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Overview of the Long-Term Load Forecast Methodology

Load Forecast Committee

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Purpose of Long-Term Load Forecast

> *"The ISO shall forecast load for the New England Control Area and for each Load Zone within the New England Control Area. The load forecasts shall be based on appropriate models and data inputs. Each year, the load forecasts and underlying methodologies, inputs and assumptions shall be reviewed with Governance Participants, the state utility regulatory agencies in New England and, as appropriate, other state agencies…"* Market Rule 1, Section III.12.8

- Long-term load forecast is an important factor in:
  - Determining region's resource adequacy requirements for future years
  - Evaluating reliability and economic performance of electric power system under various conditions
  - Planning needed transmission improvements
  - Coordinating maintenance and outages of generation and transmission infrastructure assets

- Annual forecast is reported in Capacity, Energy, Load, and Transmission (CELT) report and the Forecast Data workbook

Long-Term Forecast Components

- Each of the 4 load components entail distinct modeling steps
  - All forecasts are hourly
  - Base load forecast is at the load-zone level
  - HP, EV, and BTM PV forecasts have accounting at the county level

Base Load Forecast

- Statistically modeled based on historical load reconstituted for BTM PV
- Is combined with electrification forecasts to yield the gross and net load forecasts

DER (BTM PV) Forecast

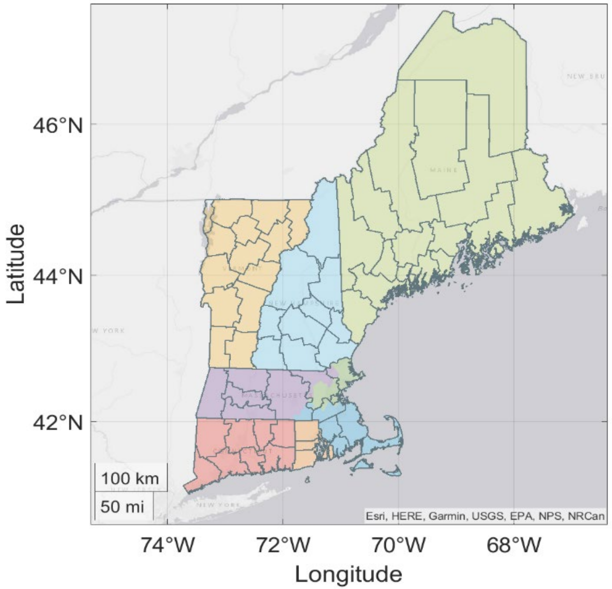
- Adoption forecasting based on NREL's dGen™ tool
- Demand reductions derived using zonal, historical hourly capacity factors

Heat Pump (HP) Forecast

- Adoption forecast along possible heating pathways
- Demand derived from simulated weather-dependent building heating needs and HP coefficient of performance (COP) curves

Electric Vehicle (EV) Forecast

- Policy-based adoption forecast (5 vehicle types)
- Demand derived from weather-sensitive battery efficiency curves and daily charging profiles



New England is comprised of 6 states, 8 load zones, and 67 counties

Key Elements of Forecast Methodology

Gross Load

- $Load_{Gross} = Load_{Net} + BTM\ PV$
- Historical and future impacts of EE are captured via historical trends and SAE drivers included as inputs to the model

Base Load Modeling

- A daily energy model that feeds 24 individual hourly models
- Combination of linear regression and neural networks
- Expanded set of weather and calendar explanatory variables

Temporal Granularity

- Modeling includes simulations of all hours for all load components, enabling the forecast to capture the dynamic interplay between components and their profiling

Expanded Weather Data

- Use of ERA5 reanalysis weather data from ECMWF
- Climate-adjusted weather data reflecting 70 weather years
- 23 weather locations, 8 weather concepts

Hierarchical Forecasting

- Regional forecast is the sum of zonal forecasts to capture the spatial diversity of weather and load characteristics
- Zonal EV, HP, and BTMPV forecasts start at the county-level

Extended Forecast Horizon

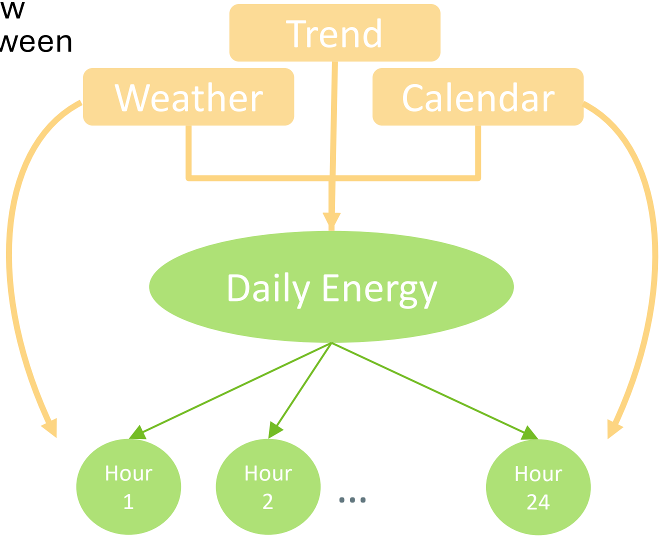
- All load components are forecast out 20+ years, enabling the forecast to support longer-term planning studies

COMPONENT FORECASTS

Base Load, DER PV, Heat Pumps, and Electric Vehicles

Base Load Forecast

- Forecast of net load, reconstituted for BTM PV
- Linear regression daily energy model
  - About 25 weather features, including transformations of dry bulb, dew point, wet bulb, wind speed, cloud cover, and some interactions between variables
    - Groups of weather variables for each season
  - More than 40 calendar features, including day of week, monthly, monthly "walk" variables, various holiday binaries
  - Three trend variables
    - Xheat is interacted with heating season weather variables
    - Xcool is interacted with cooling season weather variables
    - Xother is interacted with calendar variables
- 24 hourly neural network models
  - Ingests output of daily energy model
  - 13-15 weather variables, depending on hour of day
  - Mostly similar (~40) calendar variables as daily energy model
- Models are trained on 9-10 years of historical data
- For each year of the forecast horizon, models are used to simulate hourly demand using 70 years of climate adjusted weather and forward-looking trend variables



