Long-Term Load Forecast Methodology Overview

Load Forecast Committee

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LOAD FORECASTING

Objectives

1. Discuss the methodologies used in the long-term load forecast process, including its inputs and outputs
2. Obtain LFC feedback on methodology and the presentation materials herein

Topics

- General purpose and intent of the load forecast
- Behind-the-Meter Photovoltaic (BTM PV) Reconstitution
- Energy Efficiency (EE) Reconstitution
- Gross Load Forecast Inputs
  - Economics
  - Weather
- Modeling and Forecasting
  - Energy modeling and forecasting
  - Peak demand modeling and forecasting
- Net Load Forecast
  - EE Forecast
  - PV Forecast
- Reporting and Downstream Outputs

Acronyms

ARA	Annual reconfiguration auction	FITs	Feed-in-tariffs
BTM	Behind-the-meter	HDD	Heating degree day
CDD	Cooling degree day	ICR	Installed Capacity Requirement
CELT	Capacity, Energy, Load, and Transmission	ITC	Investment tax credit
DB	Dry bulb	NEL	Net energy load
DG	Distributed generation	NEM	Net energy metering
DOE	Department of Energy	OP	Operating procedure
DP	Dew point	PRD	Price-responsive demand
EE	Energy efficiency	PV	Photovoltaic
EEI	Edison Electric Institute	RSP	Regional System Plan
EEM	Energy Efficiency Measures database	SBC	System benefit charges
EIA	Energy Information Administration	THI	Temperature- humidity index
EISA	Energy Independence and Security Act	WS	Wind speed
EOR	Energy only resources	WTHI	Weighted THI
FCM	Forward Capacity Market		

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

Forecast Timeline

The Load Forecast Committee (LFC) is the primary stakeholder forum through which the ISO's long term load forecast is discussed. Below is an approximate schedule of meetings and topics used in each forecast cycle.

September
- Discuss model methodology
- Introduce new topics

November
- Continue discussion of new topics

December
- Macroeconomic update
- Draft Energy Forecast

February
- Draft summer/winter demand forecasts

March
- Final draft gross and net load forecasts

What is the Load Forecast?

- ISO's long-term load forecast is a 10-year projection of *gross and net load* for states and New England region
  - Annual gross and net energy
  - Seasonal gross and net peak demand (50/50 and 90/10)
- Gross peak demand forecast is probabilistic in nature
  - Weekly load forecast distributions are developed for each year of forecast horizon
  - Annual 50/50 and 90/10 seasonal peak values are based on calculated percentiles for the peak week in appropriate month (July for summer; January for winter)

Long-term load forecast is entirely different from the *three-day system demand forecast* used in ISO System Operations (different models, data inputs, forecast horizon, etc.)

Data Sources

Long-term load forecast utilizes a variety of data sources to develop estimates of historical and forecast gross load

Data Series	Source(s)
Economic data	Moody's Analytics
Weather	Vendor supplied
Historical electricity prices	Department of Energy (DOE)/Energy Information Administration (EIA)
Load (NEL)	ISO internal database (settlements data)
Behind-the-meter photovoltaic (BTM PV)	Internal/distribution owner/vendor supplied
Energy efficiency (EE) performance	ISO energy efficiency measures database (internal)
Price-responsive demand (PRD)	ISO internal database (settlements data)
Passive distributed generation	ISO internal database (settlements data)

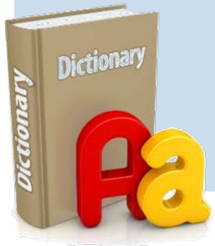
Net Energy for Load and Reconstitution of Load Definitions

Net Energy for Load (NEL)

Determined by metering, is the net generation, plus net interchange across external tie lines, less energy required for storage at energy storage facilities:

$$NEL = \sum Generation + \sum NetInterchange_{External} - EnergyStorage$$

Energy storage facilities include pumped hydro and other energy storage devices that participate in wholesale energy market as dispatchable asset-related demand



Reconstitution of Load

- Performed by adding back historical load reductions from Demand Capacity Resources that participate as supply in Forward Capacity Market (FCM), including:
  - Price-responsive demand (PRD), which is flexible load that is dispatched in real-time
  - Passive (non-dispatchable) distributed generation (DG) resources
  - Energy-efficiency (EE)
- Behind-the-meter photovoltaic (BTM PV) installations that do not participate in wholesale markets but reduce metered load

Net Load and Gross Load Definitions

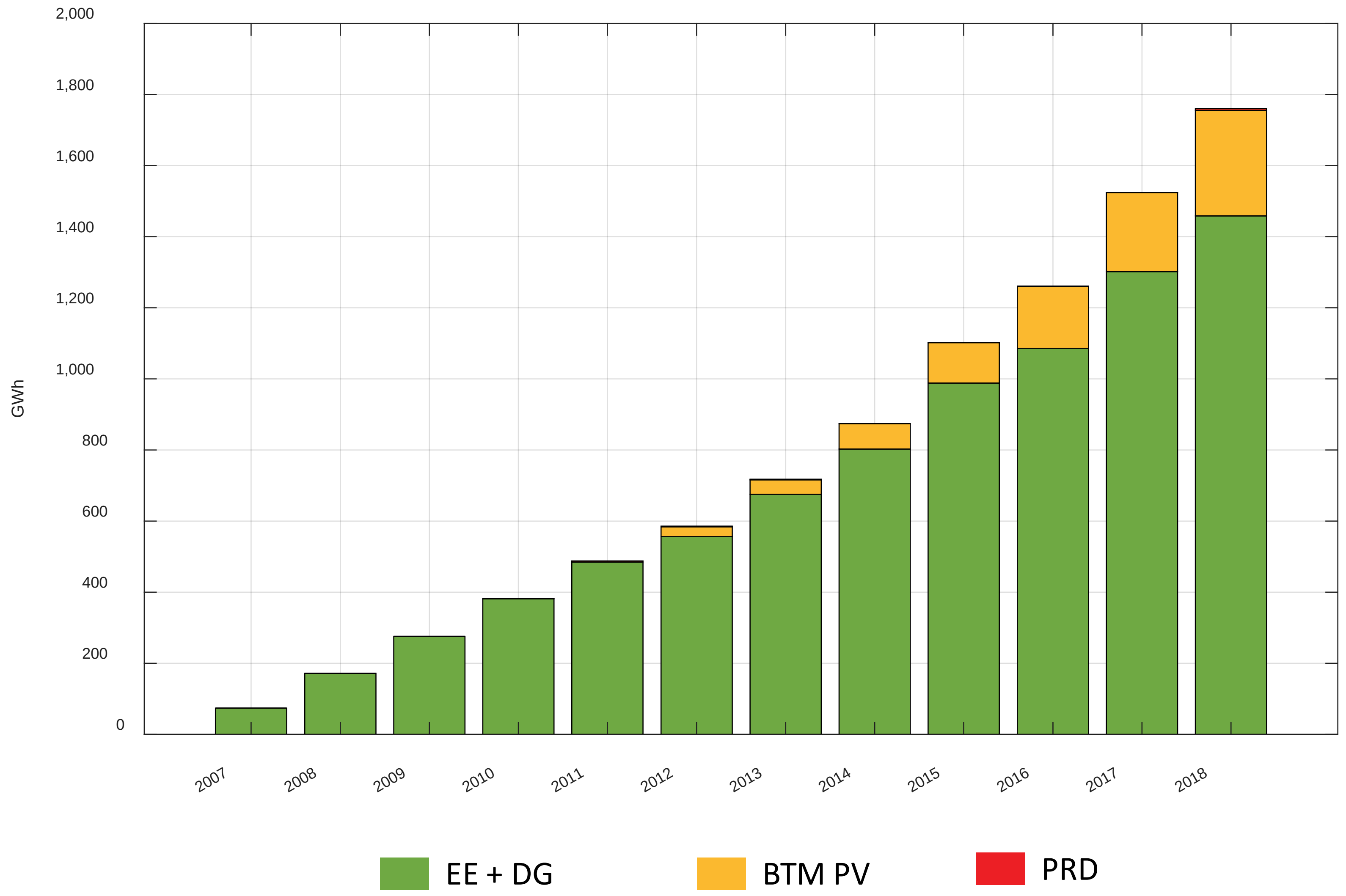
Net Load	Gross Load
$Load_{Net} = NEL + PRD$	$Load_{Gross} = NEL + PRD + EE + DG + BTMPV$

- All energy and demand forecast modeling uses historical gross load as inputs
- Reconstitution of PRD, EE, DG, and BTM PV to develop historical gross load is performed at the hourly level, for the region, and each of the six New England states

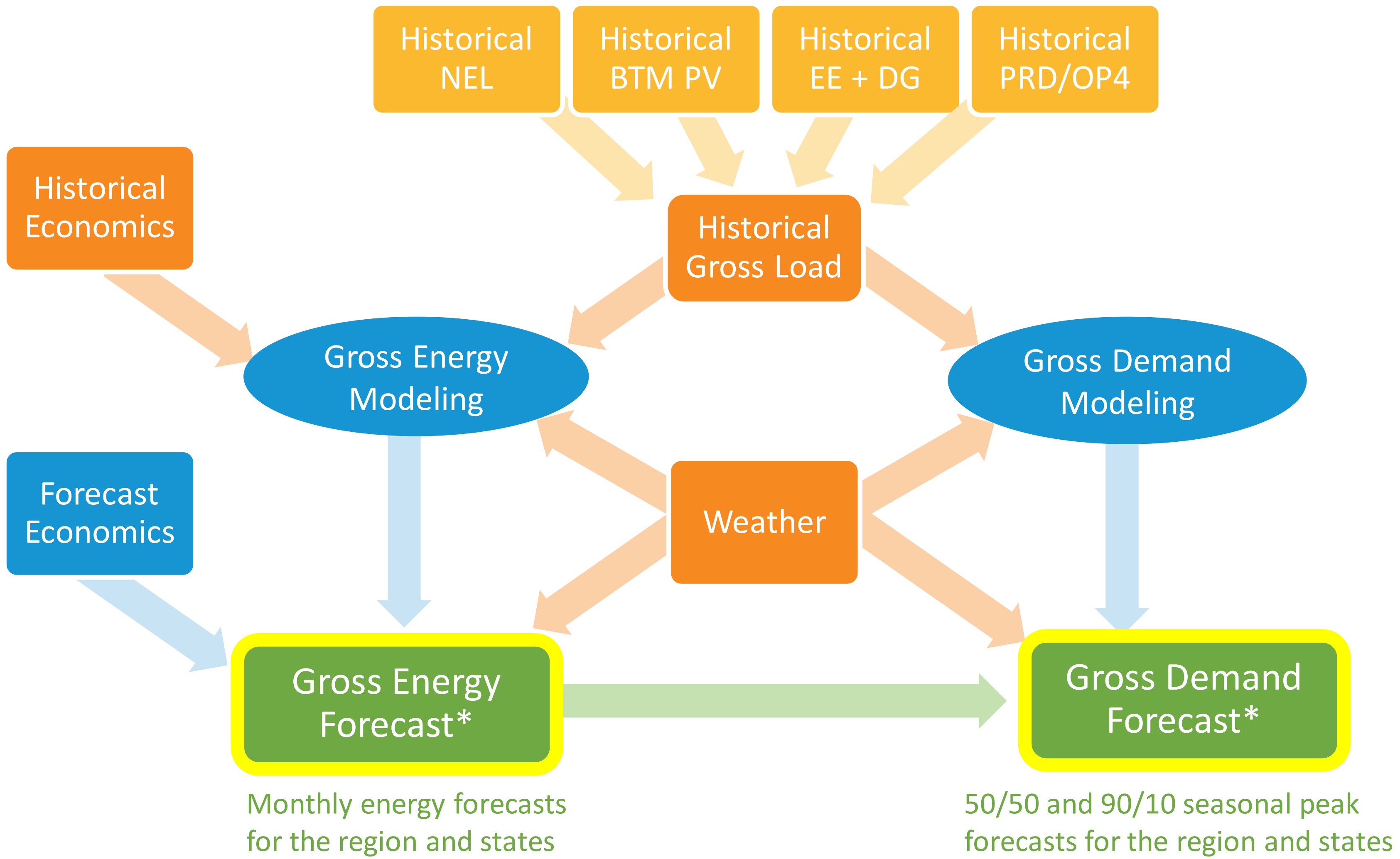
> Methods used for developing the hourly EE and BTM PV reconstitution needed to *gross up* the historical loads are described in the next two sections

Example of Reconstituted Monthly Energy

New England – July



High-Level Process Flow Chart



* Gross forecasts may also be informed by post model inputs

Energy Efficiency (EE) Reconstitution

Energy Efficiency Reconstitution

Background

"Any realized Demand Capacity Resource reductions in the historical period that received Forward Capacity Market payments for these reductions, or Demand Capacity Resource reductions that are expected to receive Forward Capacity Market payments by participating in the upcoming Forward Capacity Auction or having cleared in a previous Forward Capacity Auction, shall be added back into the appropriate historical loads to ensure that such resources are not reflected as a reduction in the load forecast that will be used to determine the Installed Capacity Requirement, Local Sourcing Requirements, Maximum Capacity Limits and Marginal Reliability Impact values for the relevant Capacity Commitment Period."
Market Rule 1, Section III.12.8(d)

Since EE participates as a supply-side resource in FCM, its corresponding demand reductions are reconstituted to ensure EE is not double-counted (as both supply and demand)

Energy Efficiency Reconstitution

Background, continued

- For EE measures, load reduction quantity is the difference between estimated energy consumption of an installed EE technology and what the energy consumption would have been had a standard technology been in place (i.e., baseline conditions)
  - What load would have been is counterfactual and cannot be observed directly
  - Measurement and verification studies conducted by EE program administrators (PAs) assume a baseline load in order to quantify the load reduction produced by an EE measure
- Each PA submits EE performance data to ISO via the energy efficiency measures (EEM) database
  - Monthly MW values reflect load reductions during seasonal performance hours
- ISO uses these monthly megawatt (MW) values as a starting point to estimate monthly and hourly energy needed for EE reconstitution

Method for Estimating Energy Efficiency Reconstitution

Monthly Energy Efficiency Energy and Hourly Energy Efficiency Performance

Monthly Energy Efficiency Energy

Estimated using a three-year average of monthly load factors, monthly average weekday EE performance, and number of hours in that month as follows:

$$EE_{Energy,month} = EE_{MW,month} * LoadFactor_{3yrAvg} * nHours_{month}$$

Monthly energy is estimated by load zone and grossed up by 8% to account for transmission and distribution losses.

