Load Forecast Model Development

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Resource Adequacy Planning

Load Analysis Subcommittee
September 12, 2022

- After an RFP process, PJM engaged with Itron starting in late April to perform a model review and to make recommendations for potential model enhancements as we transition to an hourly model for the 2023 Load Forecast.
  - Early discussion and feedback session at Load Analysis Subcommittee (LAS) on June 10, 2022
  - Itron presented their review and recommendations, and solicited feedback at LAS on July 28, 2022
  - Itron delivered their final report to PJM consistent with their presentation from July 28, 2022

Itron’s Recommendations

1) Replace Annual/Quarterly End-Use Indices with Monthly/Daily Indices

2) Continue with Weather Simulation Approach

3) Replace Daily Models (Energy, Zone peak, and Coincident peak) with Hourly Load Models

4) Adjust Loads for Solar and New Technologies Through the Simulation Process

5) Capture Increasing Temperature Trends

Recommendation #1

1. Replace Annual/Quarterly End-Use Indices with Monthly/Daily Indices

Heating, cooling, and base-use load indices can be derived from monthly class SAE models. The SAE models are well documented, used by many utilities for long-term sales and energy forecasting, and are relatively robust in the sense that adding new data and dropping old data does not generally result in significant changes in the model parameters. Indices based on monthly (vs annual models) provide significantly more observations and as a result require fewer years of historical data; resulting in estimated model parameters that will be more representative of the current and forecast periods. Monthly models will also result in stronger heating and cooling coefficients because there is generally more weather variation in monthly data series than in an annual data series.

- Shift away from using annual data to benchmark heating, cooling, and non-weather sensitive trends and instead use monthly data
- Stronger models that better represent end-use trends and allow to use fewer historical years.

Recommendation #2

2. Continue with Weather Simulation Approach

Given the diversity of weather across PJM zones, it is nearly impossible to define a normal daily or hourly weather pattern for the entire system. The current method of developing load distributions from zonal weather simulations represents the best approach for estimating expected long-term demand. Twenty-years of historical weather data with 7 rotations within in each year provides a strong basis for simulating the distribution of load outcomes.

- Weather simulation offers ability to capture realistic diversity patterns across large geographic footprint
- Indicate that using 20 years and 7 rotations (2022 Forecast had 27 years and 13 rotations) should give a "strong basis" for the load distribution.

Recommendation #3

3. Replace Daily Models (Energy, Zone peak, and Coincident peak) with Hourly Load Models

The need to capture the impact of solar, EV, and other technologies that are reshaping demand requires an hourly modeling framework. Replacing the set of zonal daily models with the hourly model described in the report will meet this need. PJM should utilize the hourly rolling weather approach with two-part heating degree and cooling degree variables. PJM should interact these weather variables and other hourly model variables with heating, cooling, and base-use indices developed from the SAE models.

- Hourly models will provide more flexibility for incorporating future trends.

Recommendation #4

4. Adjust Loads for Solar and New Technologies Through the Simulation Process

To correctly account for solar, EVs and other load adjustments, the hourly projections for these technologies should be constructed to be consistent with the weather simulation process. Each load simulation can then be adjusted appropriately to reflect the impact of solar and other weather-sensitive technology adjustments for each simulation. The load impact of EVs and other non-weather sensitive technologies will also need to be adjusted within the simulation process, as the impact of EVs and other technologies on load depends on the net of solar simulation outcome. The adjusted hourly load simulations can then be post-process to derive zonal adjusted peak and energy and coincident peaks from the aggregation of the net zonal hourly load forecasts.

- Incorporate technologies into the simulation process at an hourly granularity.
- Better anticipation of technology impact on demand shapes and the resulting peaks.

Recommendation #5

5. Capture Increasing Temperature Trends

Long-term temperature trends should be evaluated for each of the planning zones with results used to adjust cooling and heating indices that are inputs in the hourly load models. We expect to see increasing temperatures across the PJM service area that will contribute to an increase in cooling requirements and a decrease in space heating loads. Zone-level temperature trends can be used to construct trended HDD and CDD that are in turn incorporated into the heating and cooling model indices.

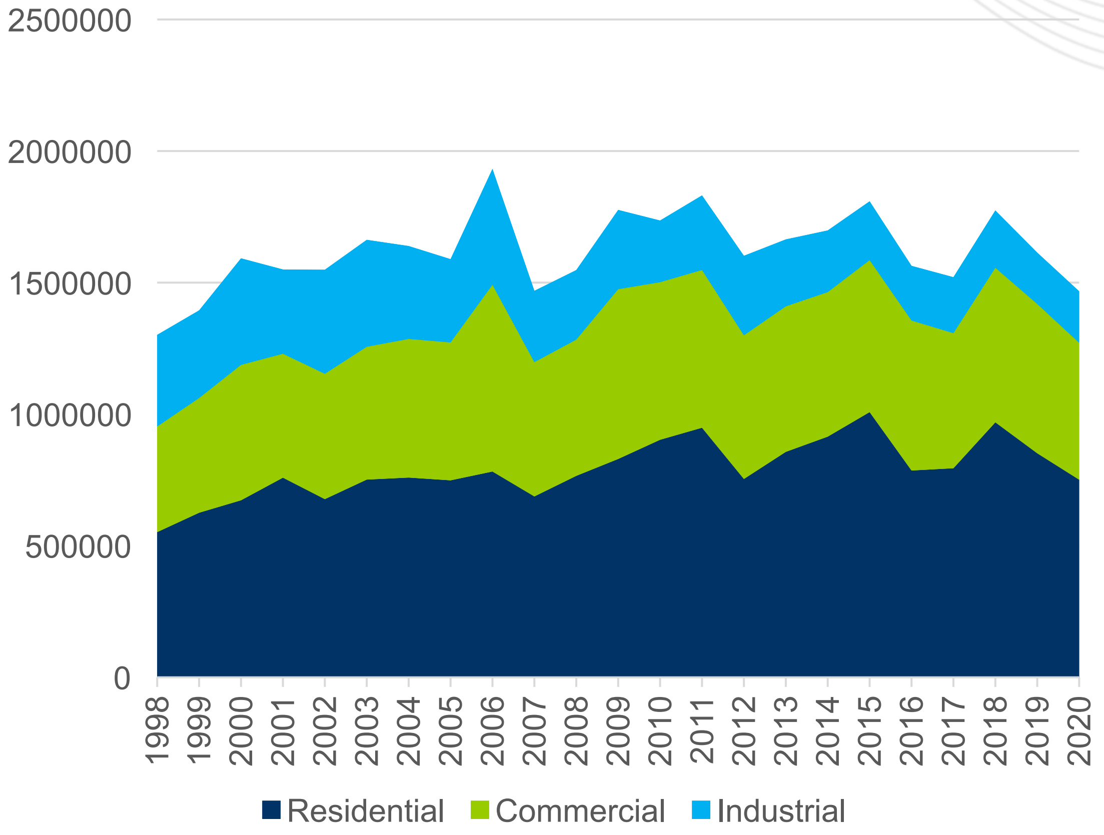
- Ongoing climate trends could have an impact on future space heating and cooling needs.
- Long-term forecasts should take these trends into consideration.