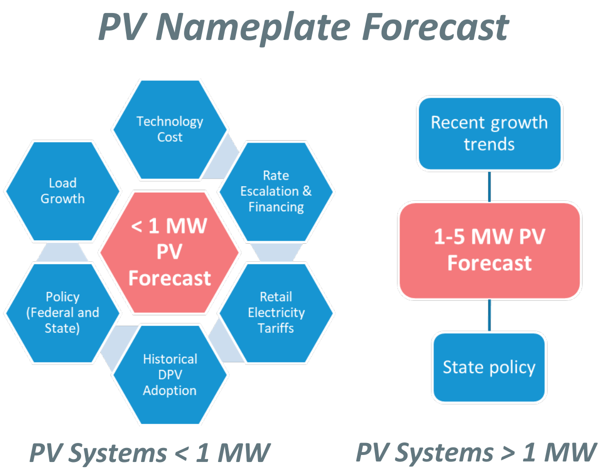
DER PV Forecast

Adoption and Demand Modeling

- The PV forecast is a projection of distributed PV resources to be used in ISO-NE System Planning studies, consistent with its role to ensure prudent planning assumptions for the bulk power system (see the 2025 DER PV Forecast for more details)

- The nameplate PV forecast is developed using the two following additive processes:
  1. For < 1 MW systems: Use residential and commercial dGen™* modeling
  2. For 1-5 MW systems: Use a policy-based approach

- PV systems outside the ISO markets (BTM PV) are identified and used to develop the BTM PV energy and demand forecasts



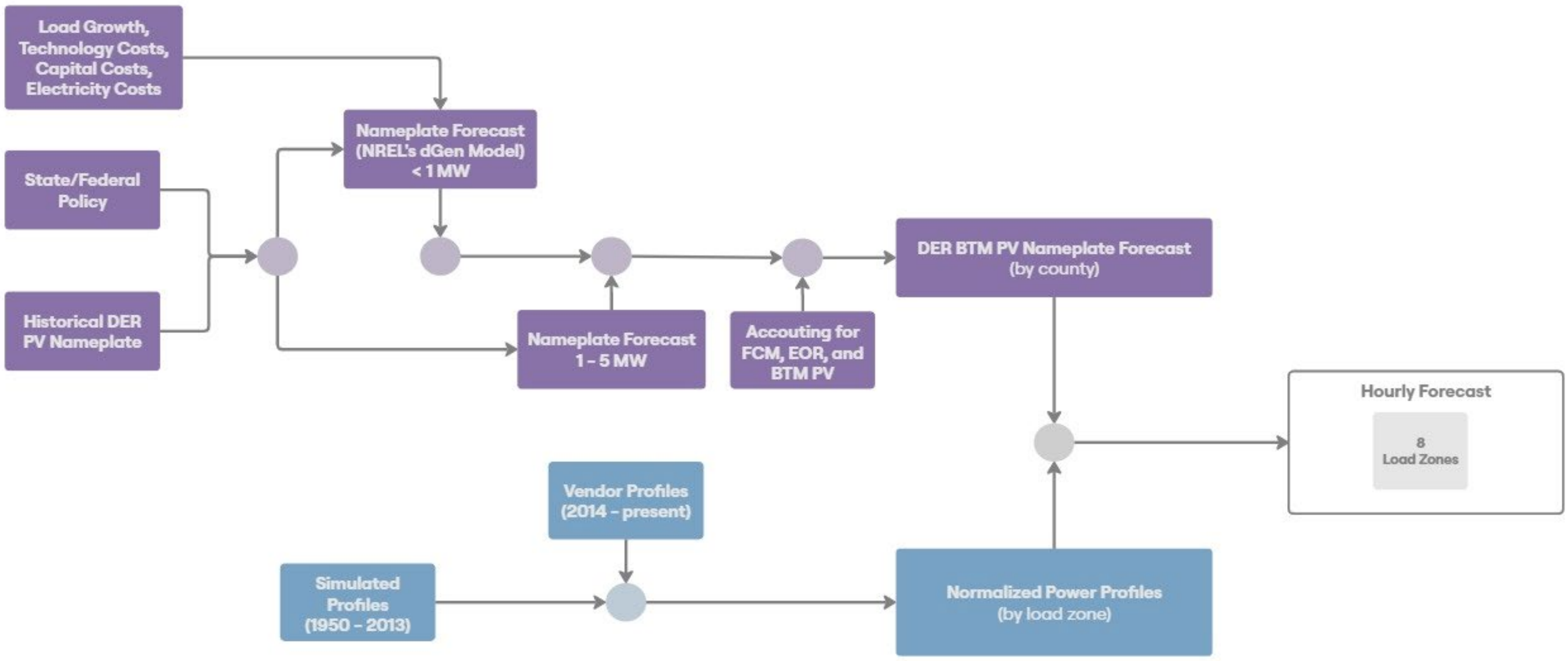
- Hourly demand forecasts are generated by combining monthly derated nameplate BTM PV forecasts are used with historical hourly capacity factor profiles to generate the 70 years of hourly forecasts, for each load zone and forecast year

- Monthly energy forecasts are the averages of the 70 monthly simulated energy values, for each forecast year
  – For example, January energy forecast is the average of all 70 January energy values, within the 70-year simulation period, for a given forecast year

** Distributed Generation Market Demand Model (dGen™) is an agent-based simulation that was developed and open-sourced by the National Renewable Energy Laboratory (NREL)*

DER PV Forecast

Process Flow



Heat Pump Forecast

Adoption Modeling

- The ISO's heating electrification forecast reflects the anticipated energy and demand impacts of regional electricity customer adoption of heat pumps (HP) to electrify space and water heating (see the 2025 Heat Pump Forecast for more details)

- Adoption modeling considers potential pathways to space and water heating electrification based on existing building stock characteristics as well as state policy and economic considerations
  - Building type and sector
  - Existing heating fuels
  - Existing heating and cooling delivery systems (e.g. ducted, non-ducted)
  - Payback period for heating technology conversion
  - Level of state policy support, incentives, and goals regarding heating electrification

Residential Heating Pathways

Heating Type	Technology Type	Heating Displacement
Space Heating	Ducted ASHP – Full	Full
	Ducted ASHP – Partial	Partial
	Ductless ASHP – Full	Full
	Ductless ASHP – Partial	Partial
	Ground Source Heat Pump	Full
	Air to Water Heat Pump	Full
	Packaged Terminal Heat Pump	Partial
Water Heating	Heat Pump Water Heater	Full

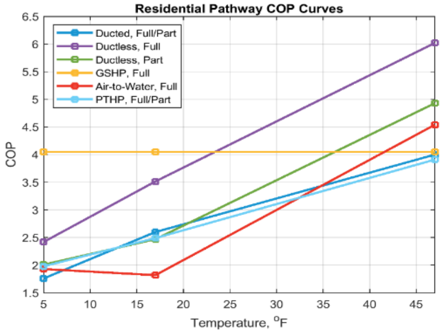
Commercial Heating Pathways

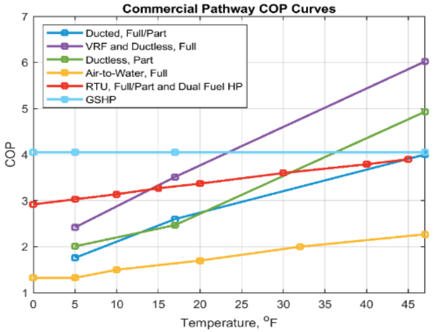
Heating Type	Technology Type	Heating Displacement
Space Heating	District Heating via Geothermal Heat Pump	Full
	Dual Fuel Heat Pump RTU	Partial
	Heat Pump RTU	Full/Partial
	VRF system (air-source)	Full
	Air-to-Water Heat Pump	Full
	Ducted Air Source Heat Pump	Full
	Ducted Air Source Heat Pump	Partial
	Ductless Air Source Heat Pump	Full
	Ductless Air Source Heat Pump	Partial
Water Heating	Heat Pump Water Heater	Full
	Heat Pump Water Heater with Booster	Partial