Hourly Energy Efficiency Performance

Factors are sorted into four categories:

1. Weekday on-peak (weekdays hours 12-20)
2. Weekday off-peak (weekdays hours 5-11, 21-24)
3. Weekend on-peak (weekends hours 5-24, weekdays hours 1-4)
4. Weekend-off peak (weekends hours 1-4)

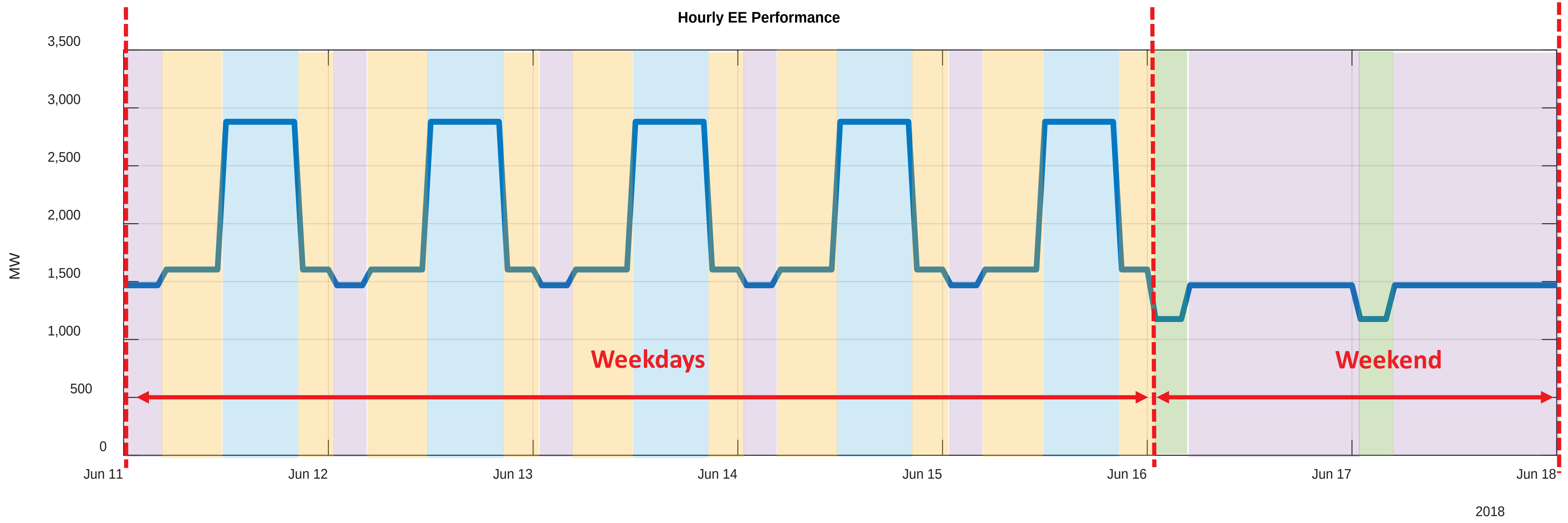
Hourly performance is estimated by multiplying the monthly peak MW value by appropriate factors for each hour

EE performance factors are solved for with multivariate Newton-Raphson using the following assumptions:

1. Sum of EE performance across all hours in a month is equal to the monthly energy found in previous step
2. Weekday on-peak factor = 1
3. Weekday on-peak > weekday off-peak > weekend on-peak > weekend off-peak

Example of Resulting Energy Efficiency Reconstitution

June 2018 Monthly EE Performance = 2,880 MW



Weekday on-peak (weekdays hours 12-20)
Weekday off-peak (weekdays hours 5-11, 21-24)
Weekend on-peak (weekends hours 5-24, weekdays hours 1-4)
Weekend-off peak (weekends hours 1-4)

Behind-the-Meter Photovoltaic (BTM PV) Reconstitution

Behind-the-Meter Photovoltaic (BTM PV) Reconstitution

Background

- BTM PV in the context of the long-term load forecast refers to small scale (<5MW) distributed PV systems that do not participate in ISO markets
  - Example: residential rooftop PV systems
- Net load (NEL +PRD) reflects embedded load reductions that result from the presence of BTM PV
- Gross load is intended to reflect what loads would have occurred absent the impact of BTM PV
  - Producing a gross load forecast requires that hourly historical loads be reconstituted for the impacts of BTM PV

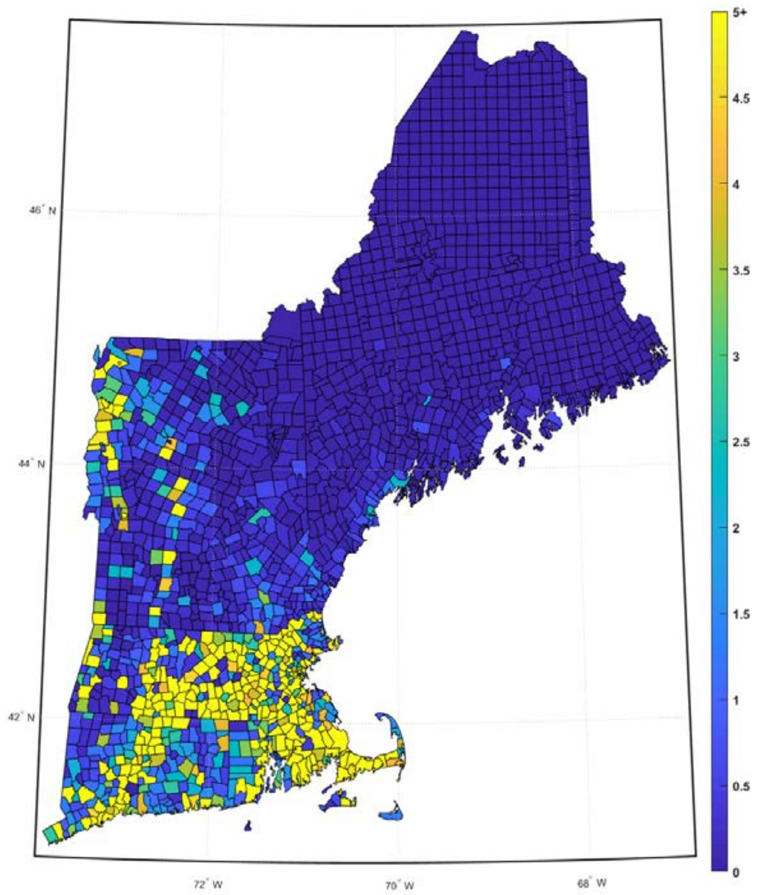
Behind-the-Meter Photovoltaic (BTM PV) Reconstitution

Background, continued

- The ISO does not have comprehensive visibility into the power and energy production of all BTM PV systems
  - A process of *upscaling* is applied to performance data obtained from a sample of BTM PV sites located throughout the region to infer aggregate BTM PV behavior
- Upscaling inputs
  - Town-level PV performance data
    - Aggregated from a sample of PV systems within each town
  - Installed PV capacity data
    - AC nameplate of all operating PV systems in New England
    - Sourced from a tri-annual survey submitted by the Distribution Owners
- Development of historical estimated BTM PV production
  - Infer hourly BTM PV fleet performance via upscaling by combining normalized profiles with installed capacity data
  - Hourly production of market-facing PV systems is then subtracted to yield the BTM PV production

Upscaling Source Data

Distribution Owner PV Installed Capacity



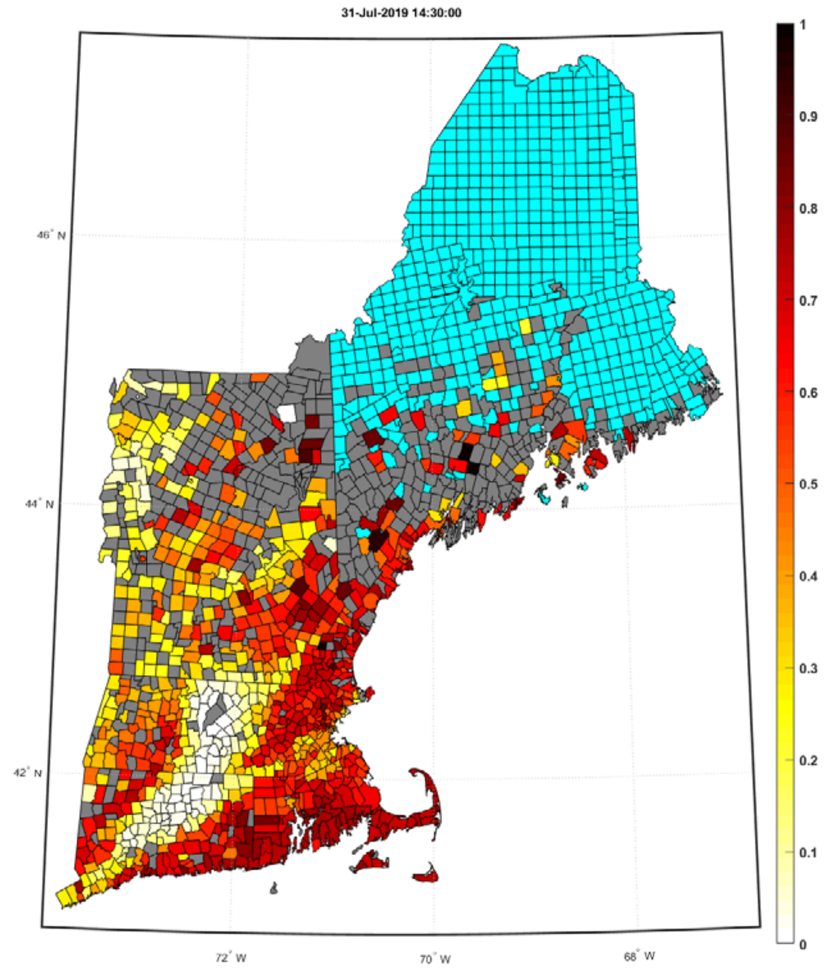
Heat map illustrates the total PV installed nameplate capacity in each town, as of 12/31/18

- Distribution Owners provide ISO with detailed PV interconnection data three times each year:
  - End of April, August, and December
- Information consists of nameplate capacity, town location, and in-service date for each installation across the region
  - Nameplate capacity reflects aggregate inverter rating
- Dataset enables ISO to monitor amounts and locations of PV installed across region over time
- Installed capacity data is filtered to omit large-scale PV systems that are not included in the long-term PV forecast

Upscaling Source Data

Behind-the-Meter Photovoltaic Performance Data

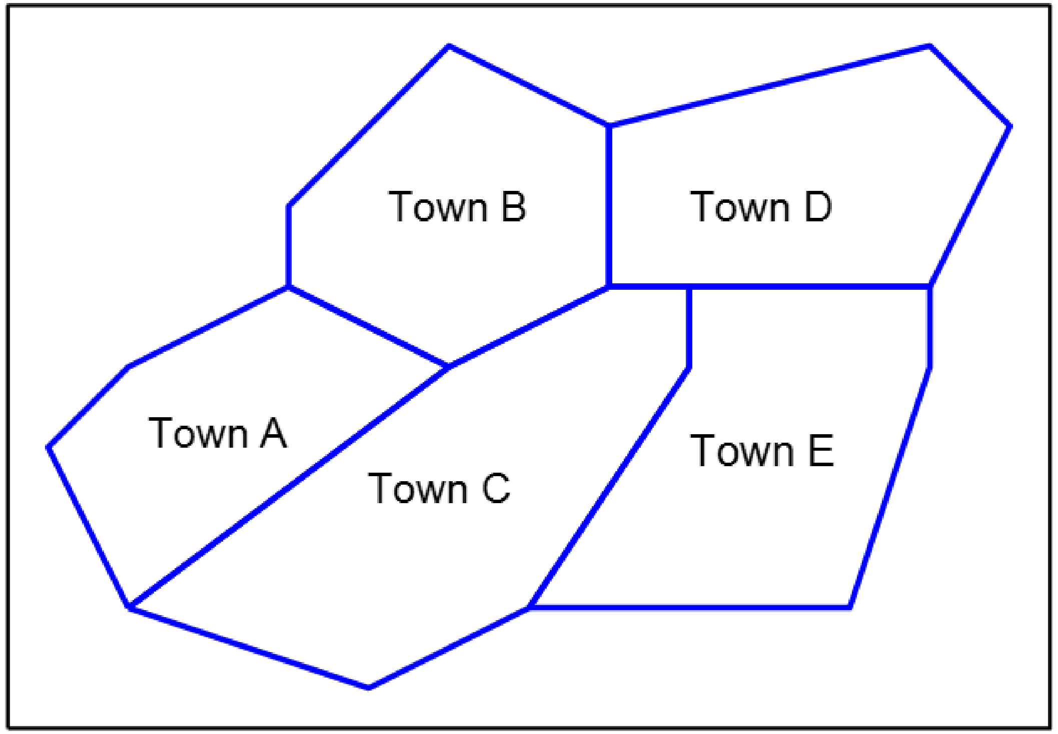
- ISO is provided performance data associated with up to 10,000 individual PV systems from a vendor
- Vendor aggregates and bins the source data at the town and 5-minute levels and normalizes all performance values as a fraction of total nameplate capacity (e.g., a value of 1 would represent that total PV output is equal to total nameplate capacity)
- Dataset provides knowledge about how BTM PV performs across the region at each 5-minute time increment of history



Heat map illustrates the data for July 31, 2019 at 2:30 p.m.

