Developing Forecasts - General Overview

Allison Campbell (PNNL), JP Carvallo (LBNL), and Brittany Tarufelli (PNNL)

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BERKELEY LAB

NREL

Pacific Northwest
NATIONAL LABORATORY

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The authors are solely responsible for any omissions or errors contained herein.

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 & Eran Schweitzer (PNNL)
2) Developing Forecasts - General Overview
    - **October 23, 4-5 p.m. Eastern**
    - Brittany Tarufelli & Allison Campbell (PNNL) and J.P. Carvallo (LBNL)
3) Developing Forecasts – Load Expansion
    - **October 29, 4-5 p.m. Eastern**
    - Sean Murphy & J.P. Carvallo (LBNL) and Christine Holland (PNNL)
4) Developing Forecasts – Distributed Energy Resources
    - **November 6, 2-3 p.m. Eastern**
    - Sean Murphy & Margaret Pigman (LBNL) and Shibani Ghosh (NREL)

Webinar Series Overview

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

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

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

Developing Forecasts – General Overview

- Our objective is to demystify basic forecasting methods, their application at both the bulk-power system and distribution system levels, and how they feed into utility decision making.
- Overview:
  - Introduction to electricity forecasting (Allison Campbell)
  - Distribution system vs. bulk power system forecasts (JP Carvallo)
  - Best practices and how forecasts feed into utility decisions (Brittany Tarufelli)

Introduction to Electricity Forecasting

Allison Campbell (PNNL)

What are the components to an electricity forecast?

Inputs

- Spatial Aggregation
- Time Frame
- Variables
- Forecast Purpose
- Algorithm/Method

Methods

- Time Series (Econometric)
- Multiple linear regression
- Bottom-up engineering/physics based
- Adjustments to forecast for specific end uses
- Probabilistic/Scenario-based

Outputs

- Annual Energy (kWh)
- Peak Demand (MW)
- Hourly Load Profiles

Electricity Forecast Inputs

What is the **spatial aggregation**?	Balancing Authority, Customer Class (Residential & Commercial, Industrial), 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?	Temperature Time cycles Demography Economics
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?

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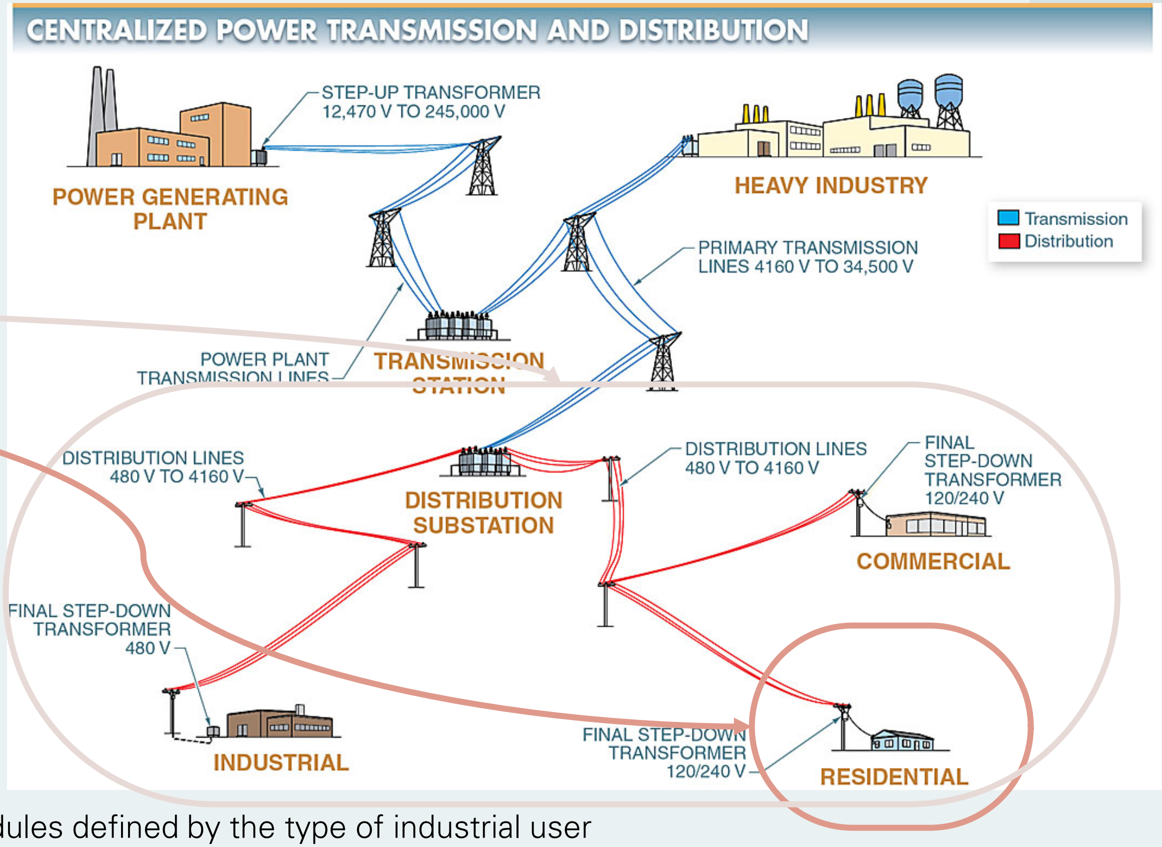
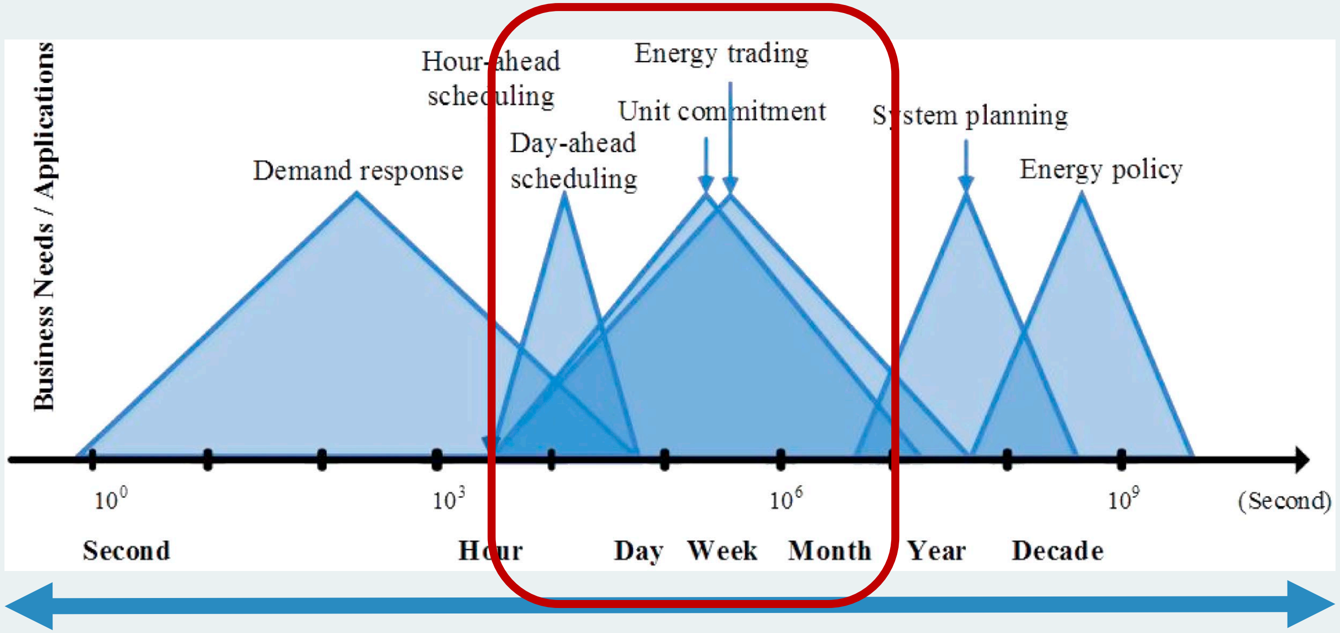
Spatial Aggregation



