Load forecasting with climate variability for transmission and distribution system planning

Rui Yang[1] and Juliet Homer[2] (with research support by Brittany Tarufelli[2])
[1]National Renewable Energy Laboratory
[2]Pacific Northwest National Laboratory

Innovations in Electricity Modeling
Training for National Council on Electricity Policy
November 1, 2021

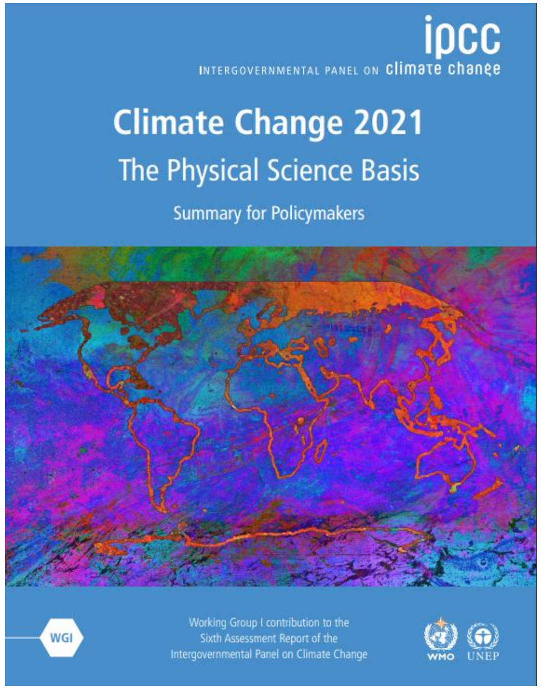
This presentation was funded by the U.S. Department of Energy's Office of Electricity and Building Technologies Office.

Agenda

- Framing
- Current forecasting best practices
  - Load
  - Distributed energy resources (DERs)
  - Electric vehicles (EVs)
  - Examples
  - Limitations
  - Stakeholder areas of concerns
  - Identifying distribution hot spots and solutions
- Principles of forecasting
- Emerging practices and capabilities
- Challenges
- Considering climate change
- Questions states can ask
- Resources for more information

Framing

IPCC Climate Change 2021 Science Basics for Policymakers

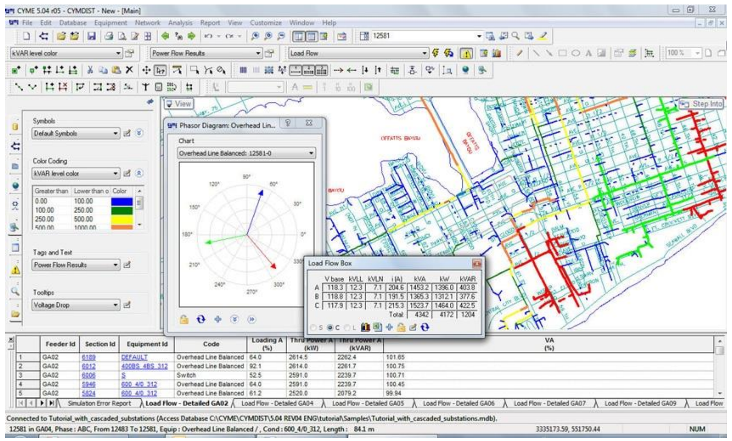


- "Human-induced climate change is already affecting many weather and climate extremes in every region across the globe. Evidence of observed changes in extremes such as **heatwaves**, **heavy precipitation**, **droughts**, and **tropical cyclones…** has strengthened .." (IPCC 2021)
- Although *all electric utilities — and their customers — will be affected by climate change*, few utilities are currently engaged in planning for climate change impacts
- Some considerations utilities will need to account for (not exhaustive):
  - **Higher average and extreme temperatures** can increase demand for electricity, while simultaneously reducing the operating efficiency of thermoelectric resources and the carrying capacity of transmission and distribution lines
  - "**Changing precipitation patterns**, wherein drought conditions can force the curtailment of hydroelectric and other water-dependent generation and heavy precipitation and flooding can damage or destroy transmission and distribution infrastructure
  - **More intense storms and greater wildfire activity** that can cause major damage to energy infrastructure and lead to widespread transmission and distribution outages

Current forecasting best practices

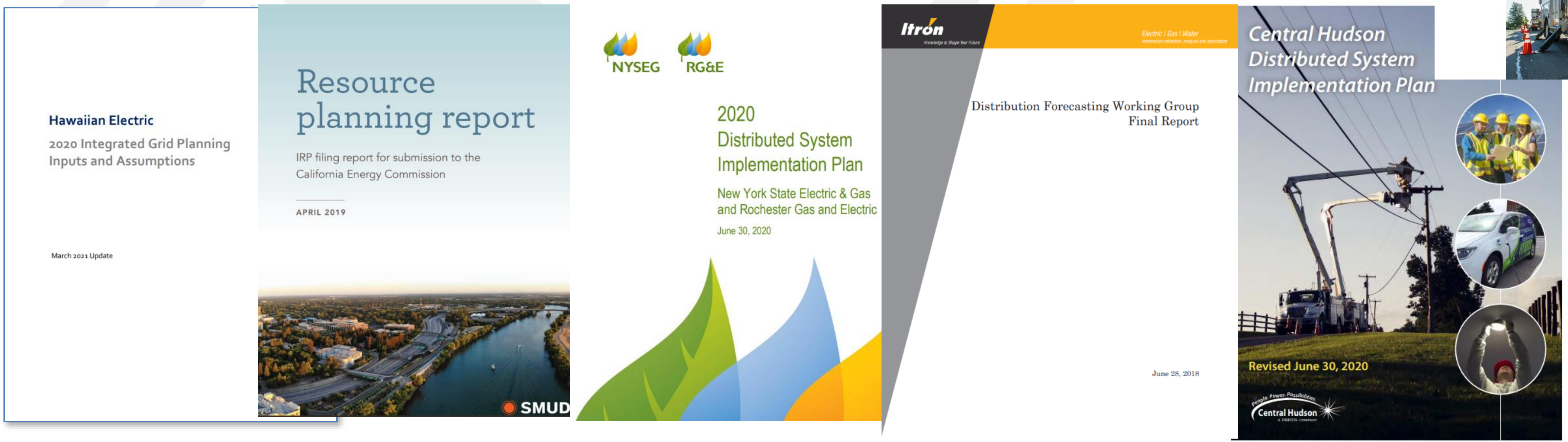
Current forecasting best practices (1)

- **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
    - CYMEDIST
    - SYNERGI
    - GridLab-D
    - 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



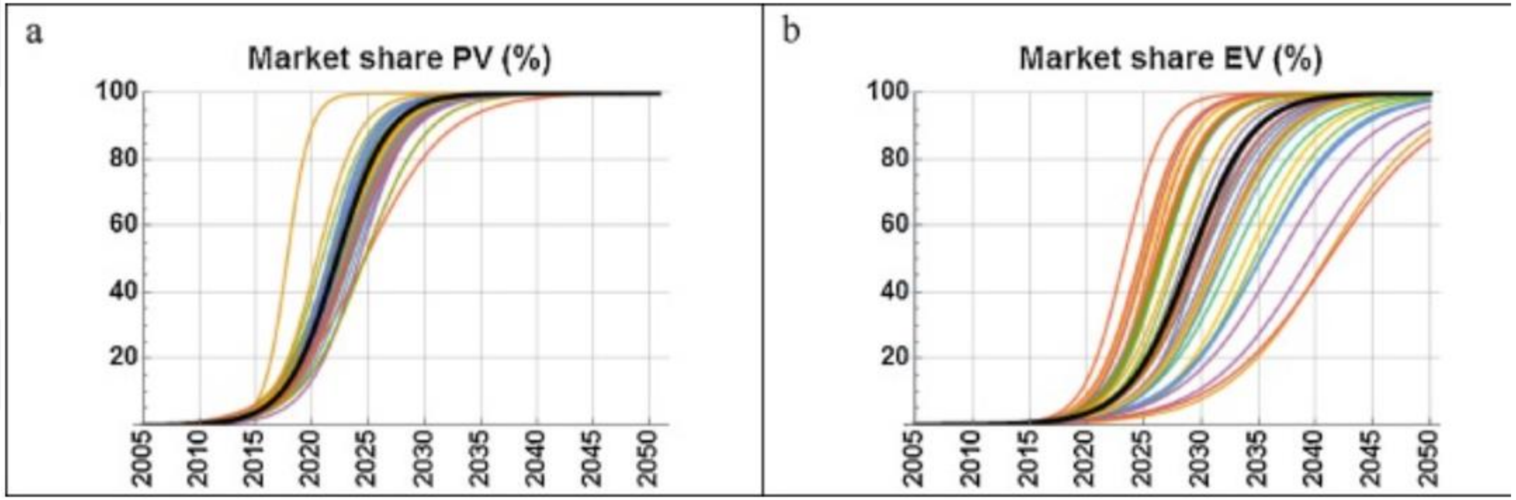
Current forecasting best practices (2)

