerful are the chargers (level 1, 2, or 3)?
- Is there adequate EVSE to accommodate EV growth in densely populated areas? If not, adoption may lag.
- Will charge management be in place?
- Is there an incentive program?

Limitations on ability to forecast load

- Data availability
- 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

Key takeaways

- Gather data now:
  - At the very least, estimate the total vehicle stock to know what the end goal (electricity consumption) looks like – transitioning vehicle types and potential battery capacities
  - Know the barriers to commercial and industrial investment in EV and charging infrastructure to better understand their rates of adoption
- For aggregate stock modeling, diffusion models offer a simple solution
- If resources are limited, segment your analysis by focusing on areas with the greatest hosting capacity constraints with the greatest amount of ‘untransitioned’ vehicle stock
- Charge management will be critical for grid health
  - V2G and EV aggregation may be important topics in the near future.

Buildings

Sean Murphy (LBNL)

Content

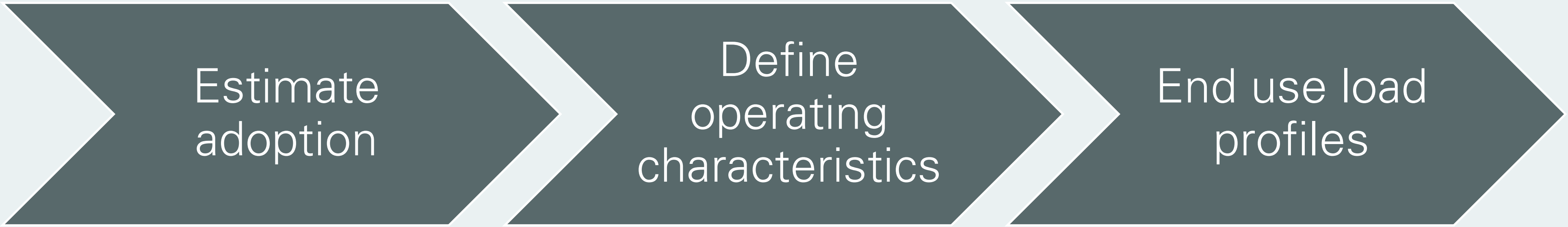
- Motivations
- Methods
- Dealing with uncertainty
- Applying forecasts
- Key takeaways

Motivation

- Utilities are planning for increasing building loads that result from the adoption of new technologies such as heat pumps
  - Consumer preferences and state programs drive adoption

- There is uncertainty in the:
  - Timing and magnitude of adoption
  - Timing and magnitude of loads for each adopted technology
  - Methods and data that utilities can use to incorporate load expansion into forecasts

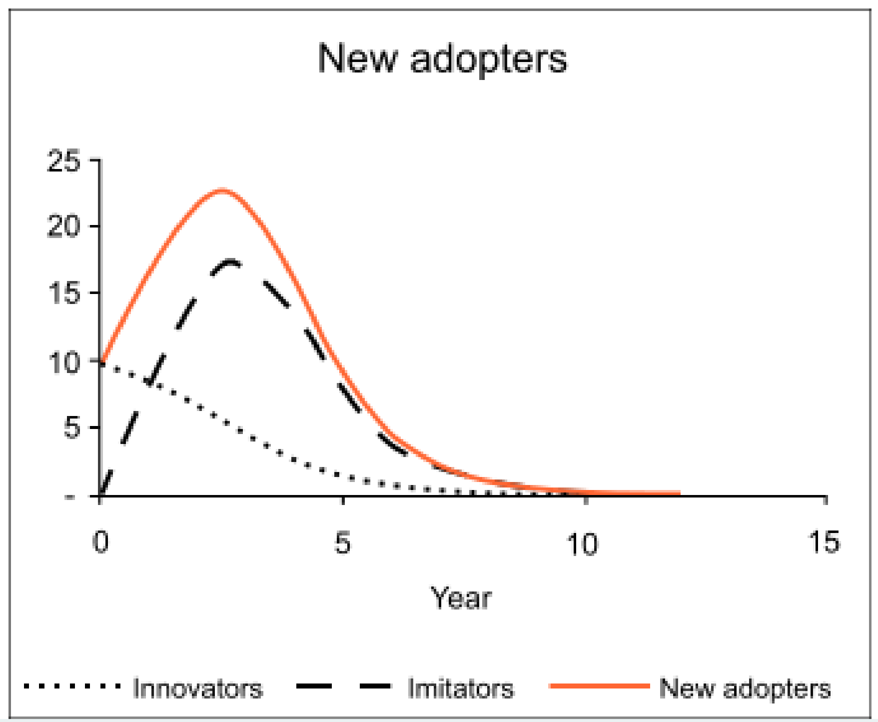
Methods - overview



Methods – estimating adoption (1)

- Utilities can estimate *system-wide* adoption of new building loads based on:
  - State targets or requirements
  - Expected consumer uptake (e.g. Bass diffusion model)

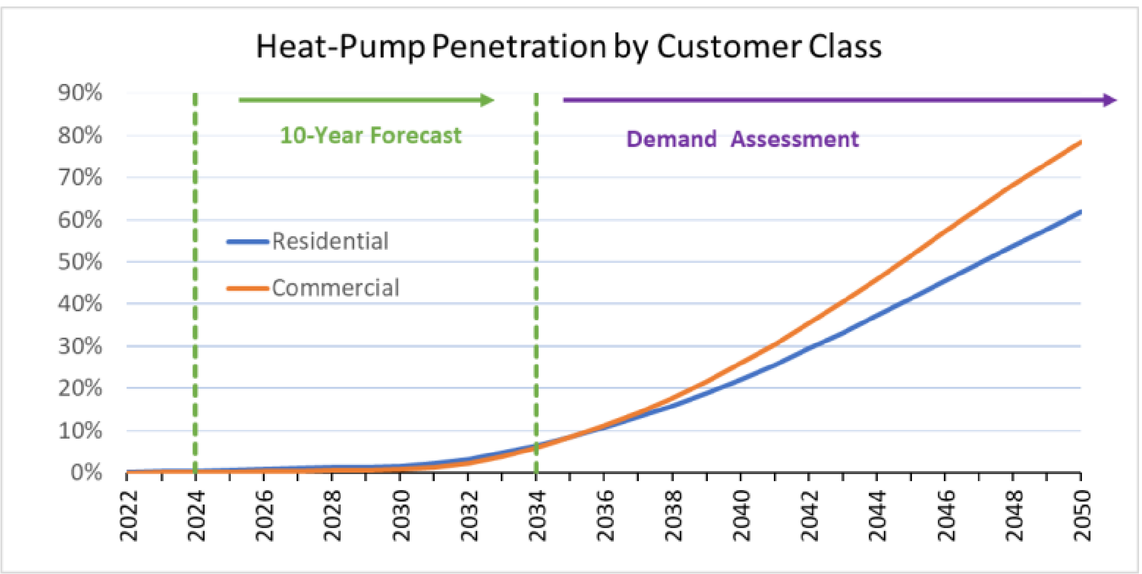
- Utilities can estimate *feeder-level* adoption by allocating system-wide adoption to feeders based on:
  - Number of customers or load on a feeder proportional to systemwide values
  - Propensity models that predict the likelihood of adoption within the feeder



Source: Christopher Berry

Methods – estimating adoption (2)