- 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/

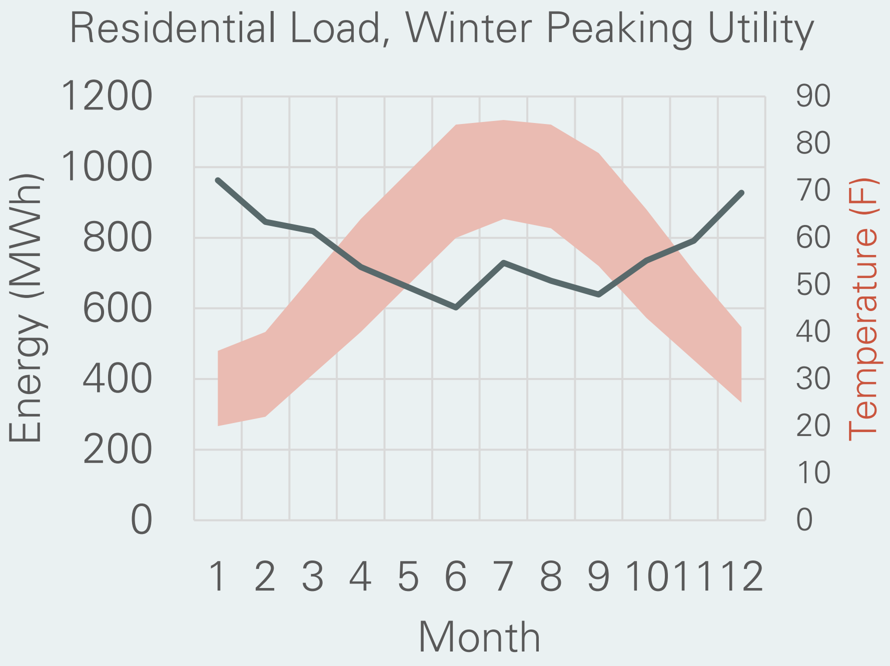
Time Frame: Short Term



- bottom-up
- stochastic
- physics-based

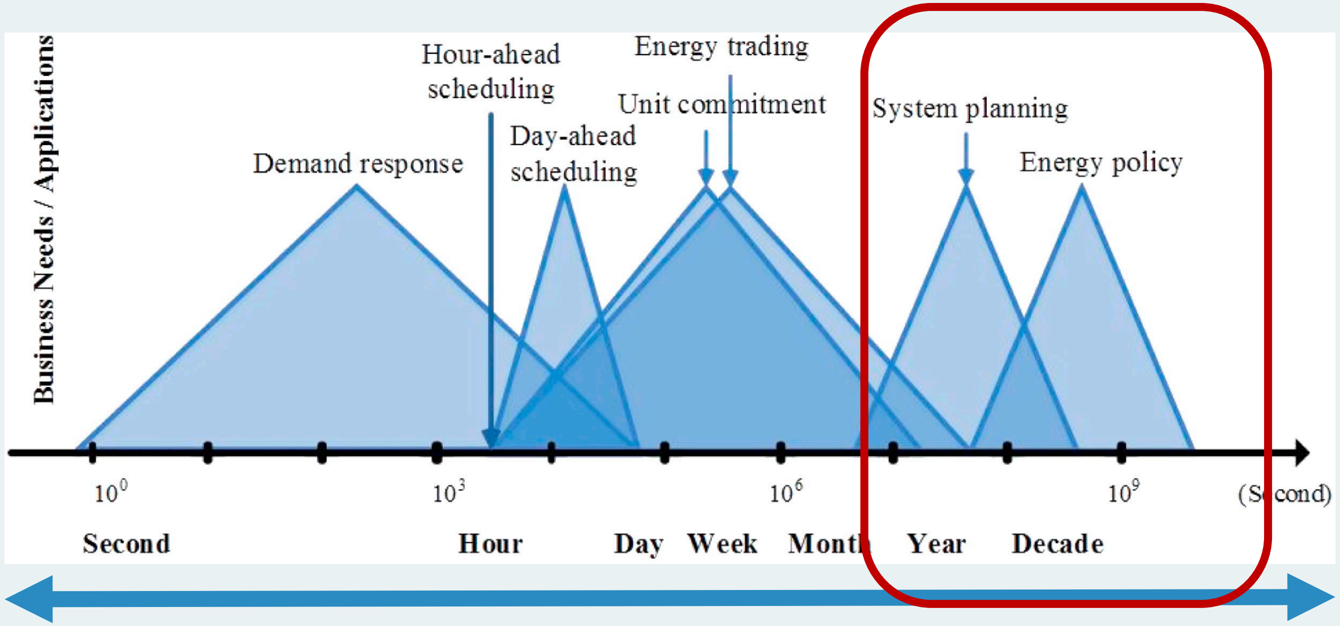
- top-down
- overall trend
- economics-based

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



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.

Time Frame: Long Term



- bottom-up
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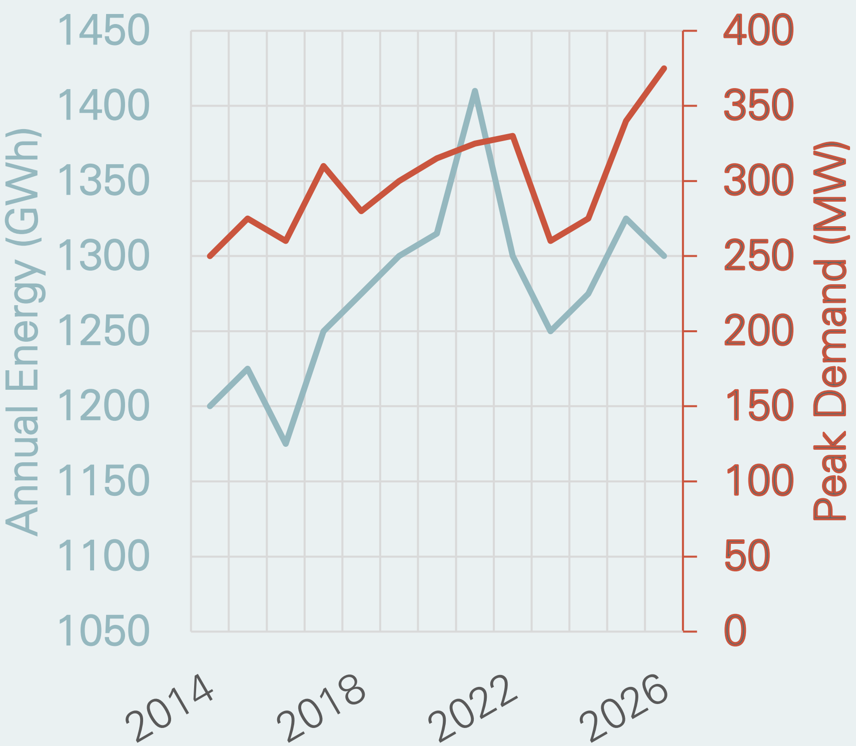
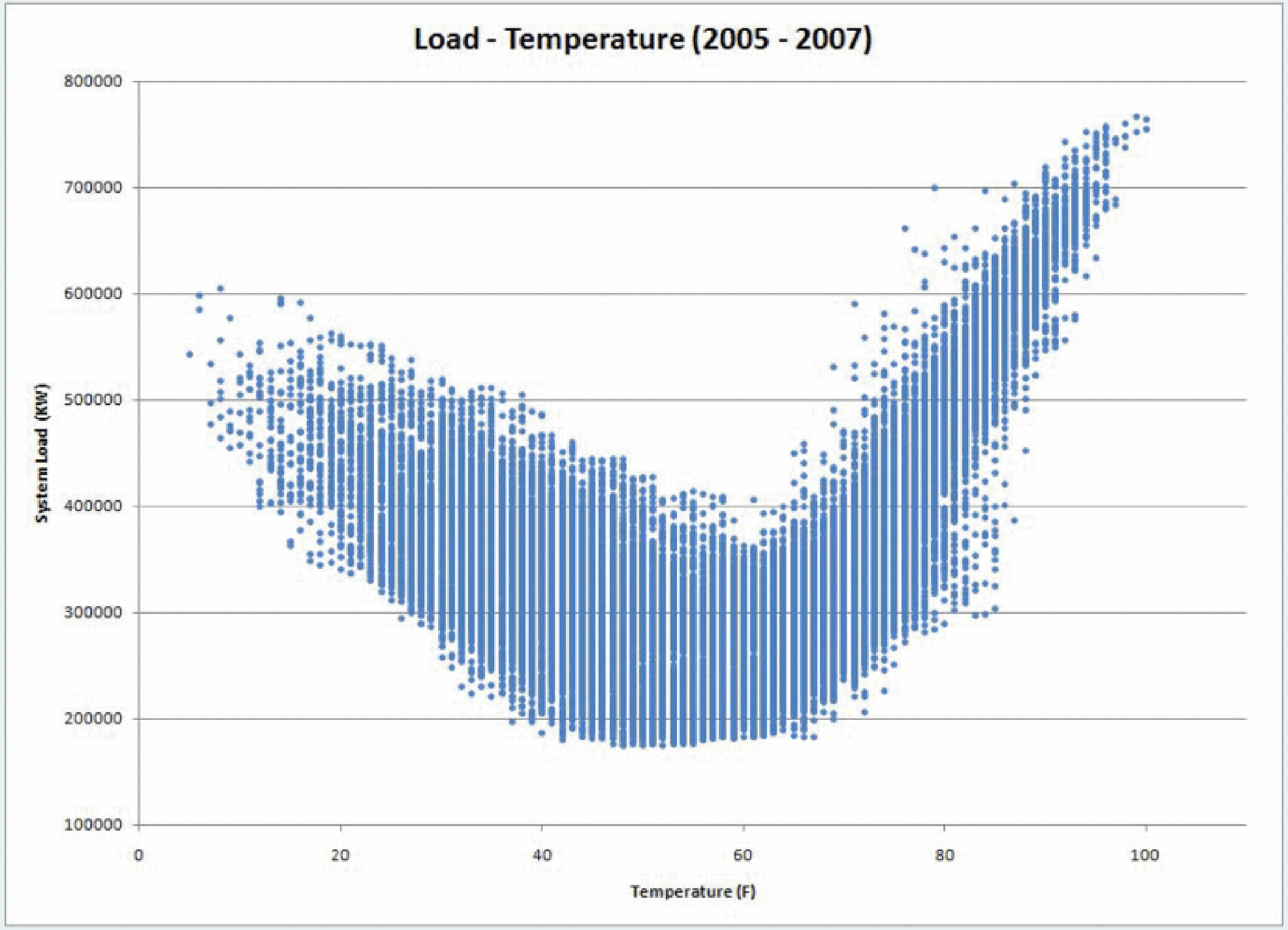
On the system planning and policy time scale, forecasts are largely built from **load growth** and **overall** trend of system peak.