Heat Pump Forecast

Demand Modeling

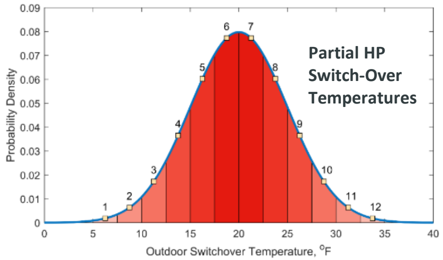
1. Development of hourly heating load relationships to outdoor temperature for all building types was based on heating usage profiles within NREL's ResStock and ComStock databases that break out energy usage by end use





2. For each pathway, the associated reference make/model heat pump's coefficient of performance was used to convert hourly heating requirements into electricity demand

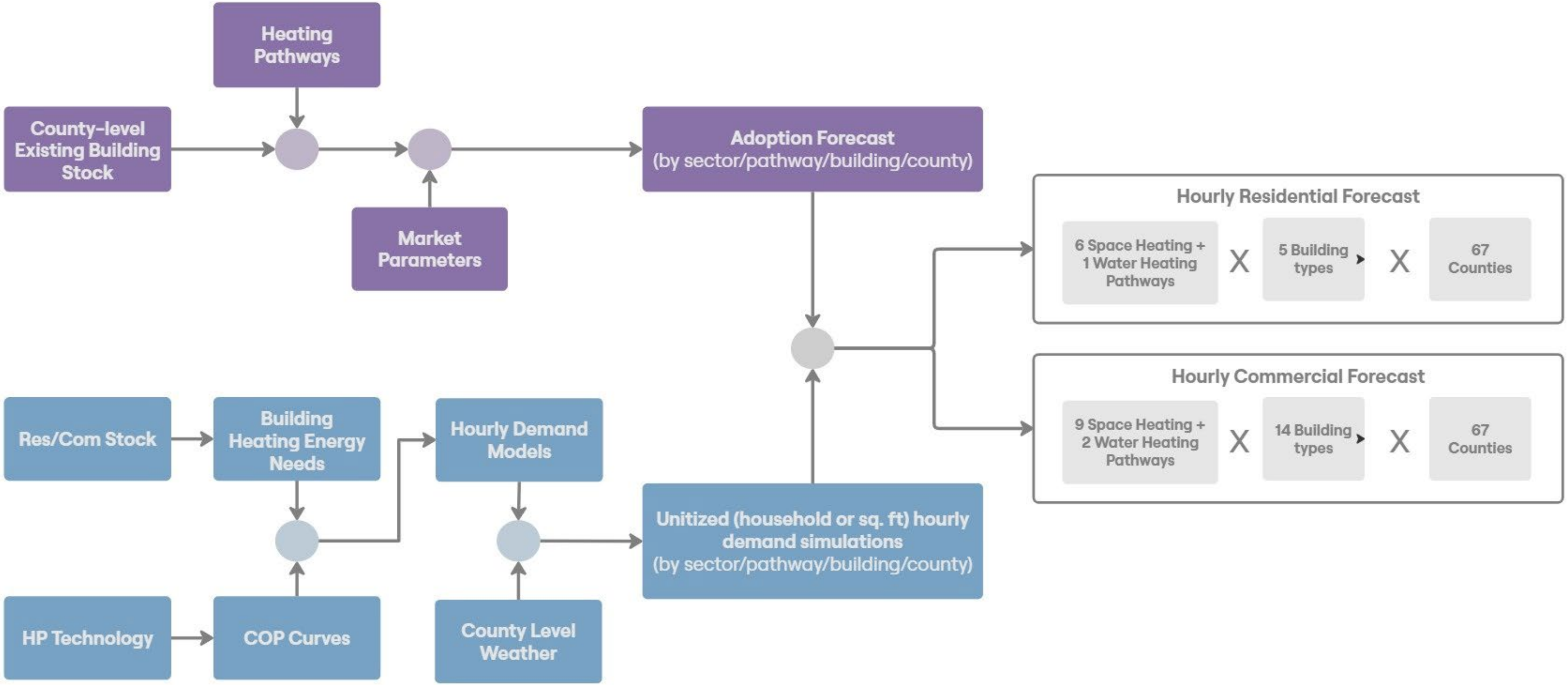
3. Models for heat pump electricity demand assume:
   - Space heating demand is initiated when outside temperatures are below 62°F
   - For partial heating pathways, all heating load needed at temperatures below the HP's switchover temperature is provided by a supplemental, non-electric heating system
     - Partial heating demand profiles are blends of demand profiles resulting from a range of normally distributed switchover temperatures
   - For full heating pathways, electric resistance heat is assumed to be used to meet any load unable to be met by the HP
   - Water heating profiles have no weather sensitivity (are located in conditioned spaces)



- Hourly demand forecasts are generated by applying demand models to 70 years of climate-adjusted weather data and scaling by adoption forecasts

Heat Pump Forecast

Process Flow



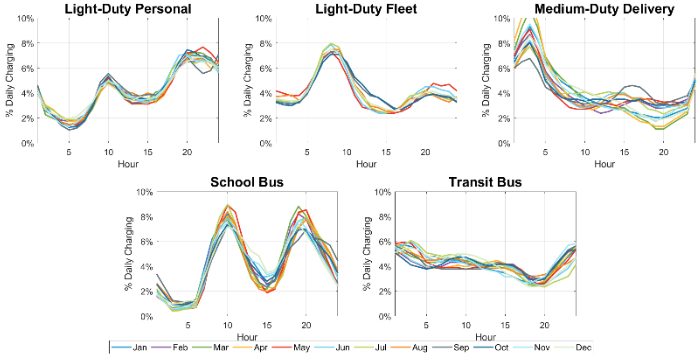
Electric Vehicle Forecast

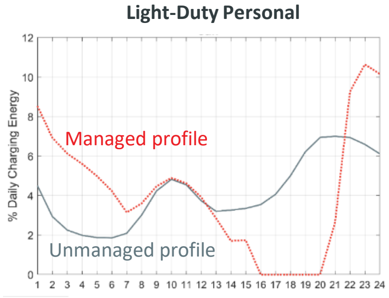
Adoption and Demand Modeling

- The ISO's EV forecast reflects the anticipated energy and demand impacts of regional electricity customer adoption of EVs in 5 categories of vehicles (see the [2025 Electric Vehicle Forecast] for more details):
  - light-duty personal, light-duty fleet, medium-duty delivery, school buses, transit buses