- We reviewed filings from 9 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 (3)

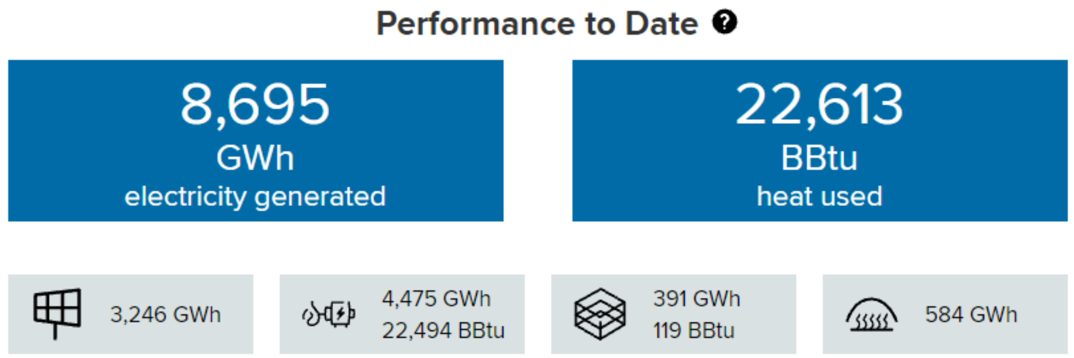
- **DER forecasts**
  - Some utilities use **econometric methods** to analyze the historical relationship between DER adoption and other economics variables to forecast future adoption
  - Some utilities forecast DER adoption by fitting innovation diffusion curves to historical data, typically using 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**, and **LoadSEER**



Source: [van der Kam et al. 2018]

Current forecasting best practices (4)

- **DER forecasts, cont.**
  - Some utilities start with top-down, system-wide DER forecasts that they disaggregate between substations
  - Three classes of disaggregation techniques described in the CA Distribution Forecasting Working Group Final Report:
    - **Proportional allocation** - disaggregates the DER forecast to circuits based on utility data for the circuit (load, energy, or number of customers)
    - **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
    - **Adoption models -** use a bottom-up adoption forecast based on observed adoption patterns and estimated adoption model parameters; includes S-Curve/Bass Diffusion Models
  - Utilities with 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.
- NYISO is currently relying on the NYSERDA DER database as an interim source in its forecasts. The database includes DER locations across the state, aggregate DER data, and current and past performance data from New York DER projects



Current forecasting best practices (5)

- **EV forecast**
  - Advanced utilities forecast customers' propensity to adopt EVs using **propensity models** (using regression techniques or machine learning to identify key variables correlated with customer adoption) or **Bass diffusion models** (used to fit diffusion curves) at a granular (ZIP code) level based on characteristics such as energy use, weather, number of customers, and geographic location.
  - EVs are then allocated to the circuit level based on factors such as load, energy, or number of customers.
  - Other tools are also being explored, including transportation modeling to simulate EV charging behaviors using **POLARIS** (Planning and Operations Language for Agent-based Regional Integrated Simulation), an agent-based model developed by Argonne National Laboratory.
  - Hawaiian Electric Integrated Grid Planning example:
    - EV forecast adoption model was developed by Integral Analytics by combining macro-level Bass Diffusion models with geospatial customer-level, agent-based models through its proprietary load forecasting tool, LoadSEER
    - Total number of vehicles were segmented into charging profile segments. Hourly changing profiles were developed using charging station telemetry, load research, and AMI data
    - Hourly load modeling and statistical sampling were used to develop a core set of EV charging profiles
  - Some utilities are working with Electric Vehicle Supply Equipment companies to develop EV load profiles for various EV charging use cases

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**^{TM}, 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.


National Grid

Distributed System Implementation Plan Update

of

Niagara Mohawk Power Corporation

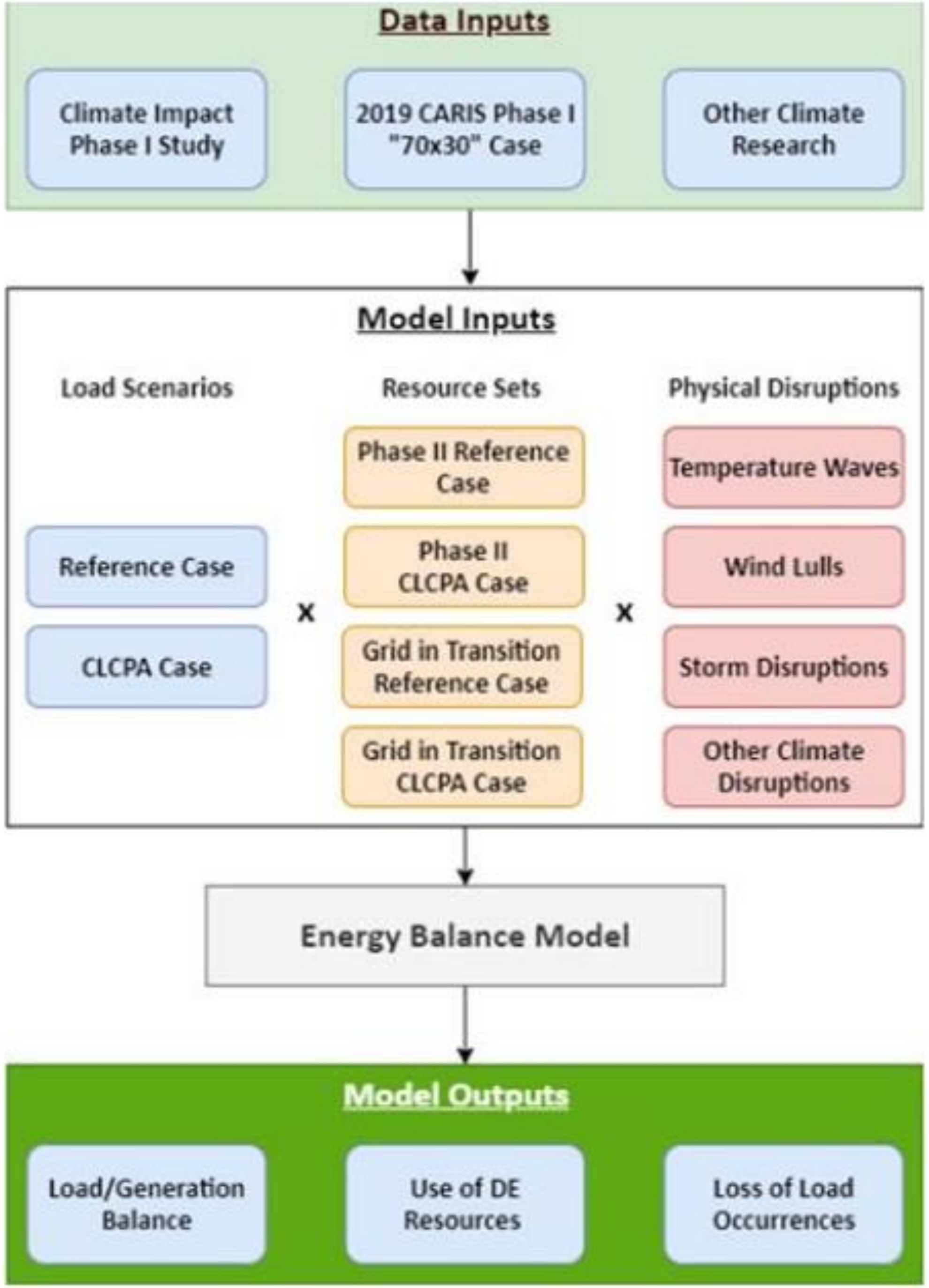
d/b/a National Grid

Case 16-M-0411
DSIP Proceeding
June 30, 2020

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

Advanced forecasting example – New York Independent System Operator (NYISO)

- NYISO conducted a reliability study (Phase II study) to evaluate impacts of climate change and climate policy on reliable operations of NYISO
- New York State Climate Leadership and Community Protection Act (CLCPA) requires100% emission reduction by 2040
- Reliability study built on previous Phase I study that included energy, peak, and hourly load projections for NYISO through 2050 with climate change
- Developed Energy Balance Model to simulate power system operations in 2040, with separate balancing across and within 11 NYISO load zones.



