



# 2024 Load Forecast Supplement

PJM Resource Adequacy Planning Department

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## Introduction and Overview

This document serves as a supplement to the 2024 PJM Load Forecast report. It is intended as a reference, to provide details of the processes used to develop the load forecast and the data and assumptions used. It describes the load forecast model that produces the forecast as well as non-model adjustments to it.

This document acts as a resource to help describe the load forecast process. For details such as parameter estimates and model outputs, additional resources are available on the PJM website:

<https://www.pjm.com/planning/resource-adequacy-planning/load-forecast-dev-process.aspx>.

This is the second year in which PJM has employed the use of an hourly forecast model, as a result of a multi-month engagement in 2022 with Itron. Their final report can be found here (<https://www.pjm.com/-/media/planning/res-adeq/load-forecast/pjm-model-review-final-report-from-itron.ashx>) and should be viewed in conjunction with PJM documentation.

## Summary of Changes from 2023 Methodology

PJM contracted with S&P Global to provide an electric vehicle forecast for use in the 2024 Load Forecast. S&P Global provided PJM with zonal vehicle counts and charging impacts for light, medium, and heavy duty electric vehicles.

PJM added a third cold variable to the forecast model that acts like a spline when weather gets very cold. The HD3 variable adds another breakpoint after our HD2 variable. These HD variables are meant to capture different relationships of load to weather under different conditions. The additional cold weather variable, HD3, was added in response to testing after Winter Storm Elliott.

## Sector Models

Sector models are a key part of the load forecast process, providing insights into why load trends are happening. The job of a forecaster is to use models to understand what has happened such that they can make an informed judgment about the future. Looking at total peak and energy trends over time only tells us part of the story: what is happening. Sector models can give us greater insight into why things are happening.

Sector models are where we incorporate the independent assumptions on economic trends and end-use adoption and efficiency. The load forecast process considers three sectors: Residential, Commercial, and Industrial. Each sector has its own set of models and inputs.

### *Residential*

The Residential Sector model is actually two models, a customer model and an average use model. The product of these two concepts—customers and average use—provides total residential use. Total Residential use is considered according to the three use classes of Heating, Cooling, and Other.

Customers are modeled for each zone as a function of households. Monthly customer data is obtained from the EIA 861 dataset. Households are an economic concept, with quarterly history and forecast provided by Moody's Analytics. The relationship of customers to economics is defined by the below equation.

Equation 1. **Residential Customers**

$$customers = B_1 * households + B_2 * y_{2021}$$

Where

$$y_{2021} = 1 \text{ when year is greater than or equal to 2021 and 0 otherwise}$$

Average use per customer is modeled as a function of Heating, Cooling, and Other. Average use data is obtained from the EIA 861 dataset. Heating, Cooling, and Other are functions of end-use concepts provided by Itron (based on data from the EIA's Annual Energy Outlook) and economic concepts that are provided by Moody's Analytics (household size and real household income). The relationship of average use to Heating (xheat), Cooling (xcool), and Other (xother) is defined by the below equation.

Equation 2. **Residential Average Use**

$$use_t = B_0 * xheat_t + B_1 * xheat_{t-1} + B_2 * xcool_t + B_3 * xcool_{t-1} + B_4 * xother_t$$

The table below provides a list of residential end-uses and indicates how they are allocated to Heating, Cooling, and Other. For each end-use, data provided by Itron includes saturation (% of customers with device), efficiency (relative efficiency of device), and intensity (use per device accounting for saturation and efficiency).

Table 1. **List of Residential End-Uses and Assignment**

<u>Bucket</u>	<u>Use Type</u>	<u>Definition</u>
Heating	EFurn	Electric furnace and resistant room space heaters
Heating	HPHeat	Heat pump space heating
Heating	GHPHeat	Ground-source heat pump space heating
Heating	SecHt	Secondary heating
Cooling	CAC	Central air conditioning
Cooling	HPCool	Heat pump space cooling
Cooling	GHPCool	Ground-source heat pump space cooling
Cooling	RAC	Room air conditioners
Other	EWHeat	Electric water heating

Other	ECook	Electric cooking
Other	Ref1	Refrigerator
Other	Ref2	Second refrigerator
Other	Frz	Freezer
Other	Dish	Dishwasher
Other	CWash	Electric clothes washer
Other	EDry	Electric clothes dryer
Other	TV	TV sets
Heating	FurnFan	Furnace fans
Other	Light	Lighting
Other	Misc	Miscellaneous electric appliances <sup>1</sup>

Heating ( $x_{heat}$ ) is a function of heating end-uses as identified in the above table with adjustments for weather, real income per household, population per household, and building shell efficiency.

Equation 3. **Residential Heating Variable ( $x_{heat}$ )**

$$x_{heat}_t = sae_{heat}_t * hdd_{in}_t$$

Where

$$sae_{heat}_t = (EFurn_t + HPHeat_t + GHPHeat_t + SecHt_t + FurnFan_t) * (Population\_per\_household_t)^x * (Income\_per\_household_t)^y * Structural\_Heating_t$$

Where x and y are elasticities provided by Itron and Structural\_Heating is a measure of building size adjusted for relative building shell efficiency.

and

<sup>1</sup> Residential end-use data has always included a category referred to as Miscellaneous, which represented a catch-all of the non-named appliances listed. In 1998, Miscellaneous represented about a fifth of non-weather sensitive uses and now represents about half; a trend spurred as much by growth in Miscellaneous as declines in non-Miscellaneous end-uses.

$$hdd\_in_t = \frac{hdd_t}{hdd_{2016}}$$

Cooling (xcool) is a function of cooling end-uses as identified in the above table with adjustments for weather, income per household, population per household, and building shell efficiency.

Equation 4. **Residential Cooling Variable (xcool)**

$$xcool_t = sae\_cool_t * cdd\_in_t$$

Where

$$sae_{cool_t} = (CAC_t + HPCool_t + GHPCool_t + RAC_t) * (Population\_per\_houeshold_t)^x * (Income\_per\_household_t)^y * Structural\_Cooling_t$$

Where x and y are elasticities provided by Itron and Structural\_Cooling is a measure of building size adjusted for relative building shell efficiency.

and

$$cdd\_in_t = \frac{cdd_t}{cdd_{2016}}$$

Other (xother) is a function of other end-uses as identified in the above table with adjustments for income per household, and population per household.

Equation 5. **Residential Other Variable (xother)**

$$xother_t = sae\_other_t * Days\_Idx_t$$

Where

$$sae_{other_t} = (EWHeat_t + ECook_t + Ref1_t + Ref2_t + Frz_t + Dish_t + CWash_t + EDry_t + TV_t + Light_t + Misc_t) * (Population\_per\_houeshold_t)^x * (Income\_per\_household_t)^y$$

Where x and y are elasticities provided by Itron

and

$$Days\_Idx_t = \frac{Days\ in\ Month}{30.42}$$

The results of Equation 2 (Residential Average Use) are fitted values, which includes historical weather. For comparability in heating and cooling trends over time, this then needs to be transformed to be on a consistent weather basis.

Equation 6. **Formulation of HeatUse, CoolUse, and OtherUse**

Heating and Cooling are adjusted to be consistent with 2016 weather for all years.

$$HeatUse_t = B_0 * norm\_xheat_t + B_1 * norm\_xheat_{t-1}$$

$$CoolUse_t = B_2 * norm\_xcool_t + B_3 * norm\_xcool_{t-1}$$

$$OtherUse_t = B_4 * xother_t$$

where B0, B1, B2, B3, and B4 are from Equation 2

and

*norm\_xheat* and *norm\_xcool* are the same as *xheat* and *xcool* but using 2016 weather

Total residential use then is the product of customers and each of these defined average use terms.

**Equation 7. Total Residential Use**

$$ResHeat_t = Customers_{quarter,year} * HeatUse_{quarter,year}$$

$$ResCool_t = Customers_{quarter,year} * CoolUse_{quarter,year}$$

$$ResOther_t = Customers_{quarter,year} * OtherUse_{quarter,year}$$

## Commercial

The starting point for analysis is Commercial energy provided through the EIA 861 dataset. The Commercial models utilize two sets of data: economic and end-use. Economic concepts used are service sector employment, working-age population, and real services output, and are provided by Moody's Analytics. End-use concepts are provided by Itron (based on data from the EIA's Annual Energy Outlook), and are summarized in the following table.

Table 2. List of Commercial End-Uses and Assignment

<u>Bucket</u>	<u>Use Type</u>	<u>Definition</u>
Heating	Heating	Heating
Cooling	Cooling	Cooling
Other	Ventilation	Ventilation
Other	WtrHeat	Water Heating
Other	Cooking	Cooking



Other	Refrig	Refrigeration
Other	Lighting	Lighting
Other	Office	Office Equipment (PCs)
Other	Misc	Miscellaneous

Equation 8. **Commercial Use**

$$use_t = B_0 * xheat_t + B_1 * xheat_{t-1} + B_2 * xcool_t + B_3 * xcool_{t-1} + B_4 * xother_t$$

Where

$$xheat_t = Heat_t * ComEconVar_t * hdd_{in_t}$$

$$xcool_t = Cool_t * ComEconVar_t * cdd_{in_t}$$

$$xother_t = Other_t * ComEconVar_t$$

*Heat*, *Cool*, and *Other* are end-use intensities from categories in the above table. *ComEconVar* is a 30/30/40 weighed combination of services employments, real services output, and working-age population, respectively.

For comparability in heating and cooling trends over time, this then needs to be transformed to be on a consistent weather basis.

Equation 9. **Formulation of HeatUse, CoolUse, and OtherUse**

Heating and Cooling are adjusted to be consistent with 2016 weather for all years.

$$Com\_Heat_t = B_0 * norm\_xheat_t + B_1 * norm\_xheat_{t-1}$$

$$Com\_Cool_t = B_2 * norm\_xcool_t + B_3 * norm\_xcool_{t-1}$$

$$Com\_Other_t = B_4 * xother_t$$

where B0, B1, B2, B3, and B4 are from Equation 8

and

*norm\_xheat* and *norm\_xcool* are the same as *xheat* and *xcool* but using 2016 weather

## Industrial

The starting point for analysis is Industrial energy provided through the EIA 861 dataset. Industrial modeling utilizes two sets of data: economic and intensity. The economic concept used is real industrial output, using data from Moody’s Analytics. Intensity data is pulled from national data from EIA on electricity per real output.

Real industrial output is an aggregate of output in goods-producing industries (see list). Moody’s Analytics currently only forecasts employment for these series at the metro area level, not output. However, output is available at the state level and thus output at the metro level is imputed by using state productivity (output divided by employment).

Equation 10. **Metro Area Real Industrial Output**

$$\begin{aligned}
 & \mathbf{Output}_{sector,metro,year} \\
 & = \mathbf{Employment}_{sector,metro,year} \\
 & * \mathbf{Output}_{sector,state,year} / \mathbf{Employment}_{sector,state,year} \\
 \\
 & \mathbf{Output}_{metro,year} = \sum_{sector} \mathbf{Output}_{sector,metro,year}
 \end{aligned}$$

where metro areas are assigned to states based on location

And Sectors are defined as follows:

- Natural Resources and Mining
- Construction
- Manufacturing – Machinery
- Manufacturing - Transportation Equipment
- Manufacturing - Chemicals; Energy; Plastics and Rubber
- Manufacturing - Electronic and Electrical
- Manufacturing - Furniture and Miscellaneous
- Manufacturing - Metals and Mining
- Manufacturing - Textile; Fiber and Printing

Industrial intensity is defined as industrial energy use per real output. The concept is based on national data, but is customized to zones through the availability of sector detail. Historical and forecast energy use by sector is compiled from the EIA Annual Energy Outlook (AEO) and the EIA Manufacturing Energy Consumption Survey (MECS). Economic data by sector is provided by Moody’s Analytics as was described in the prior paragraph. Zonal industrial intensity series are then a weighted average of national sector indexes.