- Colors reflect BTM PV performance as a share of nameplate capacity
- Source data are unavailable for gray towns
- Data not requested for blue towns

Fictional Upscaling Example



- Assume there are five towns in a zone, towns A, B, C, D, and E
  - Towns may have normalized production data
  - All five towns have installed PV
- **Objective**: Upscale the normalized 30-minute, town-level PV data such that it reflects the aggregate BTM PV performance

Data for Fictional Upscaling Example

Normalized Photovoltaic Profiles and Installed Capacity

- Example town-level normalized production data is tabulated to the right
  - No data provided for Town E
- Total installed nameplate capacity for each town is tabulated below

  Note: Town E is missing production data, but has installed capacity

	Installed Cap. (MW)
Town A	12
Town B	6
Town C	8
Town D	16
Town E	8
total	50

time	Town A	Town B	Town C	Town D	Town E
6:00	0.00	0.00	0.00	0.00	
6:30	0.03	0.03	0.03	0.03	
7:00	0.06	0.05	0.05	0.06	
7:30	0.11	0.09	0.09	0.10	
8:00	0.20	0.17	0.17	0.19	
8:30	0.31	0.28	0.27	0.29	
9:00	0.42	0.38	0.37	0.41	
9:30	0.52	0.48	0.45	0.50	
10:00	0.63	0.57	0.53	0.59	
10:30	0.75	0.67	0.63	0.70	
11:00	0.80	0.71	0.66	0.76	
11:30	0.84	0.72	0.71	0.80	
12:00	0.87	0.74	0.76	0.81	
12:30	0.88	0.76	0.76	0.81	
13:00	0.88	0.76	0.74	0.80	
13:30	0.86	0.75	0.73	0.78	
14:00	0.82	0.71	0.71	0.73	
14:30	0.74	0.63	0.66	0.66	
15:00	0.68	0.58	0.59	0.59	
15:30	0.57	0.49	0.49	0.50	
16:00	0.44	0.39	0.38	0.37	
16:30	0.30	0.27	0.26	0.26	
17:00	0.18	0.16	0.16	0.16	
17:30	0.12	0.11	0.11	0.10	
18:00	0.06	0.05	0.05	0.05	
18:30	0.00	0.00	0.00	0.00	

Determine Weights of Town-Level Profiles

- To estimate the zonal production profile, capacity-weights for town-level profiles are first developed
  - Town weights are developed using the ratio of each town's installed capacity to the sum of the installed capacities from towns with corresponding performance data
  - Towns without performance data are excluded from the capacity-weighting process
- Capacity weight calculations for the five-town zone example are tabulated below

	Installed Cap. (MW)	Calculate Weights	Weights
Town A	12	12/42	0.286
Town B	6	6/42	0.143
Town C	8	8/42	0.190
Town D	16	16/42	0.381
Town E	null	no weight	null
total	42	**n/a**	1.00

Weighting and Upscaling Zonal Profiles – Steps

- Upscaling is last step of data process
  - Zonal normalized profile represents production of all PV systems in zone at each time increment
  - Total power output for zone is calculated by multiplying normalized zonal profile by total zonal installed capacity

- Hourly data can then be derived from sub-hourly data

time	Town A	Town B	Town C	Town D	Town E	Calculate Zonal	Zonal Norm Profile	Installed Capacity	Zonal MW Profile
9:30	0.52	0.48	0.45	0.50		0.286*0.52 + 0.143*0.48 + 0.190*0.45 + 0.381*0.50	0.493	50.000	24.668
10:00	0.63	0.57	0.53	0.59		0.286*0.63 + 0.143*0.57 + 0.190*0.53 + 0.381*0.59	0.587	50.000	29.359
10:30	0.75	0.67	0.63	0.70		0.286*0.75 + 0.143*0.67 + 0.190*0.63 + 0.381*0.70	0.697	50.000	34.836
11:00	0.80	0.71	0.66	0.76		0.286*0.80 + 0.143*0.71 + 0.190*0.66 + 0.381*0.76	0.745	50.000	37.265

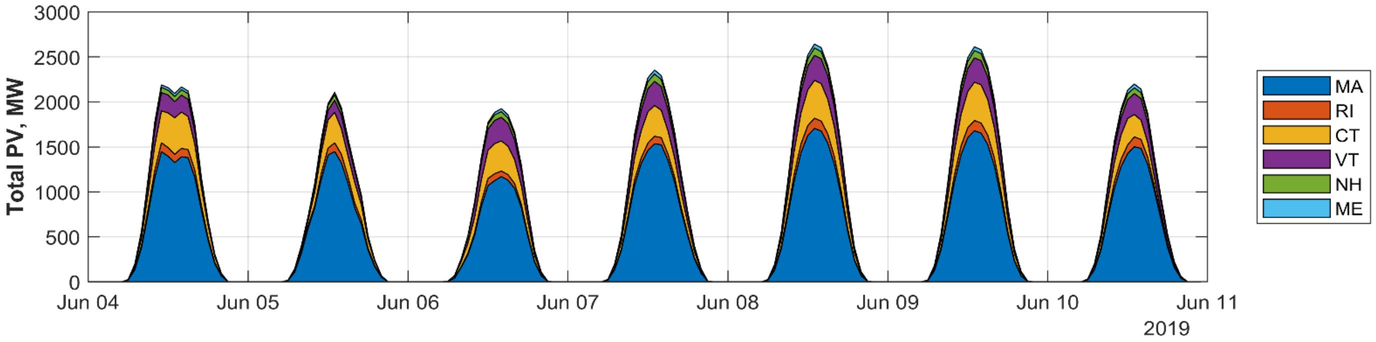
Upscaling Behind-the-Meter Photovoltaic for New England

- ISO uses process outlined on previous slides to estimate total PV production (of all PV in long-term PV forecast) for the region
- Same process can be applied to various sub-regions
  - Dispatch zone
  - Load zone
  - State
  - Region
- BTM PV reconstitution data is calculated by subtracting production from all market-facing PV from total – *refer to next slide*

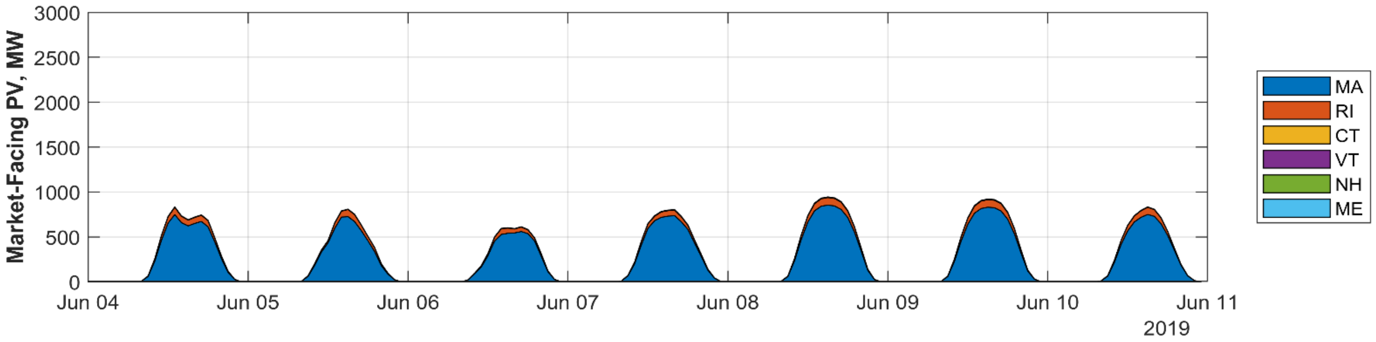
Development of Hourly Behind-the-Meter Photovoltaic Reconstitution

July 4-10, 2019 Example

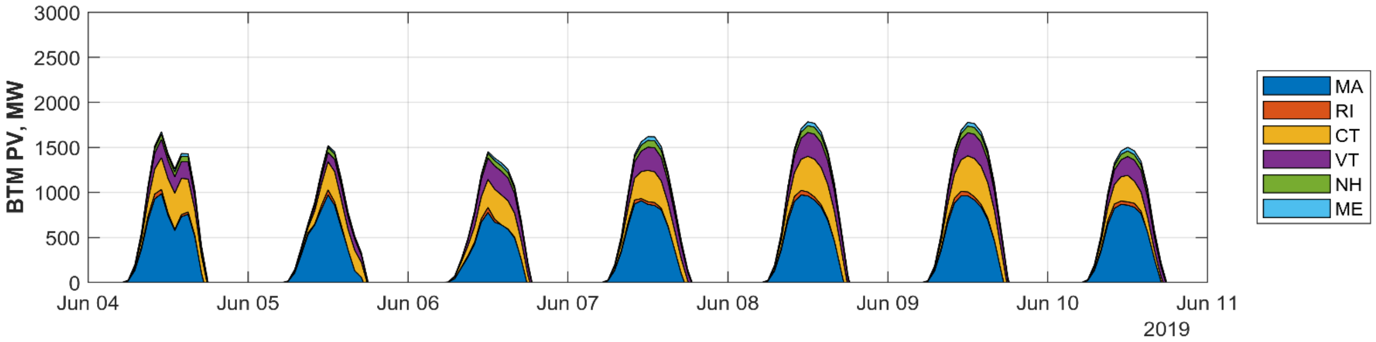
Total hourly PV energy for each state calculated via upscaling



Hourly PV energy in each state settling in ISO wholesale energy market



Total PV minus wholesale market PV yields BTM PV used for hourly reconstitution



Load Forecast Inputs

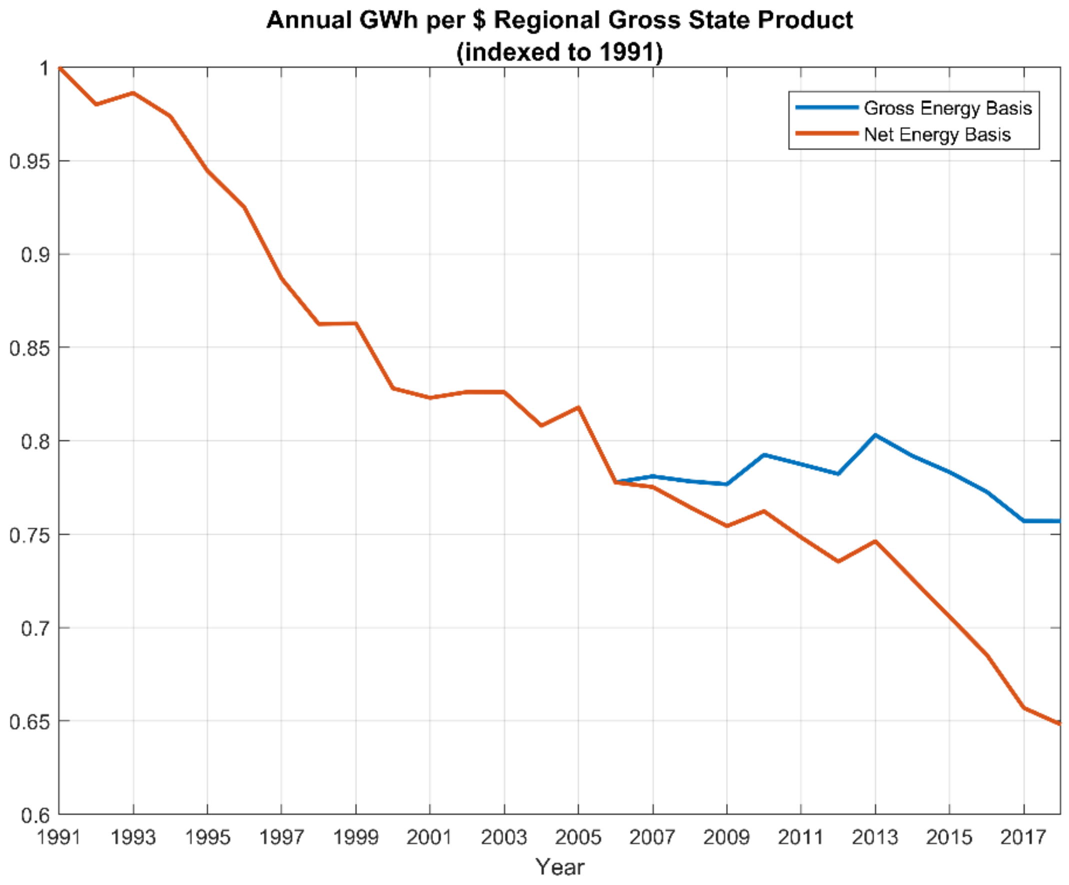
Macroeconomic Inputs

- Moody's Analytics provides actual and forecast data for a variety of macroeconomic indicators for the New England region and each of the six states, some of which may be used in the load forecast
  - Real gross state product
  - Population
  - Households
  - Unemployment rate
- Historical electricity prices stem from publically available EIA data (form 861)
  - These data may not be included if they do not pass statistical checks
- Forecast macroeconomic data provided in the fall of each year is utilized in the following year's long-term load forecast