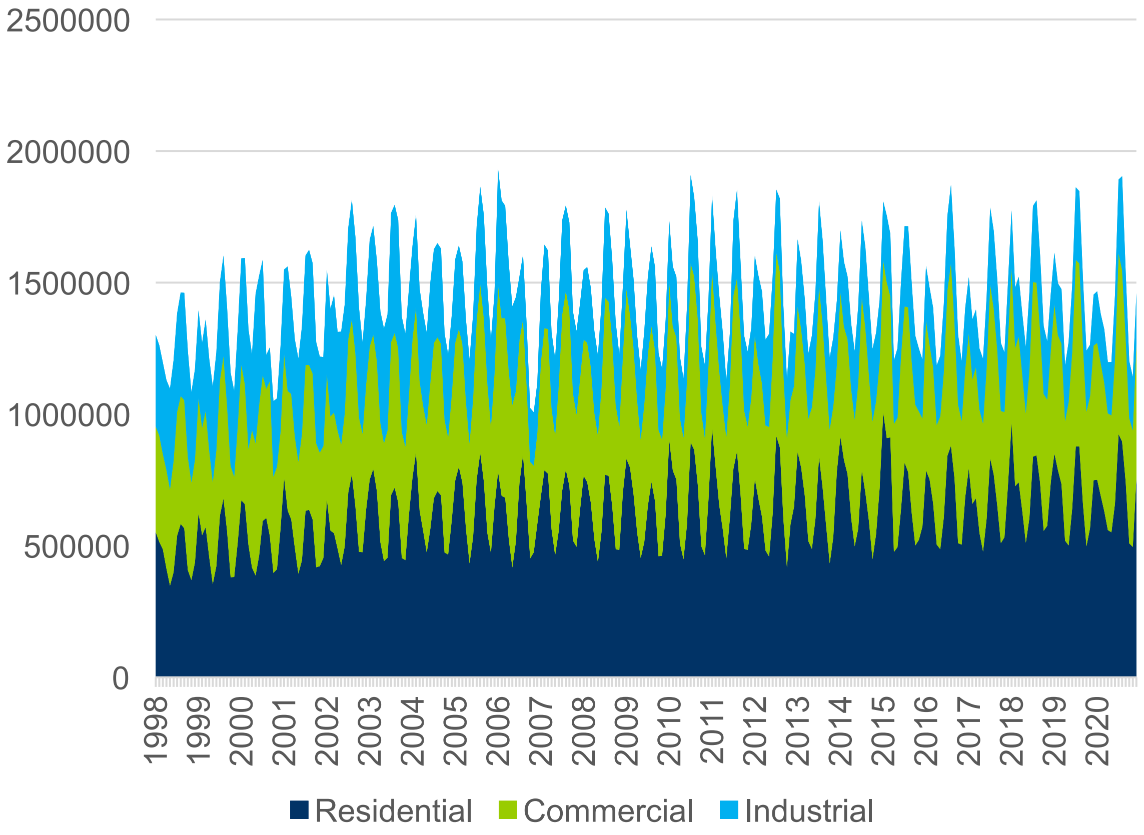
- PJM is in the process of evaluating Recommendations 1-4 for the 2023 Load Forecast, and will report on its progress through LAS.
  – Part of Recommendation #2 calls for shortening the weather history used in the simulation to 20 years. We plan on running a sensitivity to gauge the impact of this change prior to deciding on whether to incorporate.

- Incorporation of Recommendation #5 (climate trends) will require additional thought and education with stakeholders. Tentative plan to incorporate with 2024 Load Forecast following stakeholder engagement and review.

Implementing Recommendations

Sector Data – Annual to Monthly





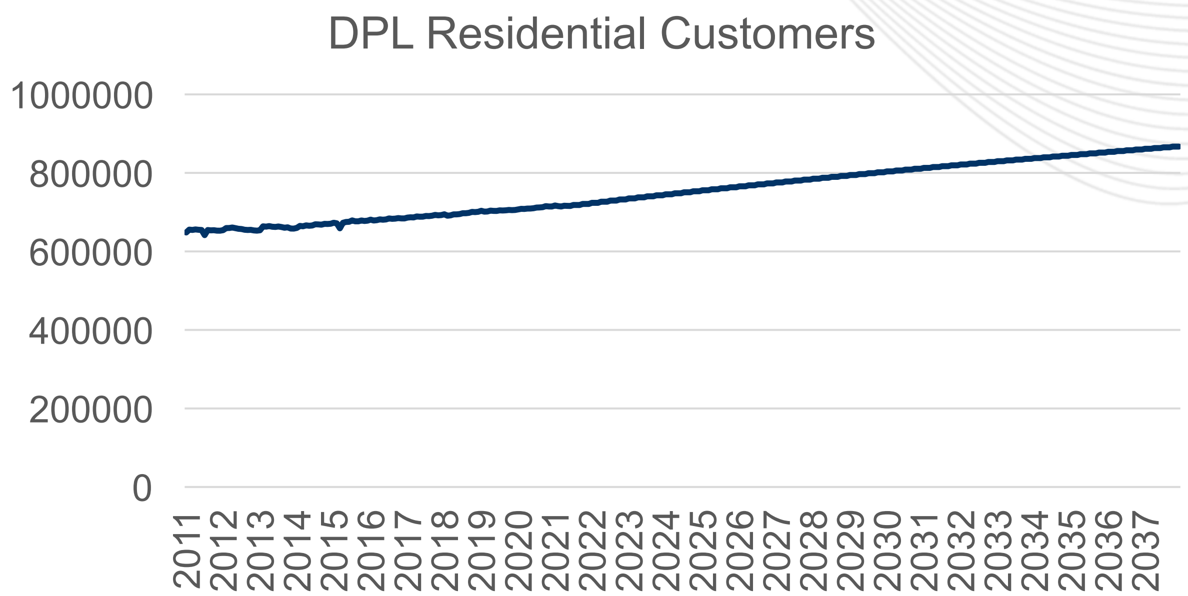
Overview of Sector Models

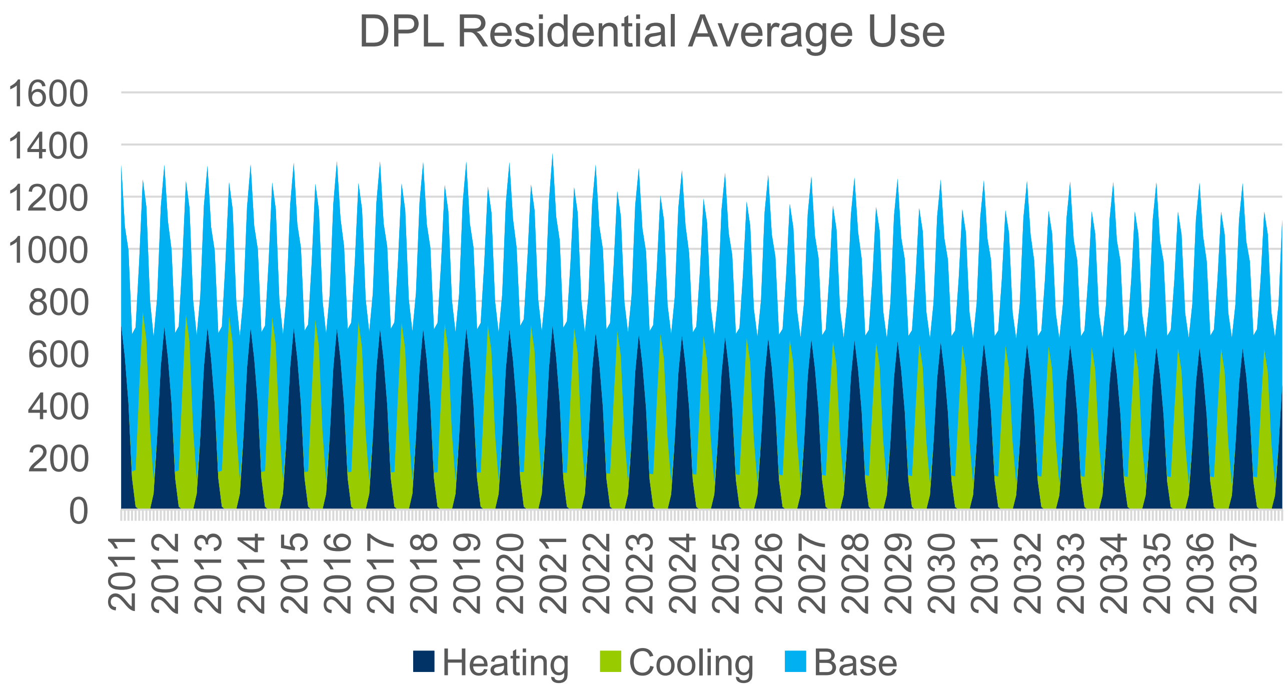
- Purpose of sector models is to derive trends for heating, cooling, and other use.