Equation 11. **Zonal Industrial Intensity**

$$Intensity_{year} = \sum_{sector} (Output_{sector,year} / Total\ Output_{year}) * Intensity_{sector,year}$$

Discussed above are the types of inputs considered, but as discussed in Itron's model review<sup>2</sup> it is challenging to fit all zones with a structural end-use model. Candidate models that consider the above described variables are constructed, and are evaluated on a zone-by-zone basis for goodness of fit and reasonableness. Reasonableness checks include items such as ensuring coefficients have the right sign and how the model performs on out-of-sample observations. Zonal industrial model selections are provided in supplemental posted materials. Each zone results in an Industrial Base component (*Ind\_Other*) and in some cases an Industrial Cooling component (*Ind\_Cooling*).

 Equation 12. **Industrial Cooling**

$$Ind\_Cooling_t = B * CDD_{2016}$$

Where *B* is the coefficient on the cooling term in the industrial model. Cooling is included in zones for which it has a positive coefficient, and excluded for which it does not.

## Usage Indexes

Heat, Cool, and Other Usage Indexes need to be constructed using the results from the Residential, Commercial, and Industrial Sector Models. First, monthly results are rolled up into single measures.

 Equation 13. **Monthly Results**

$$Heat_t = Res\_Heating_t + Com\_Heating_t$$

$$Cool_t = Res\_Cooling_t + Com\_Cooling_t + Ind\_Cooling_t$$

$$Other_t = Res\_Other_t + Com\_Other_t + Ind\_Other_t$$

At this point, *Other* is essentially complete and is simply converted from a monthly frequency to a daily frequency with each day's value within a month equal to the respective monthly value. *Heat* and *Cool* though at this point are still reflective of 2016 weather patterns in HDD and CDD. A 365 day moving average is taken of each to calculate *HeatIdx* and *CoolIdx*, such that these can later be interacted with hourly heating and cooling weather variables to capture weather sensitive load over time.

<sup>2</sup> See pages 15 and 16 for Itron's discussion of Industrial modeling: <https://www.pjm.com/-/media/planning/res-adeq/load-forecast/pjm-model-review-final-report-from-itron.ashx>

## Weather Variables

Weather variables are defined at the zone level. Zonal weather is a weighted average of weather stations<sup>3</sup>.

Table 3. **Weather Station Assignment**

<u>Zone</u>	<u>Weather Station</u>	<u>Weight</u>	<u>Zone</u>	<u>Weather Station</u>	<u>Weight</u>
AE	ACY	100.0%	JCPL	ACY	25.0%
AEP	CAK	15.1%	JCPL	EWR	75.0%
AEP	CMH	23.4%	METED	ABE	50.0%
AEP	CRW	22.6%	METED	PHL	50.0%
AEP	FWA	22.7%	PECO	PHL	100.0%
AEP	ROA	16.2%	PENLC	ERI	50.0%
APS	IAD	30.0%	PENLC	IPT	50.0%
APS	PIT	70.0%	PEPCO	DCA	100.0%
ATSI	CAK	46.5%	PL	ABE	25.0%
ATSI	CLE	30.0%	PL	AVP	25.0%
ATSI	PIT	8.5%	PL	IPT	25.0%
ATSI	TOL	15.0%	PL	MDT	25.0%
BGE	BWI	100.0%	PS	EWR	100.0%
COMED	ORD	100.0%	RECO	EWR	100.0%
DAYTON	DAY	100.0%	UGI	AVP	100.0%
DPL	ILG	70.0%	VEPCO	IAD	33.3%
DPL	WAL	30.0%	VEPCO	ORF	33.3%
DQE	PIT	100.0%	VEPCO	RIC	33.3%
DUKE	CVG	100.0%			
EKPC	CVG	25.0%			
EKPC	LEX	49.0%			
EKPC	SDF	26.0%			

<sup>3</sup> Weather station weights are provided by Electric Distribution Companies (EDCs).

## Cooling and Heating Degree Variables

Temperature-Humidity Index (THI) values are translated to CD1, CD2, and CD3 in order to allow the forecast the flexibility to capture different relationships of load to weather under different conditions (a spline). The goal in defining cut points for CD2 and CD3 is to try have it hot enough to capture any potential inflection points but not so hot such that there is limited ability to make a good statistical inference.

### Equation 14. Temperature-Humidity Index and Cooling Degrees Formulas

$$THI_t = temperature_t + 0.55 * (humidity_t/100 - .4) * max(temp_t - 58, 0)$$

Base-points are set for each hour to calculate CD1, CD2, and CD3

Hour Ending	Base Point
1	65
2	65
3	65
4	65
5	65
6	65
7	65
8	65
9	65
10	65
11	65
12	70
13	70
14	70
15	70
16	70
17	70
18	70
19	70
20	70
21	65
22	65
23	65
24	65

$$CD1_t = max(THI_t - Base\_Point_{HE}, 0)$$

$$CD2_t = max(THI_t - Base\_Point_{HE} + 10, 0)$$

$$CD3_t = max(THI_t - Base\_Point_{HE} + 15, 0)$$

Heating degree variables are then also used.

### Equation 15. Heating Degrees

Base-points are set for each hour to calculate HD1, HD2, and HD3

Hour Ending	Base Point
1	55
2	55
3	55
4	55
5	55
6	55
7	55
8	55
9	55
10	55
11	55
12	60
13	60
14	60
15	60
16	60
17	60
18	60
19	60
20	60
21	55
22	55
23	55
24	55

$$HD1_t = \max(\text{Base\_Point}_{HE} - \text{Temp}_t, 0)$$

$$HD2_t = \max(\text{Base\_Point}_{HE} - 10 - \text{Temp}_t, 0)$$

$$HD3_t = \max(\text{Base\_Point}_{HE} - 15 - \text{Temp}_t, 0)$$

These Cooling Degree and Heating Degree variables are used both contemporaneously as well as lagged transformations (Lag6CD, Lag24CD, Lag6HD, Lag24HD), interacted with weekend day-type (WkEndCD, WkEndHD), and interacted with seasons (SpringCD, FallCD, SpringHD, FallHD).

### Additional Weather Variables

The load forecast model also includes variables to capture both wind speed and cloud cover.

Equation 16. **Wind and Cloud Variables**

$$WindHD_t = WSP_t * \min(HD1_t/60, 1)$$

$$WindCD_t = WSP_t * \min(CD1_t/60, 1)$$

Where  $WSP$  is a 3-period centered moving average of wind speed

$$CloudHD_t = Cloud_t * \min(HD1_t/60, 1)$$

$$CloudCD_t = Cloud_t * \min(CD1_t/60, 1)$$

Where *Cloud* is a 3-period centered moving average of wind speed

## Forecast Model

### Model Specification

The load forecast is constructed using 24 hourly models for each zone. In each model, load is the dependent variable. In the history, we start with metered load and then re-constitute with load management addbacks, load drops associated with peak shaving programs, and distributed solar generation estimates.

Each regression model has the same set-up, with load modeled against input variables: Weather Variables, Calendar effects, and Economic and End-Use considerations. Variable names align with documentations in the posted statistical appendix and are grouped below based on whether they are related to non-weather (XOther), heating (XHeat), or Cooling (XCool).

#### Equation 17. Forecast Model Specification

$$load = \sum_{variables} B_{variable} * variable$$

Where

Calendar-type variables (Interacts with XOther)

Intercept_XOther	JanWalk	Wednesday	XMasDay
Jan	FebWalk	Thursday	NYEve
Feb	MarWalk	Friday	NYDay
Mar	AprWalk	Saturday	WkAfterNewYear
MarDST	MayWalk	MLK	WkDayBeforeHol
Apr	JunWalk	PresDay	WkDayAfterHol
May	JulWalk	GoodFri	Phase1
Jun	AugWalk	MemDay	Phase2
Jul	SepWalk	July4th	Phase3
Aug	OctWalk	LaborDay	
Sep	NovWalk	Thanks	binary1
Oct	DecWalk	FriAThanks	binary2
Nov	Monday	WkBeforeXMas	trend1
NovDST	Tuesday	XMasEve	trend2

Heating-type Variables (Interacts with XHeat)

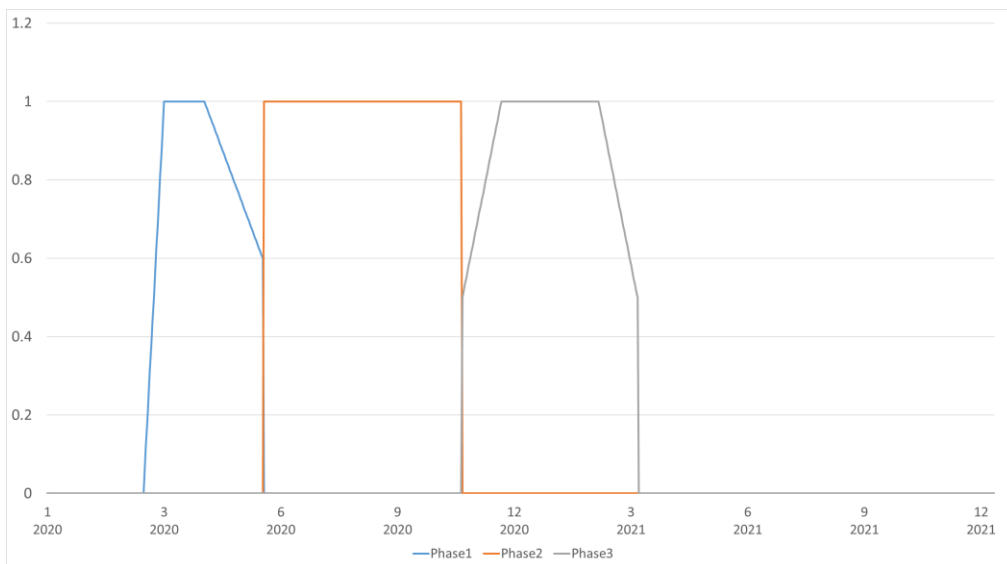
HD1	SpringHD
HD2	FallHD
HD3	WindHD
Lag6HD	CloudHD
Lag24HD	MA10_HDD
Lag24CD_HD	MA28_HDD
WkEndHD	

Cooling-type Variables ([Interacts with XCool](#))

TD1	SpringCD
TD2	FallCD
TD3	WindCD
Lag6CD	CloudCD
Lag24CD	MA10_CDD
Lag24HD_CD	MA28_CDD
WkEndCD	

### Binary and Trend Variables

COVID-19 had a large impact on electricity demand. Some of this impact is captured in aspects of the model construction via the economic inputs in the sector models. Nevertheless, it is often advisable in periods such as these to provide some controls for the abnormal event. The 2024 Load Forecast employs an approach where a series of binaries are used *Phase1* through *Phase3* with the *Phase3* variable ending April 2021. This will continue to be re-visited each year.