Electric Energy Intensity of Regional Economy

1991-2018

- Electric energy intensity of the regional economy has been declining for the past few decades, which has resulted in a decreasing influence of macroeconomics on the load forecast in recent years
- Graph illustrates the long-term trend in relationship between annual electric gigawatt-hours and real gross state product
  - Brown line is based on net load energy
  - Blue line is based on gross load energy after reconstituting for the energy savings from EE and BTM PV
- Based on difference between blue and brown lines, the effects of market-facing EE and BTM PV have been responsible for most, but not all, of this decline in intensity since 2006



Weather

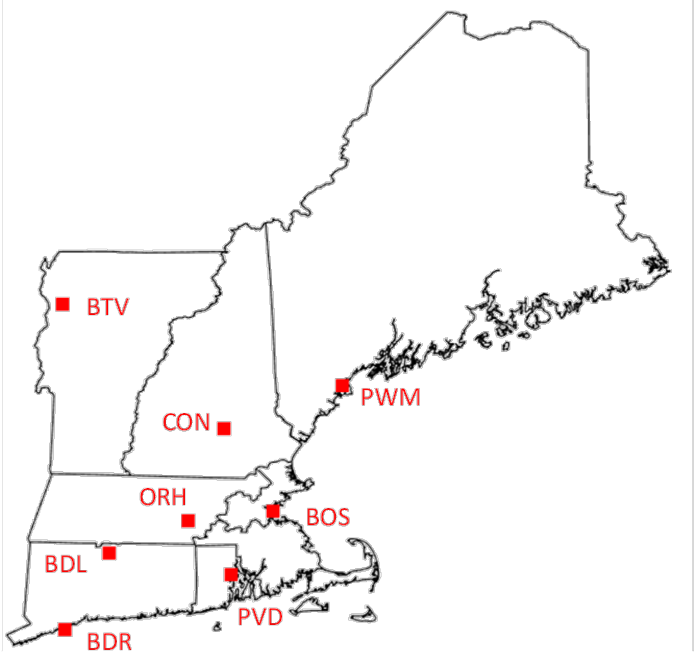
Stations, Locations, and Weights

Hourly dry bulb (DB), dew point (DP), and wind speed (WS) used in long-term load forecast are associated with eight weather stations located throughout New England

Regional and state weather are derived using station weights shown in table below

Weather Station (City, State)	Weather Station	ISO-NE Summer	ISO-NE Winter	CT	MA	ME	NH	RI	VT
Boston, MA	BOS	0.201	0.214	-	0.440	-	-	-	-
Bridgeport, CT	BDR	0.070	0.075	0.170	-	-	-	-	-
Burlington, VT	BTV	0.046	0.040	-	-	-	-	-	1.000
Concord, NH	CON	0.058	0.055	-	-	-	1.000	-	-
Portland, ME	PWM	0.085	0.082	-	-	1.000	-	-	-
Providence, RI	PVD	0.049	0.048	-	0.270	-	-	1.000	-
Windsor Locks, CT	BDL	0.277	0.277	0.830	0.160	-	-	-	-
Worcester, MA	ORH	0.214	0.209	-	0.130	-	-	-	-

Locations of weather stations



Independent Weather Variables

Creating Input Variables for Modeling

- Hourly weighted weather concepts are used to create independent variable inputs to energy and demand models, according to equations listed below
- Weather is also sometimes coupled with a time trend to capture seasonal load growth patterns

Weather Variable	Abbrev.	Equation
Temperature-humidity index	THI	$THI_h = 0.5 * DB_h + 0.3 * DP_h + 15$
3-day weighted THI	WTHI	$WTHI_h = \frac{10 * THI_h + 5 * THI_{h-24} + 2 * THI_{h-48}}{17}$
Effective temperature	EffTemp	$EffTemp = DB - \left(\frac{65 - DB}{100}\right) * (WS)$
Heating degree days	HDD	$HDD = \max(65 - AvgDB_{Daily}, 0)$
Cooling degree day	CDD	$CDD = \max(AvgDB_{Daily} - 65, 0)$
THI-based CDD	CDD_{THI}	$CDD_{THI} = \max(0.4 * AvgDB_{Daily} + 0.4 * AvgDP_{Daily} + 15 - 65, 0)$

Modeling and Forecasting

Forecast Modeling

Introduction

- Long-term load forecast consists of monthly energy models and monthly peak demand models for the New England region and each of the six states
  - 168 individual models: (7 regions x 12 months x energy and demand)
  - All historical load data used for modeling is gross load
  - Regression-based modeling
- Models are estimated based on historical gross load, economics, and weather
  - Inputs are updated annually to capture the most recent trends in historical data
  - Model specification may be re-evaluated if forecast performance issues are observed

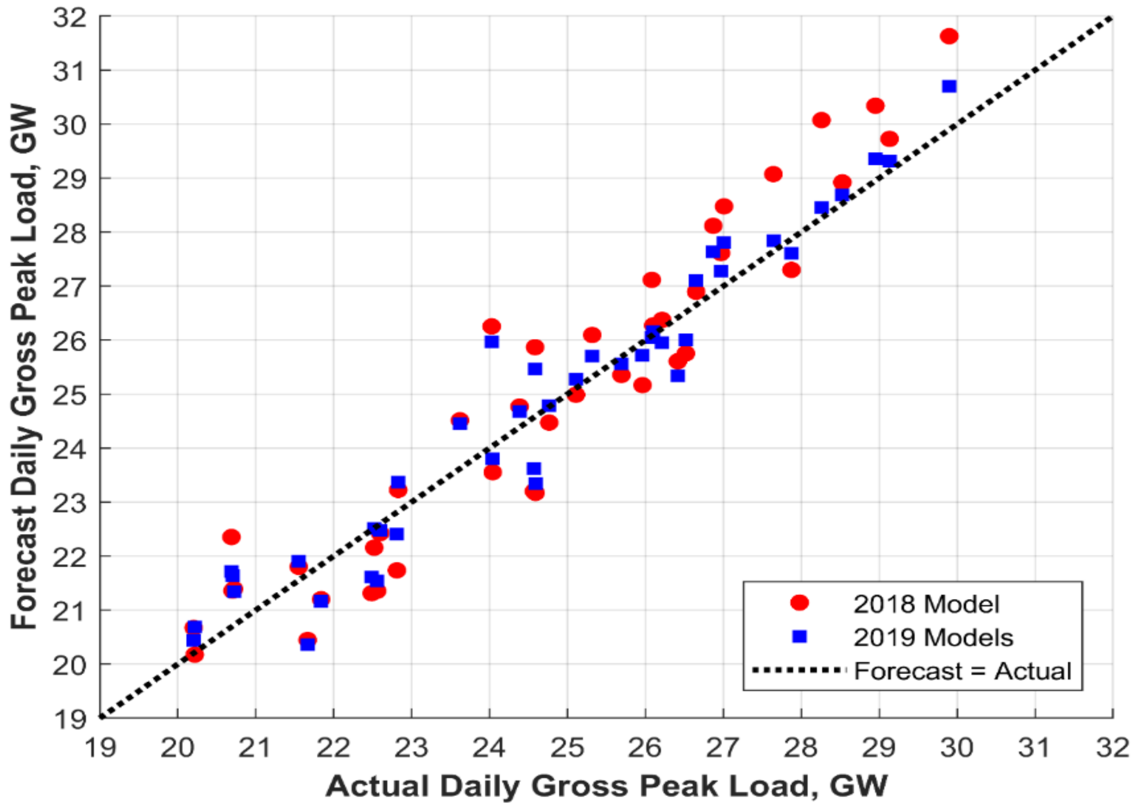
Forecast Modeling

Model Selection

- Models are selected based on a variety of statistical tests and performance metrics
- **In-sample statistics** characterize how well a model represents data used to estimate model
  - T-Statistics: explanatory power of each regressor
  - Adjusted R-squared Statistic: over all model fit
  - Tests for autocorrelation in error terms
- **Out-of-sample testing** characterizes a model's predictive accuracy on data unseen by model during model estimation process
  - Mean error (ME): average tendency of model over/under-forecast
  - Mean absolute percent error (MAPE): average magnitude of forecast errors irrespective of direction (i.e., over/under)

Graphical representations allow for visual inspection of forecast results, for example, using comparison of forecast and observed loads

Example scatter plot below illustrates a comparison of out-of-sample July/August 2018 forecast performance from two different model specifications considered during 2019 forecast cycle



Weather for Model Estimation and Forecasts

Gross monthly energy

- **Models** utilize weather aggregated to monthly level
  - Total monthly HDDs and CDDs
  - Typically includes last 27 years of weather encompassing last historical year
- **Forecasts** utilize normal monthly weather
  - Based on a 20-year historical period

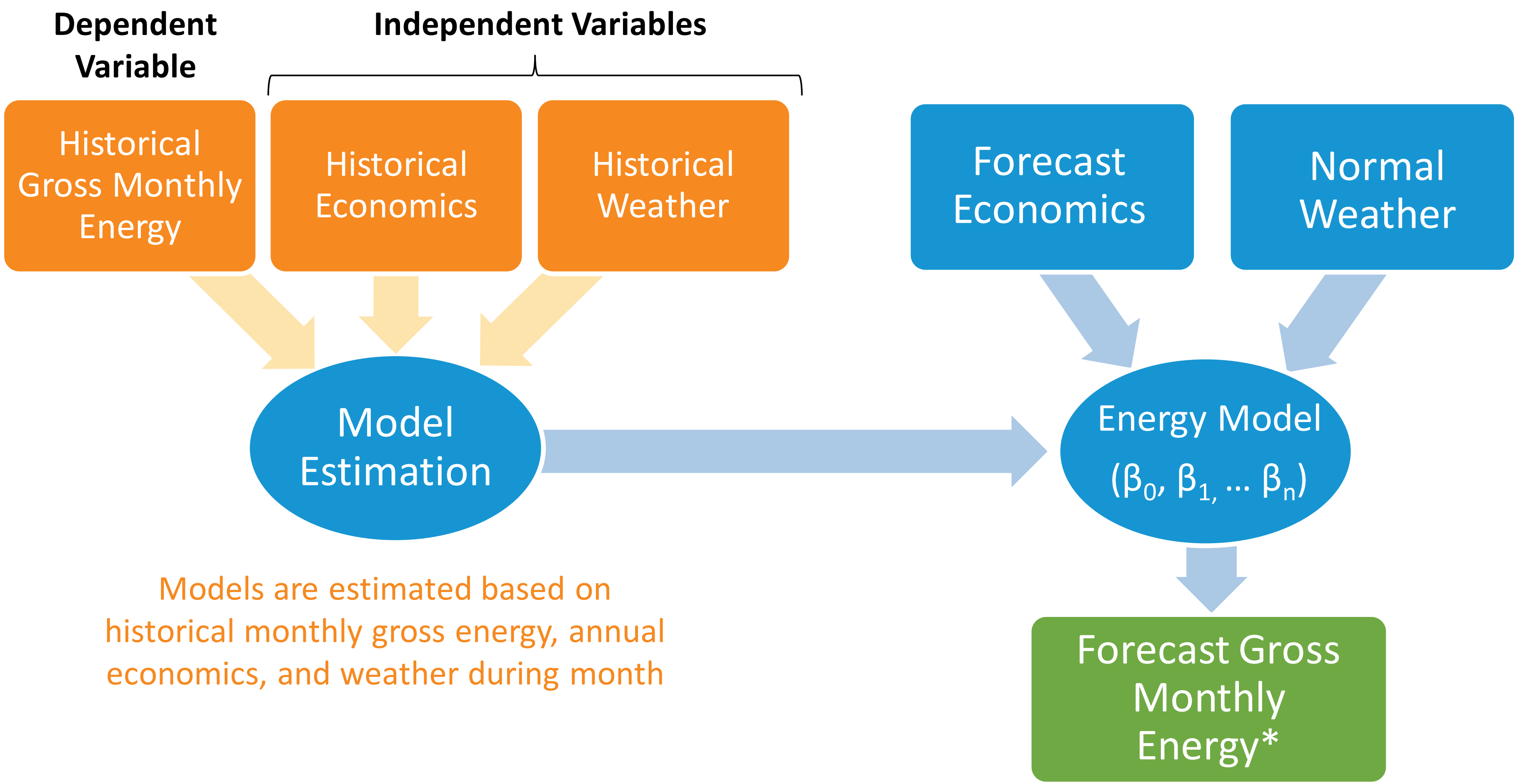
Gross peak demand

- **Models** utilize weather at the hour of the daily peak
  - WTHI and effective temperature during the hour of each daily peak
  - Daily CDDs and HDDs
  - Rolling 15-year window that includes last historical year
- **Forecasts** utilize a weekly weather distribution
  - Based on a 25-year historical period