Limitations

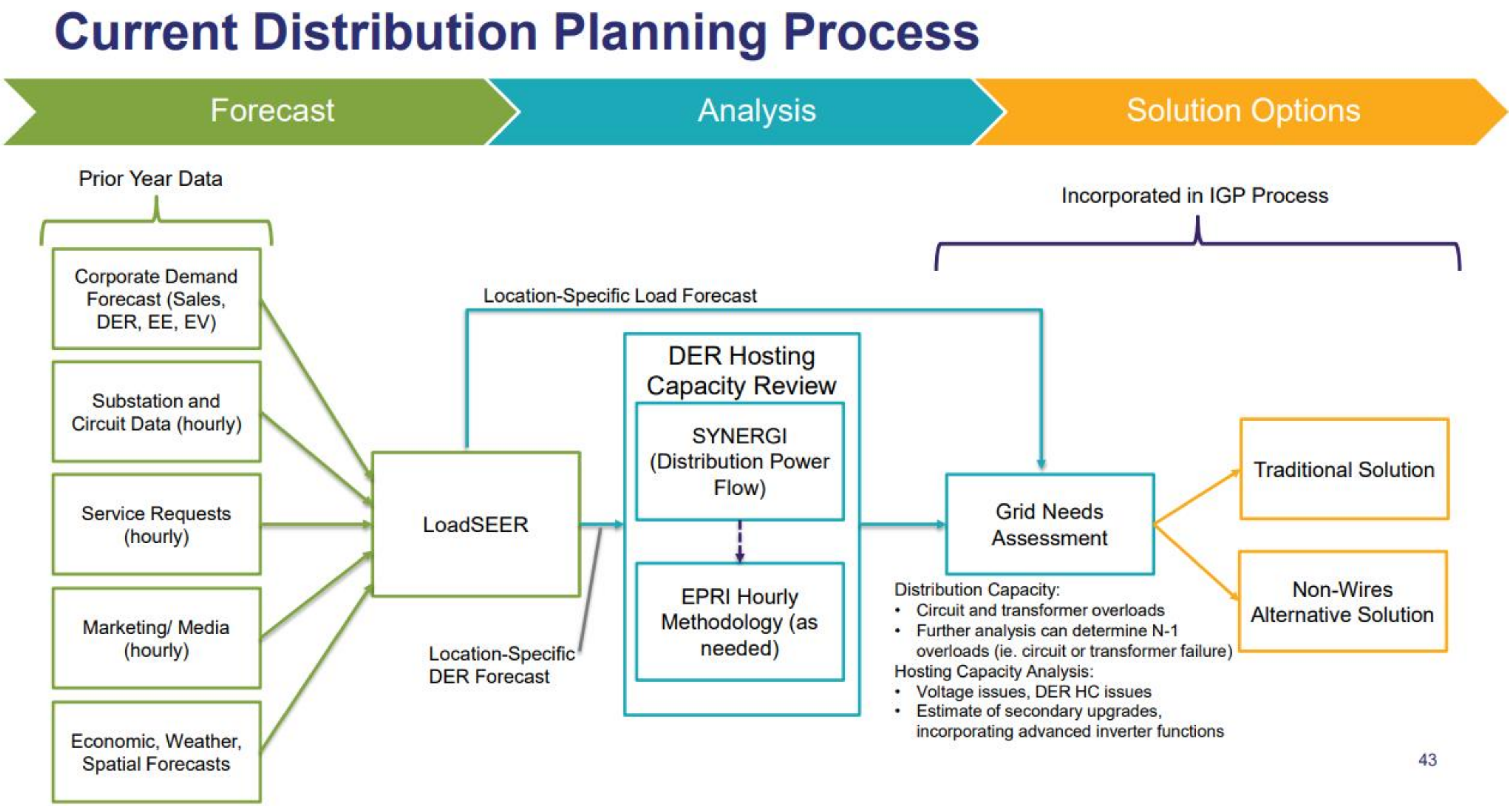
- **Data availability**:
  - A main limitation with respect to forecasting granular DER adoption is that these types of forecasts require granular data
  - Most utilities that have not yet implemented these forecasts cite the need for enhanced capabilities to collect and monitor granular data (such as from AMI, which will provide greater temporal and geospatial granularity)
  - Other utilities noted that data quality for substations and circuit locations has been a barrier for more granular load forecasting due to lack of metering or meter data gaps
    - 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 in current forecasting practices is the need for enhanced probabilistic forecasting techniques for better forecasting variabilities in weather, economic growth, proliferation of DER, etc.—which can all impact load

Stakeholder areas of concern

- 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

Identifying distribution system hot-spots and solutions

- Net-load forecasts can be evaluated in power flow modeling tools (GridLAB-D, CYME, Synergi, Milsoft, Open-DSS)
- Analysis enables assessment of:
  - system needs
  - hosting capacity
  - areas where system limits are being exceeded
- Analysis reveals where new traditional investments, or non-wires solutions, are needed

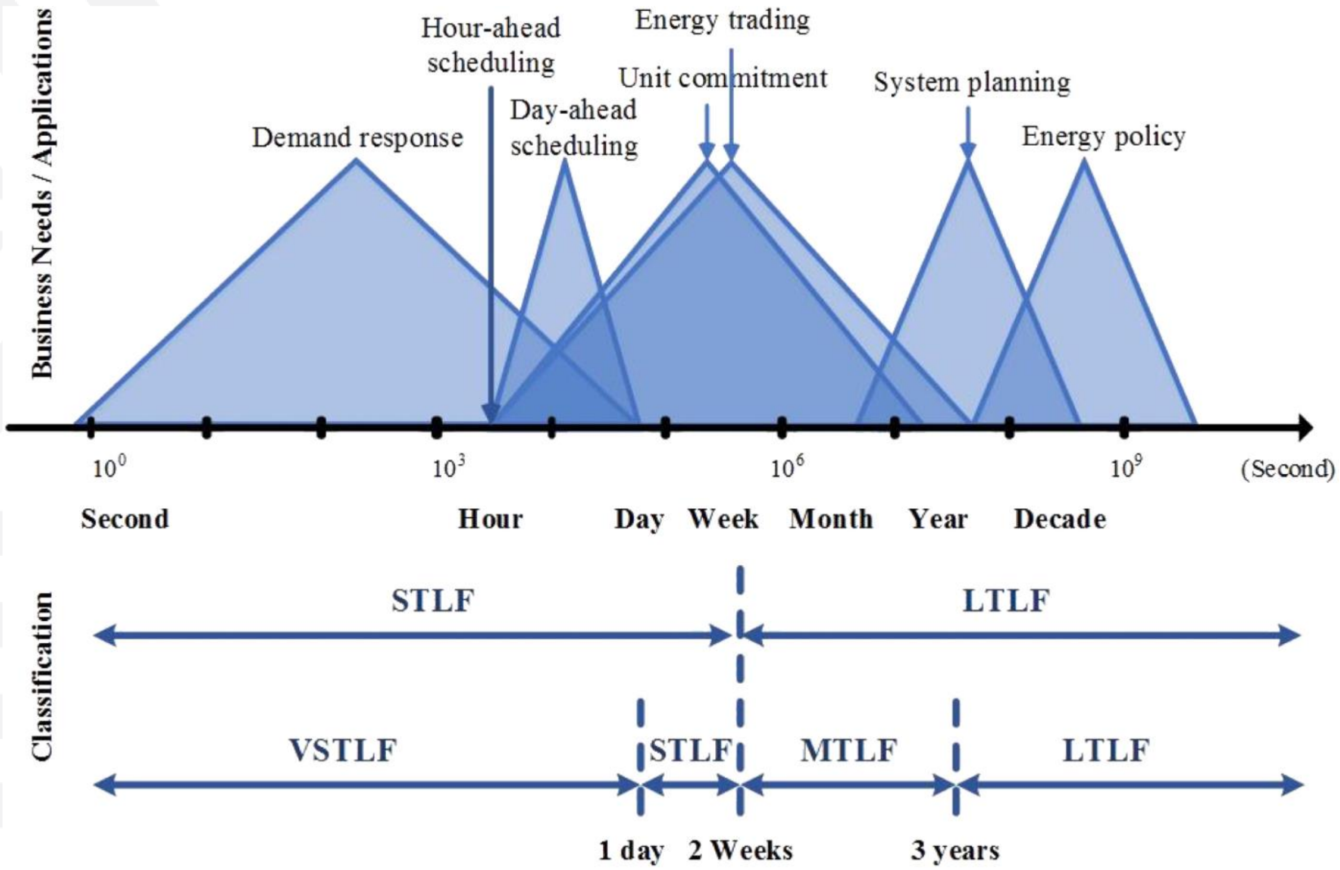


[Hawaii Integrated Grid Planning (IGP) Technical Conference June 2021]