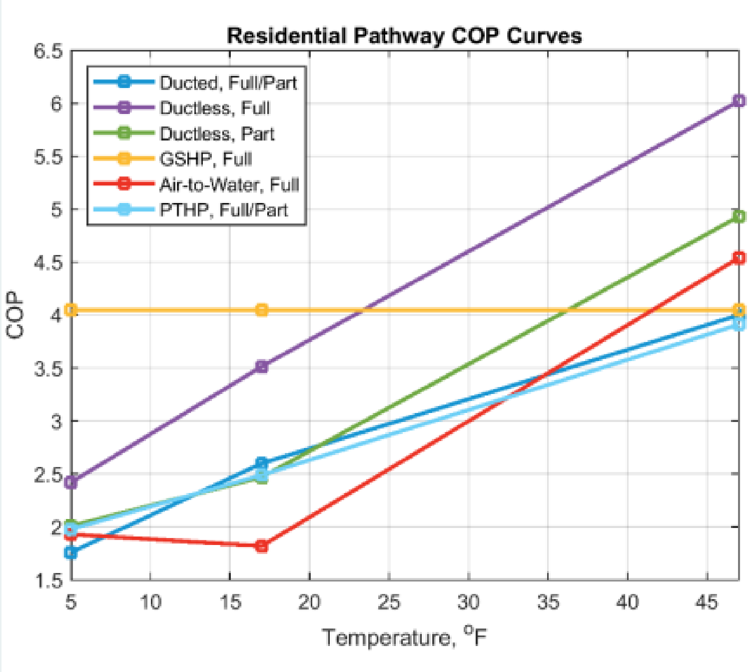
- National Grid New York estimates heat pump adoption at the *system-level* based on retrofits planned through 2030 in its demand-side programs and state-level targets from 2031-2050
- The utility allocates system-level adoption to *feeders based on:*
  - Assuming historical heat pump trends continue through in the short-run (2025-2027)
  - A propensity model that relates heat pump adoption to socio-economic variables from the Census in the medium-term (2028-2040)
  - Achievement of state targets evenly across feeders in the long-run (2041-2050)



Source: National Grid New York

Methods – operating characteristics (1)

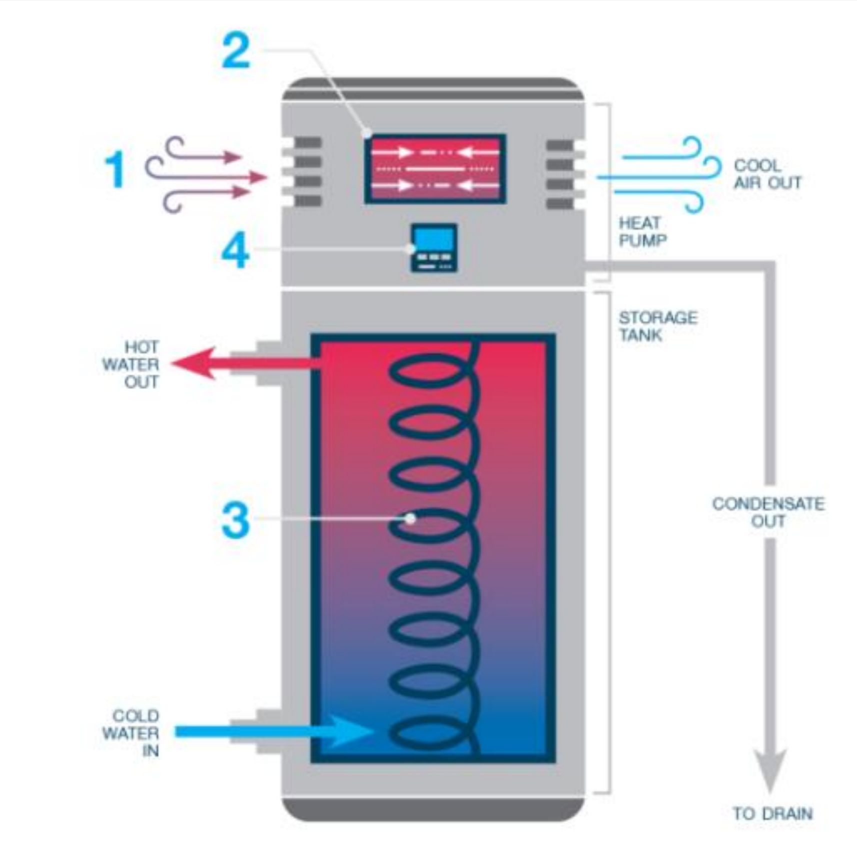
- Assumptions on how *adopted technologies operate* can impact building load forecasts
- Heat pump load profiles depends on the assumed:
  - Type of heat pumps adopted
    - Air-source vs. ground-source
    - Cold-climate
    - Ducted vs ductless
  - Coefficient of performance (COP)
    - Performance of air-source heat pumps declines as ambient temperature falls
  - Retention of back-up heating systems
    - Building can retain existing heating system for the coldest days or install electric-resistance heating that operates when heat pump compressor performance declines
  - Weather conditions
    - Eversource Massachusetts estimates peak load at -5^{0}F design day



Source: ISO-New England

Methods – operating characteristics (2)

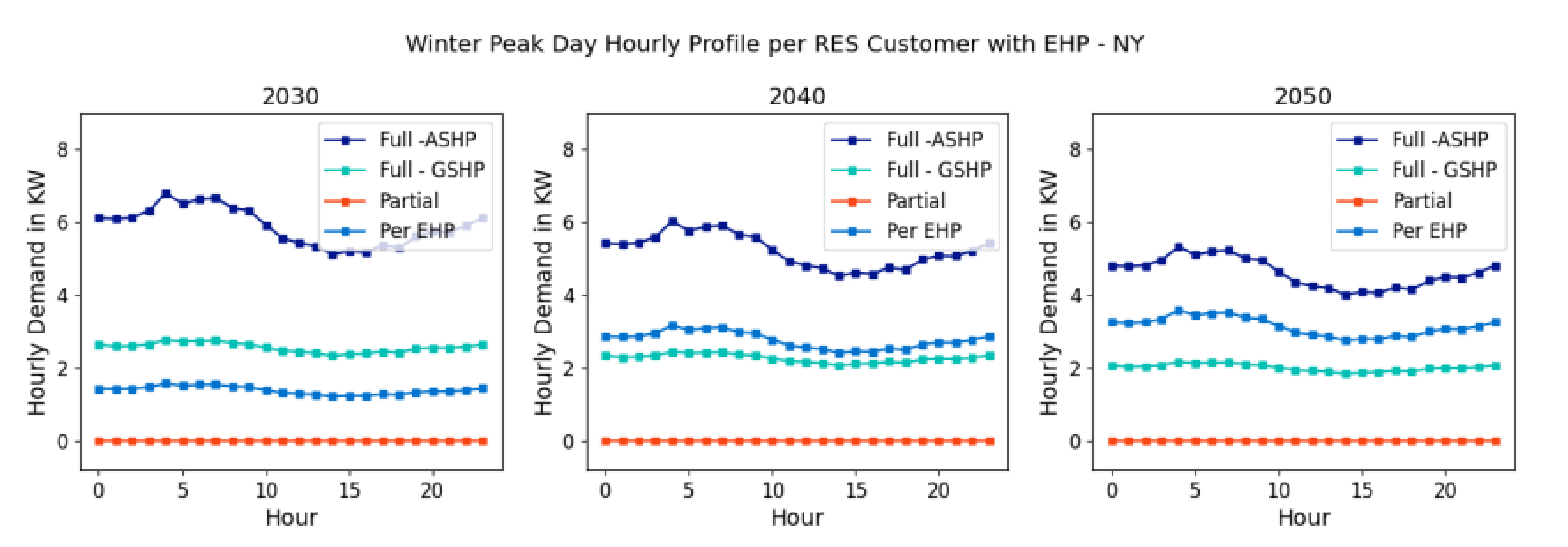
- Heat pump water heater load profiles can:
  - Depend on the assumed installation location
    - COPs will not change much if space is conditioned
    - ISO-NE assumes that heat pump water heaters are installed in conditioned or semi-conditioned paces
  - Impact heat pump load by using air conditioned by the heat pump
    - ISO-NE assumes that heat pump water heaters increase heat pump load by 1.2%