Process	Years of weather
Energy Modeling	25-30 years
Energy Forecasting	20 years
Demand Modeling	15 years
Demand Forecasting	25 years

Gross Energy Modeling

Monthly gross energy models are developed for New England region and each of the six states



* Gross forecasts may also be informed by post model inputs

Gross Energy Modeling

- Gross energy models are regression models of the general form:

$$Energy_{gross\_month} = \beta_0 + \beta_1 * Economy + \beta_2 * Weather + \beta_3 Weather * Trend_{Time}$$

Where:

$\beta_0 \ldots \beta_n$	=	*Regression model coefficients*
Economy	=	*Annual economic variable(s)*
Weather	=	*Monthly weather variable(s)*
$Trend_{Time}$	=	*Annual linear counter from an initial start year*

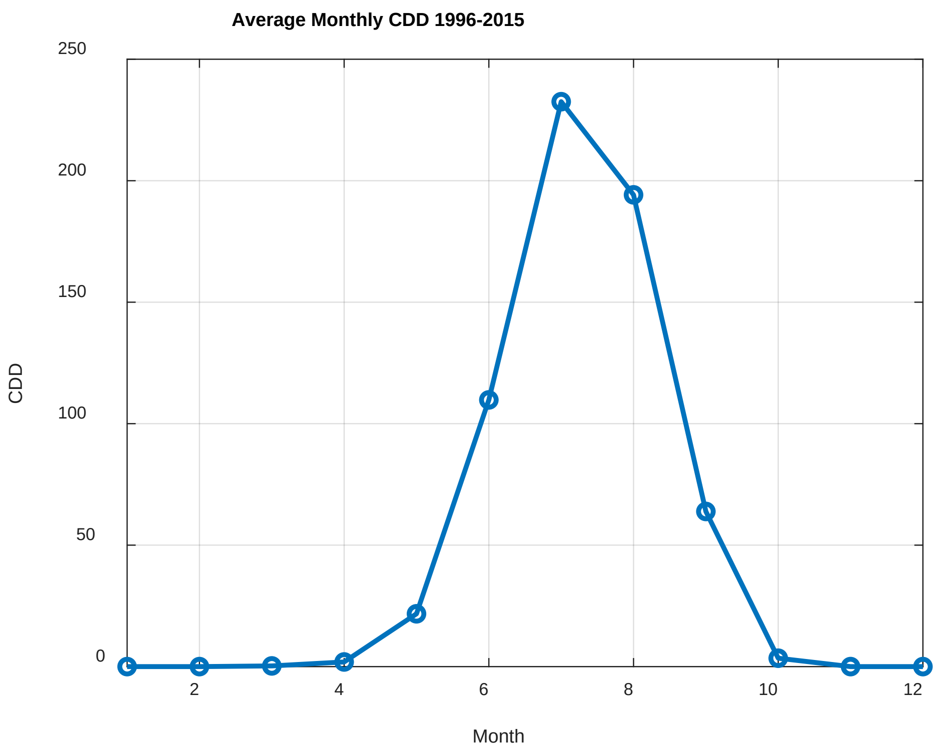
- 7 regions x 12 months = 84 individual energy models
- Monthly energy forecast modeling uses *normal* weather and baseline economic forecasts as inputs
- Normal weather based on a recent 20-year history and reflects an average monthly degree days (HDDs or CDDs)
  - Period 1996-2015 was used for 2019 CELT forecast
  - Weather constructs used in 2019 CELT include monthly total HDD and CDD_{THI}

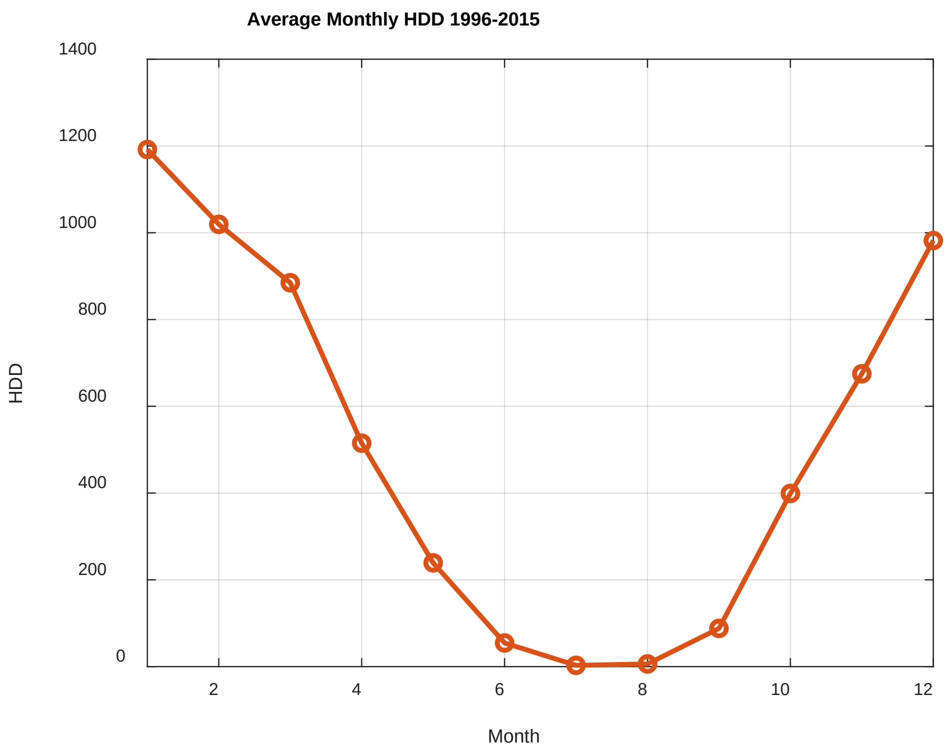
Weather Used in Energy Forecasts

Monthly Weather Normal

Gross energy forecasts are produced by using *normal weather* as inputs to monthly models

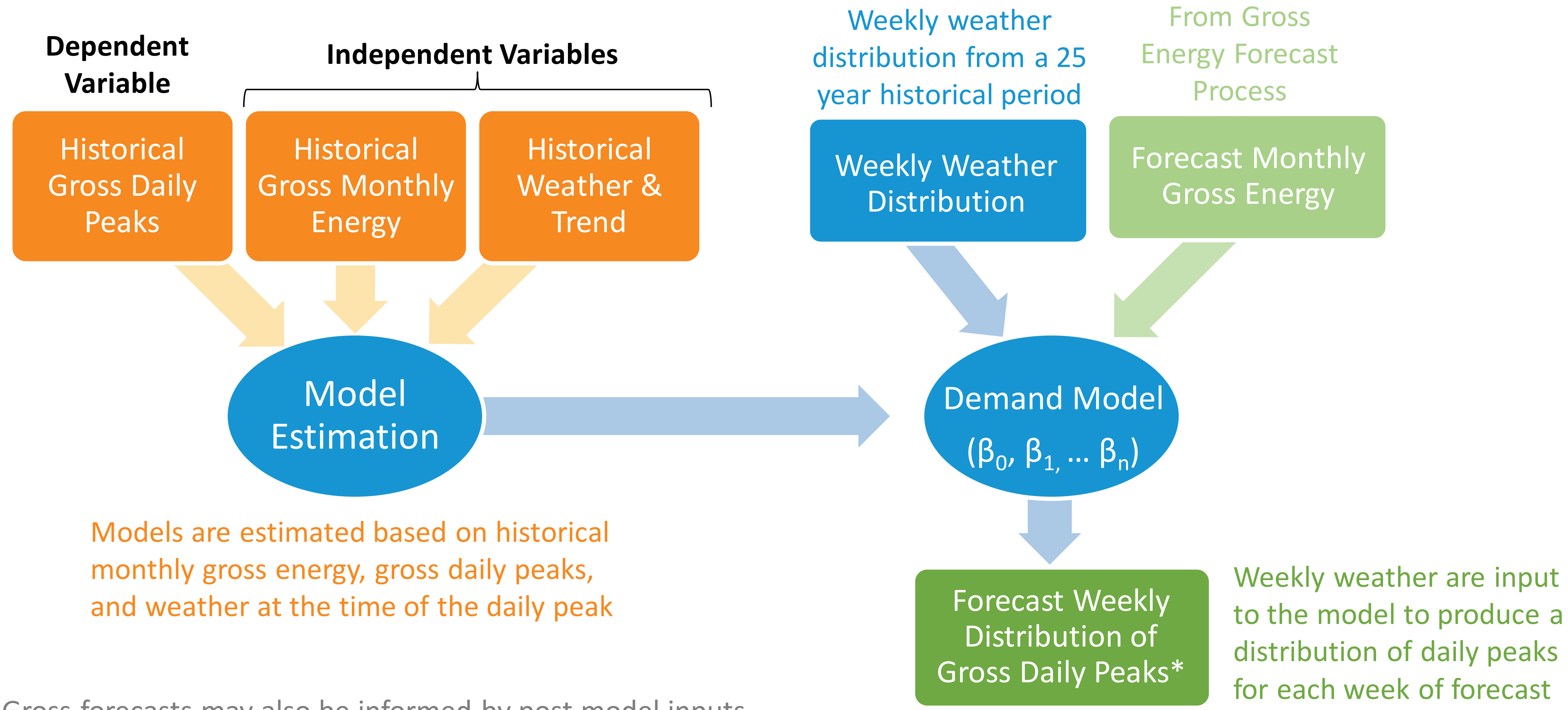
Average monthly weather over a 20 year historical period: 1996-2015





Gross Peak Demand Forecast

Monthly models of daily gross peak demand are developed for New England region and each of the six states



* Gross forecasts may also be informed by post model inputs

Gross Demand Modeling

- Gross peak demand models are regression models of the general form:

$$PeakDemand_{gross,daily} = \beta_0 + \beta_1 * Energy_{gross,month} + \beta_2 * Weather + \beta_3 * Weather * Trend_{Time} + \beta_4 * Calendar$$

Where:

$\beta_0 \ldots \beta_n$	=	*Regression model coefficients*
Weather	=	*Weather variable(s) at the hour of the peak*
Calendar	=	*Holiday or Day of Week indicators*
$Trend_{Time}$	=	*Annual linear counter from an initial start year*

- 7 regions x 12 months = 84 individual models
- Model estimation period is a rolling 15-year window of historical daily peak demand and weather data
  - Each year, window is rolled forward to capture last historical year
- Weather constructs used in 2019 load forecast included: WTHI, effective temperature, CDDs, and HDDs
  - Weather pertains to observed conditions at time of daily peak

Weather Used in Probabilistic Demand Forecasts

Developing Weekly Weather Distributions

- Probabilistic gross peak demand forecast is created using weekly weather distributions that serve as weather scenarios representing a range of possible weather for each week of the year
- Weather scenarios consist of the historical weather corresponding to all variables used in demand forecast models and are derived using a period of historical weather data
- For each weather variable, the most extreme weather values are selected from a range of typical (gross) peak load hours
  - Winter weeks: hours ending 18-19
  - Summer weeks: hours ending 14-17
- Daily weather points are aggregated into weeks *as illustrated on next slide*
  - Each historical year contributes 25 points per week

1991 (year 1) → 25 pts
1992 (year 2) → 25 pts
⋮
2015 (year 25) → 25 pts

Total, week n 625 pts

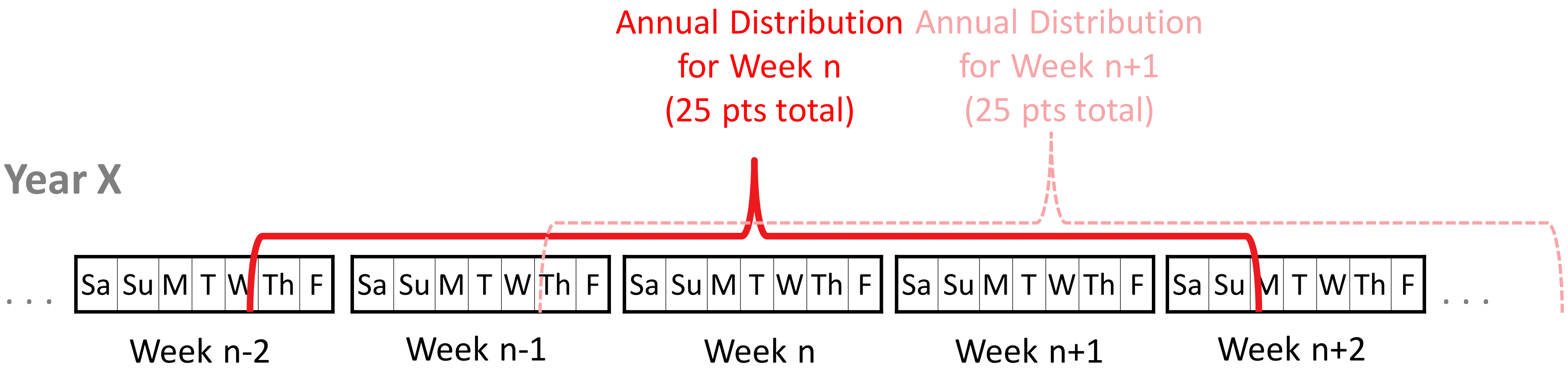
Mapping of weeks to months is tabulated

- Winter months/weeks are shaded **blue**
- Summer months/weeks are shaded **orange**