Principles of forecasting

Forecasting horizons and applications

- 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

- 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

- 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

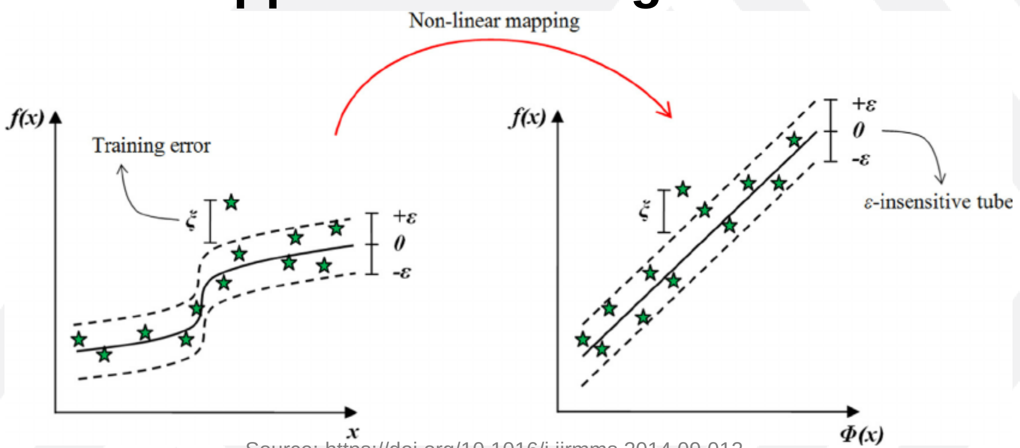
Short-term load forecasting methods – conventional

- Time-series methods
  - Model the load demand as a function of historical data
  - Data follow a certain pattern that depends on autocorrelation; trends in the data; and daily, weekly, and seasonal variations
  - Examples methods:
    - Autoregressive (integrated) moving average (ARMA/ARIMA)
    - Autoregressive (integrated) moving average with exogenous variables (ARMAX/ARIMAX)
    - State space models

- Regression methods
  - Model the load as a combination of variables related to weather, day type, and customer class
  - Weather information used: temperature, wind speed, humidity, and cloud cover
  - Coefficients are estimated using least squares and other regression techniques

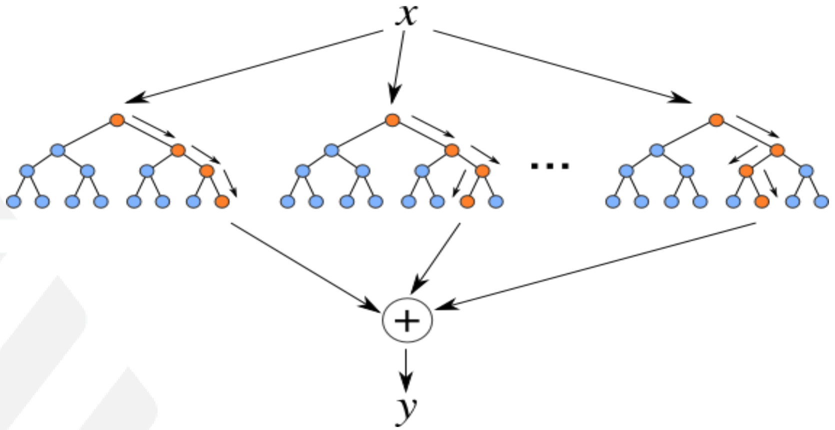
Short-term load forecasting methods – machine learning

Support Vector Regression

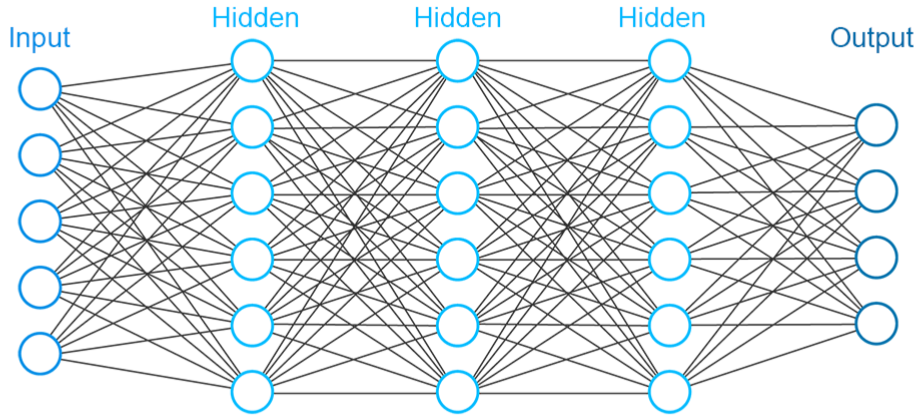


Source: https://doi.org/10.1016/j.ijrmms.2014.09.012

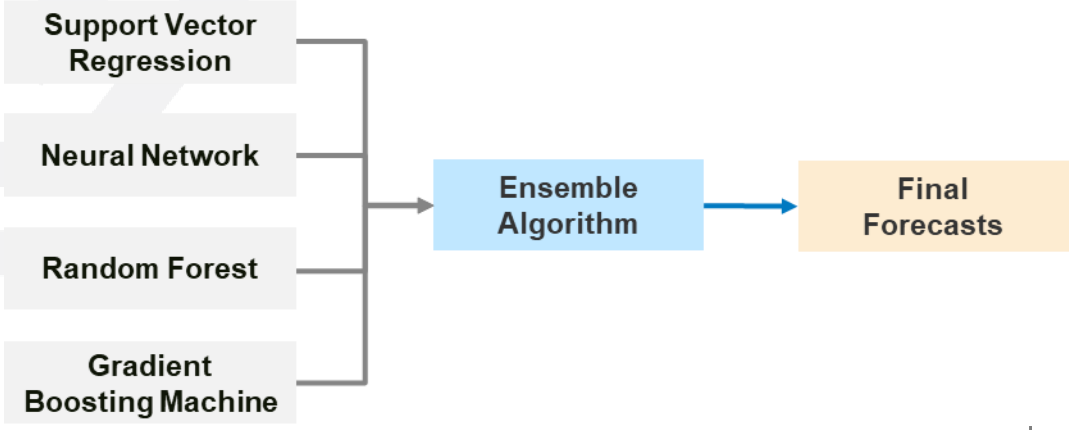
Decision Tree-Based Methods



(Deep) Neural Networks



Ensemble Learning

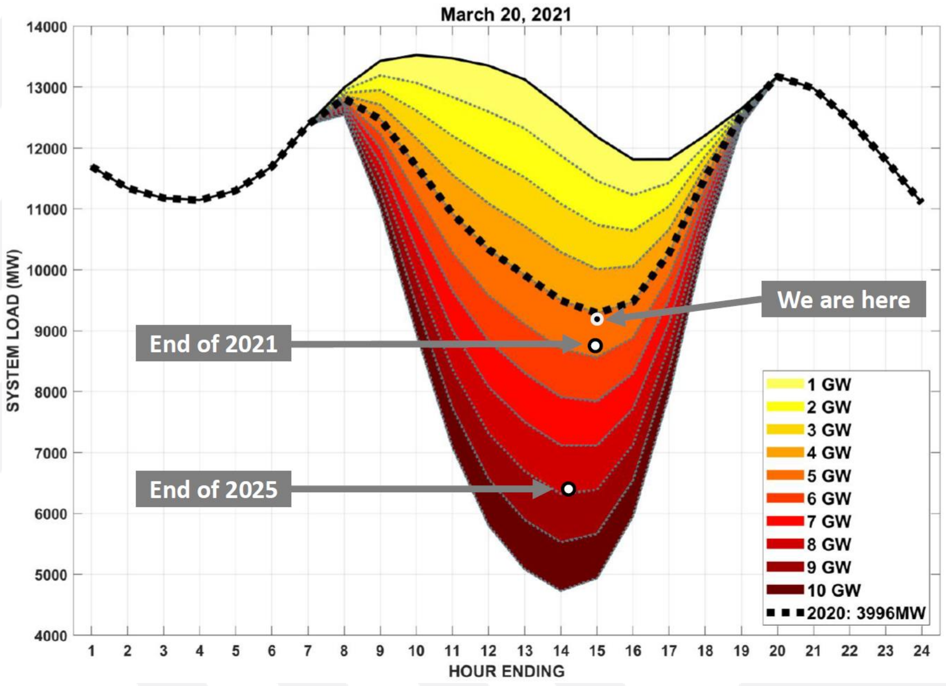


Challenges

New challenges for load forecasting – behind-the-meter (BTM) PV (1)