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

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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Variable	Avista	COPSC	Idaho	LADWP	NVPower	NW	PacifiCorp	PGE	PNM	PugetSound	Seattle	SierraPacific	Variable count
Historical sales		All	All	All	All	All	All			All	All	All	
Cooling degree days	All	All	All	All	All	Residential				All		Residential	
Heating degree days	All	All	All	All	All	Residential				All		Residential	
Population growth	All			All			All			All	All	Residential	
Electricity price/tariffs		All		All	All	Residential	Commercial/Industrial			All			
Employment	All		Commercial/Industrial				All			All	Commercial/Industrial		
Household size		Residential					Residential		Residential	All			
Number of customers					Commercial/Industrial	Residential			Residential			Residential	
Energy intensity trends		Commercial/Industrial				Commercial/Industrial	Commercial/Industrial					Commercial/Industrial	
Appliance saturation		Residential	All	All			Residential						
Time dummies (day,month,season,year)		Residential		All	All					All			
Housing stock		Residential	Residential								Residential		
Household income		Residential					Residential			All			
Gross product (national/regional)		Commercial/Industrial								All	All		
Air conditioning usage									Residential				
Model complexity	Medium complexity	High complexity	Medium complexity	High complexity	Medium complexity	Low complexity	Medium complexity		Low complexity	High complexity	Medium complexity	Low complexity	

Coding: Low complexity; Medium complexity; High complexity; Residential; Commercial/Industrial; All

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

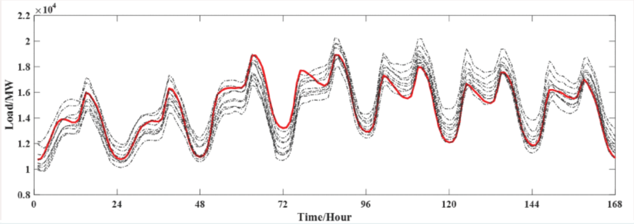
- Time series regression (Econometric)
  - Primarily relies on past observations – "auto regressive", "moving average"
  - Can incorporate "exogenous" non-linear variables influenced by the economy, such as GDP, household income, S-curve for energy efficiency or appliance adoption
- Multiple linear regression
  - 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, often by customer class	Fit an auto-regressive or moving average model to annual peak. Economic variables incorporated with S-curve: (1) $(class\ kWh)_{year} = a \bullet (income\ per\ capita)^{b}_{year} \bullet (population)^{c}_{year} \bullet (price)^{d}_{year}$
Multiple Linear Regression	All types of utilities	Trend Day, Month Temperature (2) $E(Load) = \beta_0 + \beta_1 \times Trend + \beta_2 \times Day \times Hour + \beta_3 \times Month + \beta_4 \times Month \times TMP + \beta_5 \times Month \times TMP^2 + \beta_6 \times Month \times TMP^3 + \beta_7 \times Hour \times TMP + \beta_8 \times Hour \times TMP^2 + \beta_9 \times Hour \times TMP^3$
End-Use	Mid to large utilities, to model building-level equipment (solar, EV, other DER)	Regression for each type of customer and equipment: (1) $(kWh)_i = (customers) \bullet \left(\frac{units\ of\ equipment}{customer}\right) \bullet \left(\frac{kWh}{units\ of\ equipment}\right)$
Ensemble (Combined)	Large utilities, improves the resulting forecast by combining multiple approaches	Simple average of multiple different forecasts (3) 

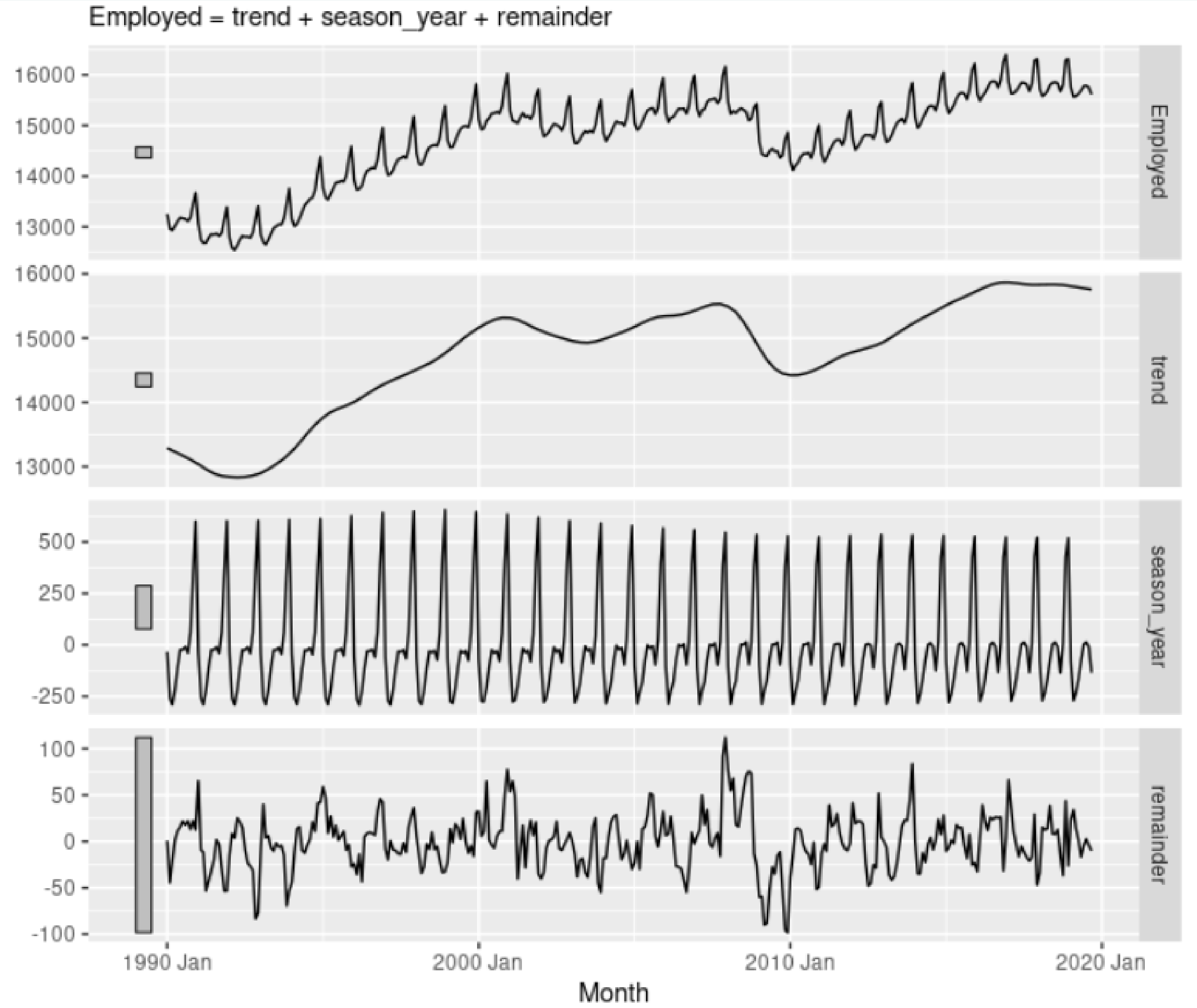
(1) https://www.rand.org/content/dam/rand/pubs/reports/2006/R3315.pdf

(2) T. Hong, P. Wang and H. L. Willis, "A Naïve multiple linear regression benchmark for short term load forecasting," *2011 IEEE PESGM*, doi: 10.1109/PES.2011.6038881.

(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, doi: 10.1109/TSG.2018.2833869.

Time Series / Econometric

- 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 – **A**uto-**R**egressive **I**ntegrated **M**oving **A**verage
- 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



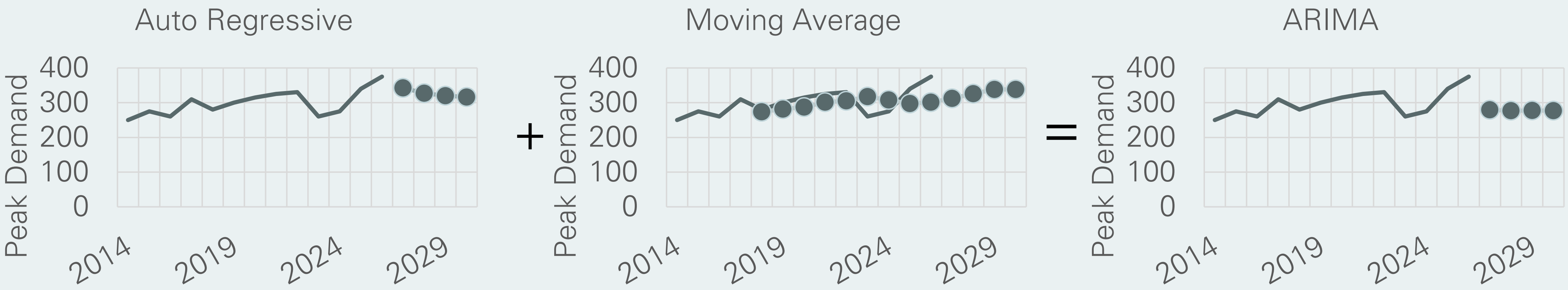
Hyndman, R.J., & Athanasopoulos, G. (2021) Forecasting: principles and practice, 3rd edition, OTexts: Melbourne, Australia. OTexts.com/fpp3. Accessed on 1/24/23

Auto-Regressive Integrated Moving Average

"Auto-Regressive": Use information from past observations to predict the future
Build a regression model only using past observations

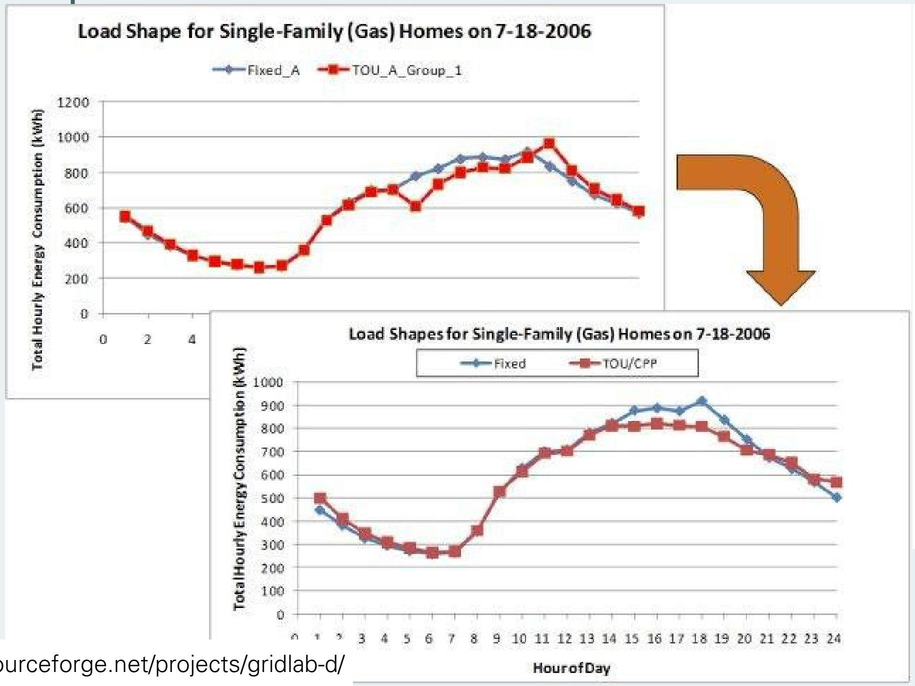
"Moving Average": The next value will be an average of the previous several values