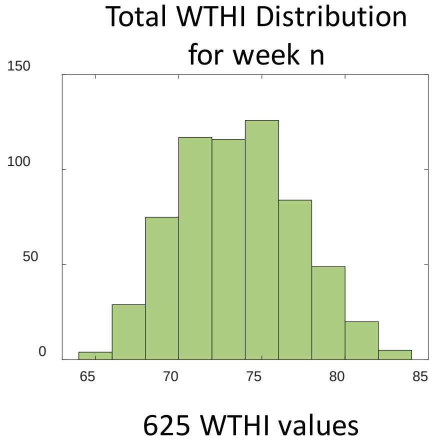
Month	Weeks
1	1-4
2	5-8
3	9-13
4	14-17
5	18-22
6	23-26
7	27-30
8	31-35
9	36-39
10	40-44
11	45-48
12	49-52

Weather Selection for Probabilistic Demand Forecasts

Developing Historical Weekly Weather Distributions



Total distribution for week n:
25 pts x 25 years = 625 pts

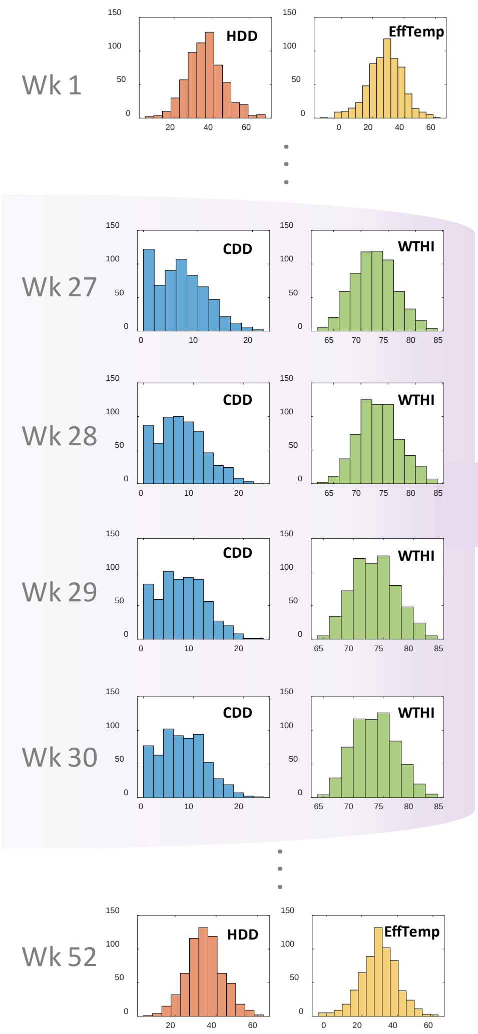


Repeat for each week and weather concept

Developing Weekly Load Distributions

July Example

Weekly Weather Distributions

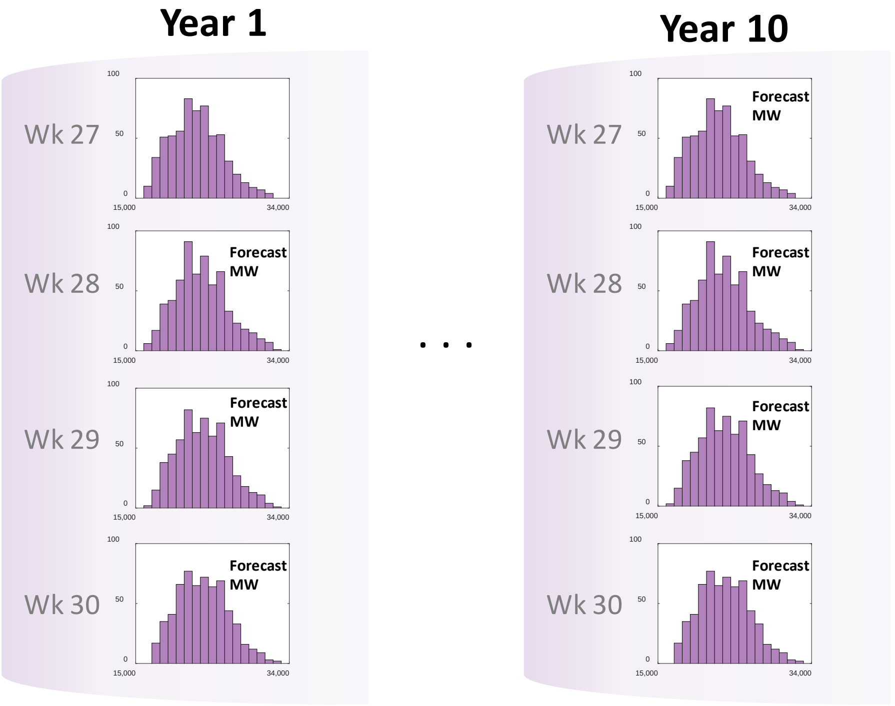


July Peak Model

Forecast is of non-holiday weekdays (other calendar variables set to zero)

Weekly weather distributions are input to monthly peak models for all weeks of 10-year forecast horizon (only July is shown)

Weekly Load Forecast Distributions

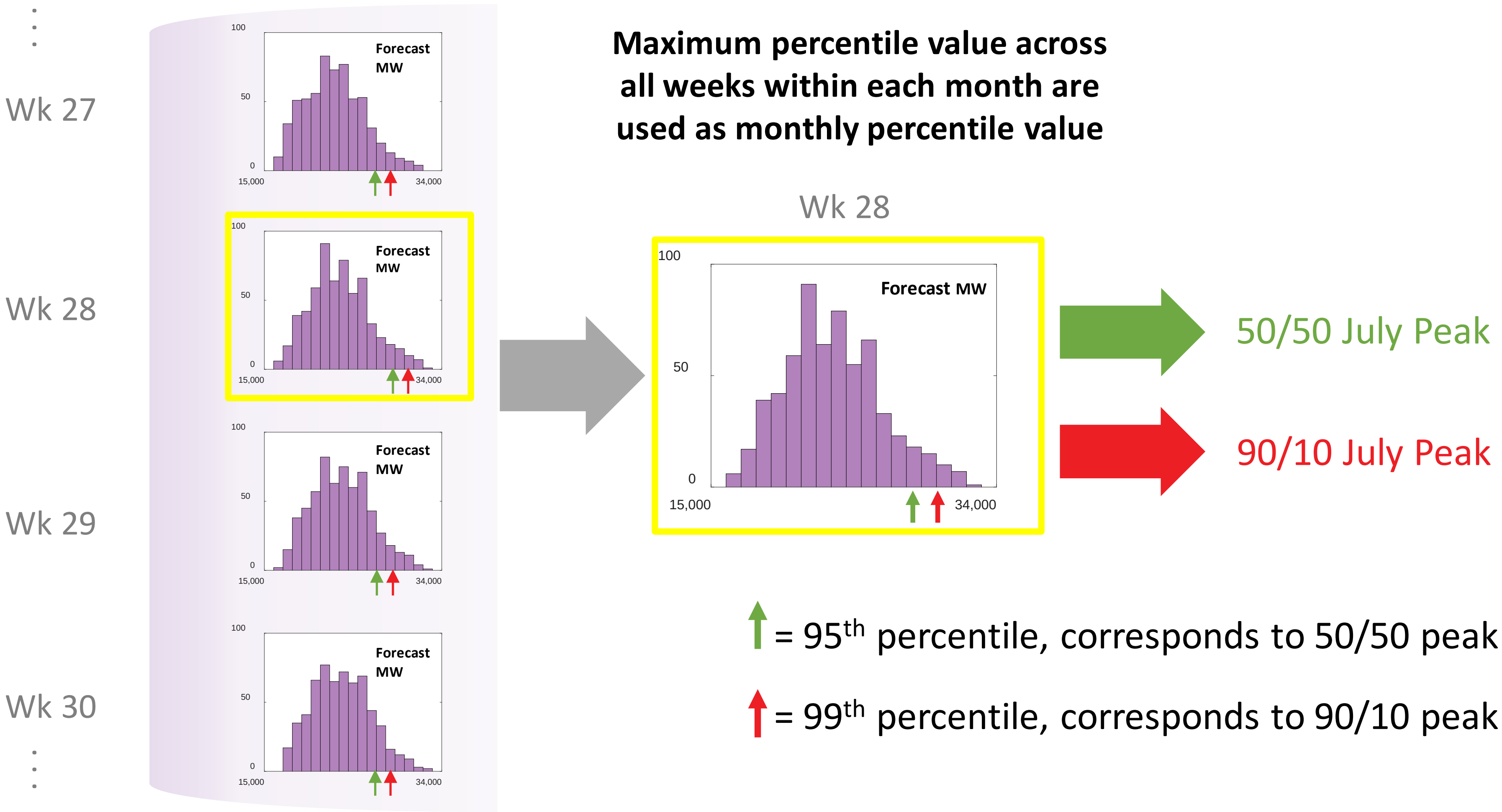


Selection of Points in Load Forecast Distribution

July Example (Weeks 27-30)

Calculate load percentiles for each week of the forecast

Maximum percentile value across all weeks within each month are used as monthly percentile value