In addition to COVID treatments, *binary1/binary2* and *trend1/trend2* variables are defined for each zone. These are intended to help tune the model and capture abnormal events in the residuals after specifying the model. None of



these trends are extended into the forecast period, so their effect is on the model parameterization and not on assumptions of future trends. Contained in the supplemental materials are hourly residual plots of before and after the inclusion of these additional model variables.

### Simulation

Once the load model is estimated, forecasts for each PJM transmission zone are produced by solving the hourly zonal equations, moving through the year day by day and hour by hour applying historical weather patterns (including conditions for distributed solar generation), as well as forecast adjustments (data centers and peak shaving), behind-the-meter battery storage, and electric vehicles .

To model the most likely weather conditions (often referred to as normal or peak-eliciting weather), a weather rotation technique is used to simulate a distribution of hourly load scenarios generated by historical weather observations, representing actual weather patterns that occurred across the PJM control region.

To enhance the simulation process, each yearly weather pattern is shifted by each day of the week moving forward six days and backwards six days, providing 13 different weather scenarios for each historical year. For early January and late December dates, data from the same calendar year is applied. The table below illustrates the shift of weather data across the scenarios.

Date	Weather Scenarios												
	Rotate Forward							Rotate Backward					
	A1995	B1995	C1995	D1995	E1995	F1995	G1995	H1995	I1995	J1995	K1995	L1995	M1995
1-Jan	1/1/1995	1/2/1995	1/3/1995	1/4/1995	1/5/1995	1/6/1995	1/7/1995	12/31/1995	12/30/1995	12/29/1995	12/28/1995	12/27/1995	12/26/1995
2-Jan	1/2/1995	1/3/1995	1/4/1995	1/5/1995	1/6/1995	1/7/1995	1/8/1995	1/1/1995	12/31/1995	12/30/1995	12/29/1995	12/28/1995	12/27/1995
3-Jan	1/3/1995	1/4/1995	1/5/1995	1/6/1995	1/7/1995	1/8/1995	1/9/1995	1/2/1995	1/1/1995	12/31/1995	12/30/1995	12/29/1995	12/28/1995
4-Jan	1/4/1995	1/5/1995	1/6/1995	1/7/1995	1/8/1995	1/9/1995	1/10/1995	1/3/1995	1/2/1995	1/1/1995	12/31/1995	12/30/1995	12/29/1995
5-Jan	1/5/1995	1/6/1995	1/7/1995	1/8/1995	1/9/1995	1/10/1995	1/11/1995	1/4/1995	1/3/1995	1/2/1995	1/1/1995	12/31/1995	12/30/1995
6-Jan	1/6/1995	1/7/1995	1/8/1995	1/9/1995	1/10/1995	1/11/1995	1/12/1995	1/5/1995	1/4/1995	1/3/1995	1/2/1995	1/1/1995	12/31/1995
7-Jan	1/7/1995	1/8/1995	1/9/1995	1/10/1995	1/11/1995	1/12/1995	1/13/1995	1/6/1995	1/5/1995	1/4/1995	1/3/1995	1/2/1995	1/1/1995
-	-	-	-	-	-	-	-	-	-	-	-	-	-
25-Dec	12/25/1995	12/26/1995	12/27/1995	12/28/1995	12/29/1995	12/30/1995	12/31/1995	12/24/1995	12/23/1995	12/22/1995	12/21/1995	12/20/1995	12/19/1995
26-Dec	12/26/1995	12/27/1995	12/28/1995	12/29/1995	12/30/1995	12/31/1995	1/1/1995	12/25/1995	12/24/1995	12/23/1995	12/22/1995	12/21/1995	12/20/1995
27-Dec	12/27/1995	12/28/1995	12/29/1995	12/30/1995	12/31/1995	1/1/1995	1/2/1995	12/26/1995	12/25/1995	12/24/1995	12/23/1995	12/22/1995	12/21/1995
28-Dec	12/28/1995	12/29/1995	12/30/1995	12/31/1995	1/1/1995	1/2/1995	1/3/1995	12/27/1995	12/26/1995	12/25/1995	12/24/1995	12/23/1995	12/22/1995
29-Dec	12/29/1995	12/30/1995	12/31/1995	1/1/1995	1/2/1995	1/3/1995	1/4/1995	12/28/1995	12/27/1995	12/26/1995	12/25/1995	12/24/1995	12/23/1995
30-Dec	12/30/1995	12/31/1995	1/1/1995	1/2/1995	1/3/1995	1/4/1995	1/5/1995	12/29/1995	12/28/1995	12/27/1995	12/26/1995	12/25/1995	12/24/1995
31-Dec	12/31/1995	1/1/1995	1/2/1995	1/3/1995	1/4/1995	1/5/1995	1/6/1995	12/30/1995	12/29/1995	12/28/1995	12/27/1995	12/26/1995	12/25/1995

This approach has two key advantages. One, by rotating the data on the calendar, peak-producing weather will be applied to peak producing days. Two, by producing scenarios over a wide range of weather conditions, the weather rotation method is able to identify both the probable and possible levels of future peak load.

The process is repeated for the remaining years of historical weather data. The 2024 Load Forecast uses 29 years of weather history that results in 377 (29 weather years x 13 days) separate forecast simulations for each year in the forecast horizon. These simulations produce a frequency distribution of NCP demands by zone.

For each weather scenario, monthly NCPs are determined by obtaining the maximum NCP for the month. Seasonal NCPs are determined as the maximum over the summer/winter/spring/fall months. For each season, the ratio of each month’s peak to the highest monthly peak is taken, and then each month’s ratio is multiplied by the seasonal peak. In

this way, one of the month's peaks is the seasonal peak while still preserving the relationship between monthly peaks.

For purposes of system planning, only a couple of the values in the forecast distribution are used. After ranking the scenario forecasts from lowest to highest MW value, the median value is selected as the base (or 50/50) forecast. This is the value used for most system planning studies. The 90th percentile (or 90/10) result is used for studies where the system is assumed to be at system emergency conditions.

## ***Coincident Peaks***

Hourly results from the method described above are rolled up to the the entire PJM RTO and Locational Deliverability Areas (LDA). Weather rotation provides an additional benefit for identifying coincident peaks - the natural diversity of weather patterns that impact the PJM footprint is simulated. This is a more plausible approach to peak forecasting than traditional methods which tend to have all weather stations having peak producing weather on the same day. Using the latter approach would overstate the PJM or LDA peak forecast by minimizing diversity.

Monthly RTO/LDA peaks are determined by obtaining the maximum for each scenario for each month (377 possible peaks). Seasonal RTO/LDA peaks are determined over the summer/winter/spring/fall months by obtaining the maximum for each scenario for each season (377 possible peaks). For each season, the ratio of each month's peak to the highest monthly peak is taken, and then each month's ratio is multiplied by the seasonal peak. From this distribution, the median result is used as the base (50/50) forecast; the values at the 10th percentile and 90th percentile are assigned to the 10/90 and 90/10 weather bands.

At this point, the values of the overall RTO peaks are set, but not the contribution of each zone. To determine the final zonal RTO/LDA-coincident peak forecasts, each zone's average contribution across the peak distribution is calculated and applied to the RTO forecast.

## **Assumption Development**

### ***Weather***

The 2024 Load Forecast uses historical weather data from 1994 to 2022 as the basis for constructing forecasts. No explicit assumption is being made about Climate Change, and thus the assumption is that future weather will resemble past weather.

### ***Vendor Data***

The 2024 Load Forecast relies on vendor and government sources.

For economic and demographic forecasts, PJM consults with Moody's Analytics and used their September 2023 forecast vintage. Zonal charts for concepts used have been posted with the supplemental materials.

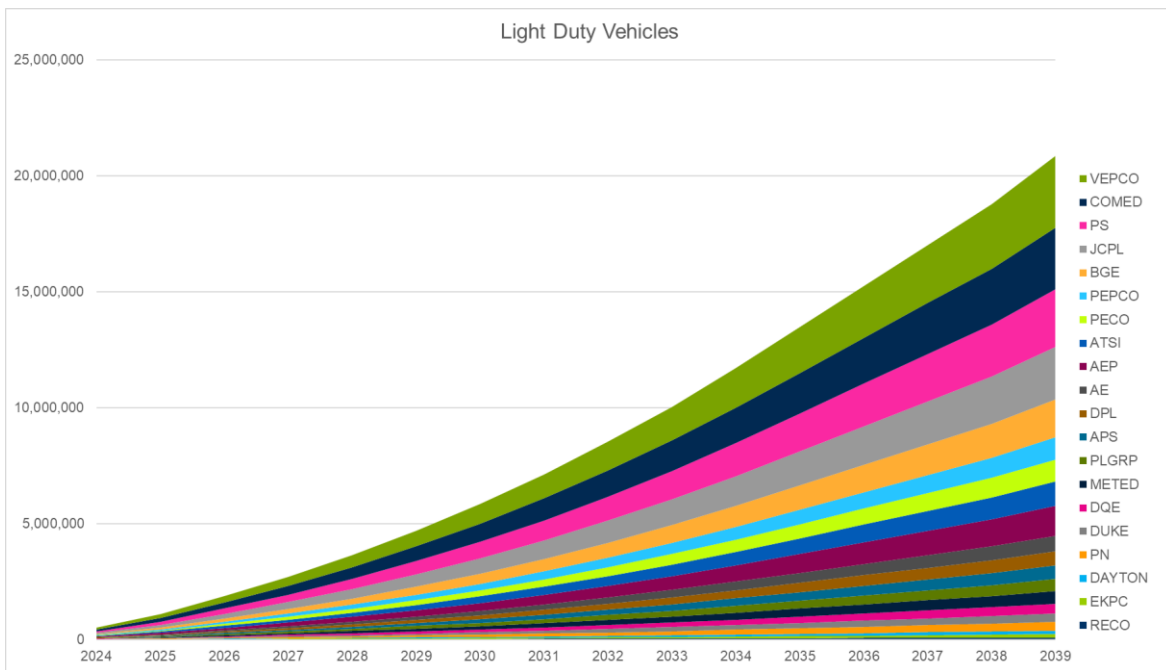
For end-use saturation/efficiency/intensity projections, PJM is a member of the Itron Energy Forecasting Group (EFG) that provides Census level history/projections for Residential/Commercial sectors. Their work derives from the Energy Information Administration’s 2023 Annual Energy Outlook.

For distributed energy resources (BtM solar and storage), S&P Global provides a BtM solar and storage additions forecast. This is combined with historical Generation Attribute Tracking System (GATS) data in order to provide cumulative nameplate capacity by zone. UL provides zonal solar production estimates, which are used in both determining historical performance and expectations of future performance.