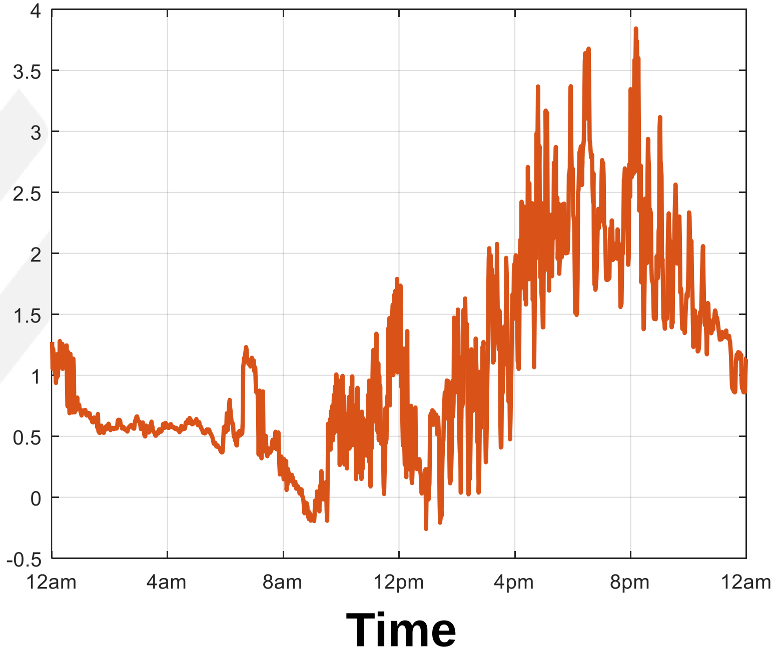
Integration of BTM PV systems leads to **changing** load patterns

Net-Load Shapes



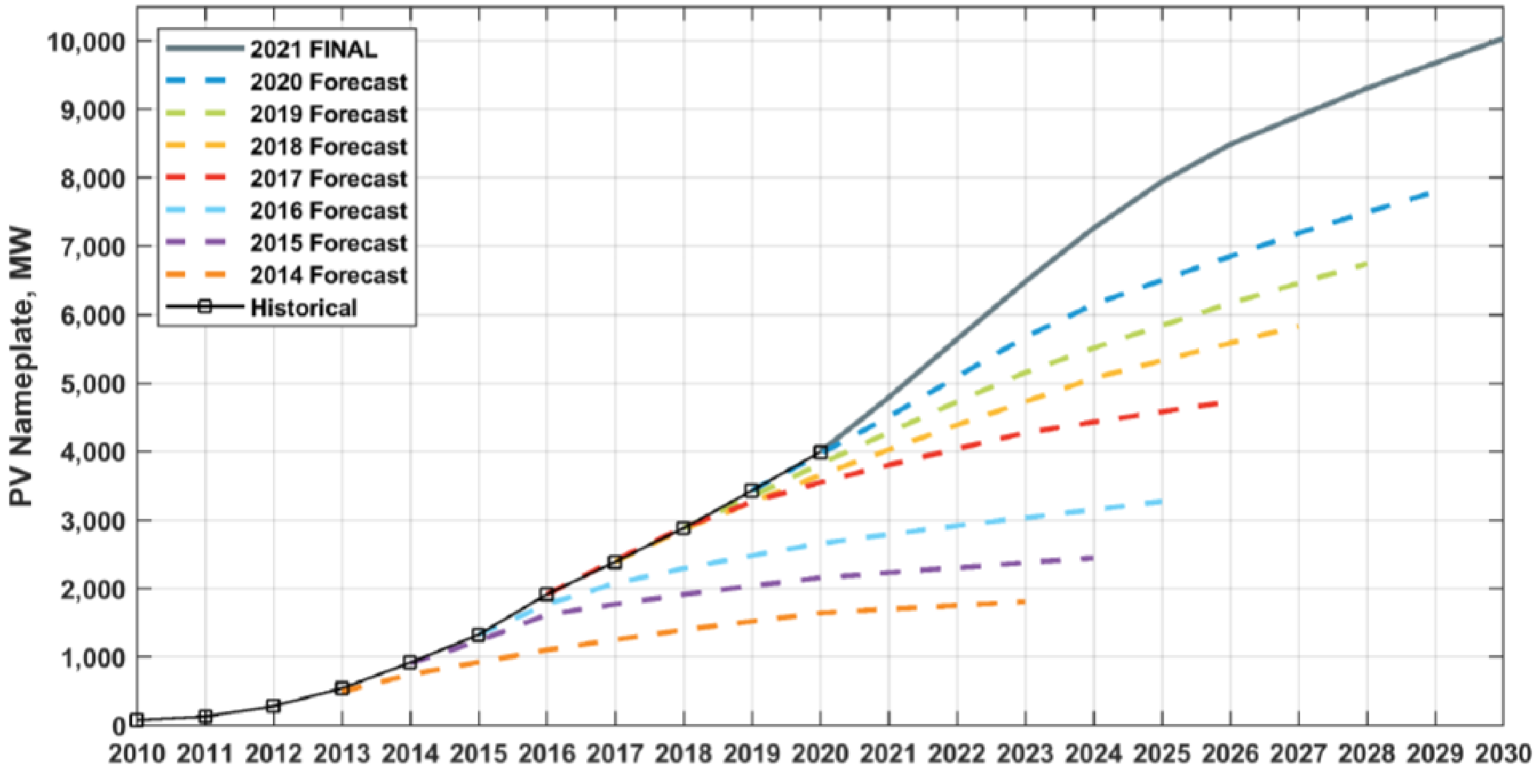
Source: ISO New England

Volatility and Uncertainty



New challenges for load forecasting – BTM PV (2)

Rapid growth of BTM PV outpaces predictions



Historical vs. forecasts of total PV in New England

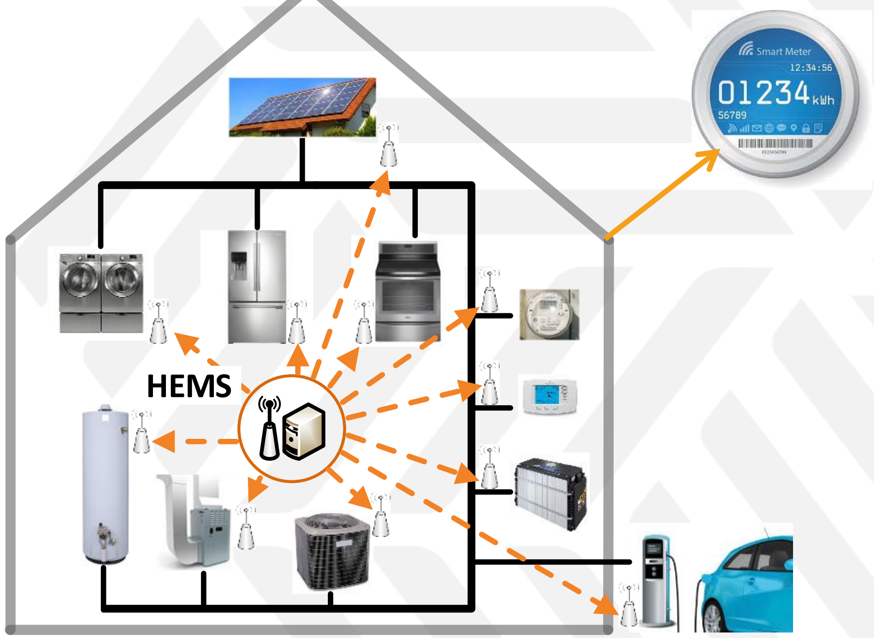
Source: ISO New England

New challenges for load forecasting – BTM PV (3)