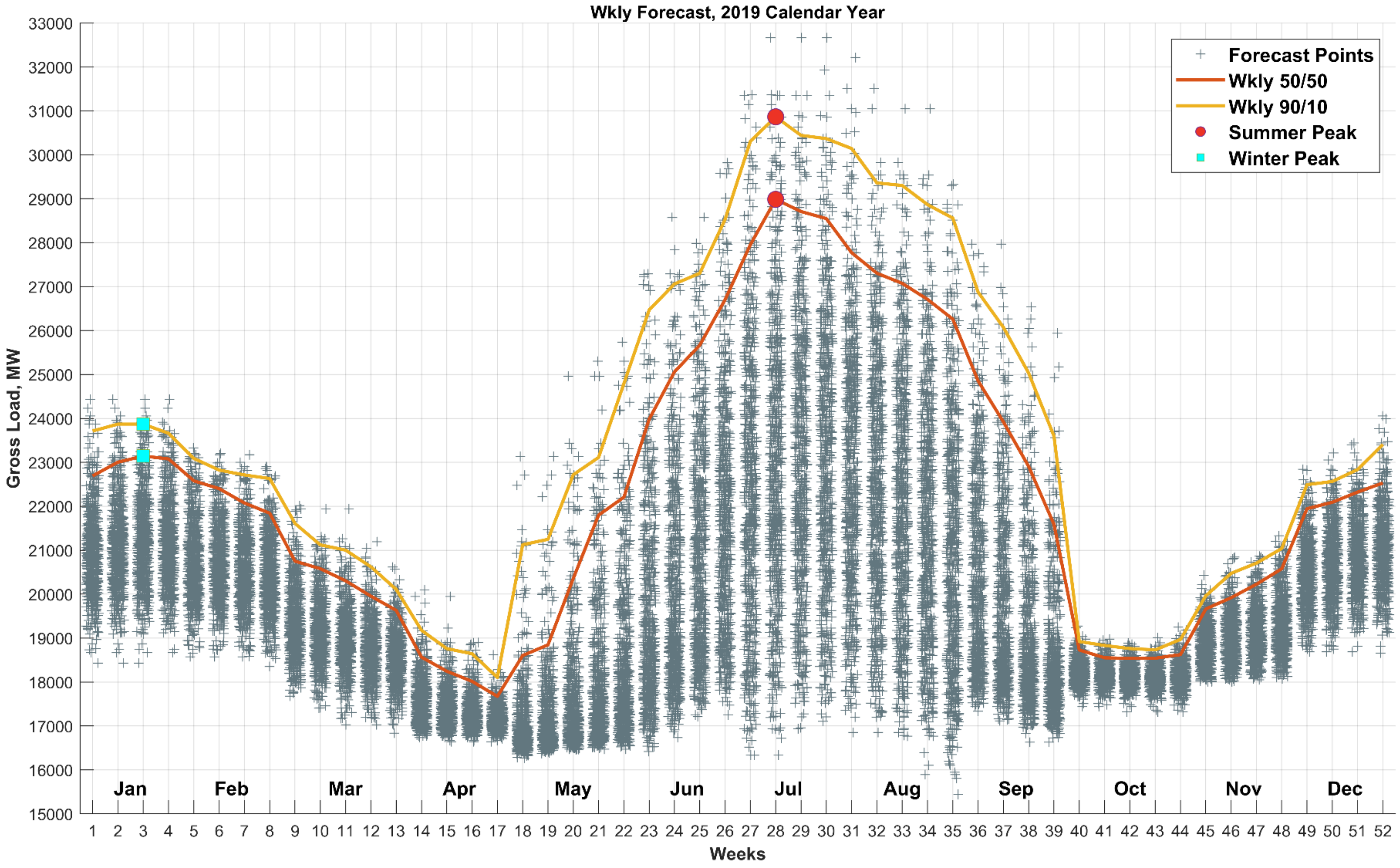


= 95th percentile, corresponds to 50/50 peak

= 99th percentile, corresponds to 90/10 peak

Resulting Weekly Gross Demand Forecasts

2019 Forecast Example

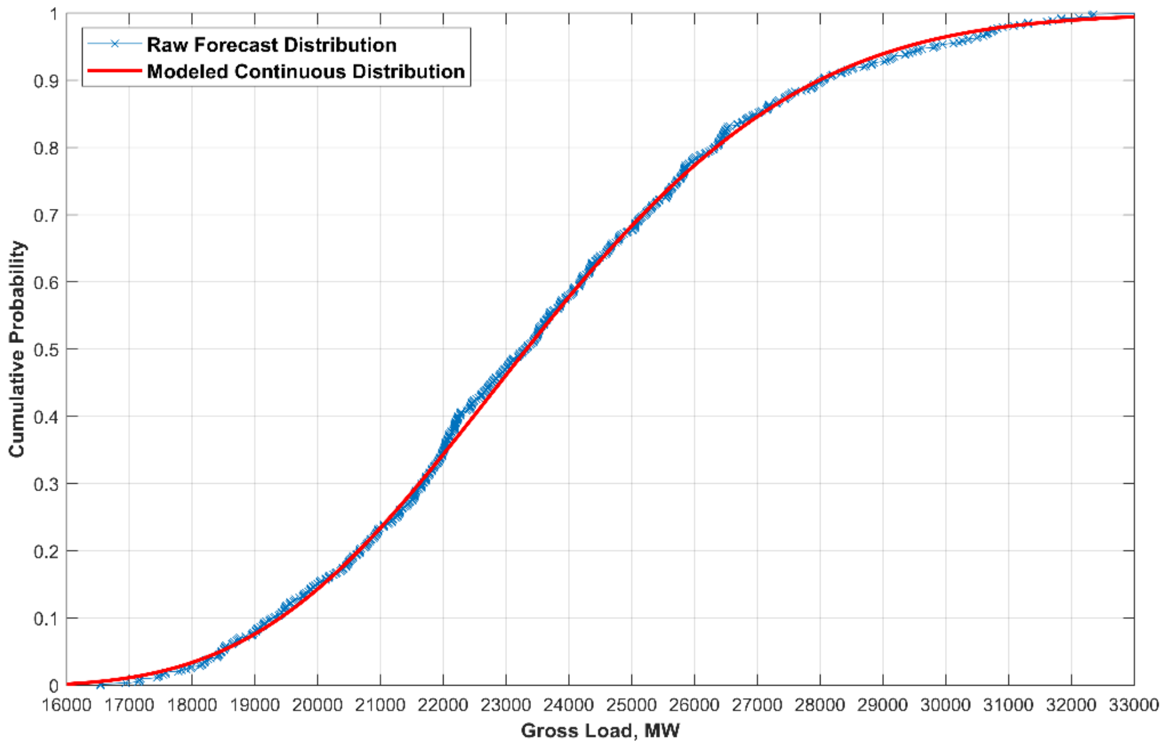


Weekly Forecast Distribution

Statistical Moments

- For each week of resulting forecast distribution, these statistical moments are calculated:
  - Mean
  - Standard deviation
  - Skewness

- Statistical moments are used to convert discrete weekly forecast distributions to a continuous forecast distribution needed for probabilistic Monte Carlo analyses used in ICR calculations
  - Plot to right shows a comparison of weekly forecast distribution and corresponding continuous forecast distribution (from 2019 CELT forecast) of the summer peak week (week 28) of forecast year 2023



Incorporating Other Trends Into Load Forecasts

- Consideration of forward-looking electricity consumption trends that are not reflected in the historical data used in econometric modeling may also be required
  - For example, the recent and projected growth of BTM PV and its impact on energy and demand
- Accounting for these anticipated impacts can often be achieved by making forecast adjustments downstream of the forecast modeling
  - For example, expected impacts of federal appliance standards promulgated by the 2007 Energy Independence and Security Act (EISA) were reflected as an adjustment to the gross energy forecast starting in CELT 2009 until CELT 2018
- Starting in CELT 2020, the development of the gross load energy and demand forecasts will include accounting for new exogenous forecast information into the final gross load forecast
  - Heating and transportation electrification forecasts will be added to the outputs from gross energy and demand forecast models

Net Load Forecast

Net Load Forecast

- Net load forecasts are developed by subtracting EE and BTM PV forecasts of energy and demand from respective gross forecasts
- EE and BTM PV forecasts are developed separately and in parallel to the annual gross load forecast
  - EE forecast is developed as part of Energy Efficiency Forecast Working Group (EEFWG) stakeholder process
  - BTM PV forecast is developed as part of Distributed Generation Forecast Working Group (DGFWG) stakeholder process
- A high-level summary of these forecasts is provided on the following slides

Energy Efficiency Forecast

- Each year the ISO forecasts long-term savings in peak demand and energy stemming from state-sponsored energy-efficiency (EE) programs for the New England region and for each state
- Resource links:
  - Energy-Efficiency Forecast Working Group web page: Committees and Groups > Planning Committees > Energy Efficiency Forecast Working Group
  - Energy-Efficiency Forecast Background Report
  - Final 2019 Energy Efficiency Forecast

Energy Efficiency Forecast

Model Inputs and General Assumptions

- EE forecast is rooted in FCM qualification values from the third annual reconfiguration auction (ARA 3)
- Forecast incremental energy and peak savings are appended to historical ARA 3 values
- Inputs:

Annual state EE budgets are provided by the Commissions or representatives on their behalf and held constant in years after latest approved budget	**Production cost escalator** is a graduated rate that begins in first year of the forecast and accumulates over forecast horizon
Peak-to-energy ratios are derived from a three-year average of recent performance and held constant through the forecast period	**Inflation rate** is extracted from economic data
Starting production costs are derived from a three-year average of recent performance	**Currently available CELT energy forecast** is used in conjunction with system benefit charges (SBC) to forecast SBC dollars

Energy Efficiency Forecast

Current Methodology (2012-2019)

EE forecast methodology is currently undergoing update

- Information on this slide represents the methodology used to produce past forecasts
- 2020 EE forecast will likely utilize a revised methodology currently under discussion at the Energy Efficiency Forecast Working Group

Model

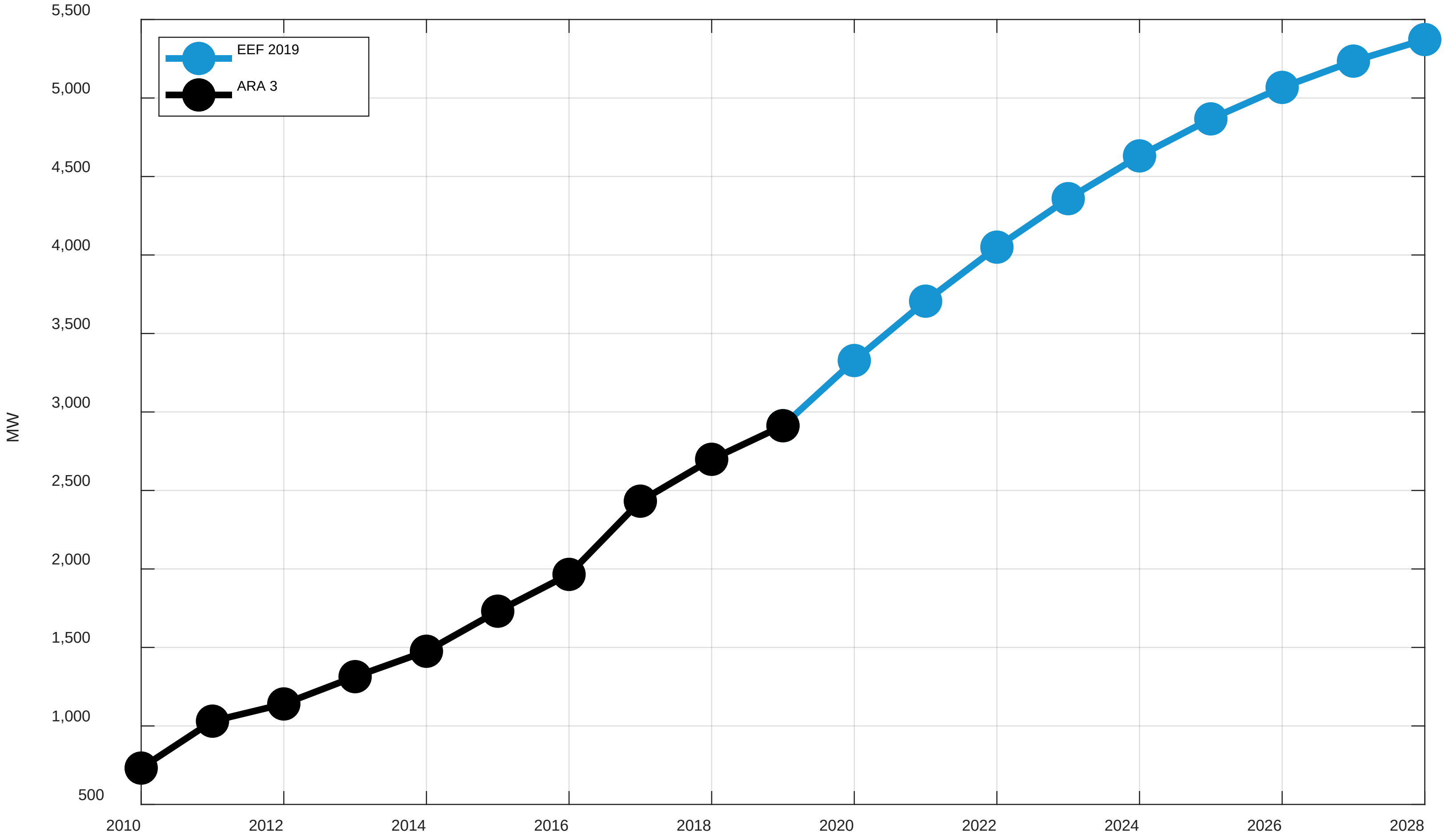
$$\text{Annual Energy Savings} = \frac{(\text{Budget})}{(\text{Production Cost}) \times (\text{Production Cost Esclator})}$$

$$\text{Annual Summer Peak Savings} = (\text{Annual Energy Savings}) \times (\text{Peak–to–Energy Ratio})$$

$$\text{Annual Winter Peak Savings} = (\text{FCM\%}) \times (\text{Annual Summer Peak Savings})$$

Energy Efficiency Forecast

2019 New England Summer Peak



Photovoltaic Forecast

- Each year ISO forecasts long-term growth and impact of PV resources for the New England region and for each state
- PV forecast incorporates a policy-based forecasting approach
  - Trends in distributed PV development largely result from policy programs developed and implemented by the New England states
  - ISO does not explicitly forecast the expansion of existing state policies or the development of future state policy programs
  - ISO makes no judgment regarding state policies, but rather utilizes the state goals as a means of informing the forecast
- Resource links:
  - Distributed Generation Forecast Working Group web page: [Committees and Groups > Planning Committees > Distributed Generation Forecast Working Group]
  - [Final 2019 PV Forecast]

Photovoltaic Forecast

Considerations and Assumptions

Many factors influence the future commercialization potential of PV resources, some of which include:

- Policy drivers:
  - Feed-in-tariffs (FITs)/Long-term procurement
  - State RPS programs
  - Net energy metering (NEM)
  - Federal Investment Tax Credit (ITC)
- Other drivers:
  - Role of private investment in PV development
  - PV development occurs using a variety of business/ownership models
  - Future equipment and installation costs
  - Future wholesale and retail electricity costs