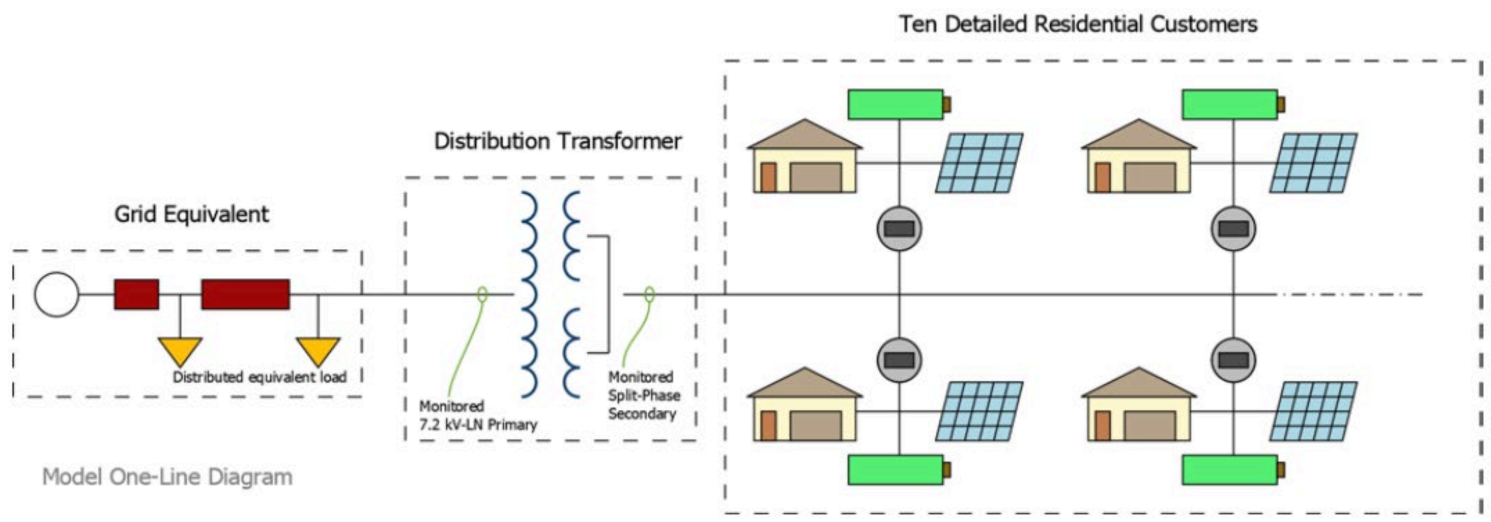
ARIMAX: All of the above, plus additional variables



Bottom-Up Engineering/Physics Based

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



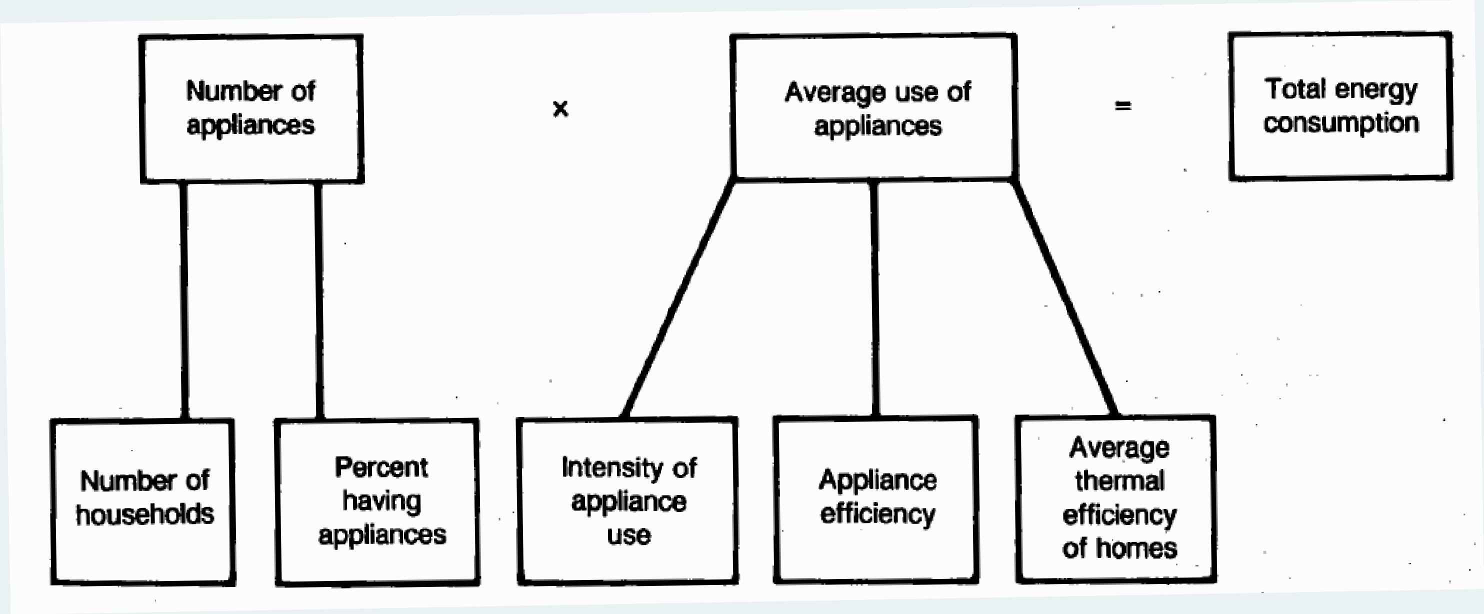


https://sourceforge.net/projects/gridlab-d/

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

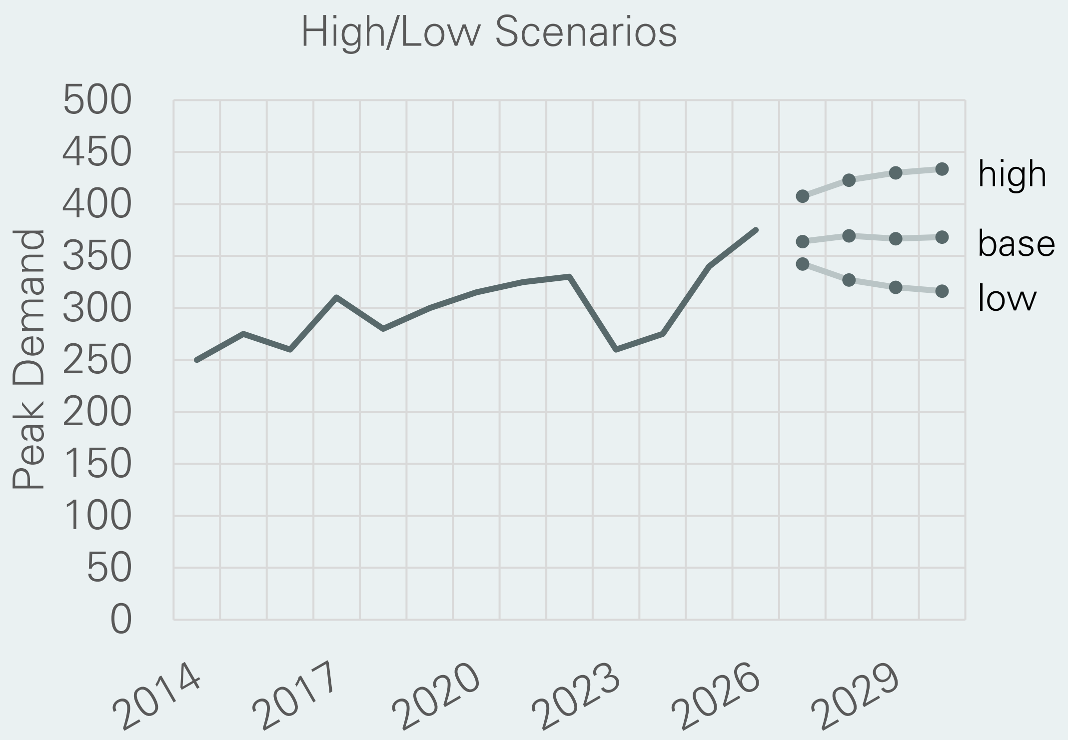
- Directly estimate energy consumption by using extensive information about **end use** and **end users**
- Information used: weather, appliances, size of houses, age of equipment, technology changes, customer behavior, and population dynamics
- Require less historical data but **more information about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



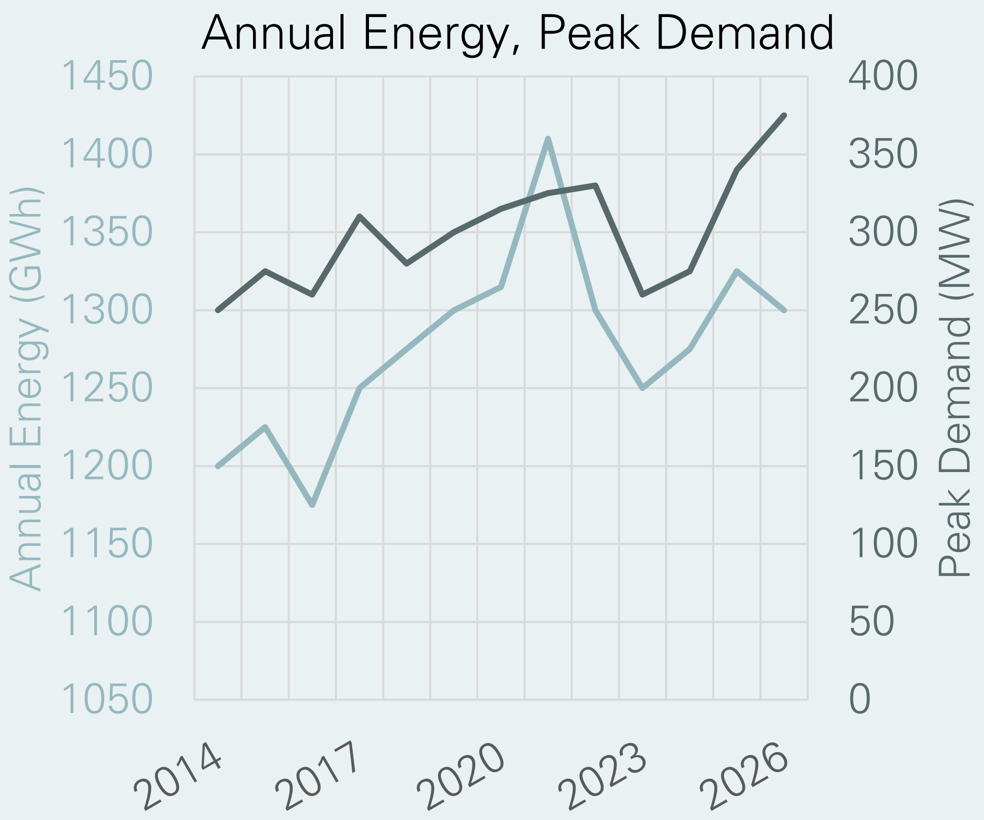
Mitchell, Ross, and Park. (1985) *A Short Guide to Electric Utility Load* Forecasting. The Rand Corporation. https://www.rand.org/content/dam/rand/pubs/reports/2006/R3315.pdf