- Estimated on monthly observations from 2011 on
  - Models
    - Residential
      - Customer
      - Average Use per Customer
    - Commercial Total Use
    - Industrial Total Use
  - Drivers
    - End-use saturation/efficiency and intensity
    - Economics
      - Households, Real Income, Population, Employment, Real Output

- Residential Sector has two models
  - Customers
    - Driven by Households
  - Average Use per Customer
    - Driven by
      - Economics (Real Income per Household and Household Size)
      - End-Use Intensity (Appliance Saturation and Efficiency)
      - Weather (Heating Degree Days/Cooling Degree Days)

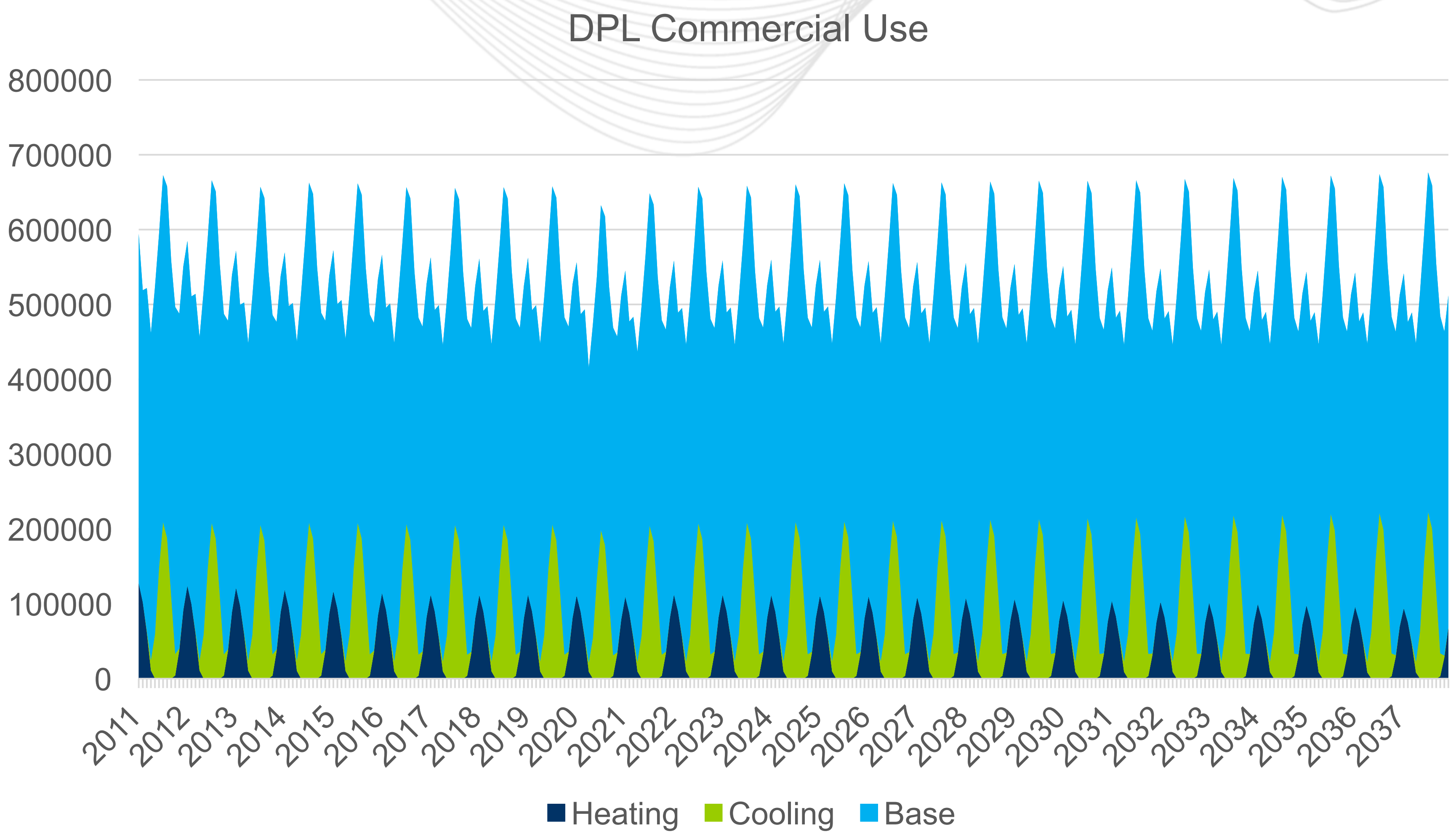
Residential Sector





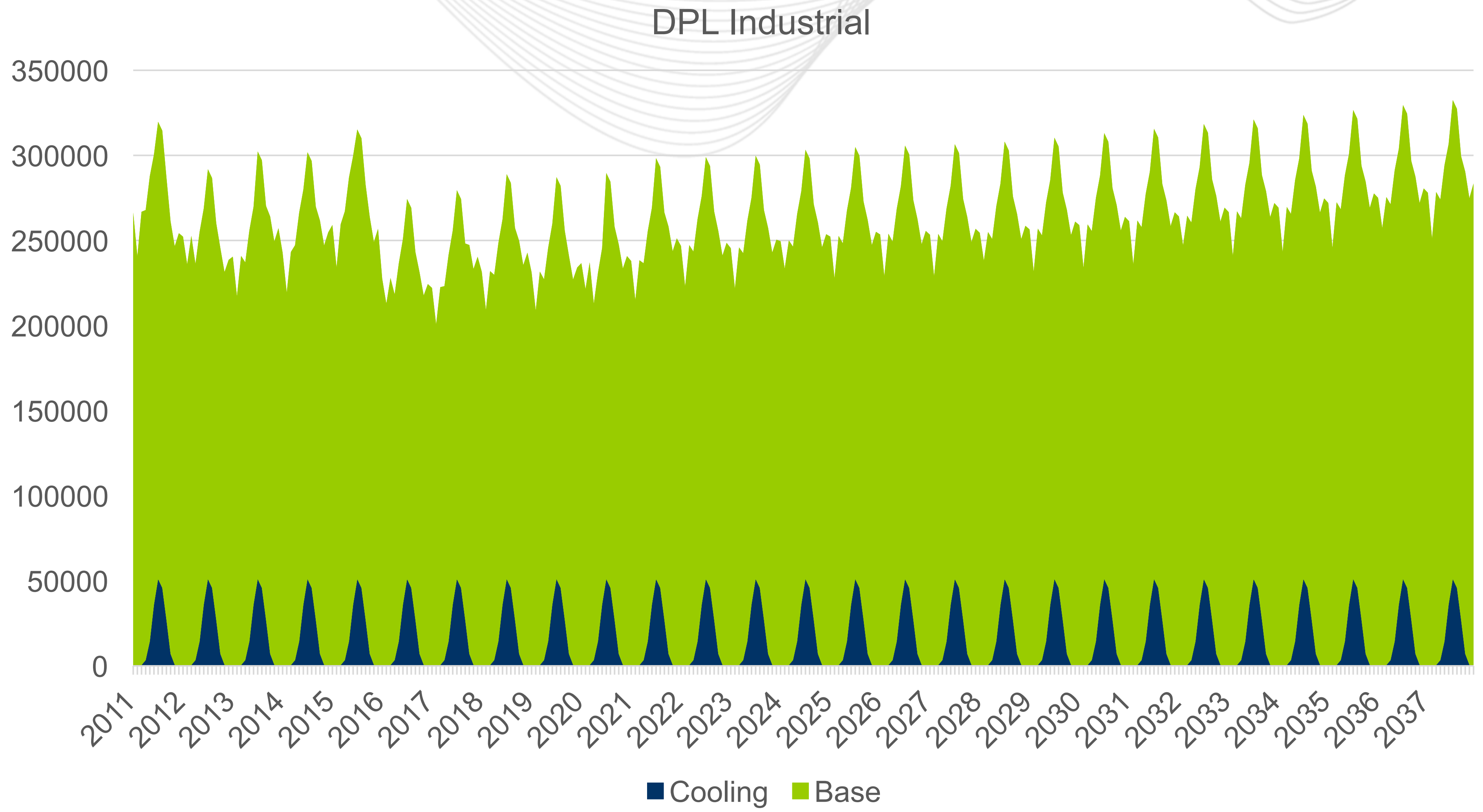
- Commercial Sector has one model
  - Driven by
    - Economics
      - Combination of three variables - Service Employment (30%), Real Service Output (30%), Working-Age Population (40%)
    - End-Use Intensity (Use per Sq Foot)
    - Weather (Heating Degree Days/Cooling Degree Days)