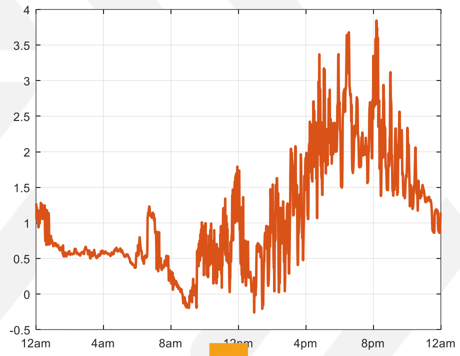
GRID MODERNIZATION LABORATORY CONSORTIUM
U.S. Department of Energy

Lack of visibility of BTM PV generation

Smart meter



Whole-House Power Consumption



PV Generation

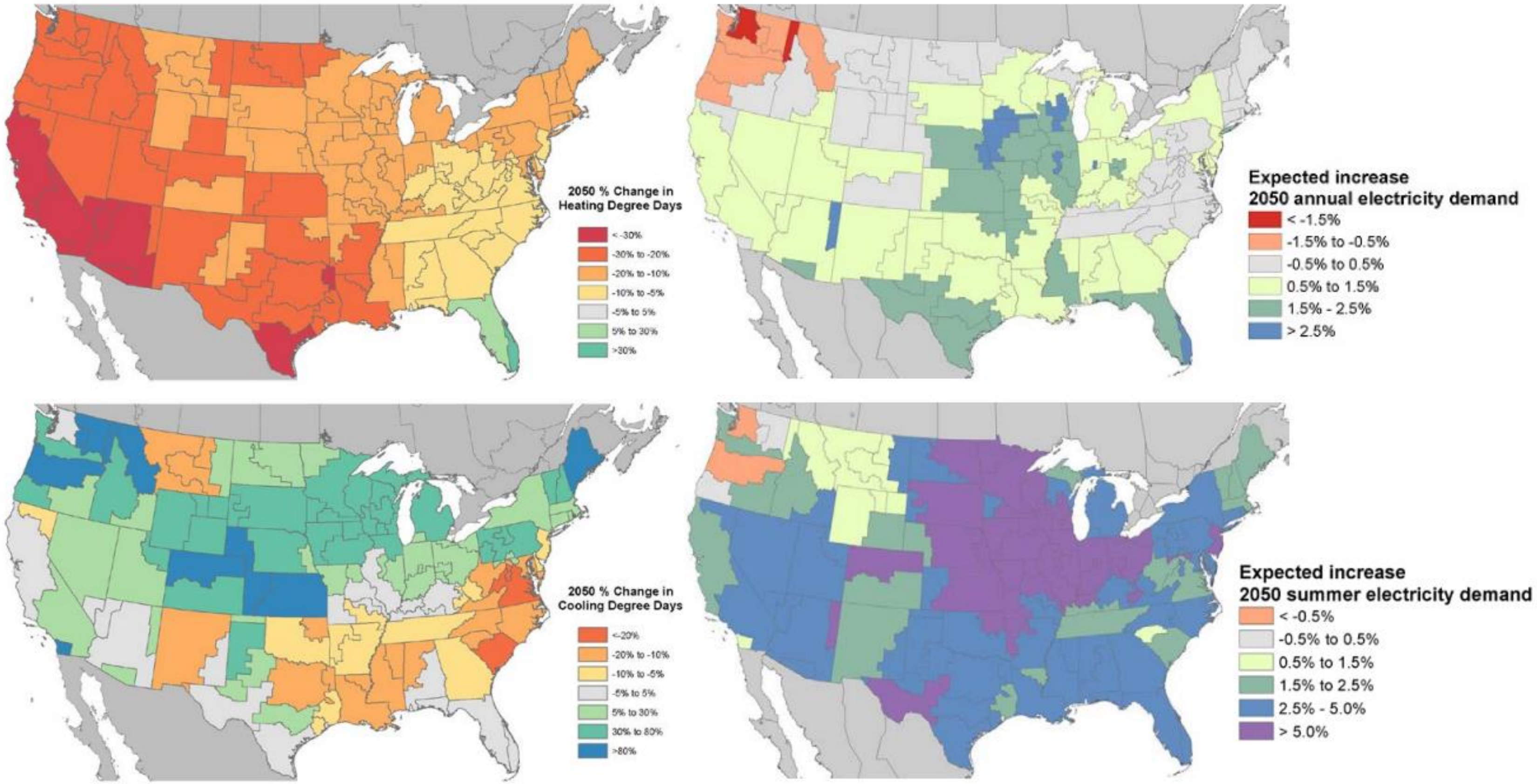
- BTM PV visibility enables:
  - More accurate net load forecasts
  - Better quantification of impacts of BTM PV on distribution systems
  - Accommodation of high penetrations of PV
- BTM PV generation needs to be accounted for in load forecasting process

Considering climate change

New challenges for load forecasting – climate change

- Impact of climate change
  - Temperature increase
  - Precipitation 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.

Questions states can ask (1)

- What model(s) is/are being used?
  - How does the utility forecast DER adoption?
  - How does the utility quantify the impact of DER adoption?
  - Are models derived from proven theoretical methods?
- 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?

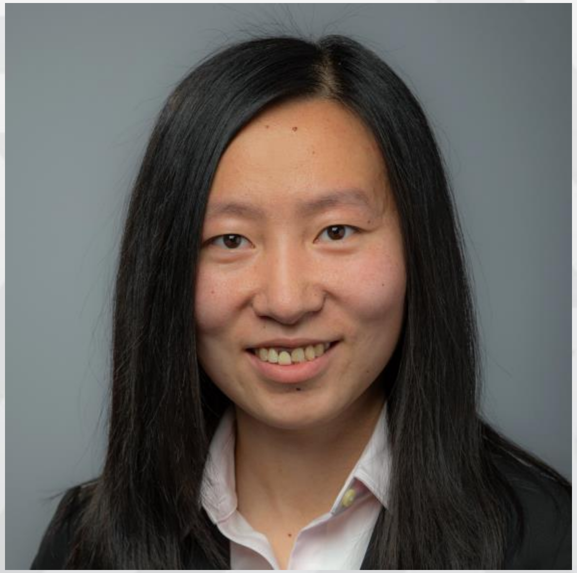
Questions states can ask (2)

- What are the outputs?
  - Do forecasts look reasonable?
  - 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 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?
  - Is an incremental approach more reasonable?
    - What are the data limitations, and can they be overcome cost-effectively?
    - Are pilots an option? (For example, some utilities, such as NYSEG and RG&E, have completed pilots with LoadSEER and anticipate having location-specific 8,760 DER and load forecasts by the end of 2025.
    - Are open-source models (such as GridLab-D) an option?)
  - Should consultants vs. in-house modeling be used to achieve forecasting goals?

Resources for more information

- PJM Load Forecasting website
- PJM 2021 Load Forecast Supplement
- van der Kam et al. Diffusion of solar photovoltaic systems and electric vehicles among Dutch consumers: Implications for the energy transition
- California Distribution Forecasting Working Group Final Report
- NYSERDA DER database
- Hawaiian Electric Company - March 2021 Update to the 2020 Integrated Grid Planning Inputs and Assumptions
- National Grid 2020 Distributed System Implementation Plan
- The National Potential for Load Flexibility: Value and market potential through 2030
- Solar Power in New England: Concentration and Impact
- Improving Solar & Load Forecasts by Reducing Operational Uncertainty
- dsgrid: Demand-Side Grid Model