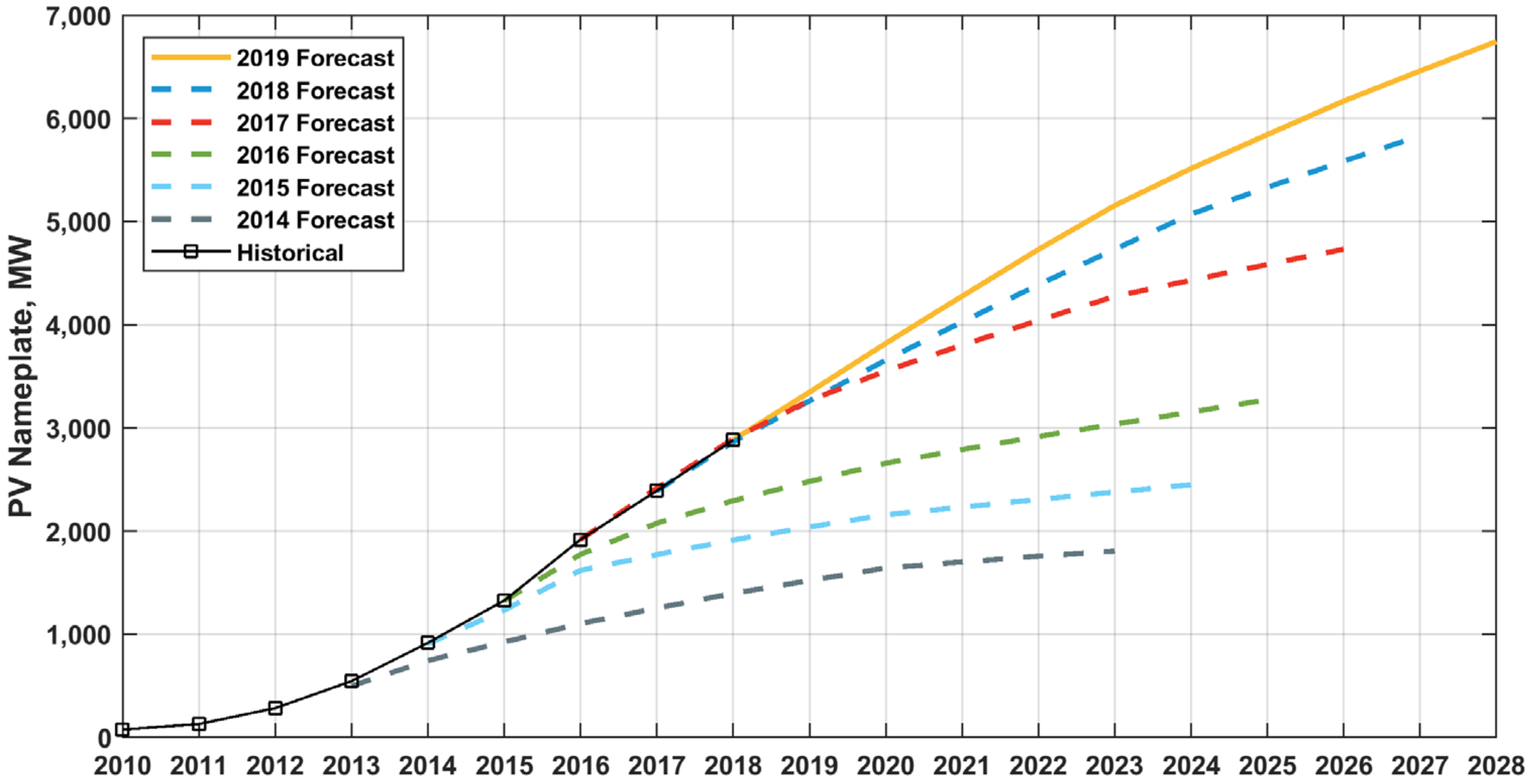
Photovoltaic Forecast

Process

- Majority of state-sponsored distributed PV (i.e., < 5 MW nameplate capacity) does not participate in wholesale markets, but reduces the system load observed by ISO
  - Therefore, forecast does not consider policy drivers supporting larger-scale projects (i.e., those >5 MW)
- To properly account for PV in long-term planning, the PV forecast is categorized as follows:
  - PV as a capacity resource in Forward Capacity Market (FCM)
  - Non-FCM Energy Only Resources (EOR) and Generators
  - Behind-the-meter photovoltaic (BTM PV)
- ISO develops estimated summer peak load reductions associated with BTM PV forecast using methodology established for 2016 PV forecast
  - See Appendix of [Final 2016 PV Forecast Details] slides

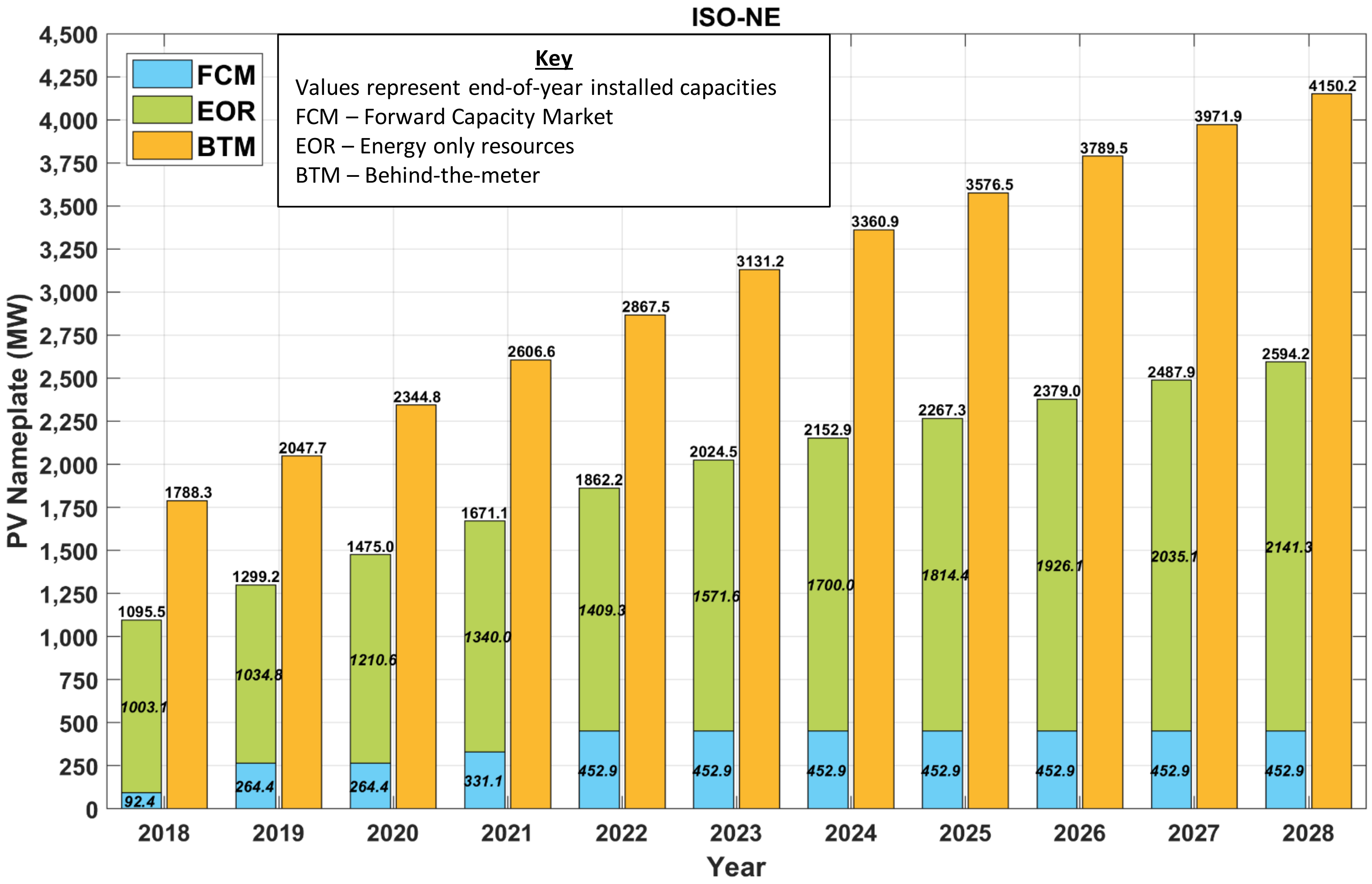
Photovoltaic Forecast

Reported Historical vs. Forecast



Classification of 2019 New England Photovoltaic Forecast

Cumulative Nameplate, MW_{ac}



2019 Behind-the-Meter Photovoltaic Forecast

July 1st Cumulative Estimated Summer Peak Load Reductions

States	Estimated Summer Peak Load Reductions - BTM PV (MW)									
	2019	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**	**2026**	**2027**	**2028**
CT	172.8	180.0	204.6	227.9	245.3	256.8	267.9	278.0	284.1	285.1
MA	345.0	392.0	422.8	446.5	468.2	485.8	495.4	501.3	505.7	509.1
ME	16.1	17.3	19.0	20.4	21.7	22.8	23.9	24.9	25.9	26.7
NH	31.1	34.1	36.7	38.3	39.4	41.2	42.9	44.5	45.9	47.3
RI	23.3	29.3	32.1	31.3	33.3	37.1	40.7	44.0	47.0	49.8
VT	119.3	124.3	126.4	127.0	127.3	128.4	129.7	130.8	131.7	132.6
Regional - Cumulative Peak Load Reductions (MW)	**707.6**	**777.2**	**841.6**	**891.4**	**935.2**	**972.1**	**1000.5**	**1023.5**	**1040.3**	**1050.6**

% of BTM AC Nameplate	35.2%	33.9%	32.5%	31.2%	29.9%	28.8%	27.8%	26.8%	25.9%	25.1%

Notes:

(1) Forecast values are for BTM PV only
(2) Values include the effect of diminishing PV production as increasing PV penetrations shift the timing of peaks later in the day
(3) Values include the effects of an assumed 0.5%/year PV panel degradation rate
(4) All values represent anticipated July 1st installed PV, and are grossed up by 8% to reflect avoided transmission and distribution losses
(5) Different planning studies may use values different that these estimated peak load reductions based on the intent of the study

Downstream Outputs

Forecast Allocations Based on Transmission Owner Load Distribution Data

- State forecasts of gross energy and demand are allocated to load zones and Regional System Plan (RSP) sub-areas via information obtained during the ISO's annual Multiregional Modeling Working Group (MMWG) network model creation process
  - Load shares by substation submitted by Transmission Owners
    - Described in Section 2.3 of the Transmission Planning Technical Guide Appendix J: Load Modeling Guide
- A list of included substations and their locational mappings can be found in each year's Load Bus Dictionary

Reporting

Forecast Modeling procedure

- A general description of the energy and peak demand forecasts
- 2019 Forecast Modeling Procedure

Energy and Peak Model Details

- Model specifications, diagnostics and statistics for energy and peak models
- 2019 Regional and State Energy and Peak Model Details

Hourly Profiles in EEI (Edison Electric Institute) Format

- Hourly forecasts based on the 2002 load shape for load zones, RSP sub-areas, and ISO-NE
- EEI Profiles are located on Load Forecast web page at System Planning > System Forecasting > Load Forecast

CELT Report

- Forecast Report of Capacity, Energy, Loads, and Transmission
- 2019 CELT Report

Forecast Data Workbook

- A description of the contents of the forecast data workbook is tabulated on the following three slides
- 2019 Forecast Data

Net Energy and Peak Load Report

- Contains monthly peak loads, monthly weather information, and monthly actual and weather-normalized energy
- Net Energy and Peak Load Report

ISO NE Seasonal Peaks since 1980

- Seasonal summer and winter peak information
- ISO NE Seasonal Peaks Since 1980

Forecast Data Workbook (1 of 3)

Description of Contents

Worksheet	Description of Contents
1	ISONE Control Area & New England States Net Energy for Load (NEL) and Seasonal Peak Load History
2A	Summer Peak Load Forecast: ISONE Control Area, States, Regional System Plan (RSP) Sub-areas, and SMD Load Zone Forecasts • Expected weather case (50th percentile), extreme weather case (90th percentile) and compound annual growth rates
2B	Winter Peak Load Forecast (Same details as 2A)
2C	Annual Energy Forecast: ISONE Control Area, States, RSP Sub-areas, and SMD Load Zones Forecasts
3	Confidence Intervals: Energy and Seasonal Peak Load Forecast and 90% confidence Intervals for ISONE Control Area, States, and RSP Sub-areas
4	ISONE Control Area and New England States Monthly Peak Load Forecast
5	Weather Normalized History & Forecast (ISONE Control Area only)

Forecast Data Workbook (2 of 3)

Description of Contents

Worksheet	Description of Contents
6	Monthly Net Energy for Load Forecast: ISONE Control Area and States
7	Seasonal Peak Load Forecast Distributions: ISONE Control Area and States
8	Energy Model Economic/Demographic Variables: ISONE Control Area and States
9	Adjusting the State Energy Forecasts to the ISONE Energy Forecast
10G	Current CELT Gross forecast differences from prior year: ISONE and the New England States
10N	Current CELT Net forecast differences from prior year: ISONE and the New England States
11	Percentage of ISONE Control Area, operating companies, and load zones portioned out to the RSP sub-areas (Summer 2019 and Summer 2028)
12	Annual Energy and Seasonal Peak Forecast (Transpose of Tab 2 data)

Forecast Data Workbook (3 of 3)

Description of Contents

Worksheet	Description of Contents
13	Westinghouse Capacity Model Program Load Inputs (Power Years)
14	Summary Tables: ISONE Control Area, States, Regional System Plan Sub-areas, and SMD Load Zones Energy and Seasonal Peak Load Forecast
15	Current CELT forecast differences from prior year: BTM PV and EE for ISONE and states

Summary

This presentation covered:

- General purpose and intent of the load forecast
- Behind-the-Meter Photovoltaic (BTM PV) Reconstitution
- Energy Efficiency (EE) Reconstitution
- Gross Load Forecast inputs
- Modeling and Forecasting
- Net Load Forecast
- Reporting and Downstream Outputs