Commercial Sector



- Industrial Sector has one model
  - Driven by
    - Economics (Real Industrial Output)
    - Intensity (Energy per Real Output)
    - Weather (Cooling Degree Days)
  - No one size fits all
    - Control for historical outliers
    - Look at what works best
      - Combination of Economics/Intensity, just Economics, or no Economics or Intensity

Industrial


DPL Industrial
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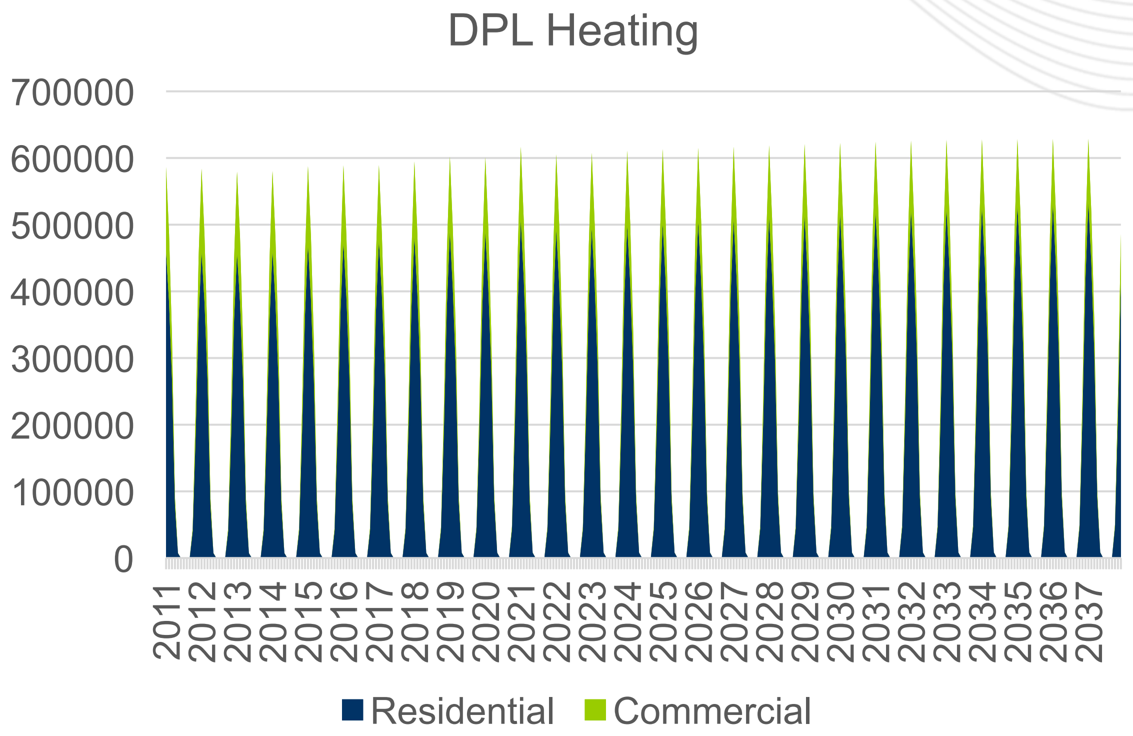
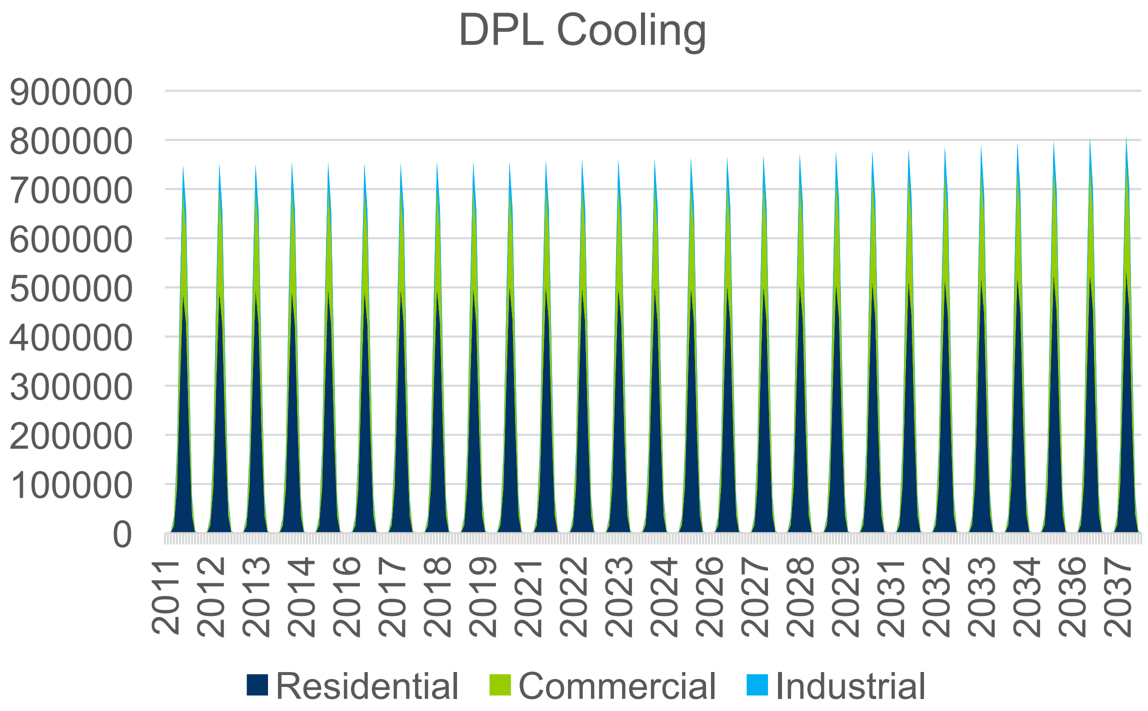
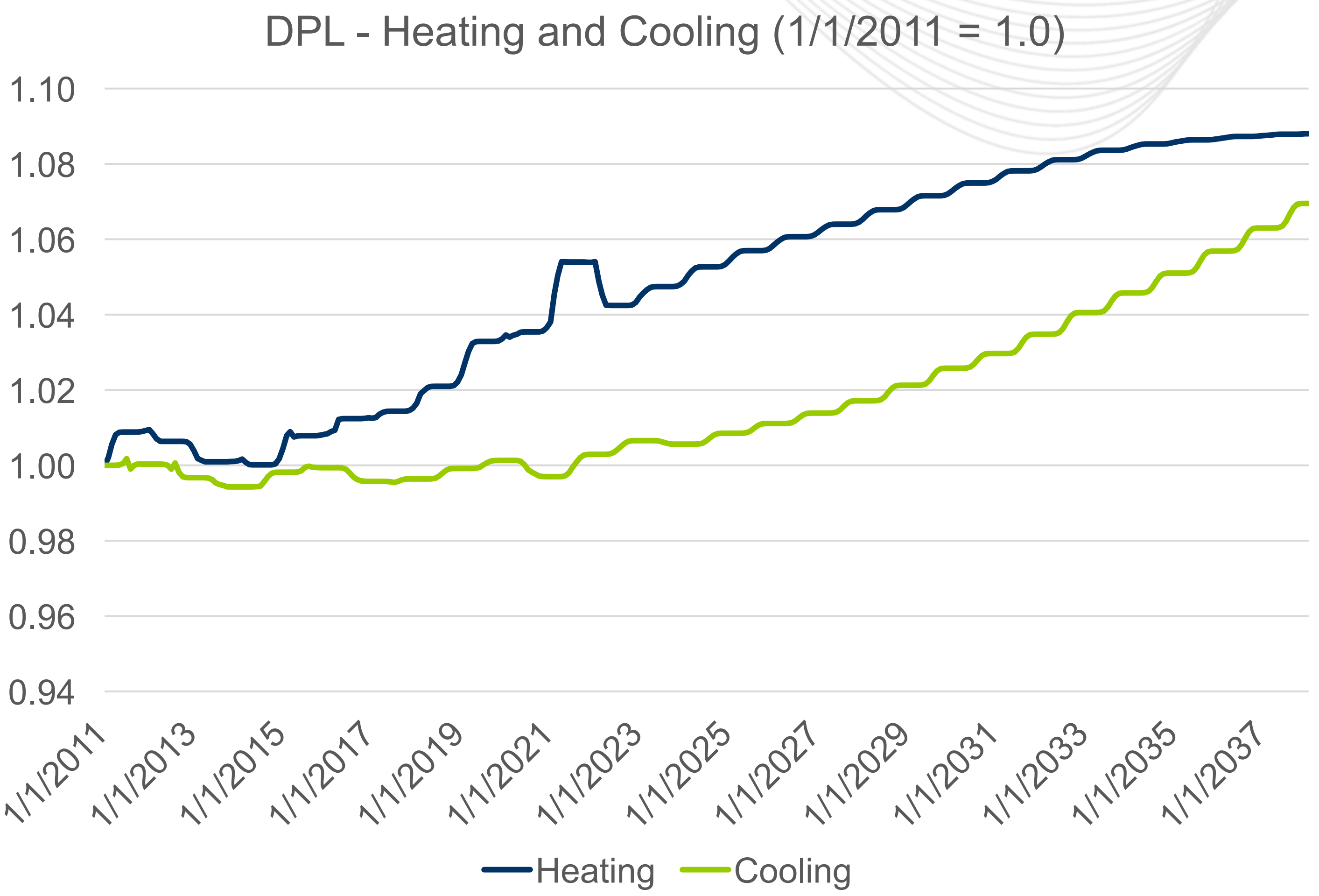
Cooling
Base