- EV adoption forecast considers New England vehicle population and policy landscape

- Demand modeling
  - Develop daily charging energy by combining vehicle-miles-traveled assumptions with temperature sensitive efficiency relationships
  - Allocate charging throughout the day using hourly allocation shapes
  - Phase-in EV managed charging assumptions for personal light-duty vehicles based on existing utility EVMC programs in New England





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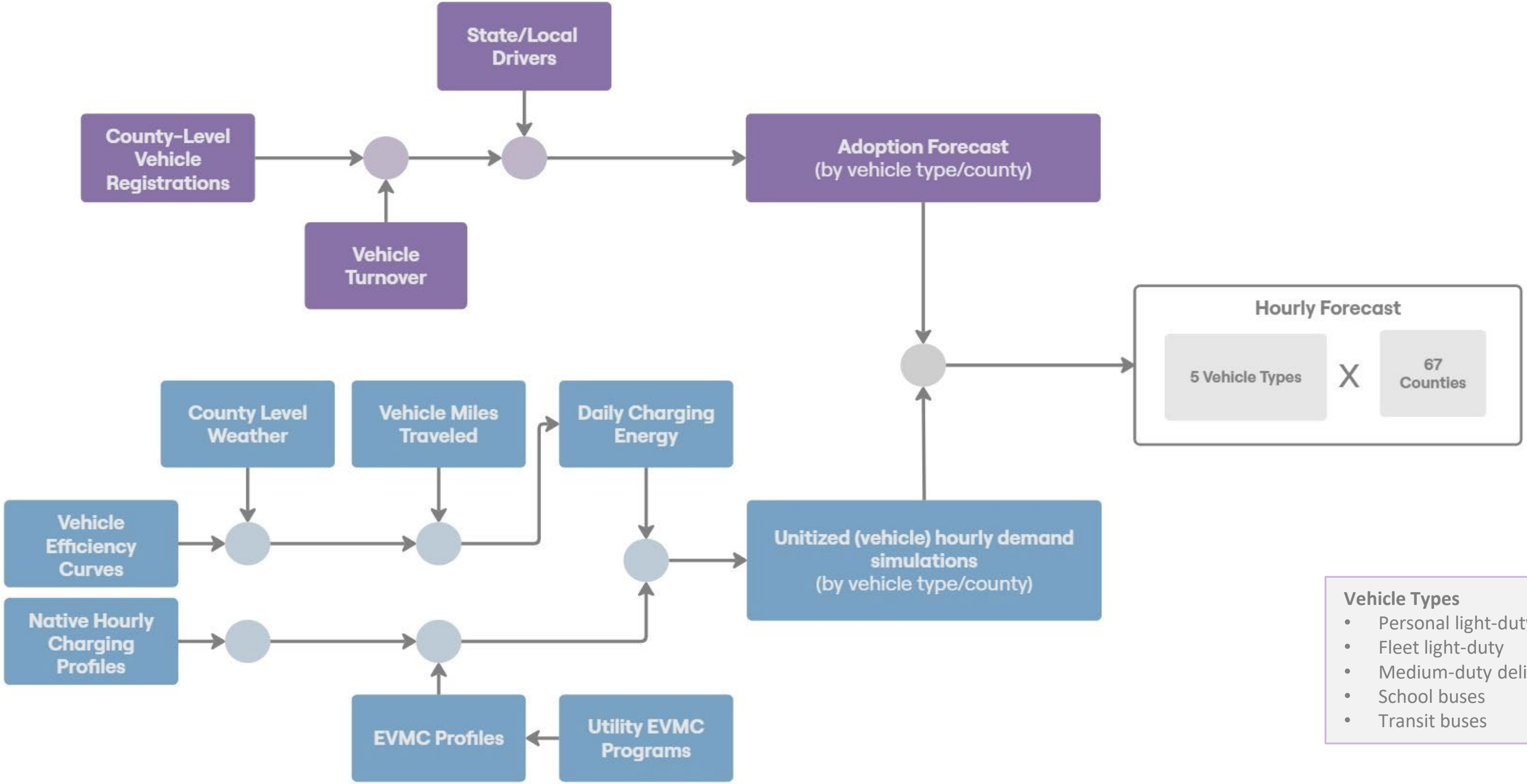
Electric Vehicle Forecast Process



Vehicle Types
- Personal light-duty
- Fleet light-duty
- Medium-duty delivery
- School buses
- Transit buses

INPUT DATA

Weather and Trend Variables

Uses of Weather in the Long-Term Forecast

Weather

Base Load Forecast

- Input to model training
- Out of sample model testing
- Forecast simulations
- Load research and analysis of historical weather events

HP Forecast

- Develop temperature dependent building heating needs
- Temperature-dependent COPs inform HP electric consumption

EV Forecast

- Weather-sensitive daily charging energy relies on temperature-dependent vehicle efficiency curves

Historical Weather

- Historical weather is used for model training and out-of-sample validation
- Reanalysis weather data is the source of historical weather
  - Climate reanalyses combine past observations with models to generate consistent time series of multiple climate variables over several decades or more
  - Reanalysis weather datasets are publicly-available, and provide a comprehensive source of weather information needed for high-fidelity load simulations
- "ERA5" is a fifth generation atmospheric reanalysis of the global climate developed by the European Center for Medium-Range Weather Forecasts (ECMWF)
  - More information about ERA5 data, including how to download it for free, is available at the Copernicus Climate Change Service (C3S) at ECMWF
  - ERA5 data also serve as the basis for climate-adjusted weather projections developed by EPRI
- Benefits of using ERA5 weather
  - Deeper weather history (ISO uses weather from 1950 onward)
  - Expanded set of weather concepts
  - Locational and temporal consistency across weather concepts over multiple decades
  - Gridded data (31 km) that can map directly to existing weather stations

Climate-Adjusted Weather

- Climate adjusted weather is used to simulate the forecast
  - See slides 9-13 of the September 2024 LFC presentation on data sources for more detail
- Climate-adjustments to ERA5 weather data were developed by the Climate Resilience Analysis team at the Electric Power Research Institute (EPRI)
  - Entire historical period is detrended and then adjusted to reflect each of 10 climate scenarios for a set of future years
    - 5 climate models representing 2 emissions pathways
    - Future years: 2027, 2032, 2040, 2050, 2060
  - Weather parameters for intervening years stem from linear interpolation
- Climate adjusted values were developed for:
  - Dry bulb temperature
  - Dew point temperature
  - Wet bulb temperature
- Other weather variables are not adjusted
  - Not all variables are projected to change significantly
  - Some variables, like wind speeds and solar irradiance, have considerable uncertainty in the projected changes reflected in climate data