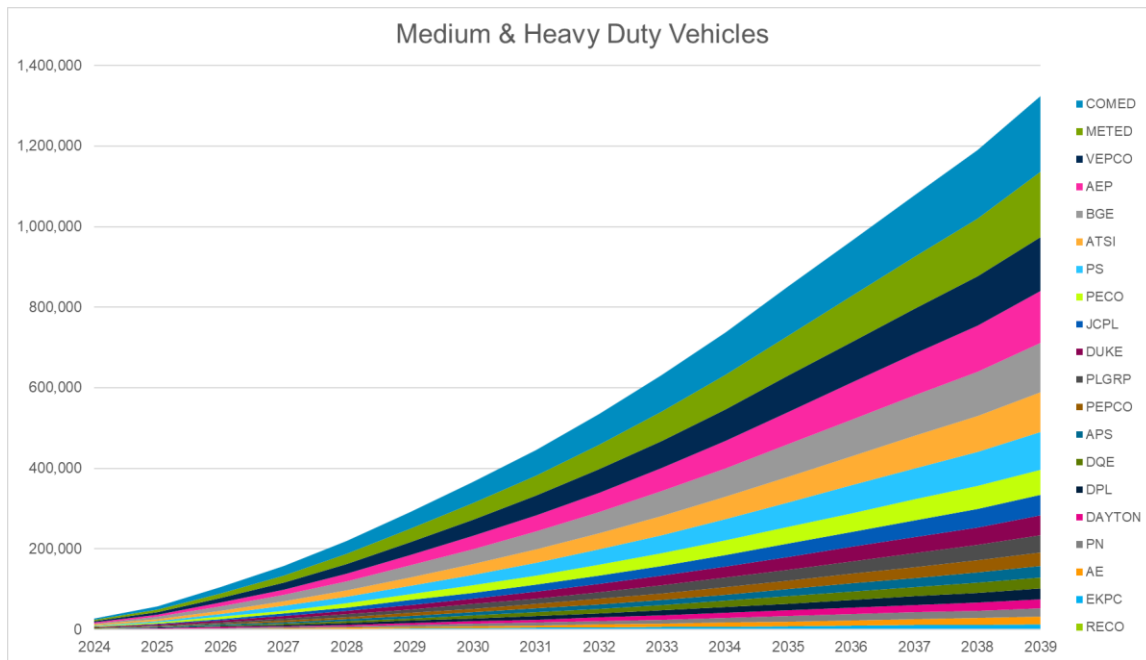
### Plug-in Electric Vehicles

Forecasts of EVs were provided by S&P Global and their zonal forecasts take into account vehicle miles traveled (VMT), vehicle efficiency, and charging behavior in their hourly charging impacts. S&P Global uses federal, state, and metropolitan level data to produce their forecast. More information on the S&P Global electric vehicle forecast methodology and assumptions can be found under the November 27, 2023 Load Analysis Subcommittee materials<sup>4</sup>.

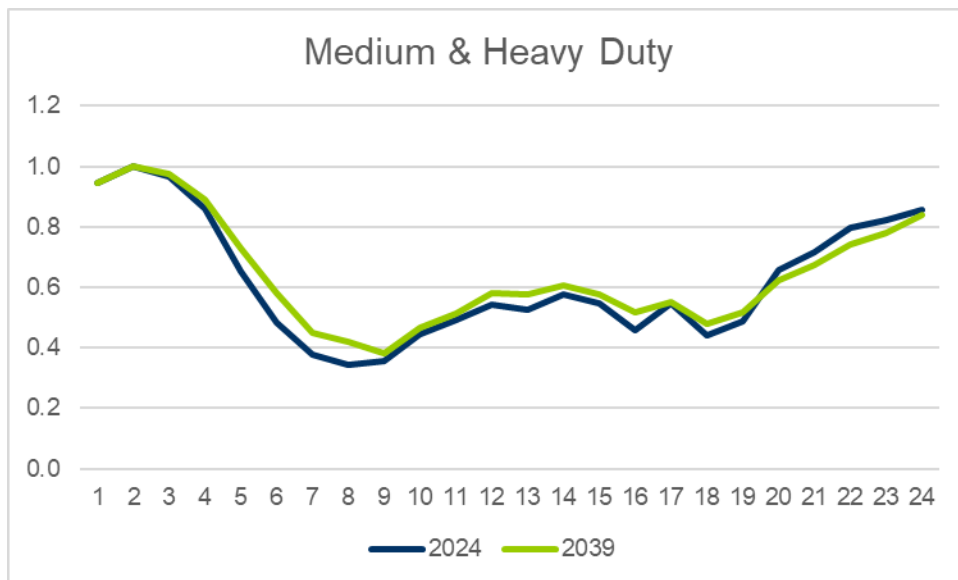
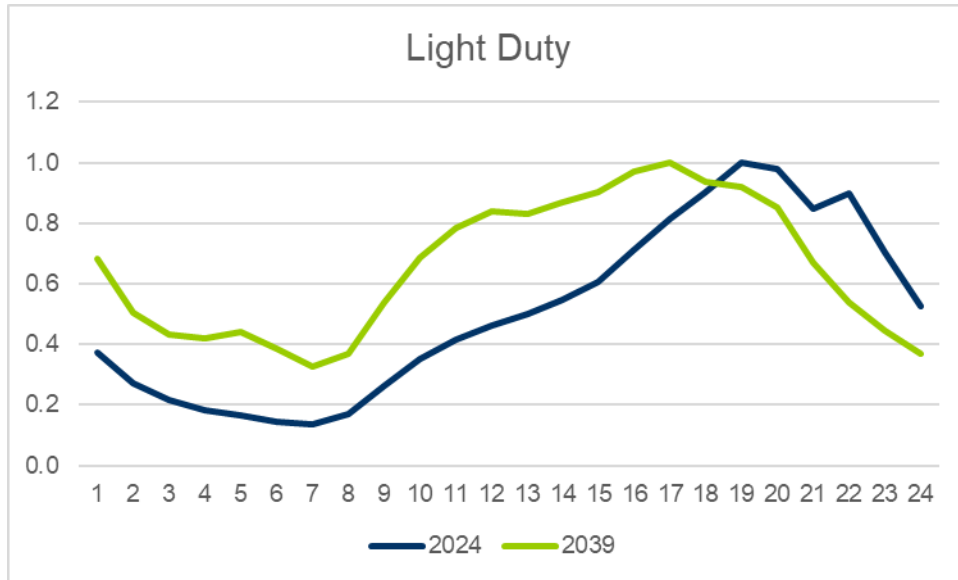
Charts below show vehicle counts for light duty electric vehicles by zone followed by medium & heavy duty electric vehicle counts by zone. The medium & heavy duty category contains delivery vans, school bus, transit bus, medium truck, short haul, and long haul vehicles.



<sup>4</sup> <https://www.pjm.com/-/media/committees-groups/subcommittees/las/2023/20231127/20231127-reference---12---spgci-consulting-methodology-and-assumptions---ev-forecast-ashx>



S&P Global provided an hourly charging impact for each zone throughout the forecast horizon. Below shows a total RTO average per-unitized charging shape from summer weekdays for light, medium, and heavy duty electric vehicles. The blue line is a charging shape for 2024 and the green line shows the per-unitized charging shape for 2039. For light duty electric vehicles, the 2024 charging shape shows more tendency to charge later in the day around hour ending 17 – 20 while the 2039 charging shape shows more levelized charging throughout the day. The hourly charging shape for medium & heavy duty electric vehicles does not show a large shift in charging behavior due to the nature of these vehicles being out delivering goods, people, etc. during the day and then back to their depots at night to charge.



### ***Behind-the-Meter Battery Storage Operation***

As indicated above, the amount of behind-the-meter battery storage is based on a forecast from S&P Global. The methodology for their forecast is based on an attachment model (storage installed with solar), and thus are assumed to be used in conjunction with distributed solar. The assumption is made that batteries available to discharge at summer peak and thus subtract from loads on the summer peak distribution.

### ***Exogenous Factors***

PJM annually solicits information from its member Electric Distribution Companies (EDC) for large load shifts (either positive or negative) that are known to the EDC but may be unknown to PJM. Once the request has been verified

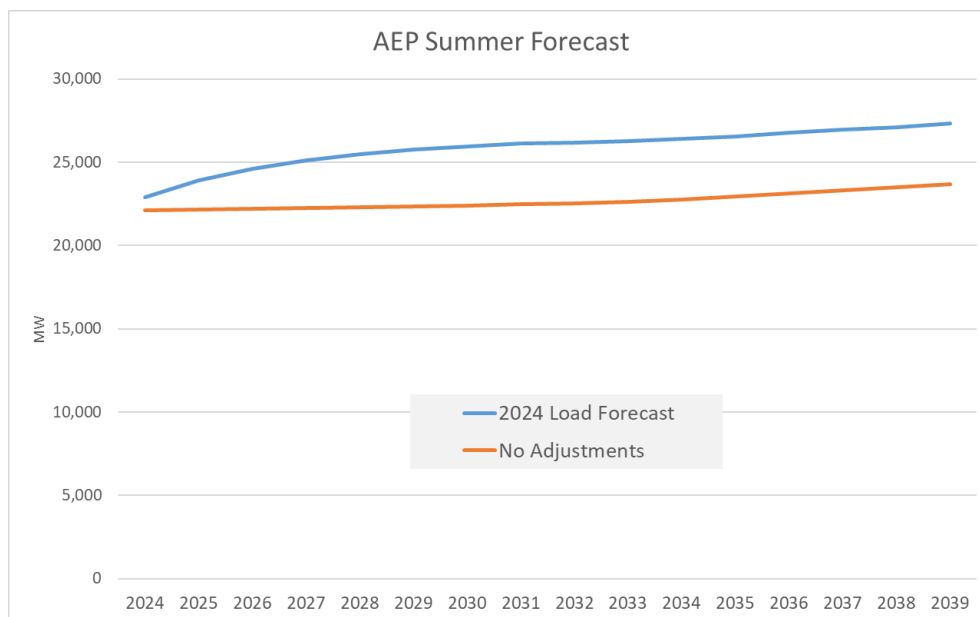
per the guidelines in Attachment B of Manual 19, PJM works towards accounting for it in its load forecast. Each request is considered on a case-by-case basis, with particular caution paid to avoid double-counting anticipated load increases or decreases. With each forecast adjustment, PJM quantifies the MW impact on the forecast that is due to this request.

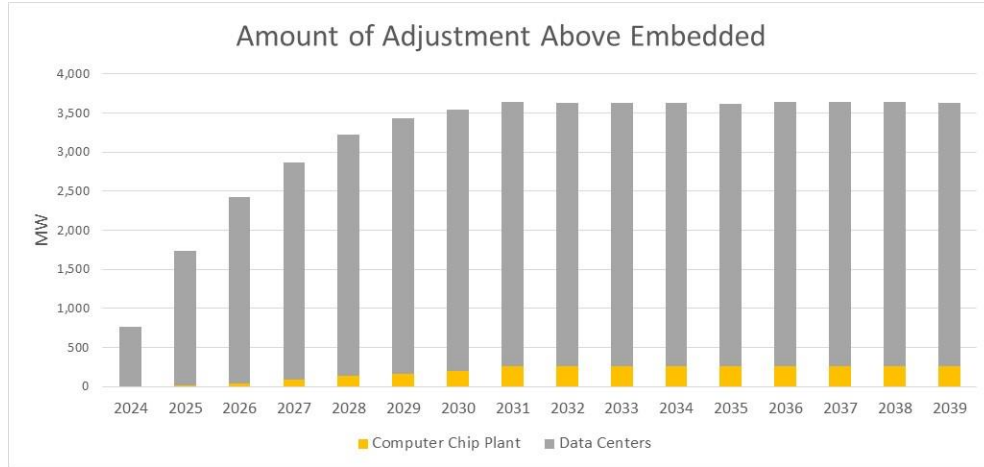
### AEP – Data Centers and Computer Chip Plant

AEP requested that PJM consider load additions related to significant growth in data centers and a computer chip manufacturing site outside of Coumbus. AEP provided forecasted data center additions as well as historical cumulative data center information. Hourly information related to historical data center load was included in the data provided. PJM removed monthly data center load from the commercial EIA data in an effort to remove any double counting. PJM also removed hourly data center load from our historical loads that get used in our model estimation.