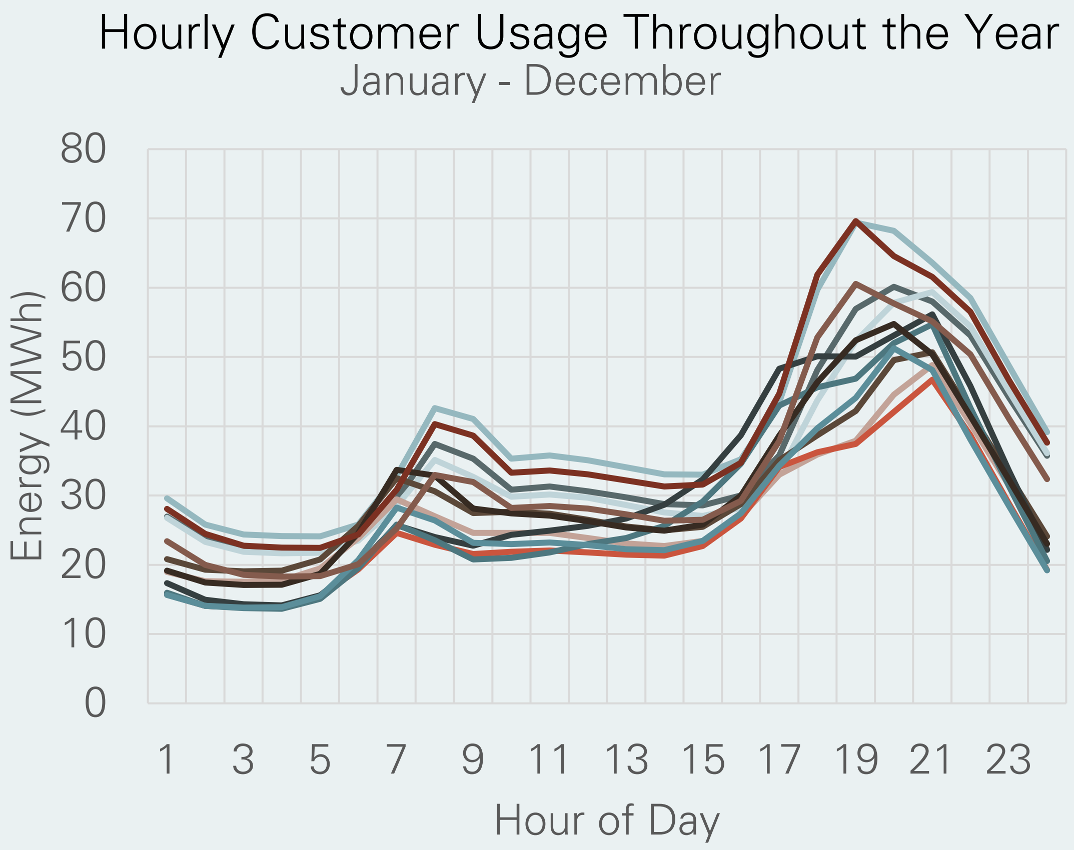
Probabilistic/Scenario Based

- Probabilistic Forecasts are created by **changing the input variable(s)**.
- 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 – "base case"
  2. Use a representative "cold" weather year to project load – "low" scenario
  3. Use a representative "hot" weather year to project load – "high" scenario
- The scenario outcomes provide a range of possible futures



Forecasts Outputs





Annual Energy and Peak Demand are often used by utilities to inform Planning Reserve Margins.

Hourly profiles by customer class can show utilities impacts of resource adoption.

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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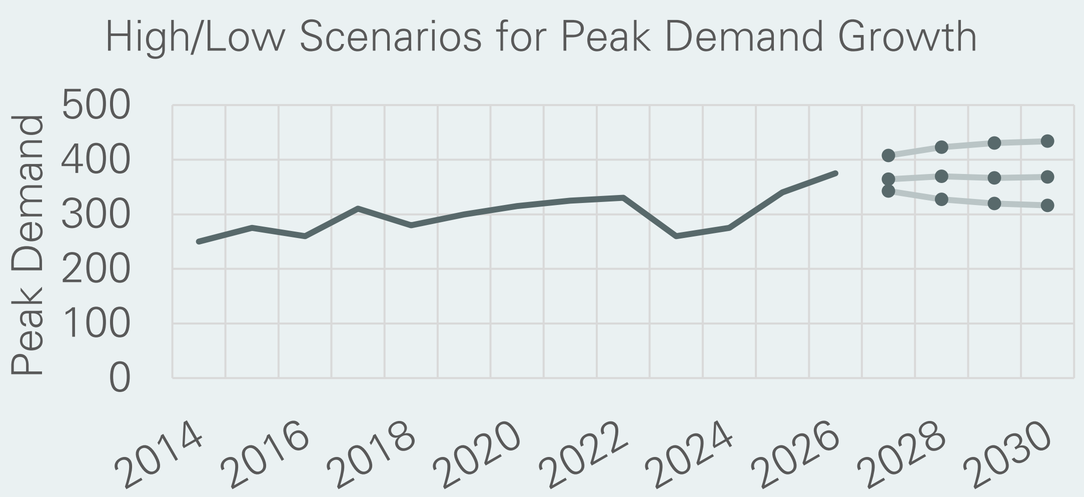
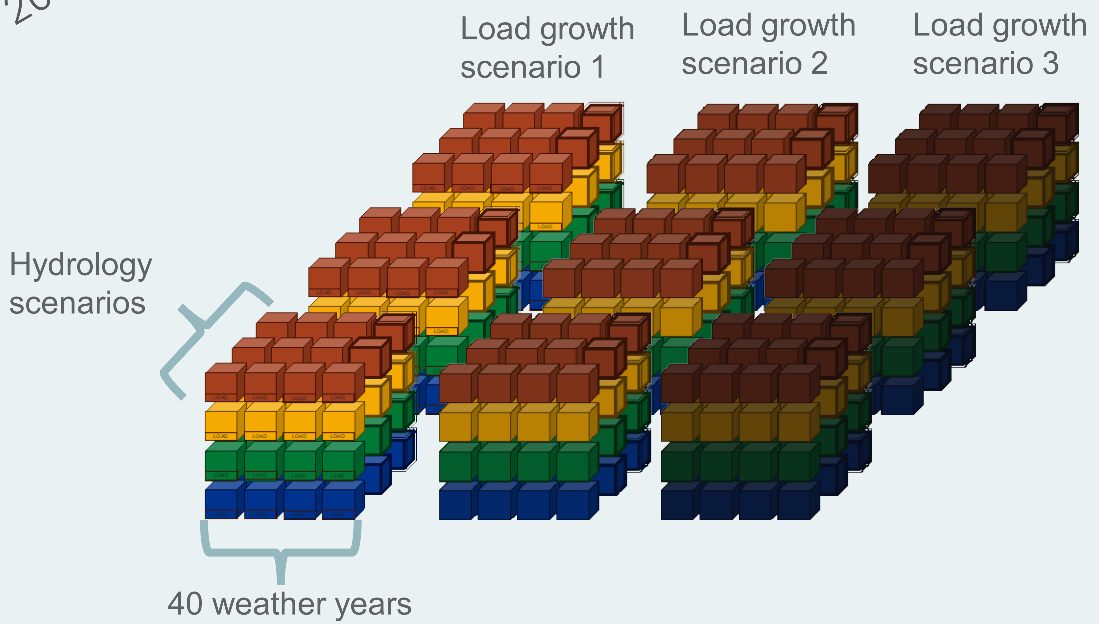


Probabilistic forecasts, such as high and low scenarios for peak demand growth, provide a range of outcomes with probability of occurrence.



Probabilistic results are driven by **uncertainty in inputs**. Resource Adequacy leverages **scenario-based hourly projections** of load and generation to ensure that demand is met for all hours, allowing for **1** day in 10 years with any shortfall.

Forecast Components by Application

Application	Type of Forecast	Spatial Aggregation	Time Resolution	Time Frame/ Horizon	Variables	Method (most common)
Transmission, distribution upgrades, Planning Reserve Margin	Peak Load	Balancing Authority, Feeder	Annual, monthly	1-10 years	Population Growth, GDP	Time Series Regression, Physics-based
Resource Adequacy	Hourly 8760 with scenarios	Balancing Authority	Hourly	1-10 years	Population Growth, GDP, Temperature	Multiple Linear Regression
Area reliability, Multi-Year Rate Plan	Energy Demand	Customer Class	Hourly	1-3 years	*Each customer class may need different variables*	Multiple Linear Regression
Identify customer adoption of distributed resources & impacts	Hourly Profiles	Customer Class, Building	Hourly	1-3 years	Temperature, Population, saturation of new appliances	Engineering- & Physics-based, end-use adjustments
Sensitivity of analysis to input variables	Low/High Scenarios	all	all	all	*all of the above: identify possible deviations*	all

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Sensitivity of analy... to input variables					...deviations	

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

Applications like Resource Adequacy, which require detailed information, must rely on **scenarios** of input variables (e.g., temperature).