Source: New Buildings Institute

Methods – end use load profiles

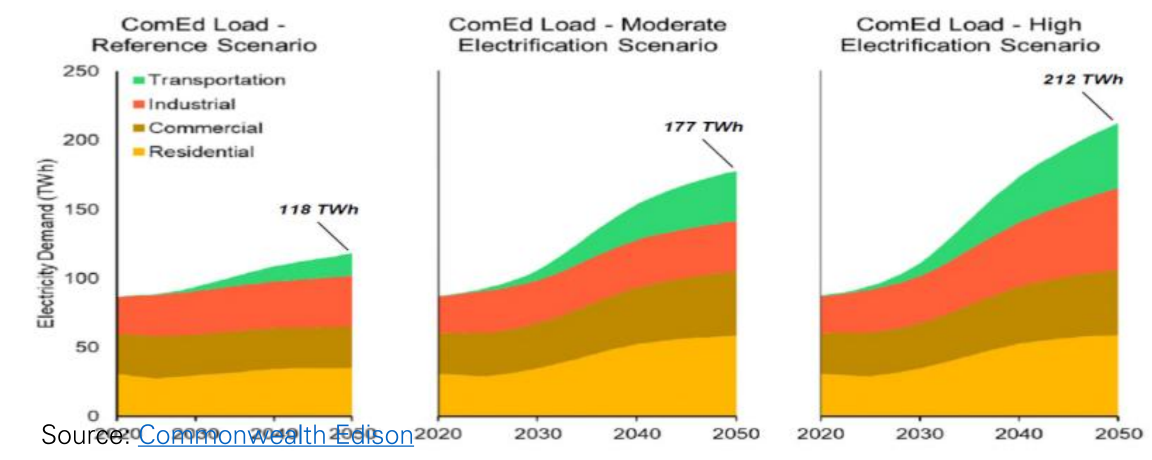
- Utilities can account for the hourly load impacts of heat pumps (and other equipment added to buildings) using end use load profiles that are *modeled* or *empirical*
  - ResStock and ComStock are the most common modeled load shapes used in load forecasts
  - Utilities also can use metered data from buildings for forecasting or for validating modeled data



Source: National Grid New York

Managing uncertainty

- Utilities can use *scenario analysis* and probabilistic methods to manage uncertainty in:
  - The timing and magnitude of adoption of technologies that increase building loads
  - Weather-dependent loads
- Commonwealth Edison considers discrete scenarios of building load growth that differ in assumed levels of heat pumps
- National Grid New York considers the probability of different DER adoption scenarios in its feeder-level forecasts
  - Probabilistic forecast that reflects likely outcomes
  - There may be uncertainty in the probability of scenarios

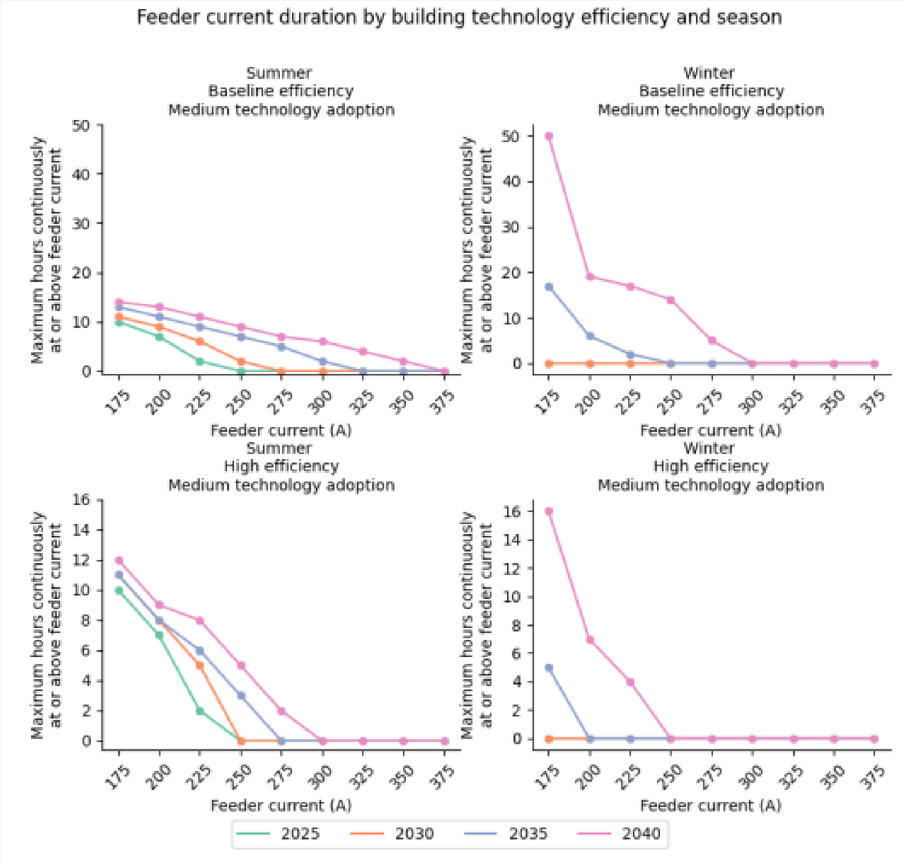


Source: Commonwealth Edison

Applying forecasts (1)

- Utilities can use load forecasts that account for building load growth to estimate *thermal risks* in distribution system infrastructure

- For Fort Collins Utilities, Berkeley Lab:
    - Estimated how long load would stay at high levels under different load growth scenarios
    - Determined whether any feeder design thresholds were violated