The computer chip plant will be a new facility so no historical data is available. PJM reviewed economic data for the computer chip plant and is using a percentage of their contract capacity.

The first chart below shows what the summer forecast would be for AEP without the adjustments in orange and with adjustments in blue. The bar chart at the bottom shows this amount above what is embedded in the forecast which is the difference between the blue and orange forecast lines.



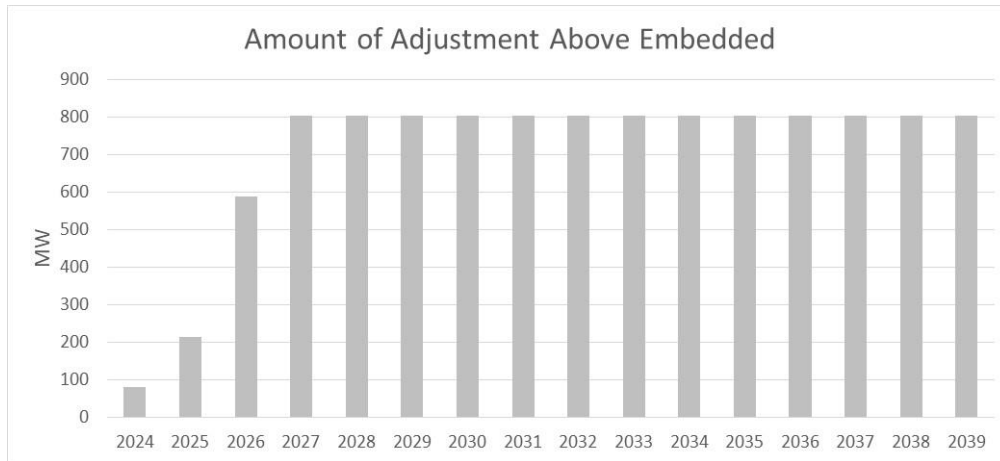
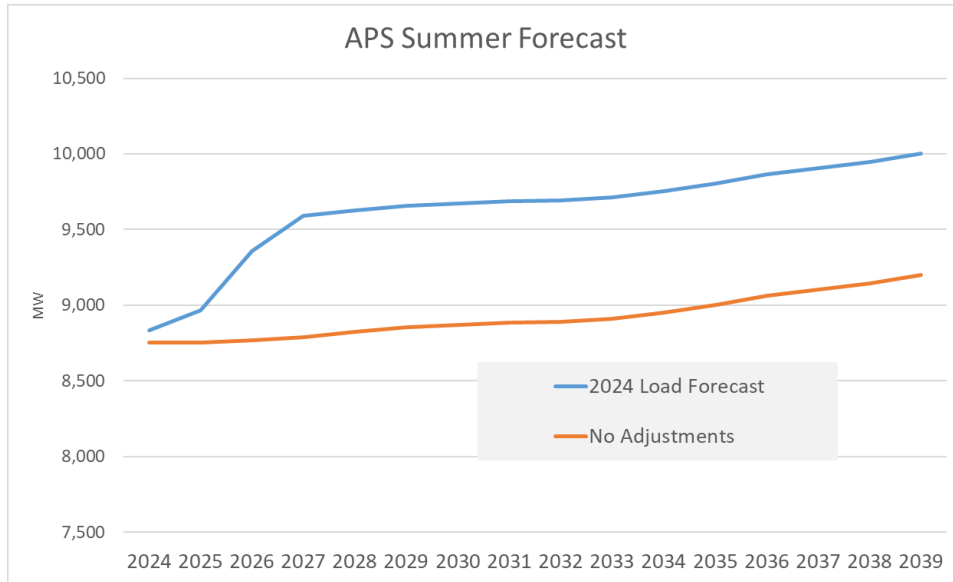


PJM had multiple meetings with AEP staff to discuss this adjustment, and it is anticipated that there might be more data center load forthcoming. PJM will continue to be in contact with AEP to understand these trends as they develop.

### APS – Data Centers

First Energy requested PJM consider load additions related to significant growth in data centers. These sites are coming online and growing through mid-2027. The load is predominately due to a single site called Quantum Loophole. This site does not have load history as it is new so no adjustment to history was made. PJM reviewed commercial base load and observed declines through the forecast horizon<sup>5</sup>. Thus, PJM concluded that there is no embedded load due to data centers in APS. Below shows what the APS summer forecast would be without the adjustment and with the adjustment. The final adjustment is shown in the bar chart. PJM has been and will continue to be in contact with First Energy to follow this development.

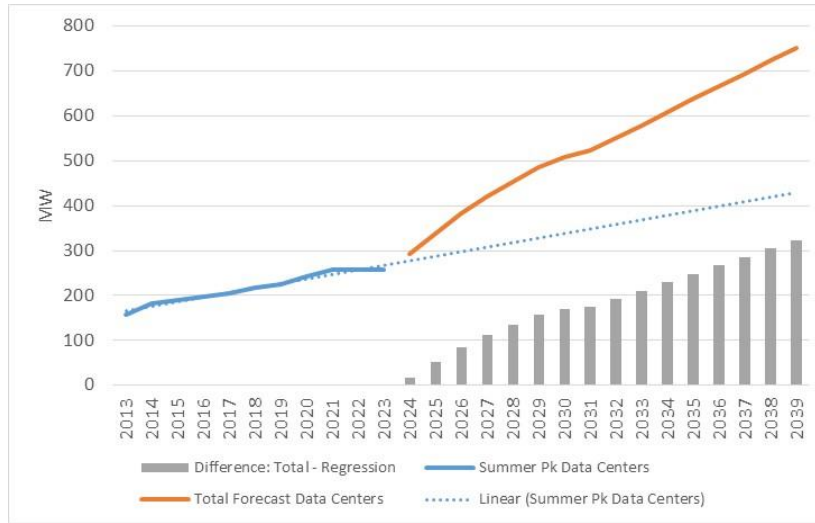
<sup>5</sup> See <https://www.pjm.com/-/media/committees-groups/subcommittees/las/2023/20231127/20231127-reference---02---residential-commercial-industrial-sectors-and-indices.ashx>



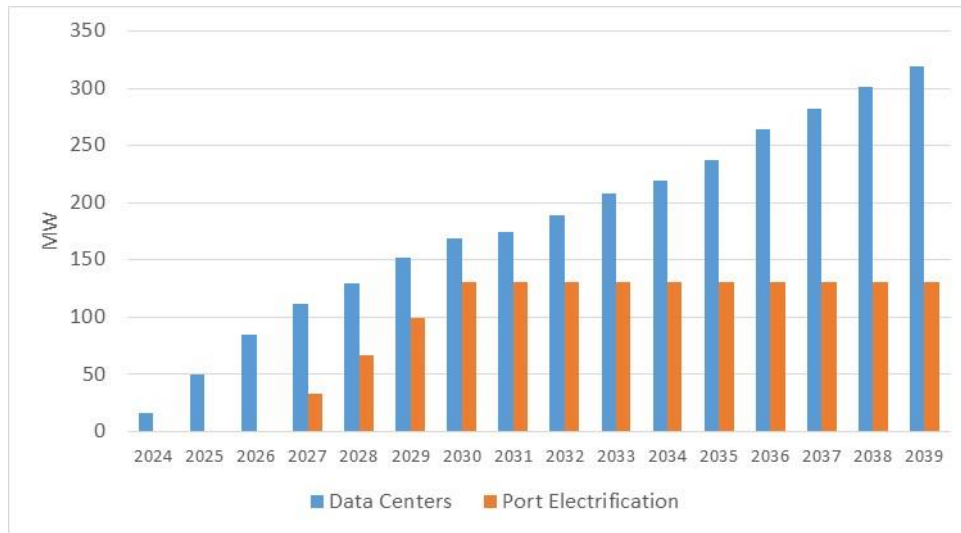
### PS – Data Centers and Port Electrification

PS requested forecast adjustments for data center growth and port electrification. PS provided historical peak history back to 2013. Since we did not have hourly historical data for data centers to remove from history we did the following; created a trend with historical peaks (dotted blue line below), compared this trend with the total amount of data center load (existing and forecasted) that we received from PS (orange line below), calculated the difference as amount forecast is adjusted (grey bars below).

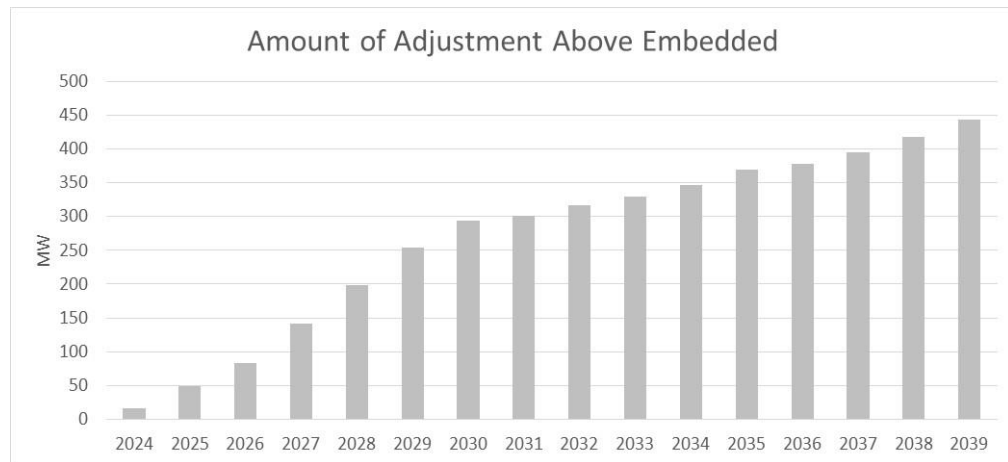
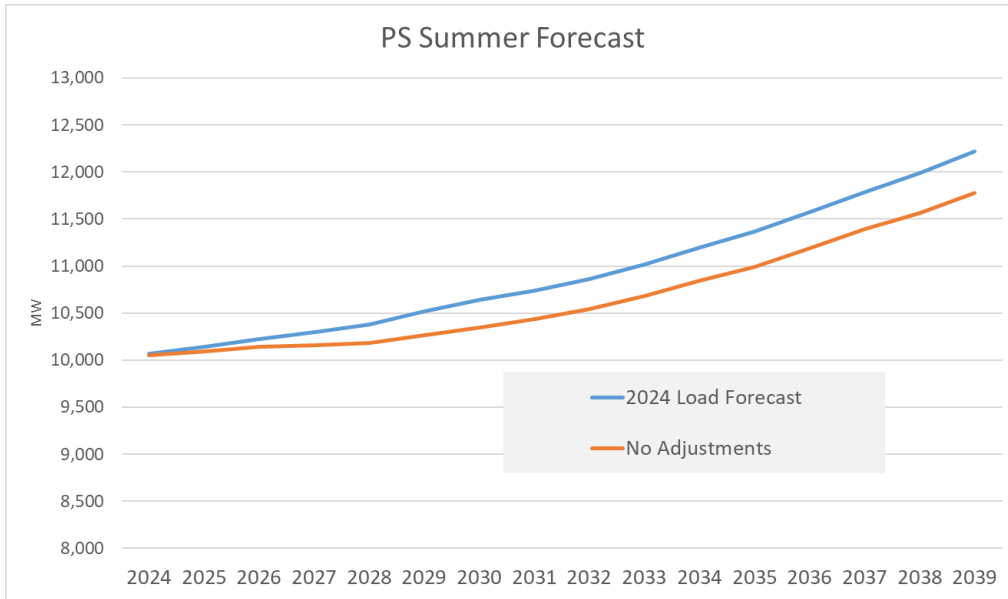




PS also submitted a request for port electrification at their Newark, Elizabeth, and Bayonne ports. The Inflation Reduction Act provides money to electrify port equipment and docked ships. This load is forecasted to grow from 2027 to 2030 and then be constant.