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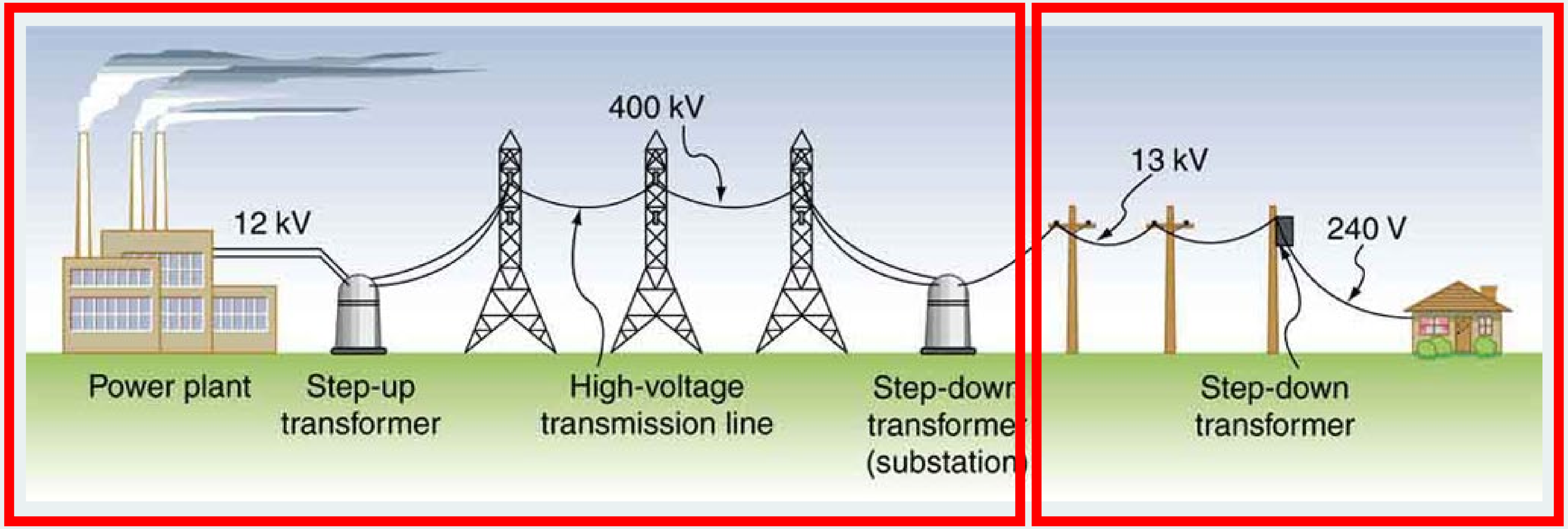
Shorter time frames/horizons can take advantage of richer datasets – this allows utilities to build models for each customer class and even buildings at a very detailed level

Distribution System vs. Bulk Power System Forecasts

JP Carvallo (LBNL)

The power system



The bulk power system

The distribution system

Two historically separated
planning processes and paradigms

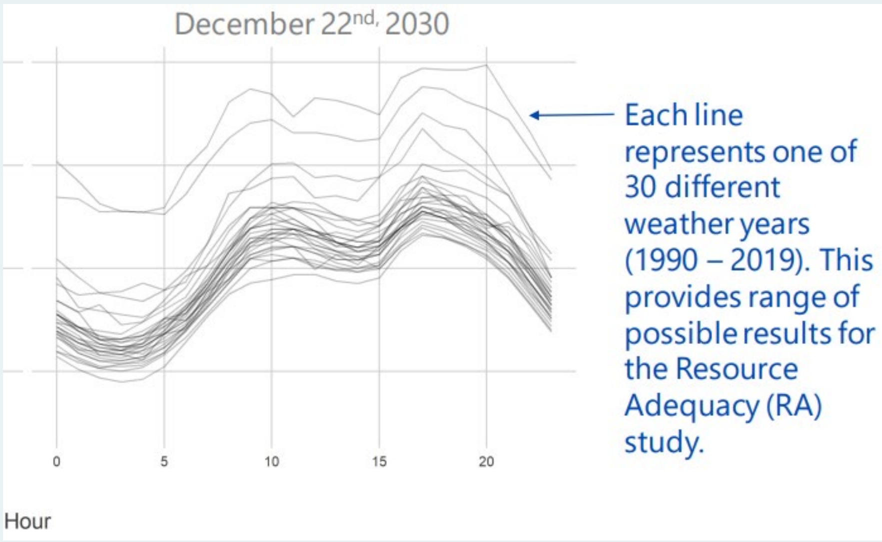
Image credit: [Ling, Moebs, and Sanny (2016)]

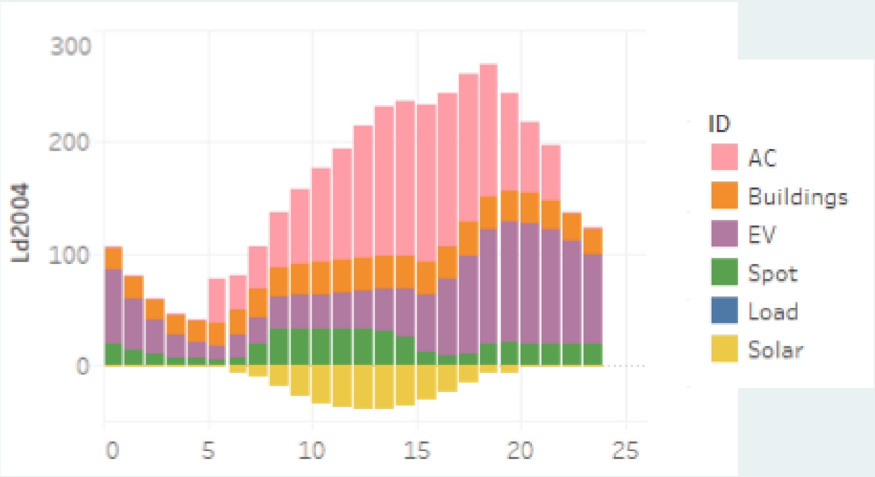
Fundamental differences inform forecasts

Bulk power system	Distribution system
Typically relies in aggregated load forecasts at a node or even system level	Highly localized load forecast, requires detailed information of customers and end uses
Aggregation allows to reflect diversity benefits, averaging out outliers and errors	Forecast reflects idiosyncrasies, should not reflect diversity, and more sensitive to error
Loads are larger; traditional customer segments are sufficient	Loads are smaller; traditional customer segments may not reflect growth patterns
Larger, consequential loads are "visible", they require interconnection	Most loads are "invisible", developing behind the meter in scattered patterns
Load aggregations require careful treatment of randomness → stochastic	Smaller loads can be treated deterministically

Common load forecasting practices

- Leading practice is to develop **hourly load forecast** that reflects:
  - Diurnal/nocturnal profiles
  - Seasonal patterns
  - Daily and weekly cumulative energy needs
- Ideally, load forecasts match the **spatial unit of analysis** of the power flow, dispatch, and expansion models
  - Recognize spatial diversity in load growth and characteristics
  - Better represent load in reliability assessment model by capturing probabilistic/statistical properties

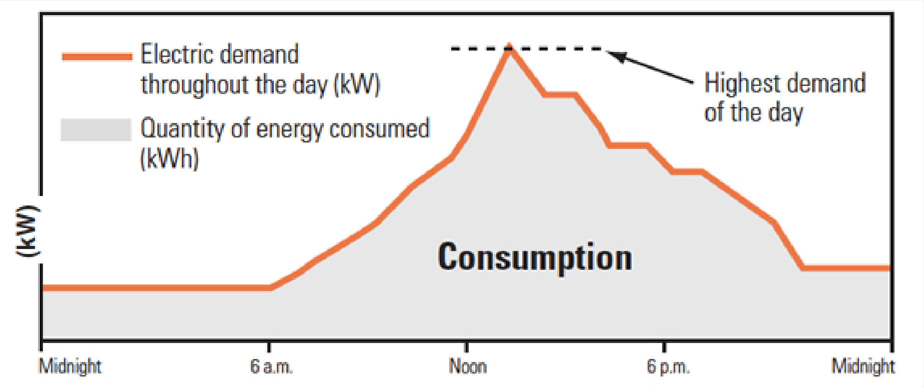




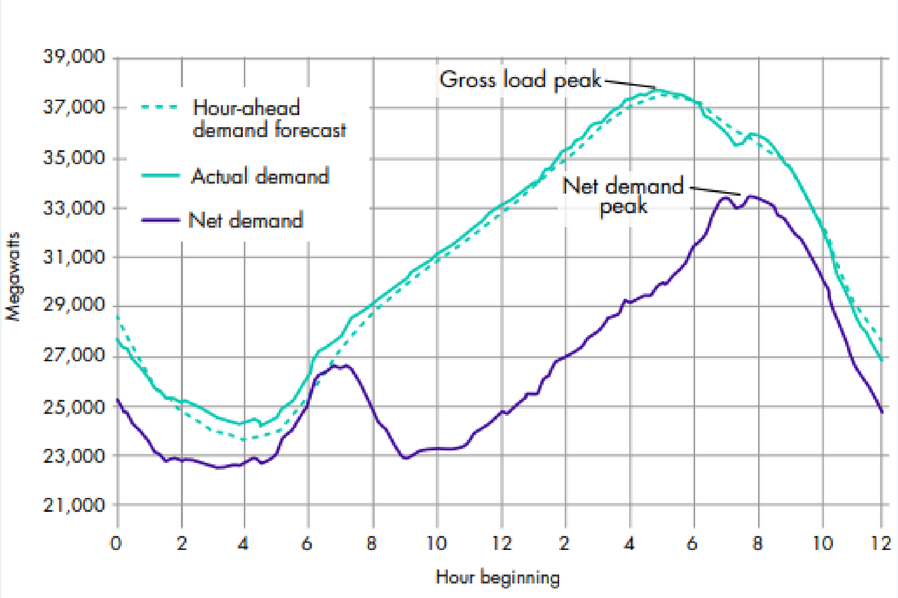
Source: [Seattle City Light's 2022 IRP]