Contact

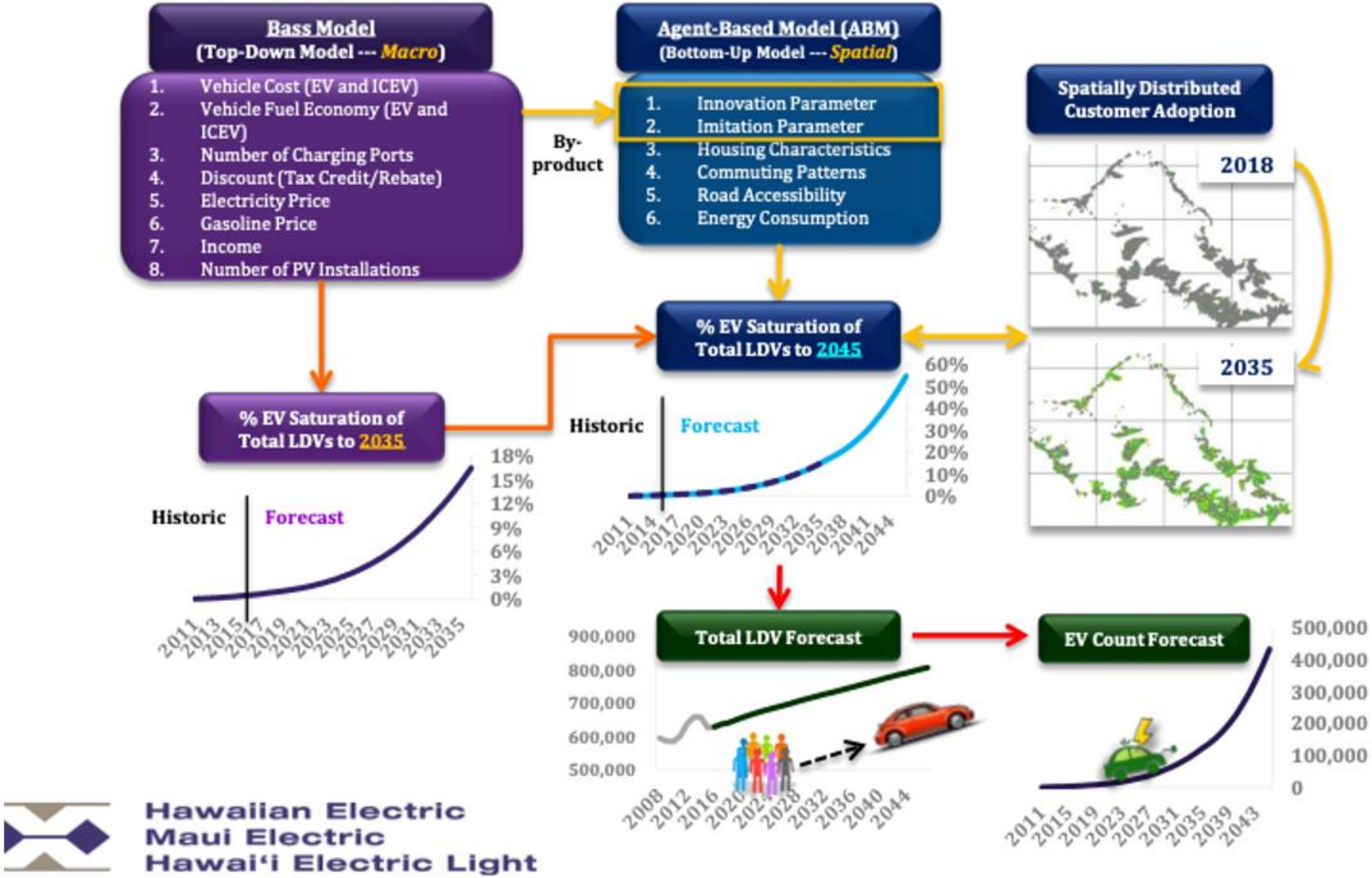


Rui Yang
Rui.Yang@nrel.gov
303-275-4336

Juliet Homer
Juliet.homer@pnnl.gov
509-375-2698

Extra slides

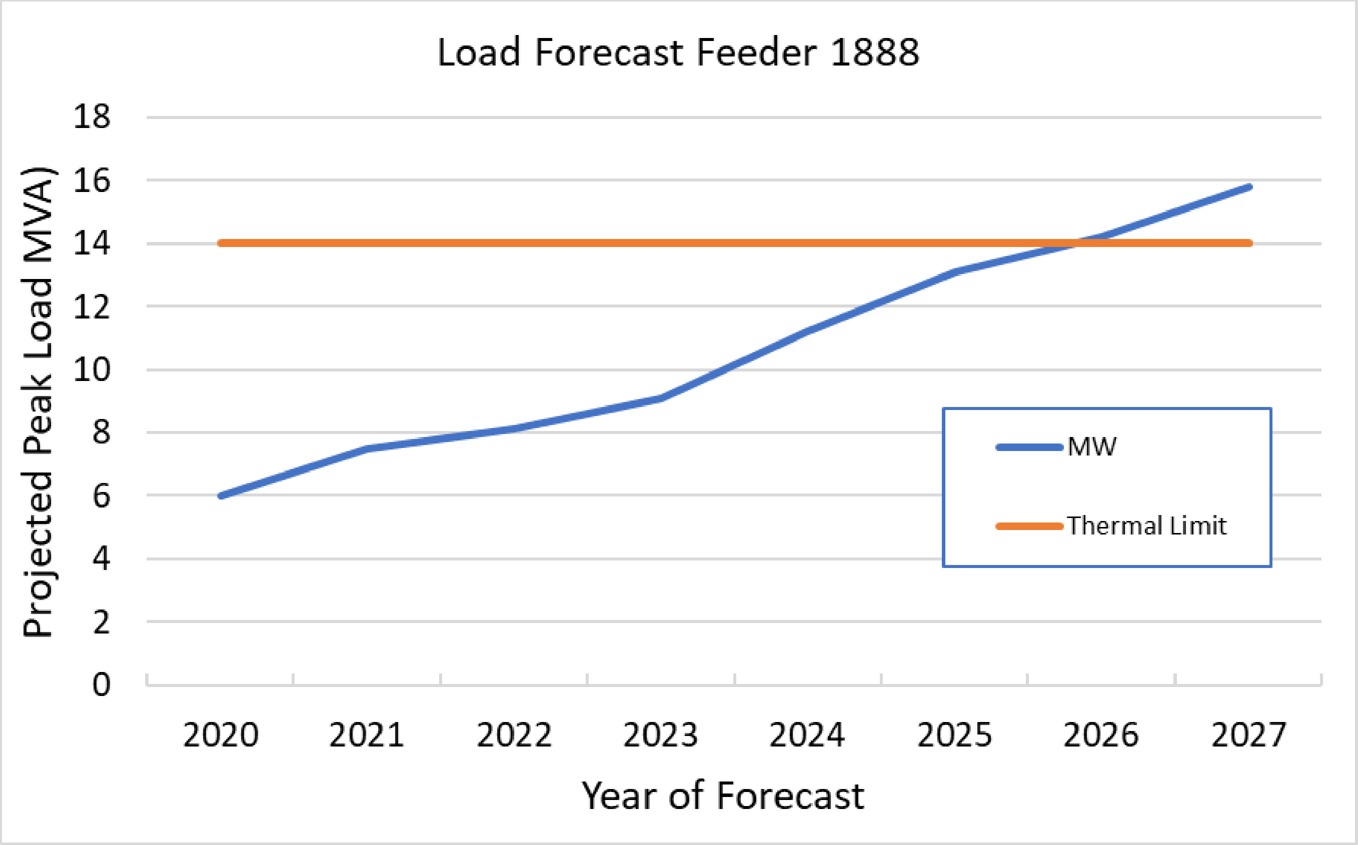
Hawaiian Electric EV forecast methodology flow



[March 2021 Hawaiian Electric 2020 Integrated Grid Planning Inputs and Assumptions]()

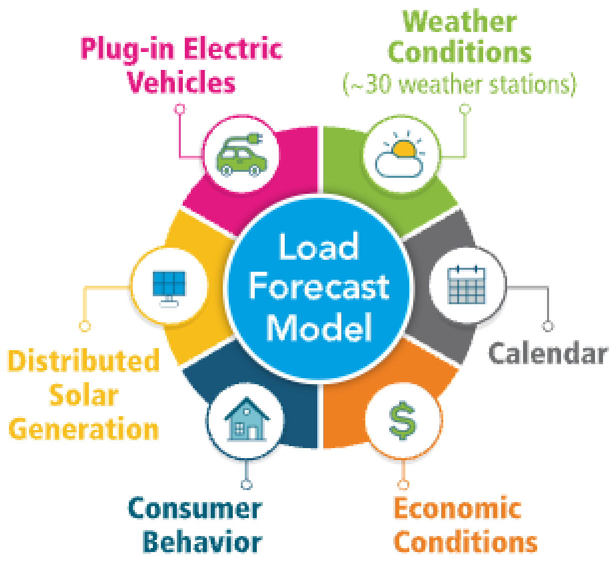
Traditional distribution load forecasting

- ► 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)