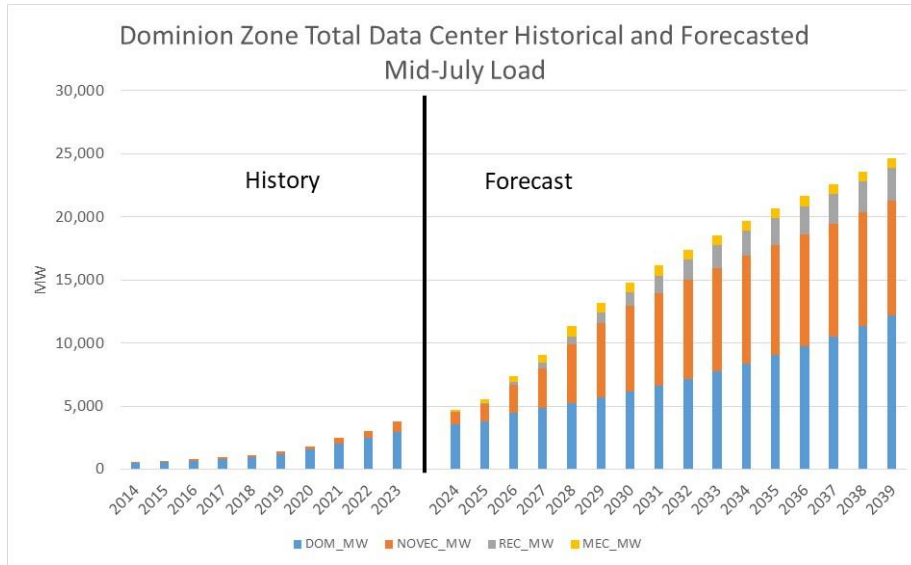


Below shows the PS summer forecast without the adjustments and with the adjustments. The final adjustment is shown in the bar chart. PJM has been and will continue to be in contact with PS to follow this development.



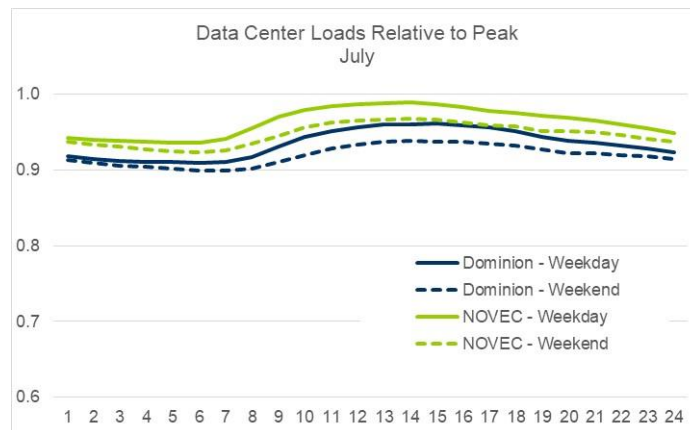
### Dominion – Data Centers

Dominion requested that PJM consider a forecast adjustment to account for the growth of data centers in Virginia. This adjustment has been in place in some form since the 2014 Load Forecast Report. Dominion and Northern Virginia Electric Cooperative (NOVEC) provide PJM with historical hourly information as well as forecasted peak information for the next fifteen years. Dominion provided forecasted data center load for non-NOVEC cooperatives Mecklenburg (MEC) and Rappahannock (REC).



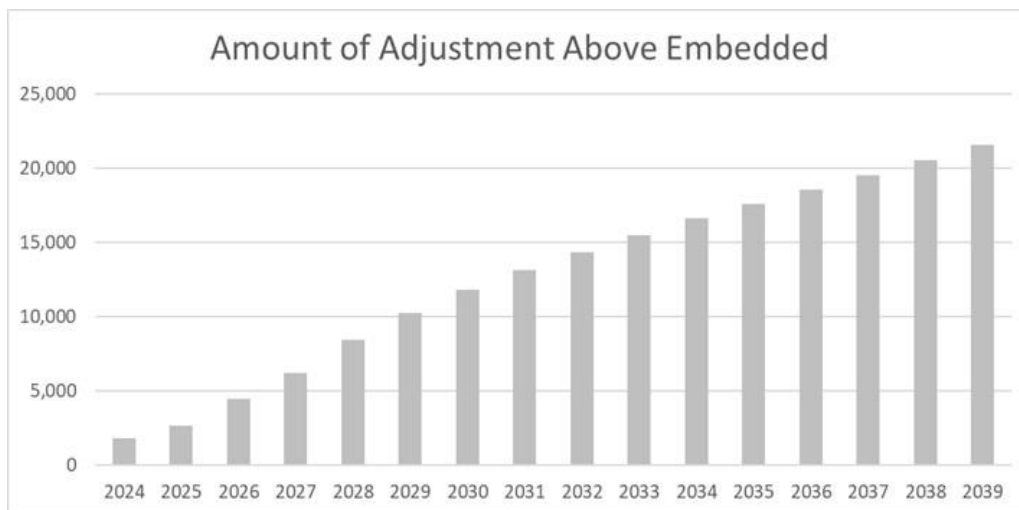
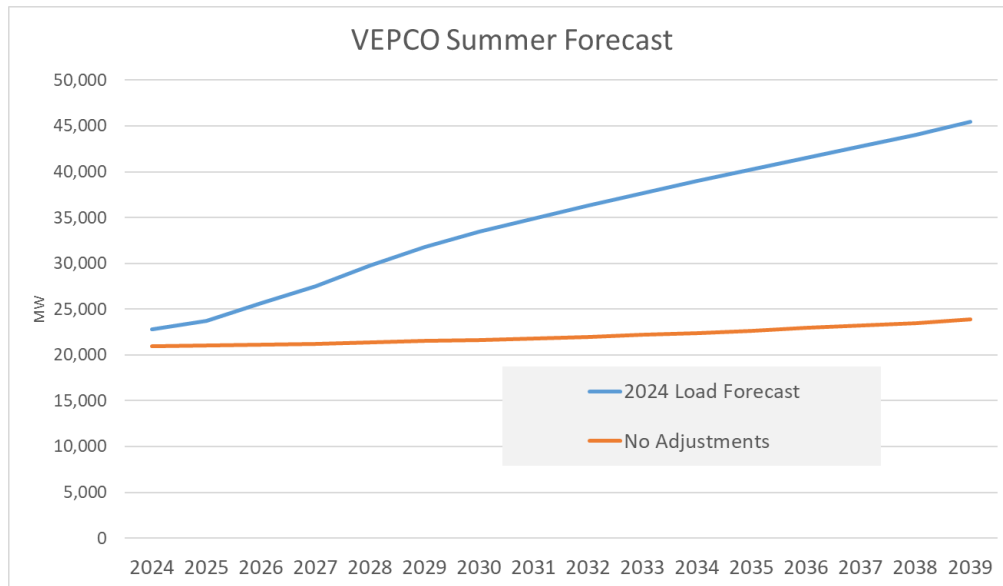
With the data provided, steps are taken to isolate the impact on the final forecast to mitigate double-counting concerns. Facility data is first removed from the historical data. This is done in both the historical hourly data used to feed the final load forecast model as well as the Commercial sector data used to help inform our understanding on usage trends.

Given that we have hourly historical data center data and the PJM forecast model is hourly, forecasted hourly loads are derived. For each of Dominion and NOVEC, by month and weekday/weekend, historical hourly data center loads are calculated as a share of the provided monthly peaks. This provides us with a weekday and weekend shape that can be applied to the forecasted monthly peaks.



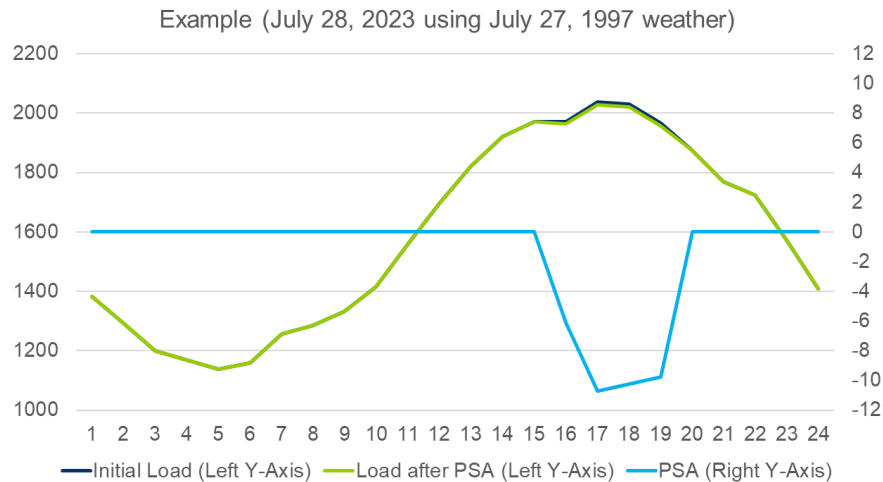
The final forecast needs to be re-constituted with the expected data center amount as the forecasted hourly loads coming from the model exclude data centers. Monthly peak amounts are combined with the calculated hourly shapes and these are added to the modeled forecast.

Below shows what the Dominion summer forecast would be without the adjustment and with the adjustment. The final adjustment for the Dominion zone is shown in the bar chart and shows the amount above what is embedded.



### EKPC – Peak Shaving Adjustment

EKPC requested a peak shaving adjustment that began with the 2023 Delivery Year. EKPC provides PJM with weather triggers as well as program response matrixes for their three programs (smart thermostats, air conditioning switches, and water heater switches). In the forecast simulation process, on days that exceed the trigger, the programs are enacted. The chart below shows an example of program implementation in the forecast. On this day in the forecast, the program is triggered and reduces load in HE16 through HE19 resulting in a peak reduction of 10MW.



After summer 2023, PJM evaluated actual performance against expected performance and used this performance rating<sup>6</sup> in the 2024 Load Forecast.

## NRBTMG to DR

PJM was notified of existing Non-Retail Behind-the-Meter Generation (NRBTMG) transitioning to participate as Demand Response starting in 2024. For the 2024 Load Forecast, these zones are adjusted upward to facilitate these resources' participation in RPM for a total of 21.2 MW.