Forecasting at the distribution system level

- Emphasis is on peak demand
  - Can rely on a p50 (1 in 2) or a p90 (1 in 10) forecast
- Forecast horizon typically three to five years
- Forecasts developed at the feeder-level, and some times sub-feeder level
  - Bottom-up, customer focused
- More recently
  - Consider DER adoption AND operation
  - Consider retail rates impacts
  - Internalize flexibility



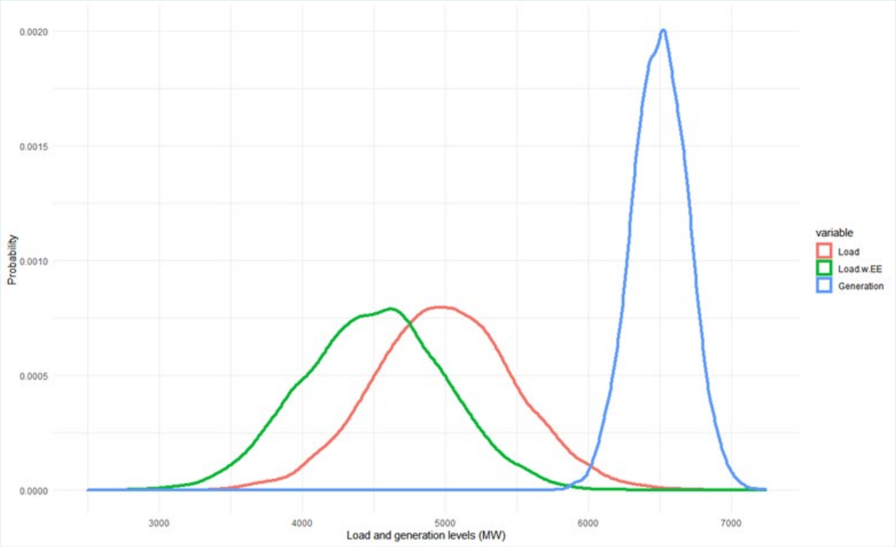
Source: We Energies (2025)



Source: CAISO (2023)

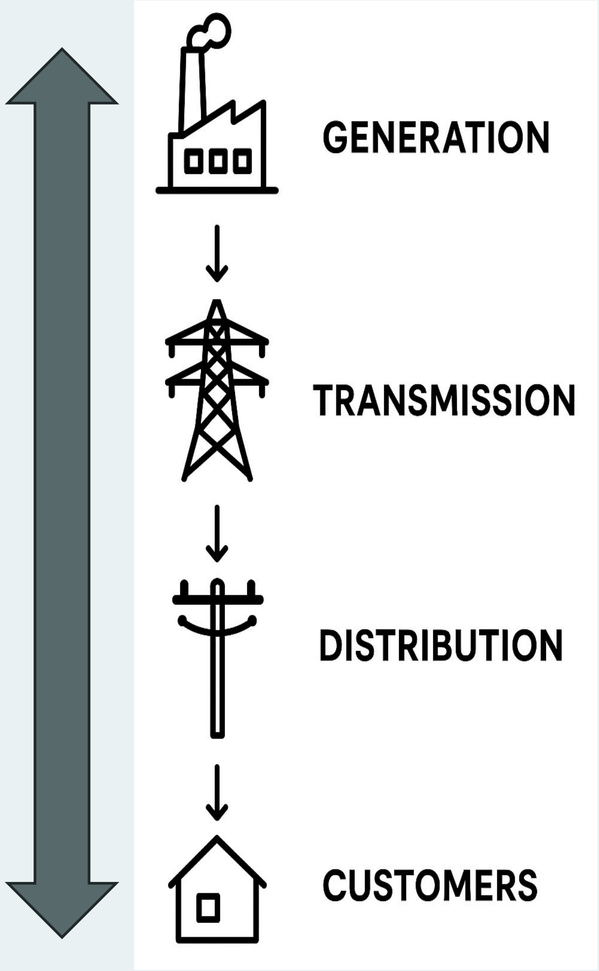
Forecasting at the bulk power system level

- Emphasis is on both energy and demand
- Energy forecast
  - Drives resource deployment
  - Deterministic, but typically develops several scenarios
- Demand forecast
  - Drives capacity needs and reliability targets
  - Stochastic, used for resource adequacy analysis with weather-sensitive models
- Load forecast scenarios
  - Developed following plausible “futures”, including economic growth, end use adoption, potential policies, etc.
- Emerging focus on individual large loads
  - Interconnection requests, speculation management
  - Probabilistic approaches for energy needs (e.g. Georgia Power)



Blurring the divide

- Several jurisdictions are testing or applying integrated system planning approaches that connect multiple planning processes (e.g., PGE, Xcel MN, Duke, FERC Order 2222)
  - Increasing number of BPS forecasts are resulting from aggregation of substation- or feeder-level load forecasts
- BPS load forecasts
  - Modeling DER adoption and operation
  - Becoming more granular
- Distribution system forecasts
  - Moving to longer planning horizons, similar to BPS
  - Starting to focus on scenarios
  - Considering the development of stochastic approaches



Two examples of BPS/Dx forecast convergence

- Single forecast approach in California
  - "forecasts used in procurement and planning processes across both the transmission and distribution domains[…] The Commission uses the single forecast set in its integrated resource plan (IRP) process, resource adequacy program, and distribution planning" (CPUC Rulemaking 21-06-017)
  - Useful for states with multiple IRP-filing entities, but also for process coordination within a load serving entity
- Duke Energy's Integrated System and Operations Planning
  - ISOP is a "planning framework that optimizes capacity and energy resource investments across generation, transmission, customer delivery (distribution) and customer solutions"
  - The utility develops a bottom-up, hourly forecast at the circuit level using the internal Morecast tool for distribution system planning (DSP)
  - Assumptions and potentially outcomes are shared from Morecast (DSP) for IRP and transmission planning

Source: Duke Energy

Best Practices & How Load Forecasting Feeds into Utility Decisions

Brittany Tarufelli (PNNL)

Overview

- Current forecasting best practices
  - Load
  - Distributed energy resources (DERs)
  - Examples
  - Limitations
- How load forecasts feed into utility decisions
- Resources for more information

These slides reference materials from:

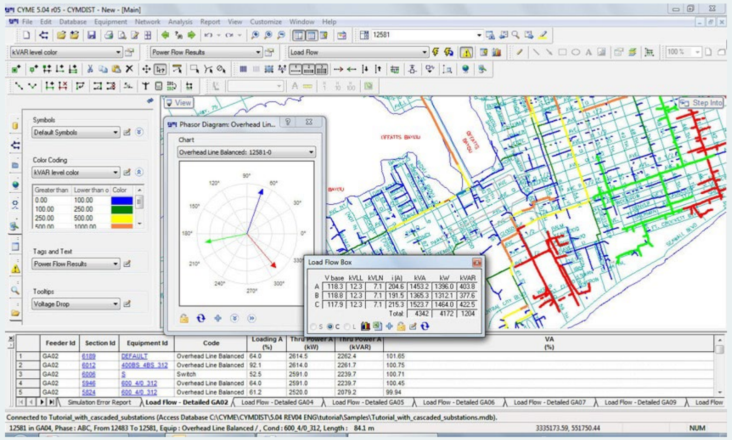
- Homer and Yang, 2021, Load forecasting with climate variability for transmission and distribution system planning, Innovations in Electricity Modeling Training for National Council on Electricity Policy, National Renewable Energy Laboratory (Golden, CO) and Pacific Northwest National Laboratory (Richland, WA).
- GMLC 4.2.2 – TA to State PUCs Forecasting Cohort Workshop #2 – Developing Forecasts: Basics and Best Practices, National Renewable Energy Laboratory (Golden, CO), Pacific Northwest National Laboratory (Richland, WA), Lawrence Berkeley National Laboratory (Berkeley, CA)

Current forecasting best practices

- We reviewed filings from nine leading utilities and looked at
  - Methods and tools used for conducting granular load forecasting
  - Methods and tools for conducting DER forecasting
  - Gaps/challenges identified
  - Stakeholder comments and commission actions related to load and DER forecasts

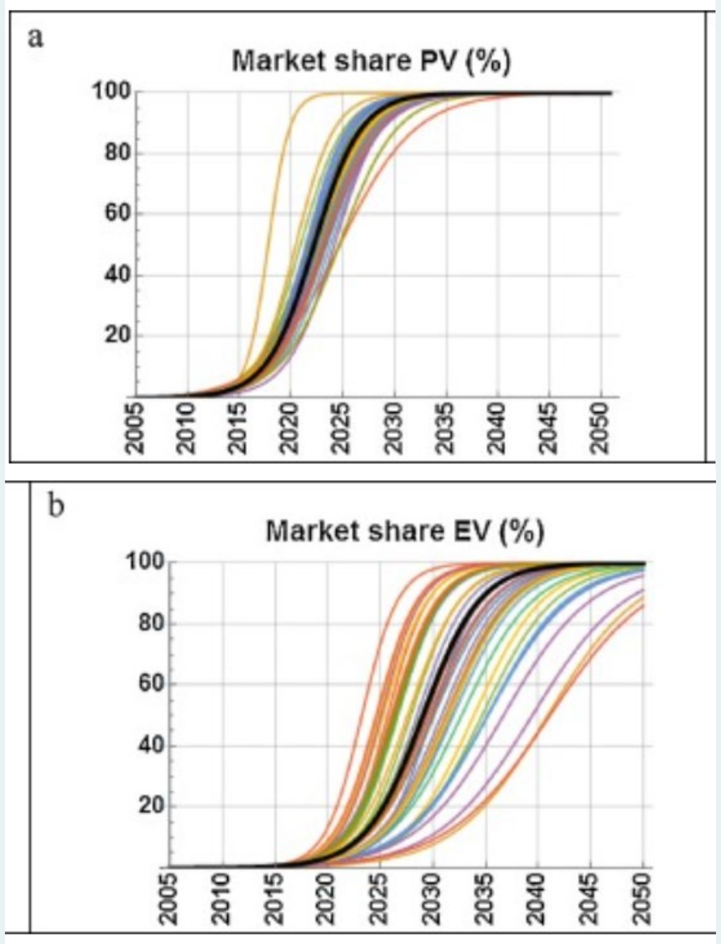
Current forecasting best practices

- Load Forecast
  - Utilities with advanced practices are creating granular load forecasts
    - Granular in time – Forecasts for all 365 days x 24 hours = 8,760 hours per year
    - Granular in space – Forecasts at the circuit and transformer level
  - A diverse set of tools are used to create these forecasts
    - LoadSEER for granular load forecasting
    - CYMEDIST for power flow modeling
    - SYNERGI for power flow modeling
    - GridLab-D open-source distribution power system modeling
    - Econometric models
    - Probabilistic forecasting techniques
  - Planner’s judgement and company projections can form basis of forecasts
  - In California, electric investor-owned utilities (IOU) start with electricity consumption and peak electricity demand forecasts for individual utility planning areas from the CA Energy Commission’s biennial Integrated Energy Policy Report (IEPR)
  - IEPR also includes PV and storage projections and potential impacts of different EV charging behaviors during hours of peak electricity demand