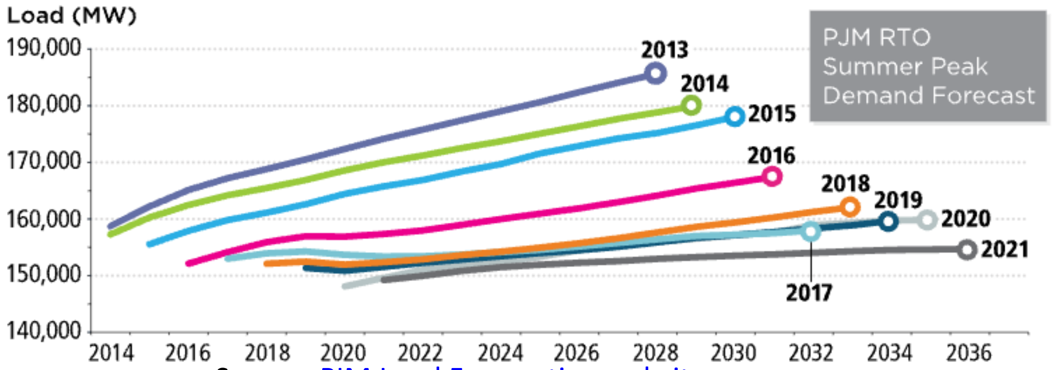


Transmission system forecasting

- 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

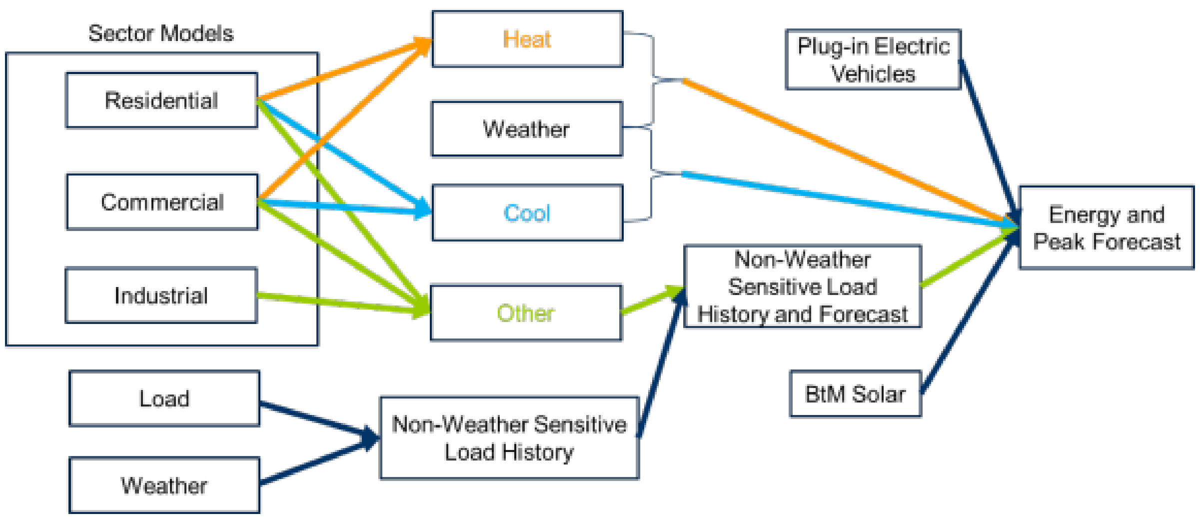


Source: PJM Load Forecasting website



Source: PJM Load Forecasting website

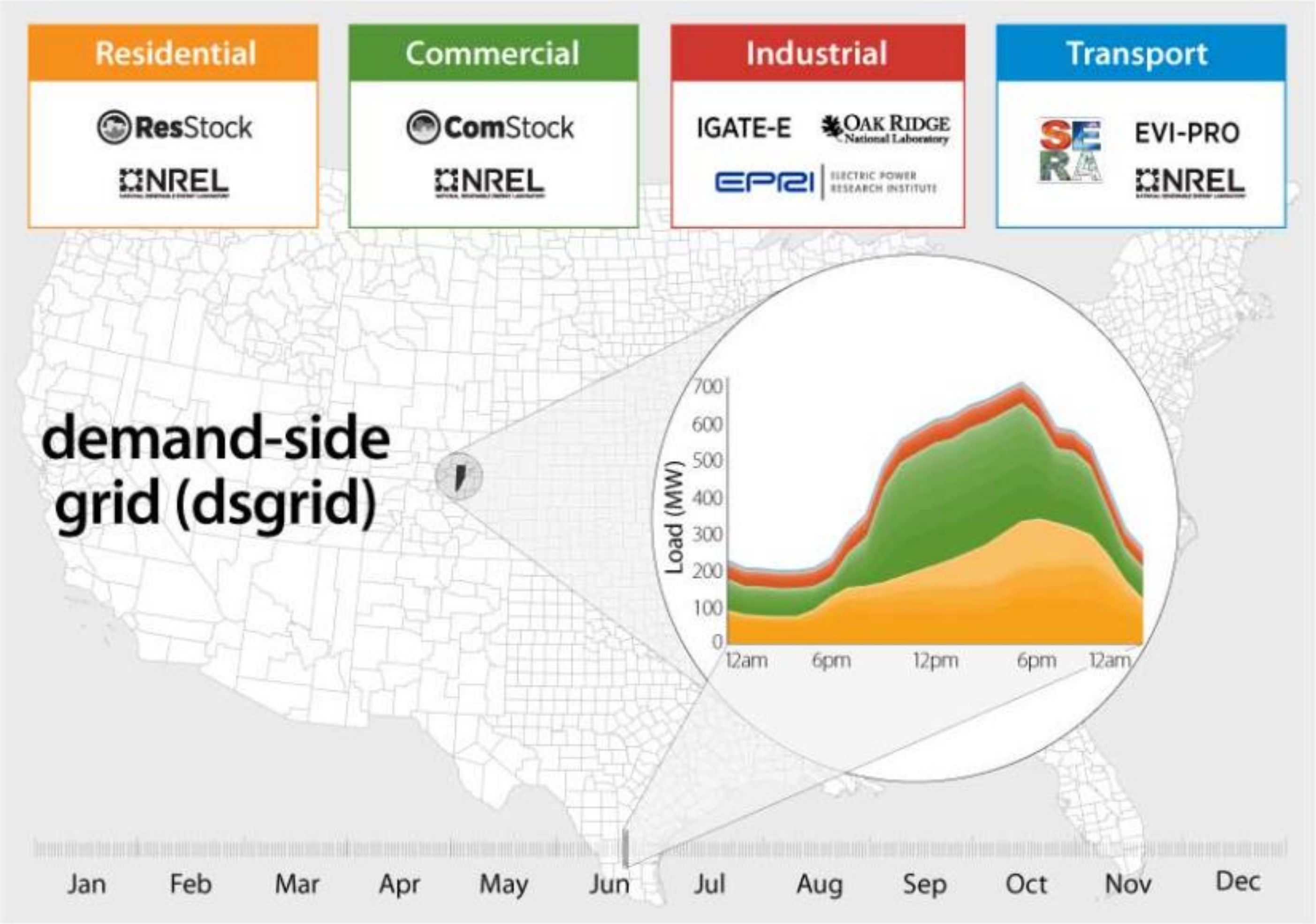
Figure 1. **Load Forecast Model Overview**



Source: PJM 2021 Load Forecast Supplement

Example tool–long-term load modeling in dsgrid

- NREL's demand-side grid model: dsgrid
  - Comprehensive electricity load data sets at high temporal, geographic, sectoral, and end-use resolution
  - Bottom-up modeling of buildings, industry, and electric vehicles
  - Future projects and what-if scenarios for load shape in addition to magnitude
  - Realistic estimates of potential load flexibility (i.e., demand response)
  - Understand interactions between energy efficiency and demand response potential (also renewables and DERs)



Source: dsgrid, https://www.nrel.gov/analysis/dsgrid.html.

Load forecasting with BTM PV example

Error Correction	Reconstituted Loads	Model Direct
• Adjust, ex post, load forecasts to account for forecasted values of PV generation	• Reconstitute the historical time series of measured load by adding back estimates of PV generation • Retrain load forecast models based on reconstituted load • Subtract PV forecast from load in forecast models	• Add PV generation data as an explanatory variable in load forecast models • Estimate the coefficients associated with the PV generation

Annual Valuation of Improved Forecasts

Year	CAISO
2012	$107,241
2013	$7,043,032
2014	$1,510,790
2015	$575,832
Total	$9,236,894

Source: F. A. Monforte, C. Fordham, J. Blanco, D. Hanna, S. Peri, S. Barsun, A. Kankiewicz, and B. Norris, “Improving Solar & Load Forecasts by Reducing Operational Uncertainty,” California Energy Commission, Publication number: CEC-500-2019-023, 2019.