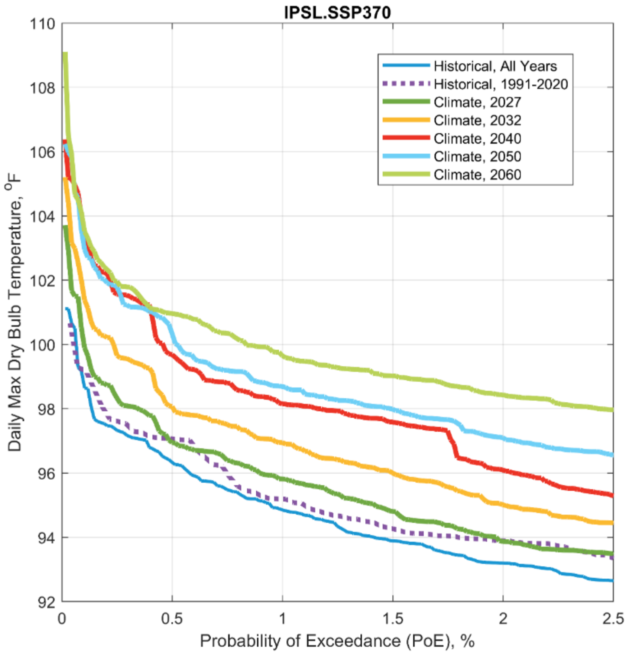
Selection of Climate Projection for Forecasting

- Plots compare the probability of exceedance of summer daily maximum (left) and winter daily minimum (right) temperatures for BDL weather station in CT
  - Extreme tails of distribution shown

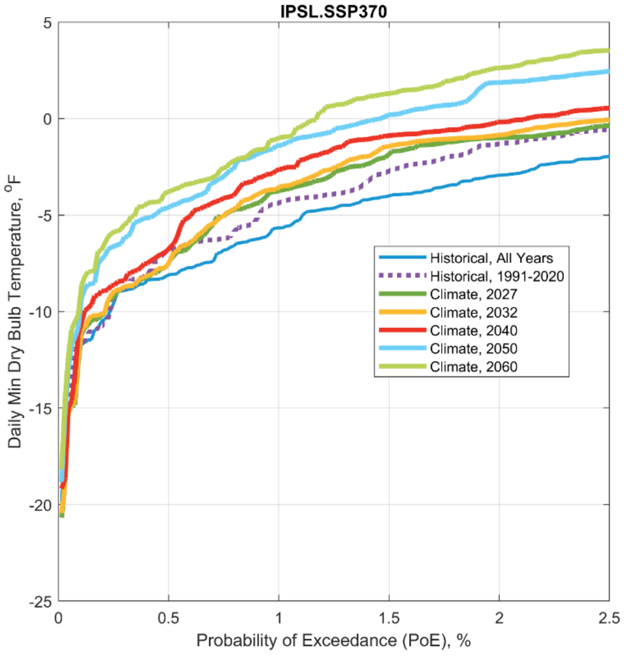
- Selected scenario: IPSL-SSP3-7.0
  - **GCM**: IPSL
  - **Emissions pathway**: SSP3-7.0

- Selection based on:
  1. Moderate warming, especially in near-term
  2. Relatively uniform pace of warming

Summer



Winter



Trend Variables

- Trend variables effectively guide base load models as structural changes occur in how electricity is consumed over time

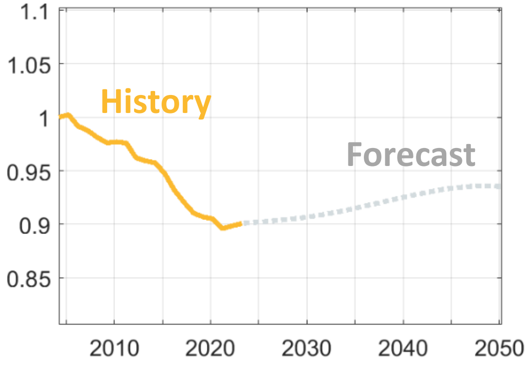
- Trend variables are intended to capture longer term influences on electricity consumption
  - Energy efficiency (e.g., equipment stock changes due to market-facing EE or “codes and standards”)
  - Economics (e.g., household demographics, business activity, electricity price)
  - Policy shifts (e.g., incentives for DERs, decarbonization)
  - Technological adoption trends (e.g., electric-based equipment, such as mowers, leaf blowers, vacuum cleaners, etc.)

- Good trend variables enable accurate modeling of demand when used in conjunction with sufficient weather and calendar variables as model inputs, and models are trained on sufficient historical data
  - Trend variables are interacted with other variables to capture changes in weather-sensitive and weather-insensitive load over time

Trend Variable Construction

- ISO's trend variables development leverages a combination of Itron's Statistically-Adjusted End-Use (SAE) framework and trends derived directly from historical load and weather data (see the [December 2024 presentation on trend variables]() for more details)
  - Weather-sensitive cooling season trend (XCool)
  - Weather-sensitive heating season trend (XHeat)
  - Weather insensitive load trend (XOther)
- History – Regression-based load analysis
  - Regression relates non-holiday weekday daily energy to heating/cooling degree days
  - Patterns of seasonal slopes and intercepts are indicative of trends that are intended to be captured via the three trend variables outlined in the SAE framework
- Forecast – Statistically Adjusted End-Use Framework (SAE)
  - Leverages data from the Energy Information Administration's (EIA) Annual Energy Outlook (AEO)
  - Develops historical and projected end-use consumption, saturation, and efficiencies for 9 census divisions