Aggregate Sectors to Total – Heating and Cooling



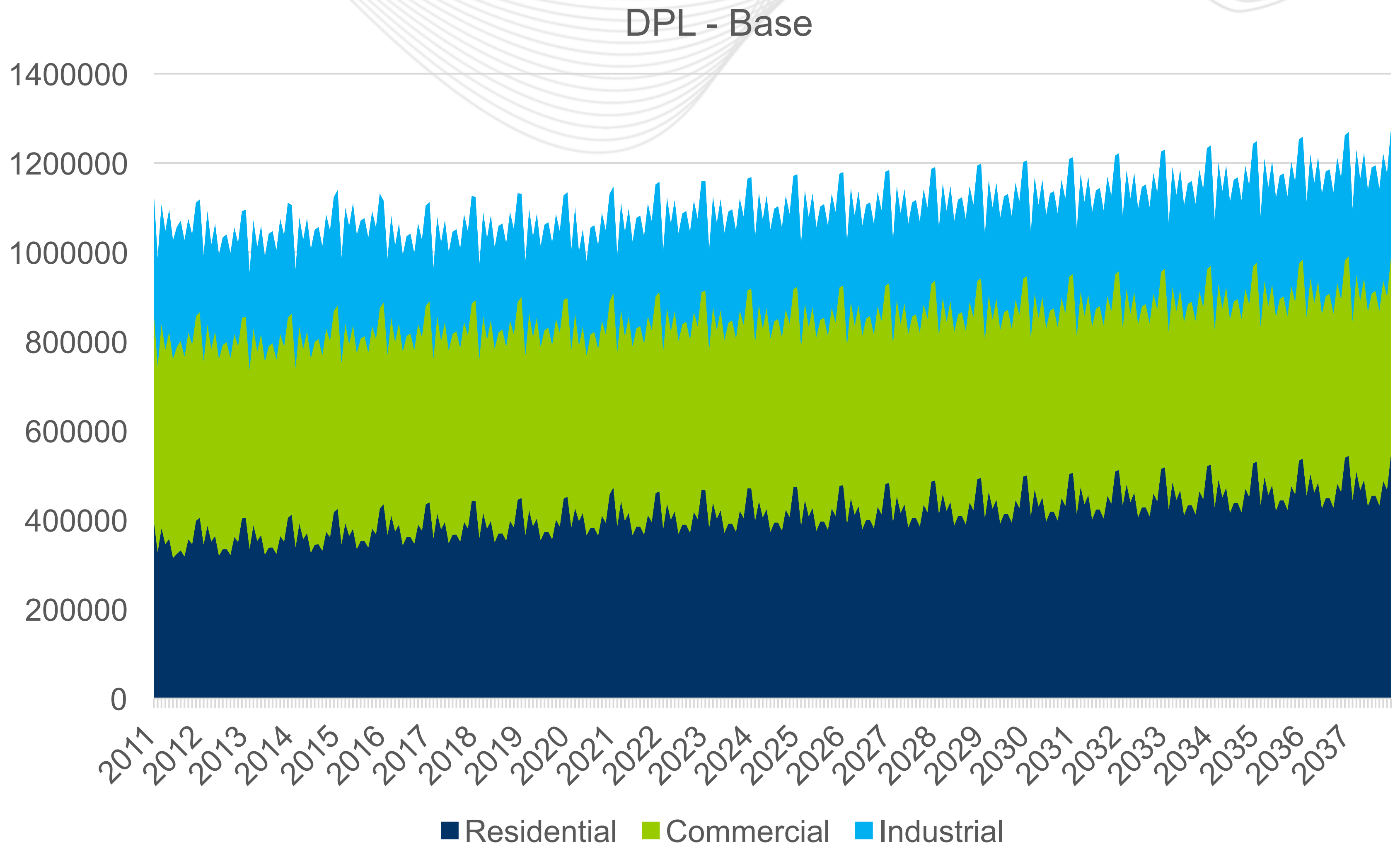


Daily Heating and Cooling Indexes

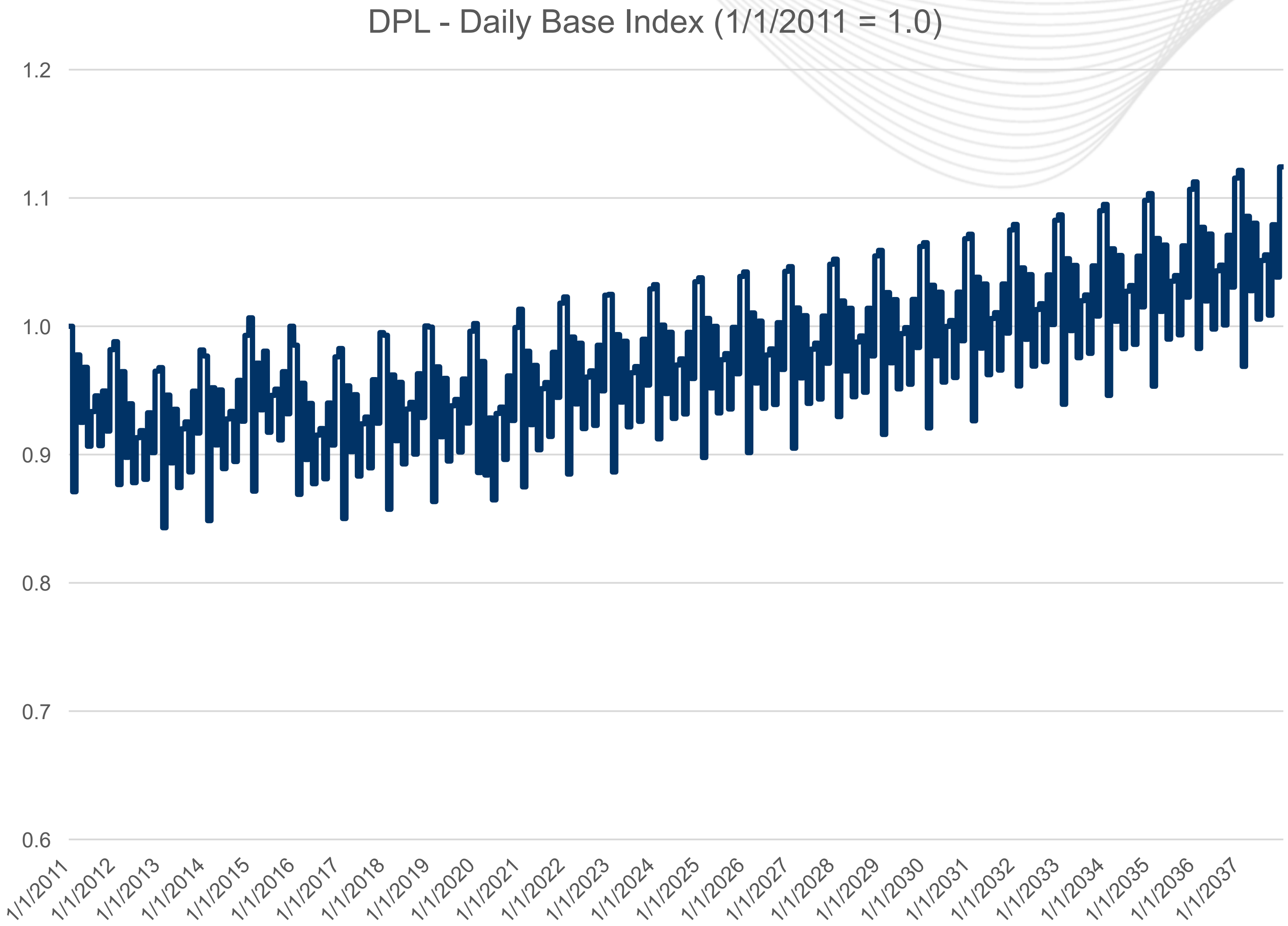


Heating and Cooling Indexes later get interacted with weather variables in the hourly model to determine weather sensitive load contributions.