- AEP: 8.7 MW
- ATSI: 1.6 MW
- DAYTON: 1.5 MW
- PPL: 2.9 MW
- PENLC: 0.5 MW
- DUKE: 6 MW

## State Policy

The State Of New Jersey's [Executive Order No. 316](#) is an executive order signed into law by Governor Phil Murphy on February 15th, 2023. The portion of the order that impacts PJM's long term load forecast is the goal that by December 31, 2030, 400,000 additional homes & 20,000 additional commercial spaces will be electrified. PJM incorporated this goal into our load forecast by modifying our end-use inputs for each zone in the state of New Jersey (AE, JCPL, PS, & RECO); specifically electric heating & electric water heating. We assumed that electrification of space heating means transitioning to electric heat pumps.

For both residential & commercial sectors, we added additional heat pumps & electric water heaters to our end-use forecast each year beginning in 2024. The total number of buildings with electric heating increases at a rate that

<sup>6</sup> <https://www.pjm.com/-/media/documents/manuals/m19.ashx> Attachment D

allows the 400,000/20,000 additional goal to be reached by 2030. This increased saturation of electric heating & water heating drives up the heating load for zones located in the state of New Jersey. This is primarily reflected in the winter peak forecast for these zones as there is not a large amount of heating load during the summer. The impacts of this goal on winter peak loads are easily noticeable when looking at the zonal waterfall charts comparing the 2023/2024 load forecasts for future delivery years. These charts are available on the Load Forecast Development Process page of PJM’s website.

## Additional Model Detail

### Calendar Variables

The forecast model includes a number of variables to capture calendar effects, represented primarily as either binary variables or fuzzy binary variables. Binary variables take a value of 1 or 0, whereas fuzzy binary variables have values ranging from 0 to 1. There is also a graduated variable to take into account the effect of the week leading up to Christmas and the week after the New Year.

Day of Week (=1 when that day, 0 otherwise)

Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
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Month (=1 when that month, 0 otherwise) and DST variables:

Jan	Feb	Mar	MarDST	Apr	May	Jun
Jul	Aug	Sep	Oct	Nov	NovDST	

Holiday variables are coded such that they have values for more than one day, and for some holidays, these values can differ year to year depending on the day of the week the holiday is observed. These variables are included because generally these days would be expected to have lower than normal loads.

MLK	PresDay	MemDay	LaborDay
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MLK (Martin Luther King Day), PresDay (Presidents’ Day), MemDay (Memorial Day), and LaborDay (Labor Day)

	Value
Day before Holiday	0.2
On Holiday	1
All other days	0

GoodFri	Thanks
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GoodFri (Good Friday) and Thanks (Thanksgiving Day)

	Value
On Holiday	1

All other days	0
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**July4th**

*July4th* (Independence Day)

	Value by Day of Week						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
July 2	0.10	0.00	0.00	0.15	0.15	0.10	0.15
July 3	0.70	0.25	0.15	0.20	0.80	0.20	0.20
July 4	1.00	1.00	0.80	1.00	1.00	0.40	0.30
July 5	0.80	0.15	0.15	0.25	0.70	0.30	0.15
July 6	0.00	0.00	0.00	0.00	0.10	0.20	0.00
All other days	0.00	0.00	0.00	0.00	0.00	0.00	0.00

**FriAThanks**

*FriAThanks* (After Thanksgiving Day)

	Value
On Holiday	1
Day After	0.2
All other days	0

**WkBeforeXMas**   **WkAfterNewYear**

*WkBeforeXMas*(If day is weekday before Christmas Day)   *WkAfterNewYear*(If day is weekday after New Year)

	<b>Value if Weekday</b>
December 18	0.14
December 19	0.29
December 20	0.43
December 21	0.57
December 22	0.71
December 23	0.86
December 24	1
All other days	0

	<b>Value</b>
January 1	1.14
January 2	1.00
January 3	0.86
January 4	0.71
January 5	0.57
January 6	0.43
January 7	0.29
January 8	0.14
All other days	0

**XMasEve**

*XmasEve* (Christmas Eve)

	<b>Value by Day of Week</b>						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
December 24	1.00	1.00	0.80	0.67	1.00	0.50	0.33
All other days	0.00	0.00	0.00	0.00	0.00	0.00	0.00

**XMasDay**

*XMasDay* (Christmas Day)

	<b>Value by Day of Week</b>						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
December 25	1.00	1.00	1.00	1.00	1.00	0.50	0.50
All other days	0.00	0.00	0.00	0.00	0.00	0.00	0.00



**NYEve**

NYEve (New Year's Eve)

	Value by Day of Week						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
December 31	0.8	0.8	0.8	0.8	1.0	0.4	0.4
All other days	0.0	0.0	0.0	0.0	0.0	0.0	0.0

**NYDay**

NYDay (New Year's Day)

	Value by Day of Week						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
January 1	1.0	1.0	1.0	1.0	1.0	0.5	0.4
All other days	0.0	0.0	0.0	0.0	0.0	0.0	0.0

**WkDayBeforeHol** | **WkDayAfterHol**

WkDayBeforeHol (weekday before Holiday)

	Value (if Weekday)
Day Before Holiday	1.00
All other days	0.00

WkDayAfterHol(weekday after Holiday)

	Value (if Weekday)
Day After Holiday	1.00
All other days	0.00

Monthly Walk variables are graduated variables that start at 1 on the first day of the month and increase by 1 each day until the last day of the month to capture any potential inter-month trends.

JanWalk	FebWalk	MarWalk	AprWalk	MayWalk	JunWalk
JulWalk	AugWalk	SepWalk	OctWalk	NovWalk	DecWalk

## Zonal End-Use Variable Calibration

The Energy Information Administration's (EIA) 2023 Annual Energy Outlook Reference Case is the starting point for data on residential end-uses. Residential end-uses fall into categories, which are then grouped according to weather and non-weather sensitive use types (i.e. Heating, Cooling, and Other). These categories are expressed as saturation rates (% of customers), efficiency metrics (use per year or efficiency term like Seasonal Energy Efficiency Ratio), and intensities (kWh per customer per year). Categories and groupings are as follows:

- Heating
  - Electric furnace and resistant room space heaters
  - Heat pump space heating
  - Ground-source heat pump space heating
  - Secondary heating
  - Furnace fans
- Cooling
  - Central air conditioning
  - Heat pump space cooling
  - Ground-source heat pump space cooling
  - Room air conditioners
- Other
  - Electric water heating
  - Electric cooking
  - Refrigerator
  - Second refrigerator
  - Freezer
  - Dishwasher
  - Electric clothes washer
  - Electric clothes dryer
  - TV sets
  - Lighting
  - Miscellaneous electric appliances

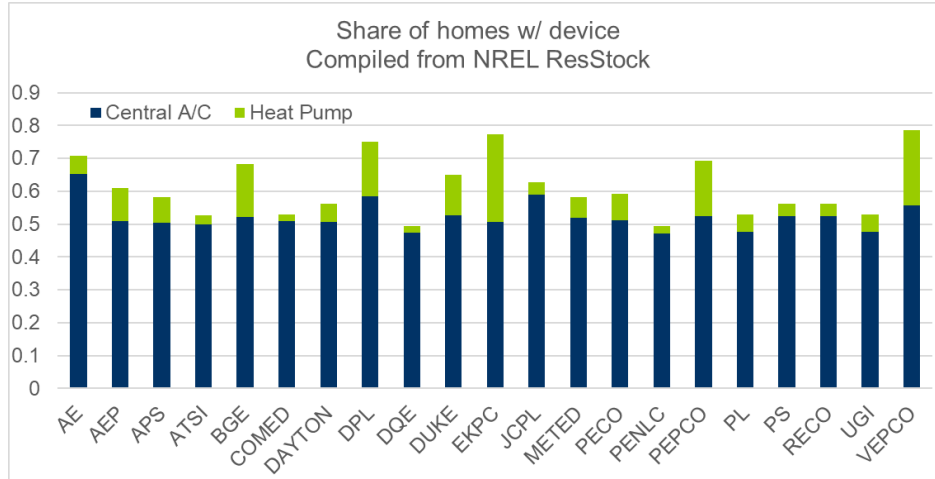
PJM receives this data at the Census division level through membership in Itron's Energy Forecasting Group. PJM then supplements this with two pieces of information:

- Zonal saturation and intensity data from NREL ResStock<sup>7</sup>
- Zonal saturation estimates from:
  - American Electric Power – all appliance categories through 2021
  - Allegheny Power – all appliance categories through 2016
  - American Transmission Systems, Inc. – all appliance categories through 2016
  - Commonwealth Edison – all appliance categories for 2019
  - Duke Energy Ohio and Kentucky – all appliance categories through 2014
  - East Kentucky Power Cooperative – Heat Pumps for Heating and Cooling, Electric Furnaces, Secondary Heating (Room Heating), Central A/C, Room Air Conditioners, and Water Heaters through 2013
  - Jersey Central Power & Light – all appliance categories through 2016
  - Metropolitan Edison – all appliance categories through 2016
  - Pennsylvania Electric – all appliance categories through 2016
  - Dominion Virginia Power – Heat Pumps for Cooling, Central A/C and Room Air Conditioners through 2014

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<sup>7</sup> <https://resstock.nrel.gov/>

Data from NREL ResStock is used to calibrate zones for 2018 to help provide granularity across PJM. Zones are mapped to counties, and then PJM uses the ResStock database to provide customized data at the zonal level on appliance saturations, appliance intensities, and average home sizes<sup>8</sup>. The below chart displays some of the information gleaned from this exercise on central cooling.

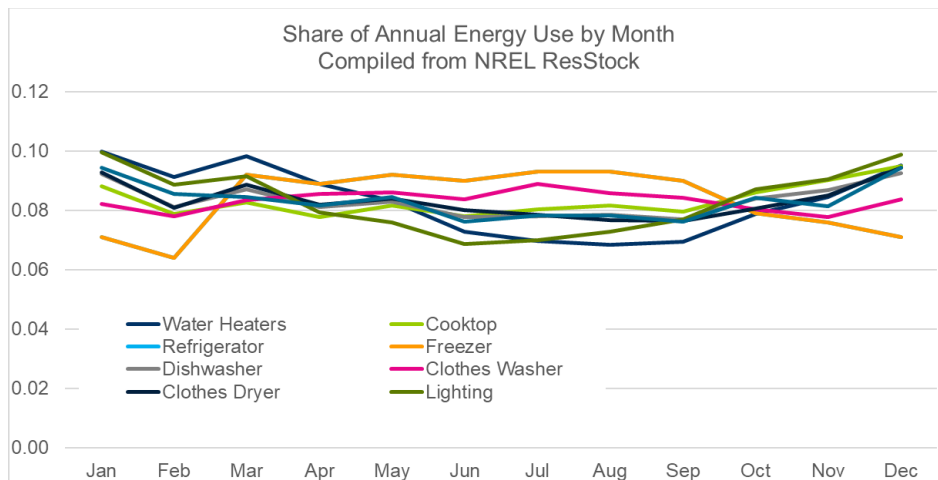


Resulting data is then aligned with zonal-supplied historical appliance saturation rates. Zones are subsequently assigned to Census Divisions for driving the forecasts. This process allows the forecast to be influenced by the historical relative mix of appliances. The below table shows the mapping of Zones to Census Divisions.