Example weather-Insensitive trend variable

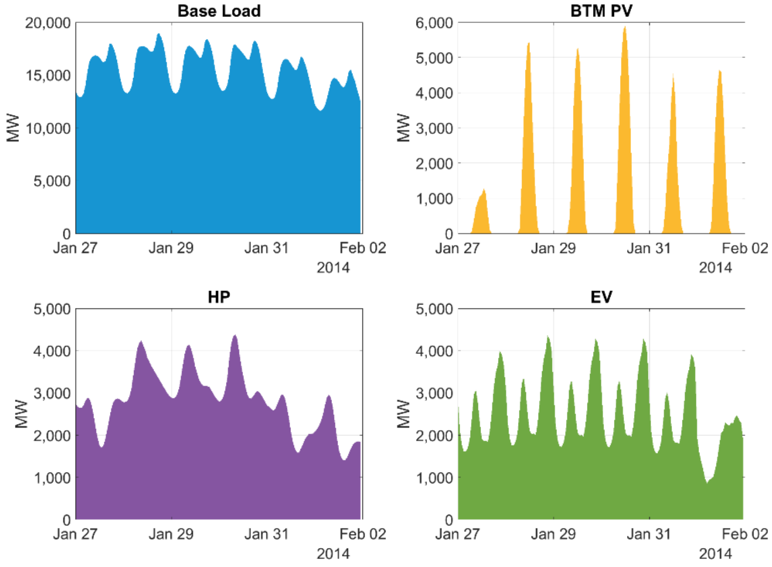


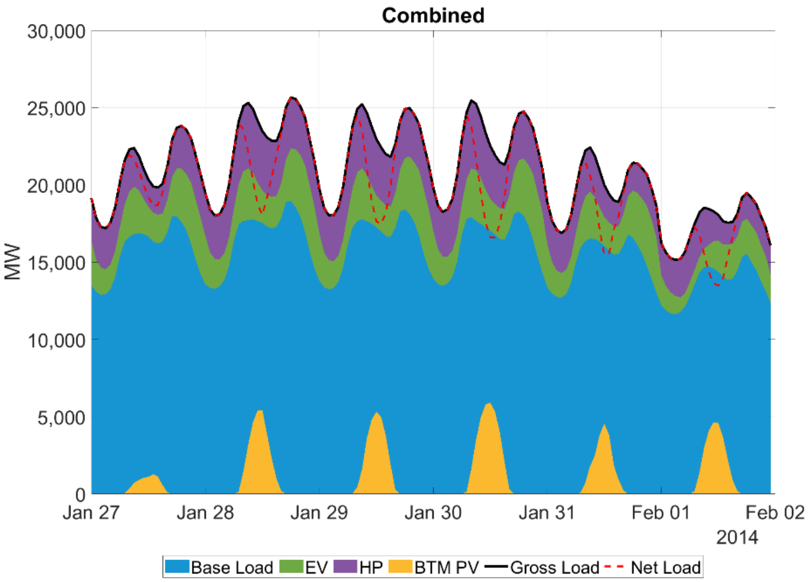
FORECAST POST-PROCESSING

Post-Processing

Load Forecast Compilation

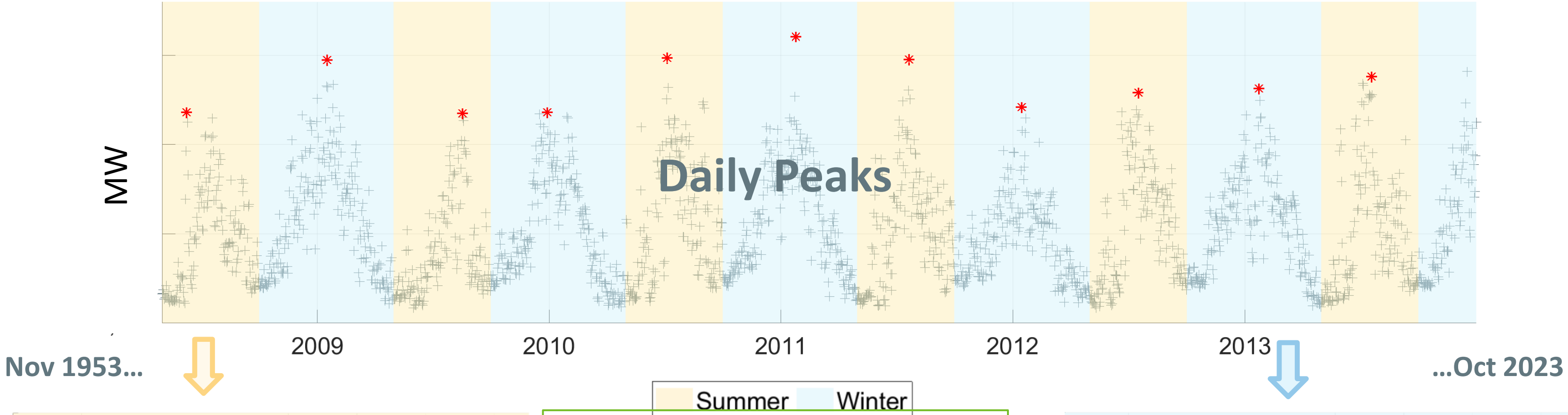
- Each forecast component (base load, EV, HP, and BTM PV) reflects coincident weather over a 70-year simulation period and are combined into forecasts of net and gross load for each zone and the region

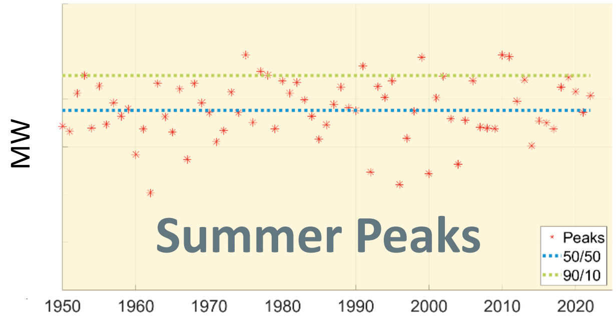




Post-Processing

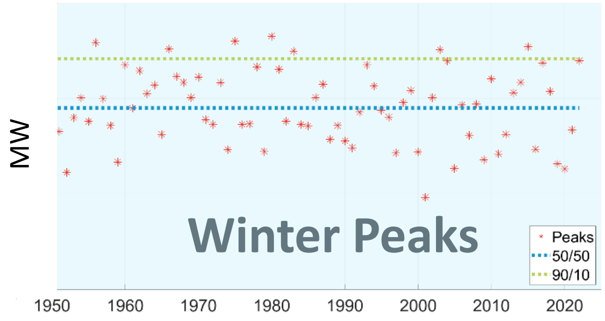
Calculation of Seasonal Peaks





Seasonal Peak Methodology

1. For a given forecast year, select seasonal peaks from each simulation year (70 values)
2. Calculate 50th and 90th percentiles from resulting seasonal peaks
3. Repeat for each forecast year