Current forecasting best practices

- DER forecasts
  - Some utilities use **econometric methods** to analyze the historical relationship between DER adoption and other economics variables to forecast future adoption
  - Some utilities forecast DER adoption by fitting innovation diffusion curves to historical data, typically using the **Bass diffusion model**
    - Requires a sufficient history of adoption
    - Not always feasible for DERs in nascent stage or those experiencing truly disruptive innovation
    - Bass diffusion optimizes three parameters (P - innovators, Q - imitators, and M – potential adopters) to explain monthly adoption patterns
  - Use tools such as **Gridlab-D, WattPlan Grid**, **dGen**, and **LoadSEER**



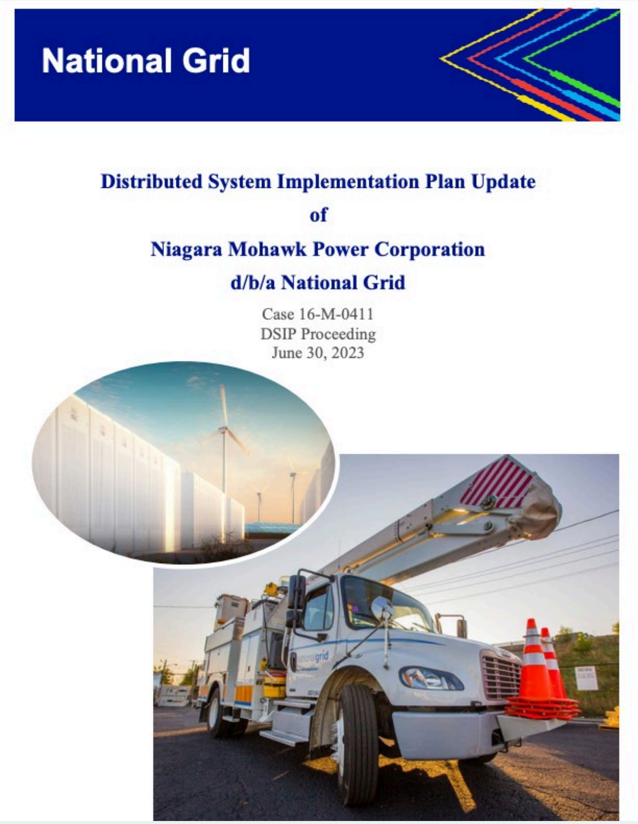
Source: van der Kam et al. 2018

Current forecasting best practices

- DER forecasts, cont.
  - Some utilities start with top-down, system-wide DER forecasts that they disaggregate between substations
  - Disaggregation techniques include:
    - Proportional allocation - disaggregates the DER forecast to circuits based on utility data for the circuit (load, energy, or number of customers)
      - SDG&E uses LoadSEER to disaggregate load forecasts to the circuit level[1]
    - Propensity models - base the disaggregation on customer characteristics that are used to compute a propensity score. Propensity models could be estimated using ZIP code data, where models relate historical adoptions to customer characteristics in each ZIP code
      - SDG&E uses SPIDER to disaggregate some of the DER forecast components to the zipcode level (which are then mapped to circuits using propensity to adopt)[1]
    - Adoption models - use a bottom-up adoption forecast based on observed adoption patterns and estimated adoption model parameters; includes S-Curve/Bass Diffusion Models
      - SCE uses Bass diffusion models the adoption of residential solar PV[2]
      - Other utilities with more granular data can predict where customers have a higher propensity for DER adoption based on characteristics such as energy use, weather, number of customers, and geographic location

1 https://www.sdge.com/sites/default/files/regulatory/R21-06-017%20SDGE%202023%20IPE%20DPAG%20Report.pdf

2 https://efiling.energy.ca.gov/GetDocument.aspx?tn=264264&DocumentContentId=100986#:~:text=1)%20Introduction,used%20in%20the%20econometric%20estimation.



Advanced forecasting example – National Grid

- Considers inputs from a top-down system-level perspective as well as a bottom-up perspective
  - Top-down: Annual peak load forecasts incorporate projected economic impacts, weather, program level and policy goals
  - Bottom-up: Forecasts consider location-specific impacts and customer demographics
- Since 2018, National Grid has generated and published 8,760-hour feeder level forecasts
  - 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
  - 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
  - High-performance cloud computing, such as Amazon Web Services, is used to improve the overall computational process
- Future enhancements will refine probabilistic forecasting techniques

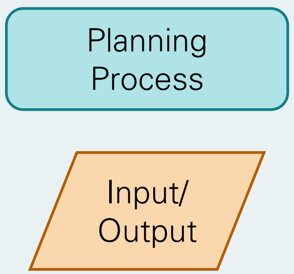
https://jointutilitiesofny.org/sites/default/files/NG_2020_DSIP.pdf
https://www.nationalgridus.com/media/pdfs/other/cases-14-m-0101-and-16-m-0411-national-grid-2023-dsip-update.pdf

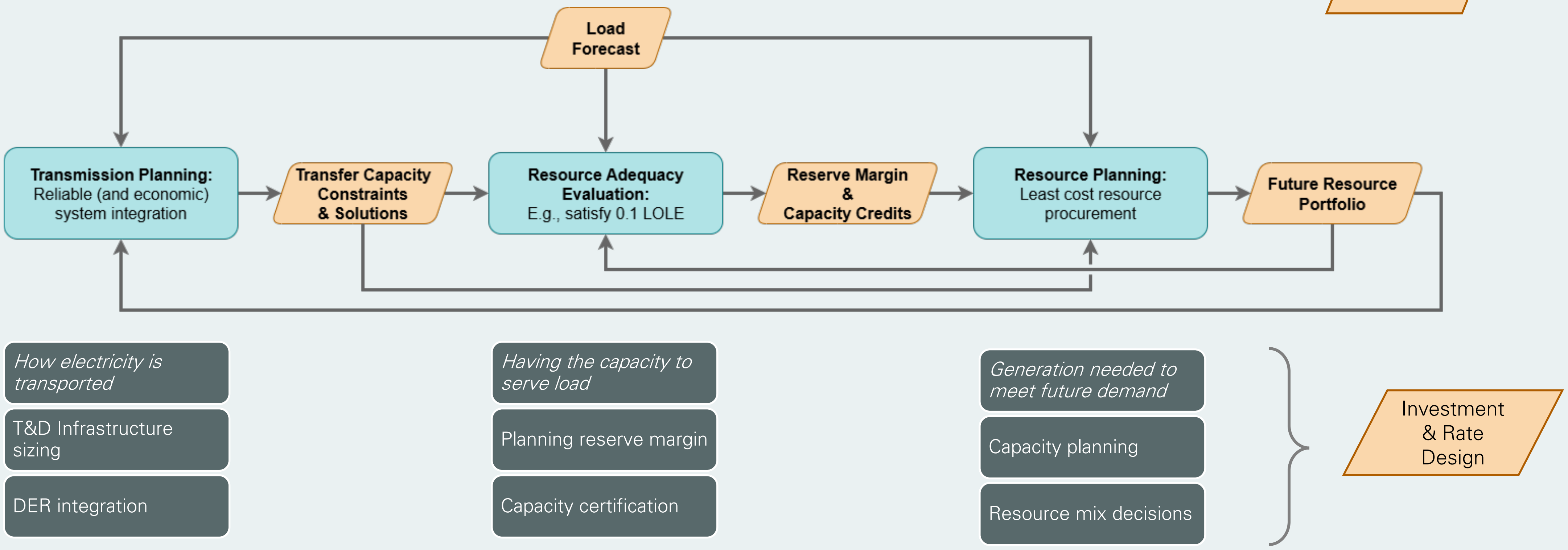
Limitations

- **Data availability**:
  - 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

How Load Forecasting Feeds into Utility Decisions

- Load forecasts feed into various utility decisions from transmission planning, to resource adequacy evaluation, to resource planning, to investment and rate design





Resources for more information

- Hawaiian Electric Company
  - 2023 Integrated Grid Plan
  - 2018 Electrification of Transportation Strategic Roadmap
- National Grid 2020 Distributed System Implementation Plan
- National Grid 2023 Distributed System Implementation Plan Update
- Orange Rockland Utilities, Inc.'s 2020 DSIP report & 2023 DSIP Report
- Central Hudson Gas & Electric Corporation's 2020 DSIP report & 2023 DSIP Report & 2025 DSIP report
- Homer and Yang, 2021. Load forecasting with climate variability for transmission and distribution system planning
- Berkeley Lab's research on time- and locational-sensitive value of DERs
- NREL's Electric Vehicle Infrastructure Projection Tool: EVI-Pro
- dsgrid: Demand-Side Grid Model

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

https://StateTAProgram.lbl.gov

Help Desk

- Online intake form w/ rolling review
- SME provides up to **4 person-hours of support**
- Intake form and support available now

Expert Match

- Online intake form w/ rolling review
- SME provides up to **100 person-hours of support**
- 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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