<sup>8</sup> In the case of RECO and UGI, this exercise yielded an insufficient sample size according to guidelines laid out by NREL for using their data. PS and PL were used, respectively, in this case.

<b>Zone</b>	<b>Census Division</b>
AE	Middle Atlantic
AEP	East North Central
APS	South Atlantic
ATSI	East North Central
BGE	South Atlantic
COMED	East North Central
DAYTON	East North Central
DPL	South Atlantic
DQE	Middle Atlantic
DUKE	East North Central
EKPC	East South Central
JCPL	Middle Atlantic
METED	Middle Atlantic
PECO	Middle Atlantic
PENLC	Middle Atlantic
PEPCO	Middle Atlantic
PL	Middle Atlantic
PS	Middle Atlantic
RECO	Middle Atlantic
UGI	Middle Atlantic
VEPCO	South Atlantic

Finally, monthly non-weather sensitive shapes are calculated from the NREL ResStock data as well. These are used to shape the end-use intensity variables used in the monthly Residential Average Use model. These can be seen below.



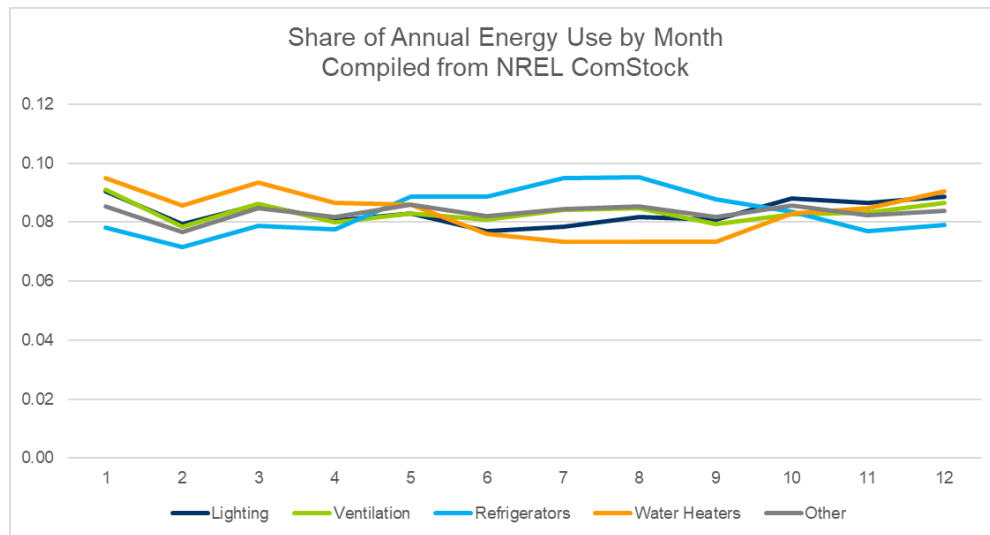
### Commercial

The EIA’s 2023 Annual Energy Outlook Reference Case is the starting point for data on commercial end-uses. Commercial end-uses fall into categories, which are then grouped according to weather and non-weather sensitive

use types (i.e., Heating, Cooling, and Other). These categories are expressed as intensities (kWh per square foot per year). These categories and groupings are as follows:

- Heating
- Cooling
- Other
  - Ventilation
  - Water Heating
  - Cooking
  - Refrigeration
  - Lighting
  - Office Equipment
  - Miscellaneous

PJM receives this data at the Census Division level through membership in Itron’s Energy Forecasting Group, and zones are assigned to Census Divisions using the same mapping as used for Residential end-uses. Like with Residential, NREL has also developed ComStock<sup>9</sup>. Monthly non-weather sensitive shapes are calculated from the NREL ComStock data. These are used to shape the end-use intensity variables used in the monthly Commercial Use model. These can be seen below.



## Economics Zonal Geographic Assignment

Economic variables come from Moody’s Analytics and geographical areas are assigned to zones per the table below.

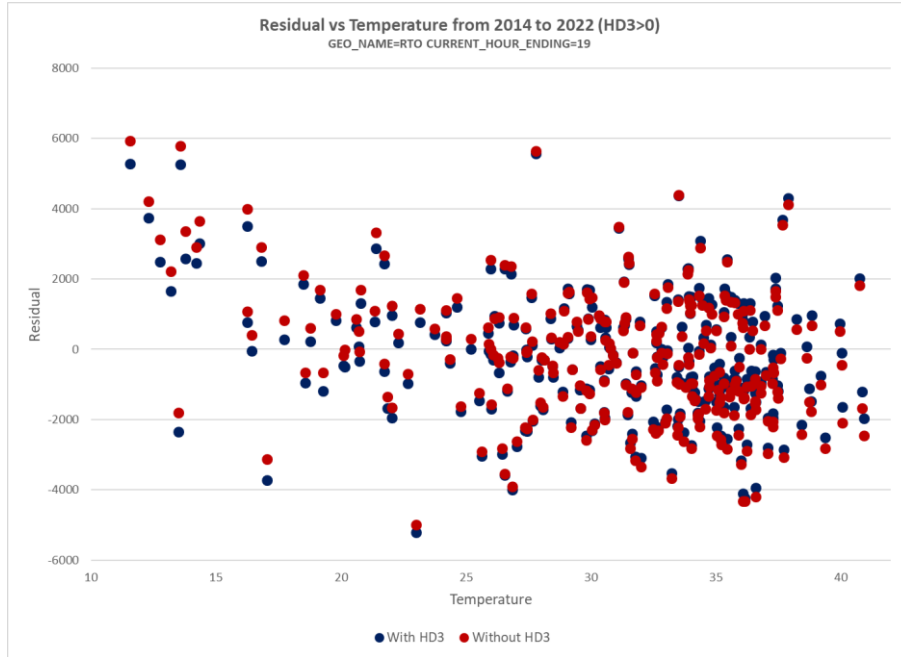
<sup>9</sup> <https://comstock.nrel.gov/>

Zone	Metro Area Name(s) or State
AE	Atlantic City-Hammonton NJ, Ocean City NJ, Vineland-Bridgeton NJ
AEP	Elkhart-Goshen IN, Fort Wayne IN, Muncie IN, South Bend-Mishawaka IN-MI, Niles-Benton Harbor MI, Canton-Massillon OH, Columbus OH, Lima OH, Kingsport-Bristol TN, Blacksburg-Christiansburg-Radford, VA, Lynchburg VA, Roanoke VA, Beckley, WV, Charleston WV, Huntington-Ashland WV-KY-OH, Weirton-Steubenville WV-OH
APS	Cumberland MD-WV, Hagerstown-Martinsburg MD-WV, Chambersburg-Waynesboro PA, State College PA, Winchester VA-WV, Morgantown WV, Parkersburg-Vienna WV
ATSI	Akron OH, Cleveland-Elyria OH, Mansfield OH, Springfield OH, Toledo OH, Youngstown-Warren-Boardman OH-PA, Pittsburgh PA
BGE	Baltimore-Columbia-Towson MD
COMED	Chicago-Naperville-Arlington Heights IL, Elgin IL, Kankakee IL, Lake County-Kenosha County IL-WI, Rockford IL
DAY	Dayton OH
DEOK	Cincinnati OH-KY-IN
DLCO	Pittsburgh PA
DOM	Virginia
DPL	Dover DE, Wilmington DE-MD-NJ, Salisbury MD-DE
EKPC	Cincinnati OH-KY-IN, Louisville/Jefferson County KY-IN, Elizabethtown-Fort Knox KY, Bowling Green KY, Lexington-Fayette KY, Huntington-Ashland WV-KY-OH
JCPL	Camden NJ, Newark NJ-PA, Trenton NJ
METED	Allentown-Bethlehem-Easton PA-NJ, East Stroudsburg PA, Gettysburg PA, Lebanon PA, Reading PA, York-Hanover PA,
PECO	Montgomery County-Bucks County-Chester County PA, Philadelphia PA
PENLC	Altoona PA, Erie PA, Johnstown PA
PEPCO	Washington D.C., California-Lexington Park MD
PL	Allentown-Bethlehem-Easton PA, Bloomsburg-Berwick PA, East Stroudsburg PA, Harrisburg-Carlisle PA, Lancaster PA, Scranton-Wilkes-Barre-Hazleton PA, Williamsport PA
PS	Camden NJ, Newark NJ-PA, Trenton NJ
RECO	Newark NJ-PA
UGI	Scranton-Wilkes-Barre-Hazleton PA

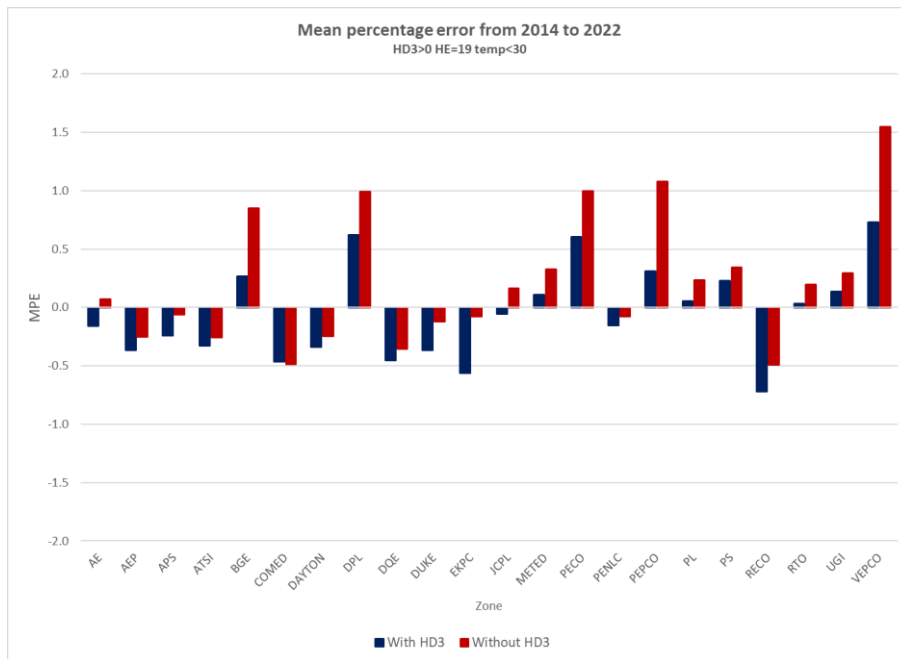
### Addition of HD3 Variable

A new variable HD3 has been added to our model to reflect the relationship of load to cold weather conditions. As stated earlier in the document, HD3 is an additional spline in the heating season (15 degrees off the hourly base point). This additional variable provides symmetry with the cooling season (TD1 through TD3 variables) and helps to address potential for underfit at colder temperatures such as during Winter Storm Elliott.

The following charts help explain the rationale for HD3's inclusion. This first chart is of RTO residuals for HE19 and shows that inclusion of this variable helps to reduce some under-fit at very low temperatures.



This next chart demonstrates zonal performance, MPE (mean percentage error) values for model with HD3 showed improvement in several noticeable zones that had previously shown more tendency to under-fit when the temperature is below 30°F.



We conclude that the addition of the new cold weather variable has improved our model, and we will continue to investigate whether further modifications may be warranted.