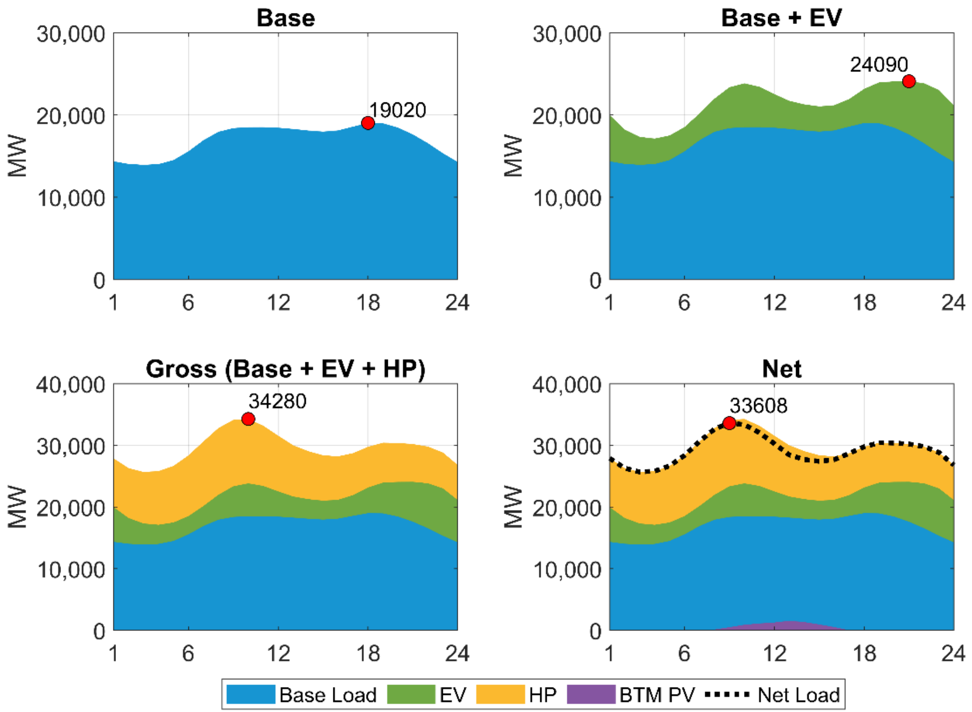


Post-Processing

Demand Impacts of Load Components: Waterfall Approach

- The hourly forecast results in a dynamic interplay of modeled load components
  - Peak hour shifts due to the growth of one component affect the peak attribution of other components
  - Attribution of peak load values to components is path dependent
- A waterfall approach to the attribution of peak load contributions is used to standardize this forecast accounting
- Waterfall method steps (refer to plot):
  1. Base = Base peak load value
     19,020 MW
  2. EV = (Base+EV) – Base
     24,090 – 19,020 = 5,070 MW
  3. HP = Gross – (Base+EV)
     34,280 – 24,090 = 10,190 MW
  4. BTMPV = Gross – Net
     34,280 – 33,608 = 672 MW