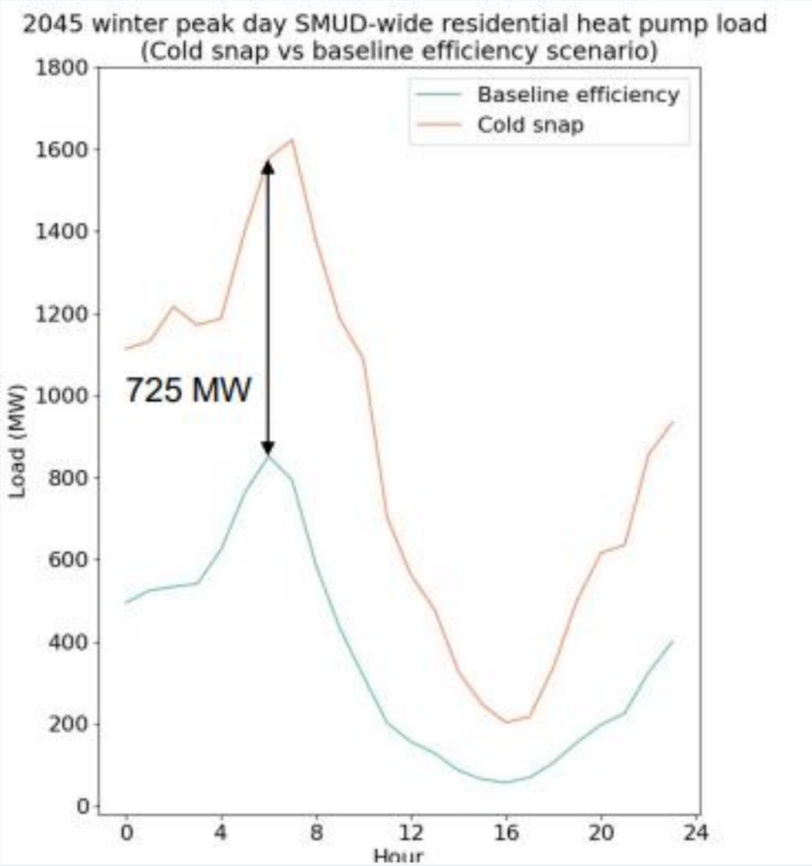


Source: Berkeley Lab

Applying forecasts (2)

- Utilities can use load forecasts that account for building load growth to estimate the *peak demand impacts of extreme weather*

- Berkeley Labestimated increases in peak demand from reductions in heat pump efficiency during a cold snap for the Sacramento Municipal Utility District
  - Peak demand estimates inform resource adequacy planning



Source: Berkeley Lab

Key takeaways

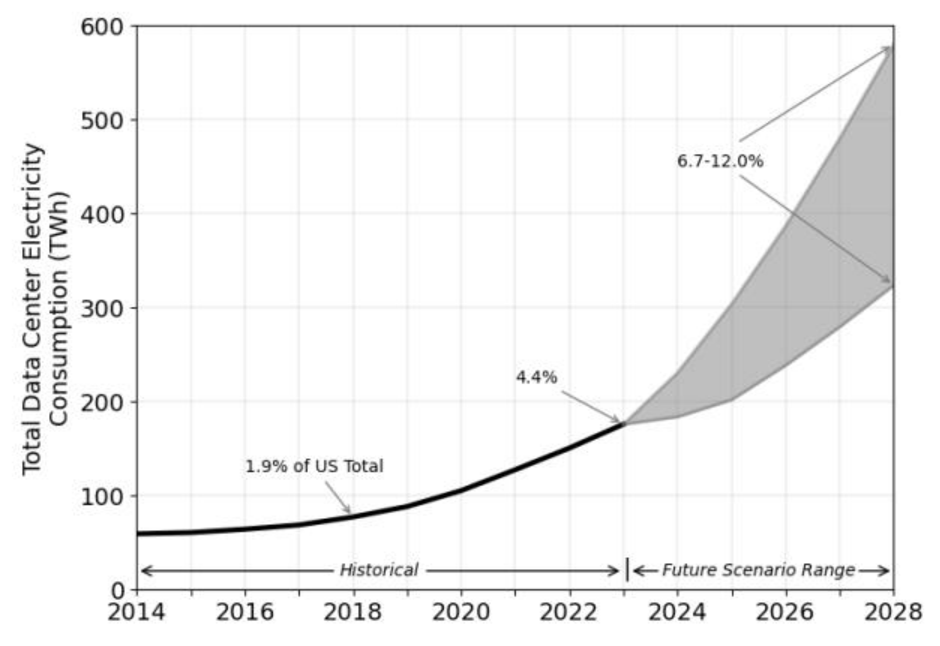
- Utilities can account for building load growth in both system-wide and distribution-level forecasts
- Key modeling decisions include the:
  - Timing and magnitude of technology adoption
  - Type and operational characteristics of technology adopted
- Utilities can manage uncertainty in building load growth forecasts with scenario analysis and probabilistic methods
- Utilities can apply building load growth forecasts to address utility planning needs

Large loads

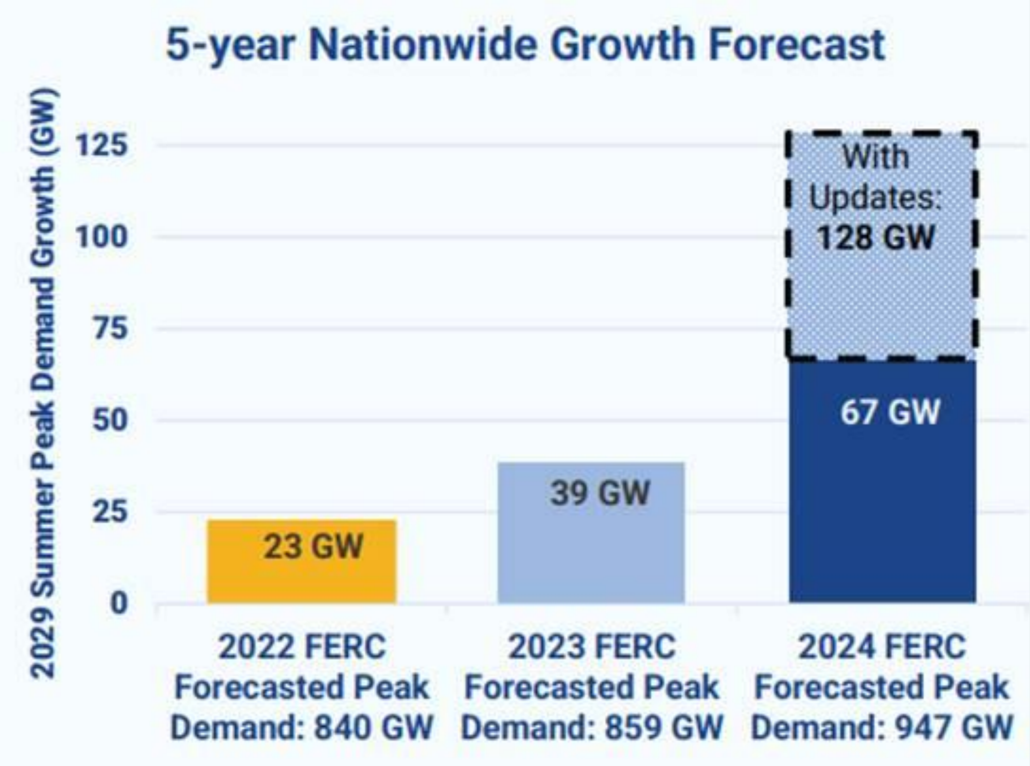
Juan Pablo “JP” Carvallo (LBNL)

Unprecedented U.S. load growth → $0.8-$1.6 trillion in investments

- Historically, IRP used high/low scenarios with small single digit spreads (±1-3% compound growth)
- Now, rate of growth is unprecedented, but also uncertain