Aggregate Sectors to Total - Base

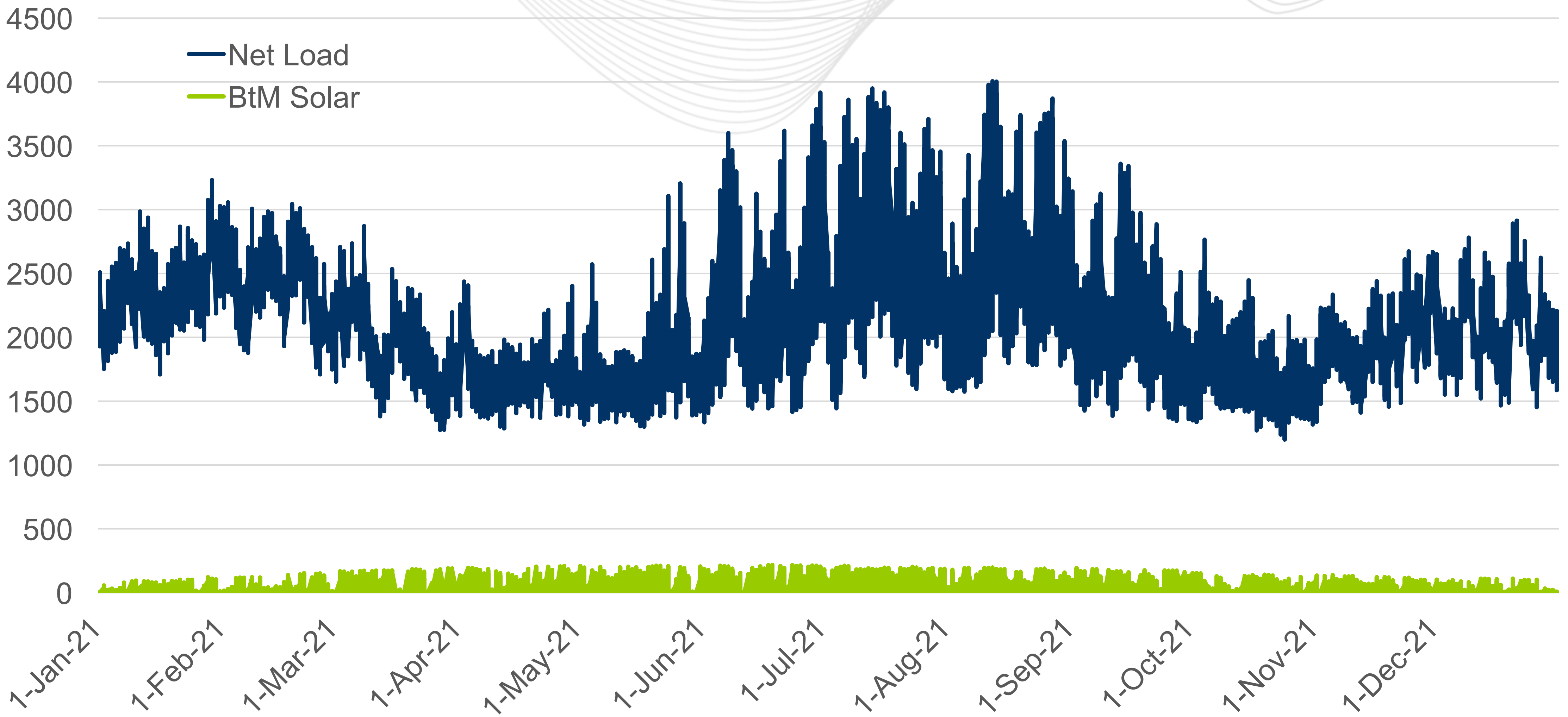


Daily Base Index

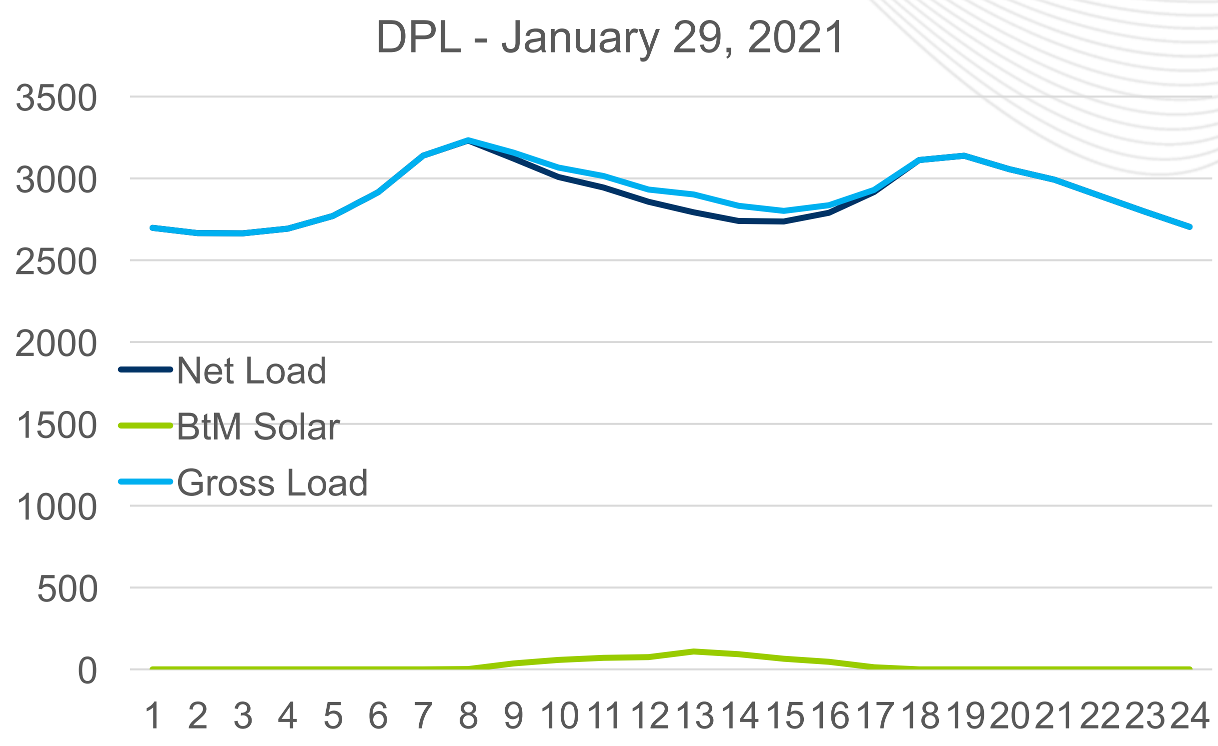


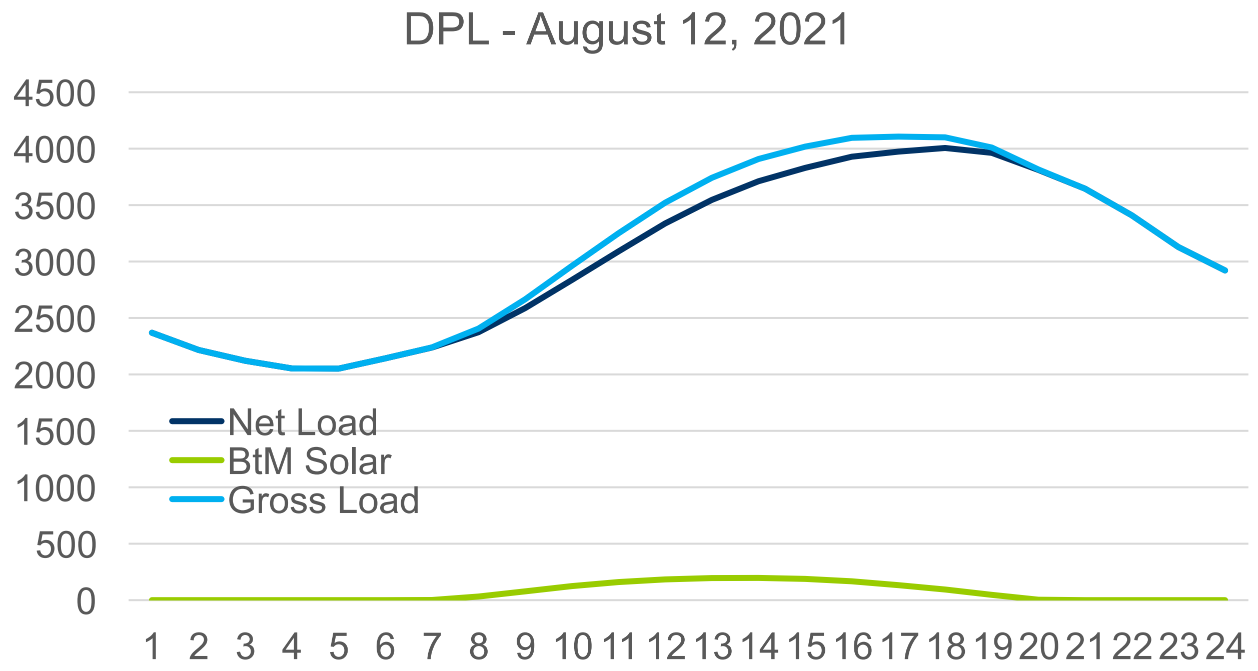
Base Index later gets interacted with calendar variables in the hourly model to determine non-weather sensitive load contributions.

Hourly – Net Load and BtM Solar



Hourly – Net Load, BtM Solar, and Gross Load





Building Hourly Models

- Gross load is the dependent variable for the hourly models
- One model for each hour
- Previously defined Heating, Cooling, and Other Indexes are leveraged and interacted with weather and calendar variables.

FIGURE 4-9: EXAMPLE OF ESTIMATED MODEL (HE18)

Variable	Coefficient	StdErr	T-Stat
DayTypes.Intercept_XOther	689.463	20.493	33.643
MonthVars.Jan	-5.379	10.614	-0.507
MonthVars.Feb	-29.739	8.883	-3.348
MonthVars.Mar	-77.148	8.422	-9.161
MonthVars.MarDST	-4.426	2.792	-1.585
MonthVars.Apr	-103.989	10.321	-10.075
MonthVars.May	-88.767	10.386	-8.547
MonthVars.Jun	-67.343	11.844	-5.686
MonthVars.Jul	-16.406	14.683	-1.117
MonthVars.Aug	-21.176	16.810	-1.260
MonthVars.Sep	-53.893	15.671	-3.439
MonthVars.Oct	-81.147	12.993	-6.245
MonthVars.Nov	-32.847	12.326	-2.665
MonthVars.NovDST	-16.495	3.604	-4.577
MonthVars.JanWalk	-1.844	1.361	-1.355
MonthVars.FebWalk	-3.773	1.100	-3.429
MonthVars.MarWalk	-0.718	1.583	-0.454
MonthVars.AprWalk	0.915	1.050	0.872
MonthVars.MayWalk	4.216	1.070	3.940
MonthVars.JunWalk	5.269	1.122	4.695
MonthVars.JulWalk	-0.608	1.049	-0.580
MonthVars.AugWalk	-2.870	0.855	-3.357
MonthVars.SepWalk	-4.592	1.119	-4.104
MonthVars.OctWalk	0.475	1.103	0.431
MonthVars.NovWalk	3.100	1.454	2.132
MonthVars.DecWalk	0.283	1.311	0.216