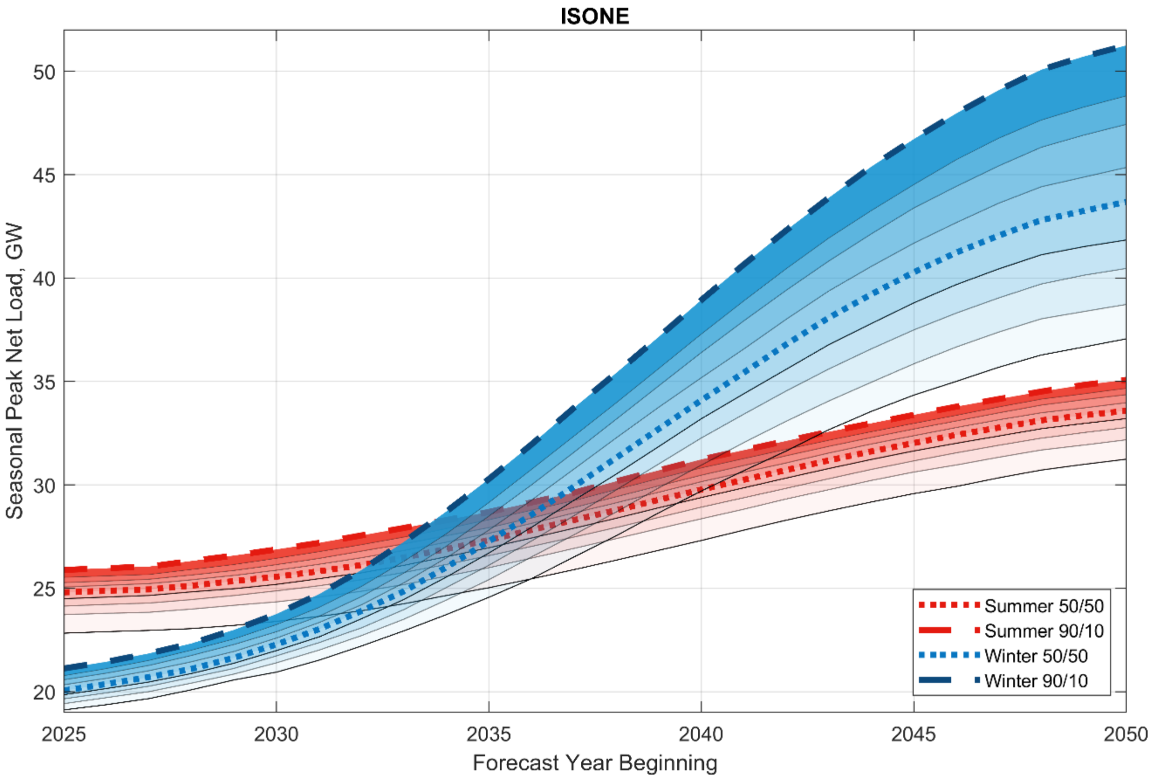
Winter Peak Day, 2045



Results from CELT 2025

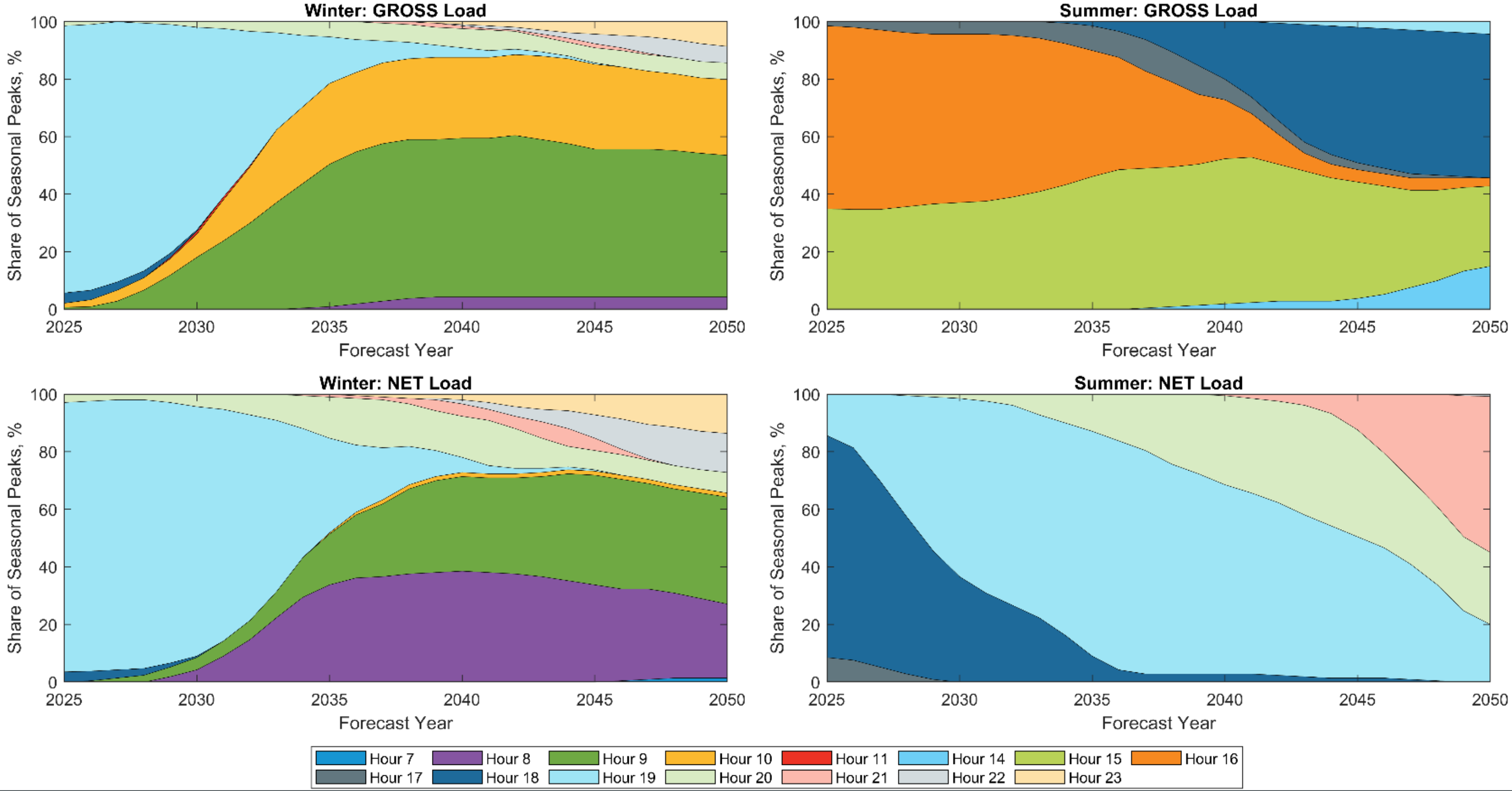
Winter and Summer Peak Convergence

- Plot shows "peak" portion of probabilistic net load forecast distribution for both winter and summer
  - Forecasts include impacts of both heating and transportation electrification
- By 2033, the 90/10 net winter demand forecast exceeds the 50/50 net summer demand forecast
- Beyond 2035, electrification is expected to cause winter peak demand to become the typical, prevailing peak season



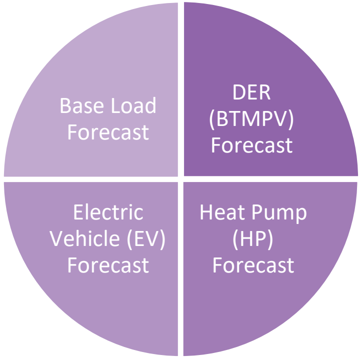
Results from CELT 2025

Evolution of Seasonal Peak Hours, 2025-2050



Load Forecast Process Summary

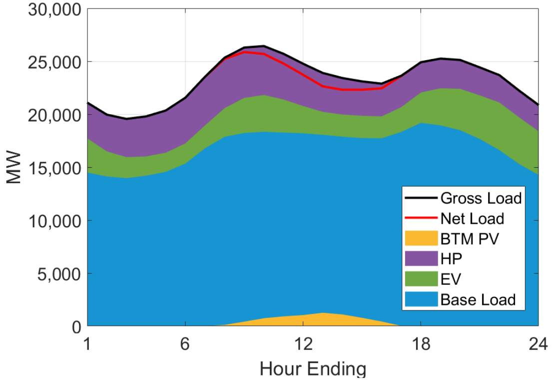
1) Four component forecasts



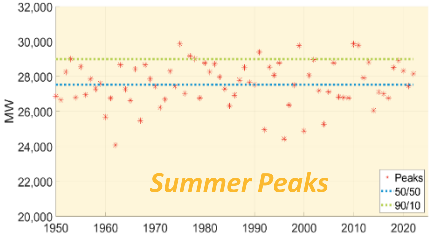
Each component forecast consists of 70 years of simulated hourly loads, for each forecast year

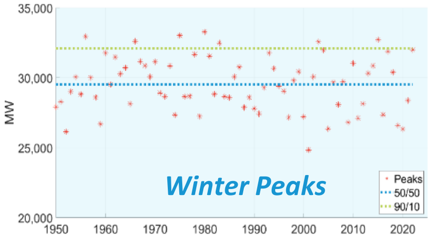
2) Hourly gross and net loads

Forecast components are combined to produce hourly gross and net loads



3) Preliminary peak percentiles

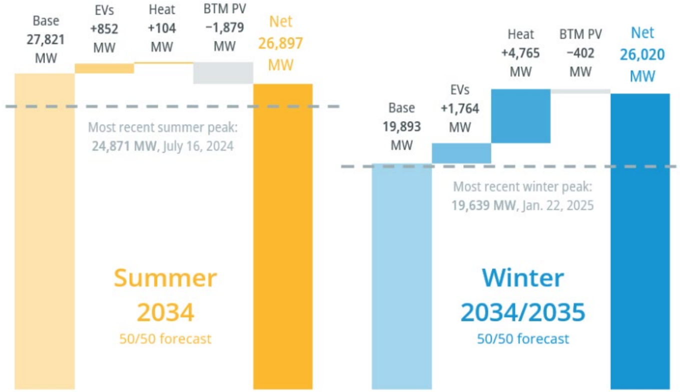




Seasonal peak gross and net loads form a distribution to extract peak percentiles

4) Final peak demand and energy

Preliminary seasonal peak percentiles are processed via a waterfall to arrive at final peak and energy for each component



Questions

Acronyms

ARA	Annual reconfiguration auction	**FERC**	Federal Energy Regulatory Commission
BTM	Behind-the-meter	**FCM**	Forward Capacity Market
CELT	Capacity, Energy, Load, and Transmission	**HP**	Heat pump
COP	Coefficient of performance	**ICR**	Installed Capacity Requirement
DER	Distributed energy resource	**LFC**	Load Forecast Committee
DG	Distributed generation	**NEL**	Net energy load
DRR	Demand Response Resource	**NREL**	National Renewable Energy Laboratory
EE	Energy efficiency	**PDR**	Passive demand resource
EV	Electric vehicle	**PV**	Photovoltaic
EIA	Energy Information Administration	**RC**	Reliability Committee