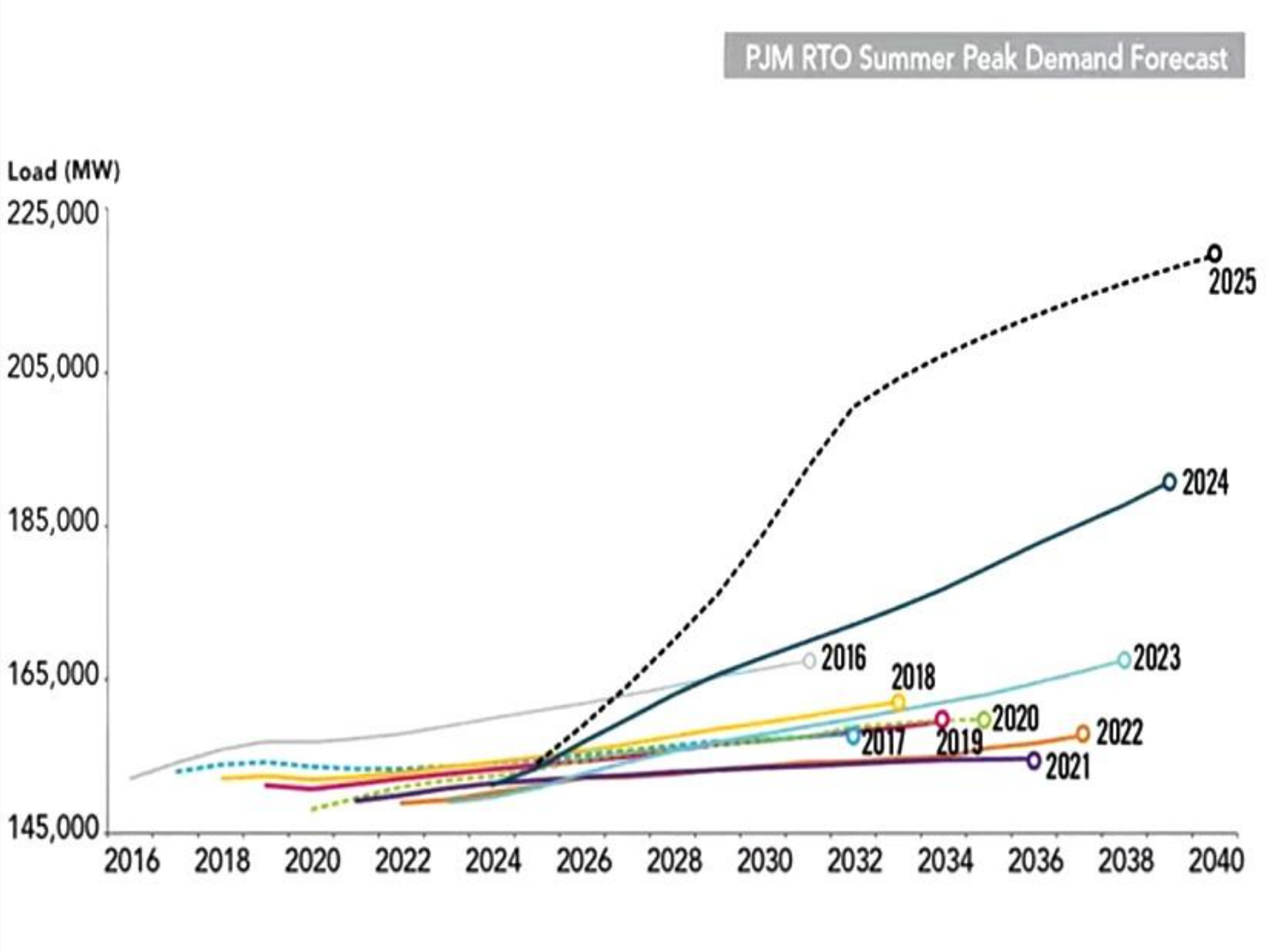


Source: LBNL. 2024 United States Data Center Energy Usage Report



Source: GridStrategies (2024). Strategic Industries Surging: Driving US Power Demand

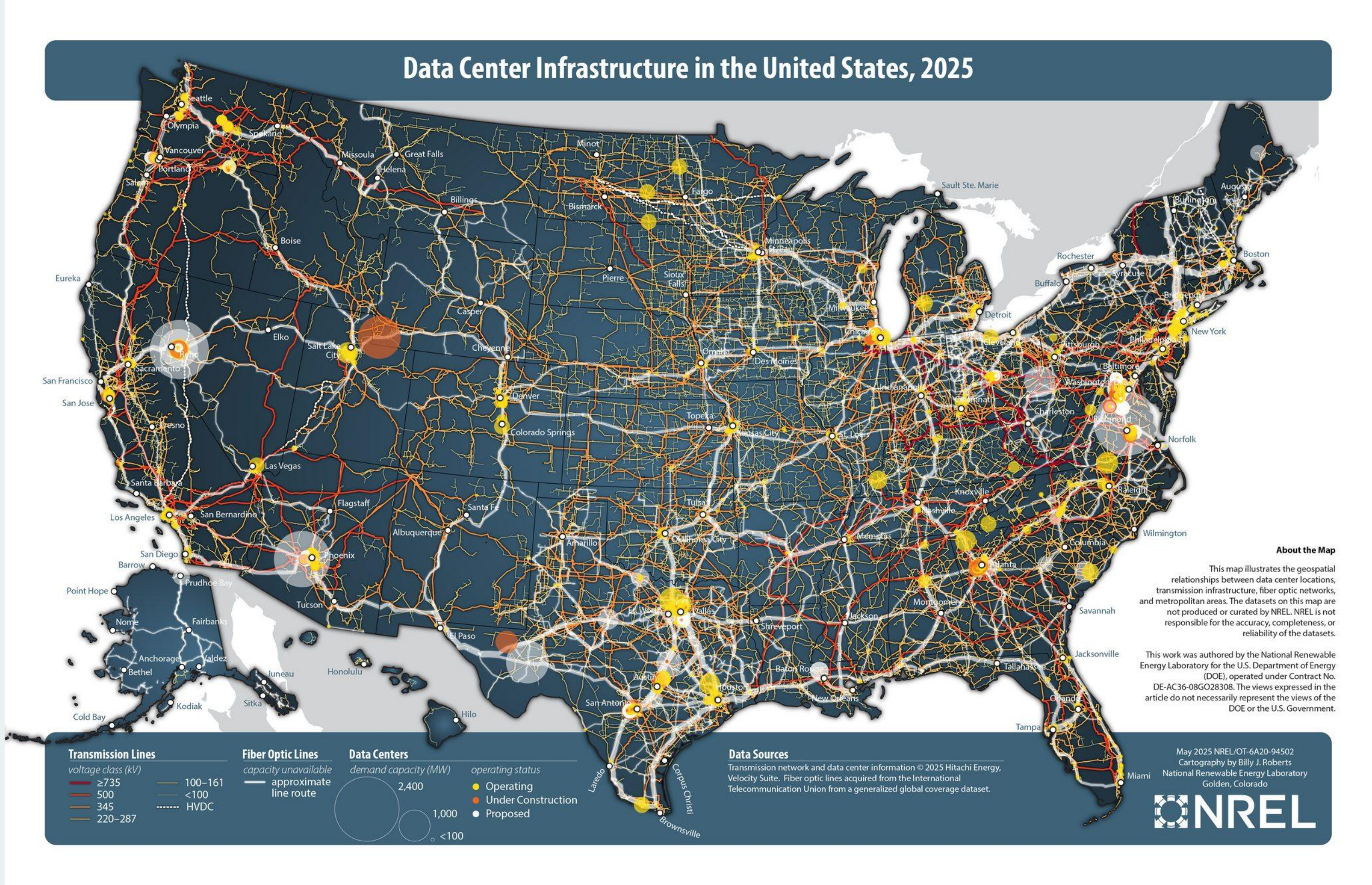
Near-term load growth in perspective: PJM