DayTypes.Monday	39.083	3.532	11.066
DayTypes.Tuesday	34.006	3.565	9.540
DayTypes.Wednesday	33.286	3.572	9.320
DayTypes.Thursday	33.936	3.558	9.537
DayTypes.Friday	25.642	3.552	7.219
DayTypes.Saturday	-12.776	2.736	-4.669

Interacts with XOther

Variable	Coefficient	StdErr	T-Stat
Calendar.MLK	37.283	50.244	0.742
Calendar.PresDay	-19.129	47.730	-0.401
Calendar.GoodFri	-8.112	54.883	-0.148
Calendar.MemDay	-114.256	49.459	-2.310
Calendar.July4th	-134.103	47.159	-2.844
Calendar.LaborDay	-39.744	50.150	-0.793
Calendar.Thanks	-378.458	49.853	-7.591
Calendar.FriAThanks	-127.570	49.667	-2.569
DayTypes.WkBeforeXMas	-7.743	15.597	-0.496
Calendar.XMasEve	-145.364	81.256	-1.789
Calendar.XMasDay	-359.132	50.854	-7.062

Variable	Coefficient	StdErr	T-Stat
Calendar.NYEve	-40.271	66.697	-0.604
Calendar.NYDay	-183.177	46.315	-3.955
DayTypes.WkAfterNewYear	20.083	10.327	1.945
DayTypes.WkDayBeforeHol	22.668	26.707	0.849
DayTypes.WkDayAfterHol	-10.909	17.254	-0.632
DayTypes.Phase1	-78.117	14.309	-5.459
DayTypes.Phase2	90.195	11.040	8.170
DayTypes.Phase3	93.289	12.771	7.305
DayTypes.Phase4	31.587	11.900	2.654
DayTypes.Trend2015	-23.962	4.451	-5.384

Heating Vars **Interacts with XHeat**

Variable	Coefficient	StdErr	T-Stat
HD1.HD1_17	12.198	4.552	2.680
HD2.HD2_17	21.169	2.171	9.751
Lag6.Lag6HD_17	7.148	2.182	3.276
Lag24.Lag24HD_17	4.650	0.729	6.381
Lag24HC.Lag24CD_HD17	-1.440	7.269	-0.198
WkEndDD.WkEndHD17	0.475	0.628	0.757
SeasHD.SpringHD17	-0.543	0.636	-0.854
SeasHD.FallHD17	-0.977	0.700	-1.397
ColdWind.WindHD17	18.443	2.617	7.047
ColdClouds.CloudHD17	36.500	4.051	9.011
Daily.MA10_HDD	1.248	0.841	1.484
Daily.MA28_HDD	0.289	1.299	0.222
TrendDD.Trend_HD17	-0.670	0.314	-2.137