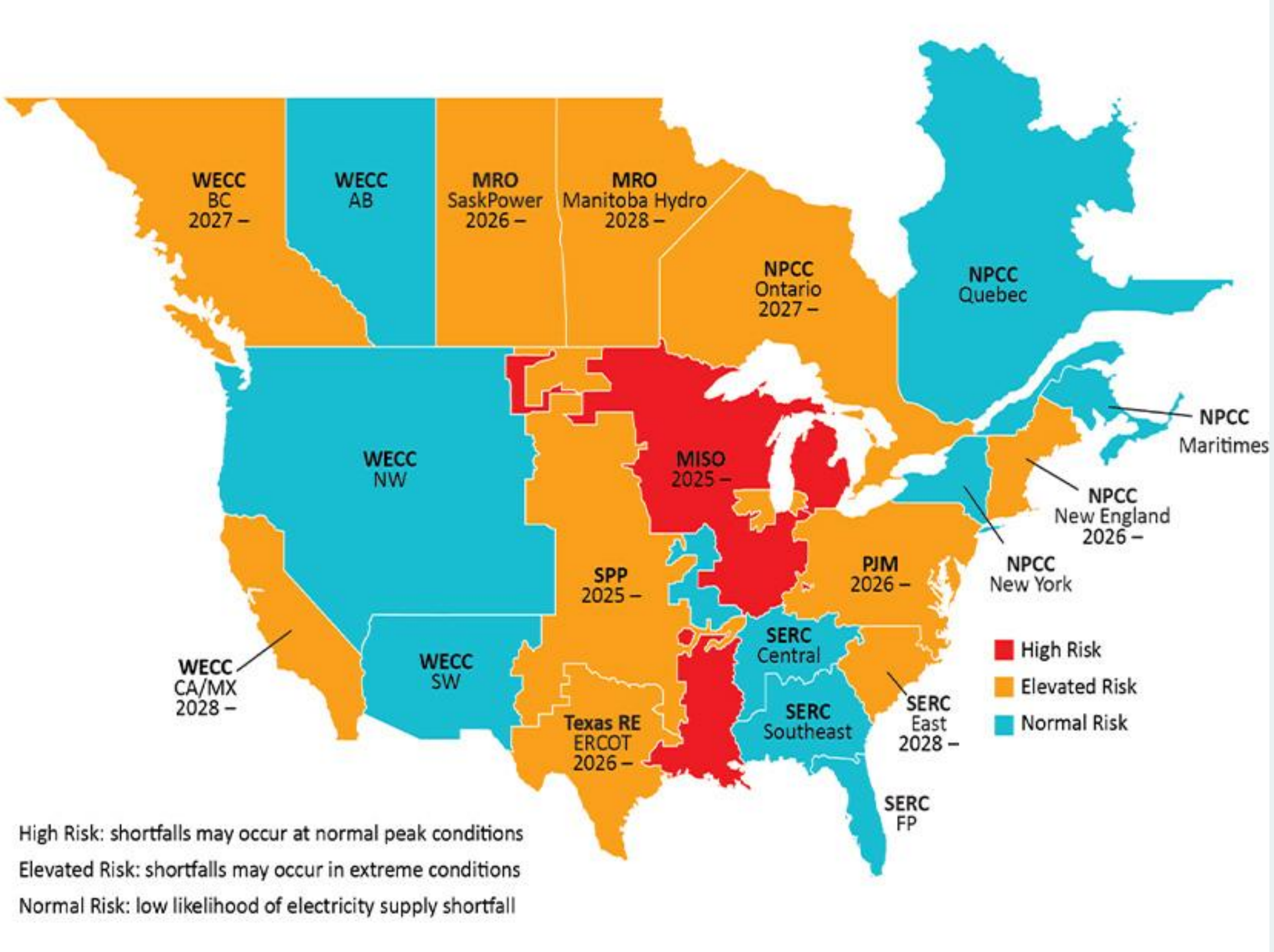
Source: [RTO Insider (2025)]

Growth rate and location

- Large loads such as data centers may have several prospective interconnection points
- For large transmission systems (certainly for RTOs/ISOs) this can be an additional source of uncertainty
- Addressing spatial/ locational uncertainty has not been a core aspect of planning



Load growth inducing higher risk



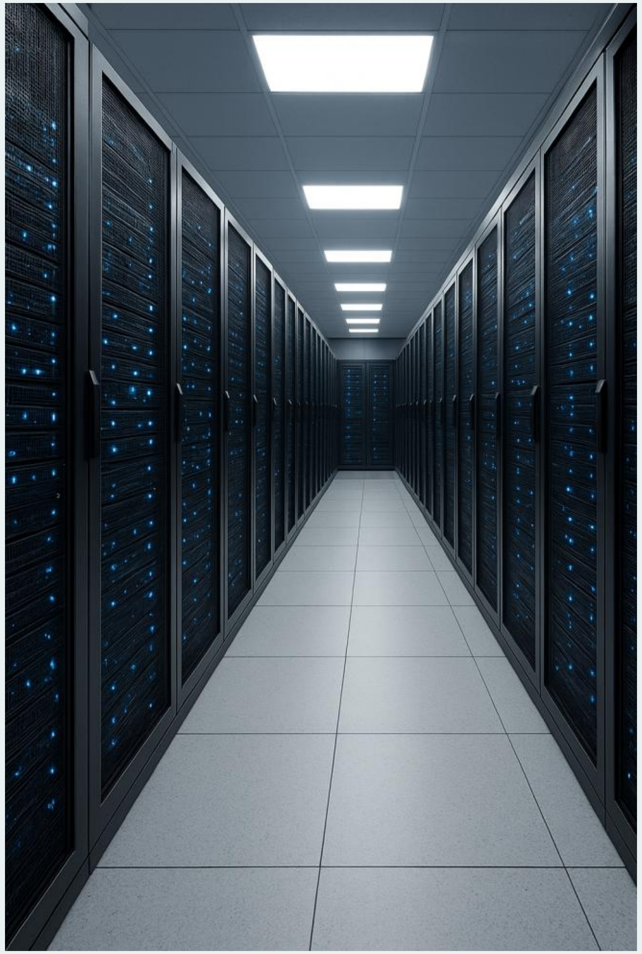
Source: [NERC LTRA (2024)]

Large load forecast approaches

Reduce speculation → Shape the forecast → Quantify growth

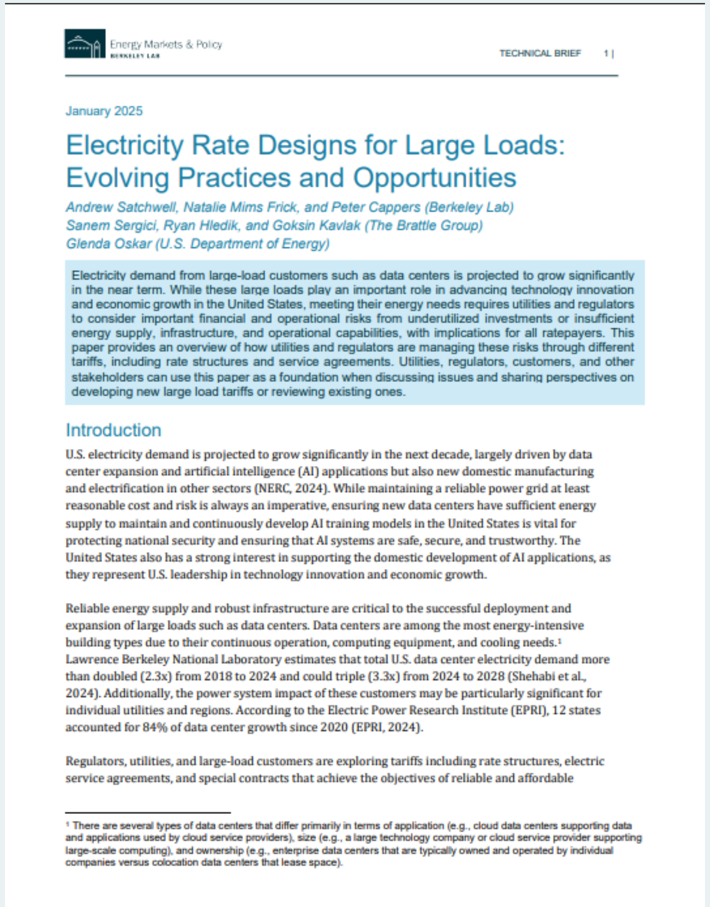
Large loads: speculation vs forecast

- Example: Same data center shops for different interconnection points depending on locational marginal prices, enhanced reliability, availability of transmission, and availability of other infrastructure
- Speculation can be reduced by improving information exchange between the utility/ISO/RTO and load
    - Criteria can be developed to determine whether potential large loads are appropriate to be included in a load forecast
- Example: Texas SB 6 (2025) requires:
    - An interconnection study fee of at least $100k
    - Demonstrated control of the site for data center development
    - A net-metering arrangement when co-locating with existing generator
    - Participation in contingency events via load shedding and backup generator dispatch, enabled by a reliability service to procure demand reductions
    - Disclosure of duplicative interconnection requests in the state
- Large loads can remain uncertain after application of criteria for load forecasting and tariff prescriptions.



Large loads: tariffs as a forecast driver

- Tariffs for large loads are predominantly focused on cost allocation and managing the risk of stranded utility assets
- Tariffs also can be useful for prescribing certain characteristics of large loads, such as their deployment timing, speed, and load shape to reduce load forecast uncertainty
- Examples
  - Minimum load size requirement characterizes what loads will be treated as large (NV Energy, Entergy MS)
  - Ramping conditions for load increase (Xcel Energy MN)
  - Obligations to buy energy and/or capacity (OH Power's Data Center Tariff) or conditions to reduce load within prescribed time (Indiana Michigan Power)
  - Requiring minimum load factors (85% in Montana-Dakota Utilities' High Density Contracted DR Rate)
  - Contract duration (NV Energy, I&M Power)
  - Ramp times (Ohio Power prescribed minimum % of contract capacity for the first four years)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TECHNICAL BRIEF 1 |

January 2025

Electricity Rate Designs for Large Loads: Evolving Practices and Opportunities

Andrew Satchwell, Natalie Mims Frick, and Peter Cappers (Berkeley Lab)
Sanem Sergici, Ryan Hledik, and Goksin Kavlak (The Brattle Group)
Glenda Oskar (U.S. Department of Energy)

Electricity demand from large-load customers such as data centers is projected to grow significantly in the near term. While these large loads play an important role in advancing technology innovation and economic growth in the United States, meeting their energy needs requires utilities and regulators to consider important financial and operational risks from underutilized investments or insufficient energy supply, infrastructure, and operational capabilities, with implications for all ratepayers. This paper provides an overview of how utilities and regulators are managing these risks through different tariffs, including rate structures and service agreements. Utilities, regulators, customers, and other stakeholders can use this paper as a foundation when discussing issues and sharing perspectives on developing new large load tariffs or reviewing existing ones.

Introduction

U.S. electricity demand is projected to grow significantly in the next decade, largely driven by data center expansion and artificial intelligence (AI) applications but also new domestic manufacturing and electrification in other sectors (NERC, 2024). While maintaining a reliable power grid at least reasonable cost and risk is always an imperative, ensuring new data centers have sufficient energy supply to maintain and continuously develop AI training models in the United States is vital for protecting national security and ensuring that AI systems are safe, secure, and trustworthy. The United States also has a strong interest in supporting the domestic development of AI applications, as they represent U.S. leadership in technology innovation and economic growth.

Reliable energy supply and robust infrastructure are critical to the successful deployment and expansion of large loads such as data centers. Data centers are among the most energy-intensive building types due to their continuous operation, computing equipment, and cooling needs.[1] Lawrence Berkeley National Laboratory estimates that total U.S. data center electricity demand more than doubled (2.3x) from 2018 to 2024 and could triple (3.3x) from 2024 to 2028 (Shehabi et al., 2024). Additionally, the power system impact of these customers may be particularly significant for individual utilities and regions. According to the Electric Power Research Institute (EPRI), 12 states accounted for 84% of data center growth since 2020 (EPRI, 2024).

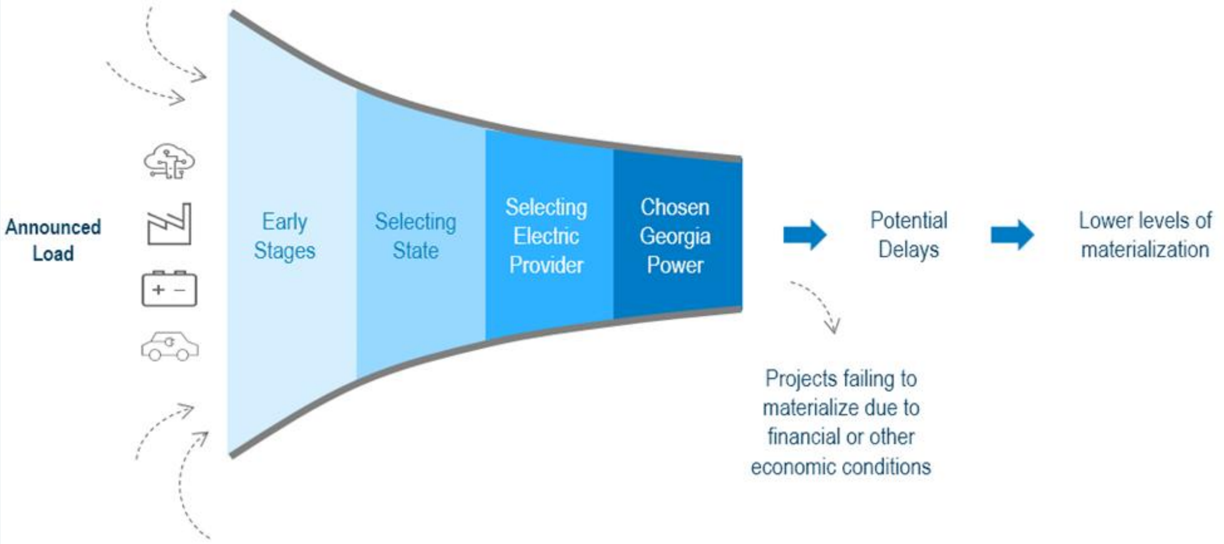
Regulators, utilities, and large-load customers are exploring tariffs including rate structures, electric service agreements, and special contracts that achieve the objectives of reliable and affordable

[1] There are several types of data centers that differ primarily in terms of application (e.g., cloud data centers supporting data and applications used by cloud service providers), size (e.g., a large technology company or cloud service provider supporting large-scale computing), and ownership (e.g., enterprise data centers that are typically owned and operated by individual companies versus colocation data centers that lease space).

Available here

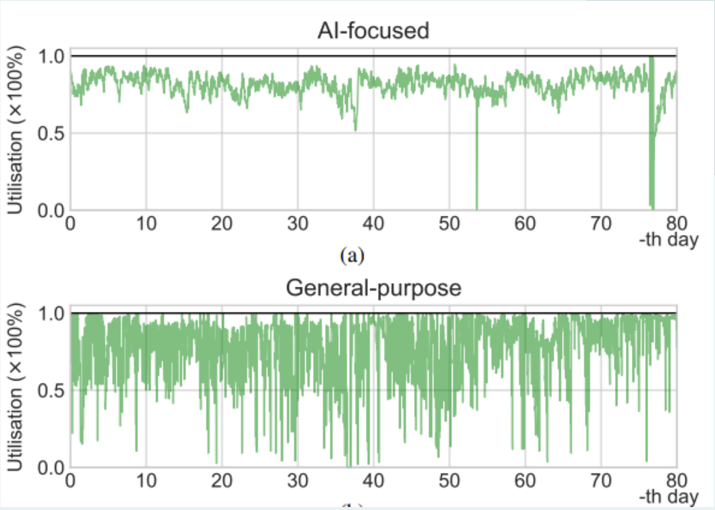
Large loads: Probabilistic modeling

- Utilities may want to quantify uncertainty in other ways.
- Example: Georgia Power's Load Realization Model (developed for the 2023 IRP Update and used in its [2025 IRP])
    - Model makes no assumption about speculation and tariff impacts, in part because it covers all large loads (crypto, data center, warehouse, miscellaneous, and distribution center)
    - Define three binary variables that describe the likelihood of:
        - Data center choosing to locate in Georgia Power's territory
        - Georgia Power serving as the electricity supplier
        - The project reaching commercial operation
    - Multiplying these three variables yields the joint probability of data center deployment success
    - The model also simulates a stochastic difference between the announced vs. the metered load once the data center is deployed, based on a triangular distribution
        - Calibration values (redacted) are individually developed for five types of large loads

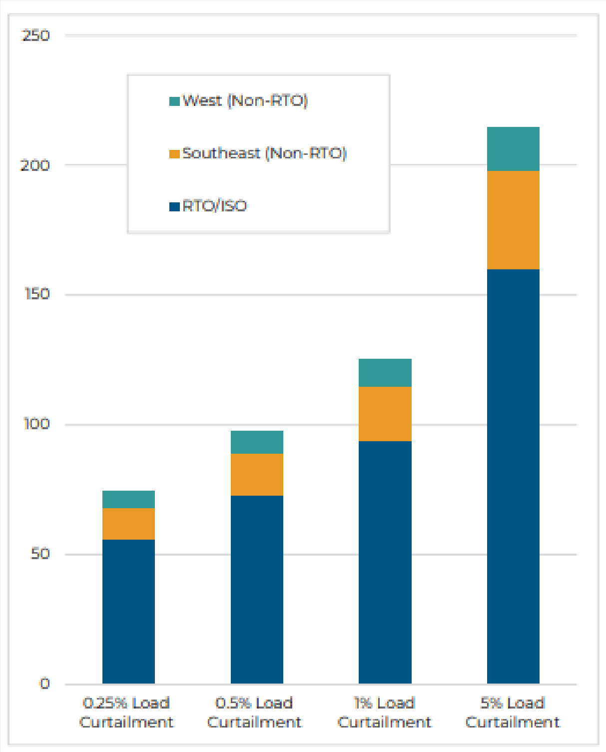


Shaping data center load

- Datacenters are largely not baseload
  - Only certain data center operations have high utilization rates
  - Average utilization rates vary widely from 20% up to 85%
- Flexibility in DC
  - Curtailing 1% of DC load could free up over 130 GW or about 15%-20% of peak needs
  - How to bring these into load forecasts
    - As a resource by bidding flexibility into capacity markets or incorporating into capacity expansion model
    - As a load modifier by the load serving entity



Data center utilization rate by type (Zhou et al (2024))



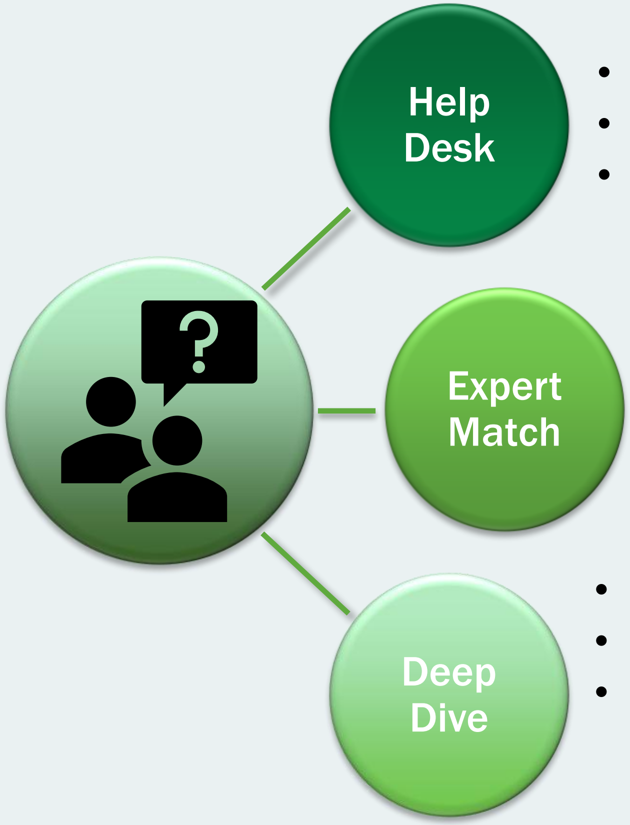
Headroom from DC curtailment (Norris et al (2025))

Key takeaways

- Load growth from large loads is unprecedented
- Three steps for large load forecast
  - Bound the uncertainty and reduce speculation
  - Use rates, flexibility, and statutes to condition load realization
  - Implement probabilistic (or scenario based models) to estimate likelihood of load growth levels
- Data center (and most large loads) demand can be shaped

DOE-funded Resources and Assistance for State Energy Offices and Regulators Program

https://StateTAProgram.lbl.gov



Help Desk

- Online intake form w/ rolling review
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Expert Match

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- Intake form and support available now

Deep Dive

- Detailed application form in planned ~6-month cycle
- Team of SMEs provide **100+ person-hours of support**
- Detailed online application available soon

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