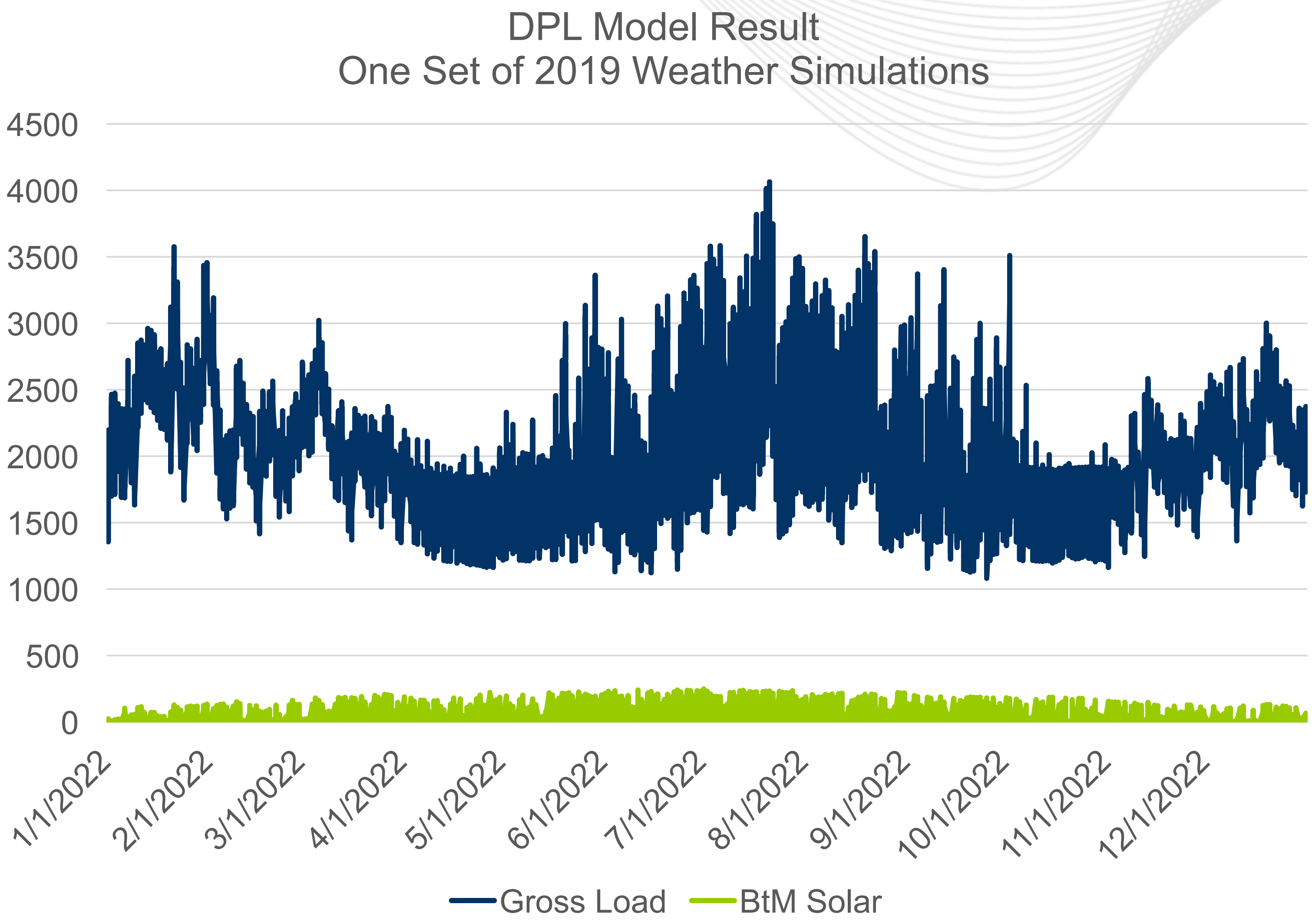
Cooling Vars **Interacts with XCool**

Variable	Coefficient	StdErr	T-Stat
CD1.TD1_17	26.219	4.517	5.804
CD2.TD2_17	8.522	1.778	4.792
Lag6.Lag6CD_17	32.113	2.969	10.817
Lag24.Lag24CD_17	6.928	1.307	5.299
Lag24HC.Lag24HD_CD17	-25.499	9.861	-2.586
WkEndDD.WkEndCD17	-0.237	0.870	-0.272
SeasCD.SpringCD17	-19.997	1.493	-13.391
SeasCD.FallCD17	-15.404	2.052	-7.509
HotWind.WindCD17	-2.640	6.026	-0.438
HotClouds.CloudCD17	-137.085	10.435	-13.138
Daily.MA10_CDD	5.254	1.645	3.195
Daily.MA28_CDD	1.096	3.090	0.355
TrendDD.Trend_CD17	1.298	0.330	3.930

- Forecast model is simulated through historical weather.
  - Calculate Gross Load
  - Simultaneously calculate BtM Solar

- Number of simulations will be dependent on:
  - Number of historical years included
    - 2022 Load Forecast used 1994-2020. Recommendation is to use last 20 years.
  - Number of rotations (13 day or 7 day)
    - 2022 Load Forecast used 13 day. Recommendation is to use 7 day.

Weather Simulation



- Model is simulated for each zone and weather scenario
- Technology shapes (Electric Vehicles and Battery Storage) can be added at this time too. These are discussed on later slides.

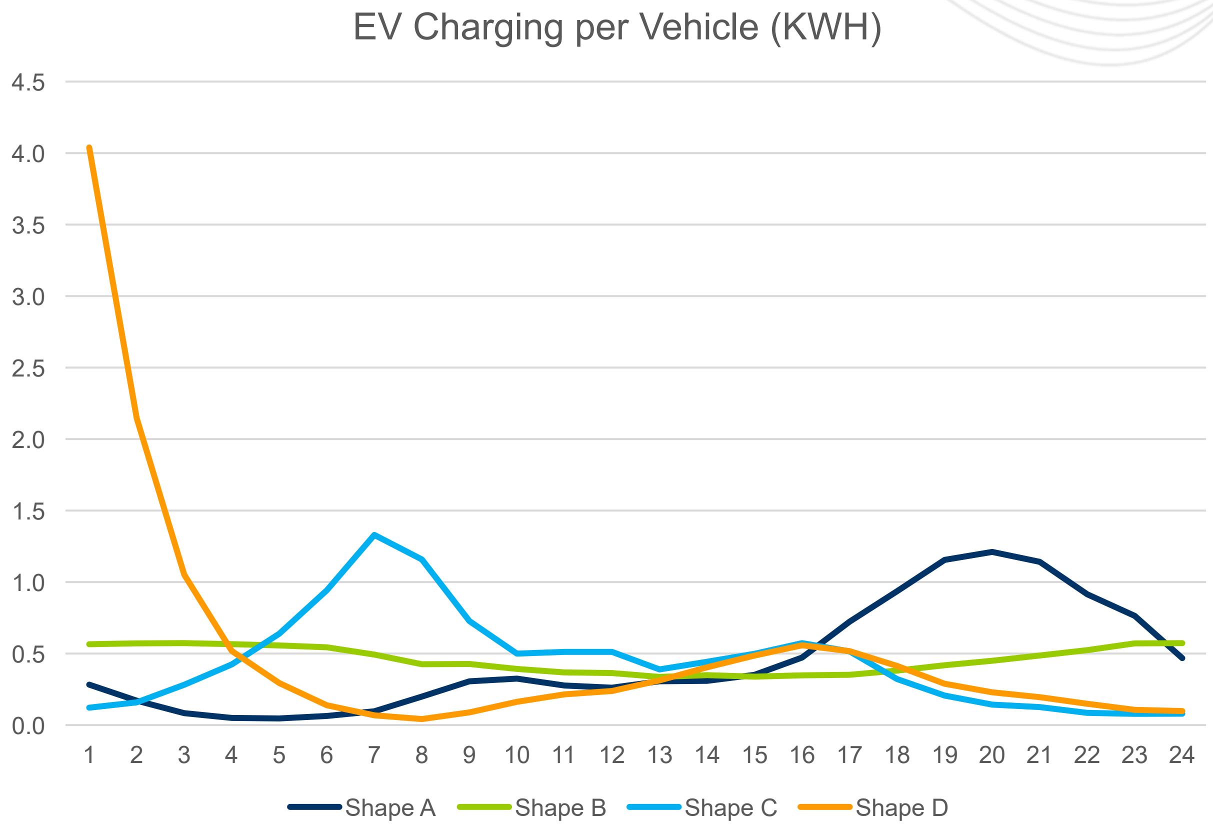
Apply Technology Shapes – Electric Vehicles

- Leverage hourly shape information from EVI-Pro (https://afdc.energy.gov/evi-pro-lite/load-profile)
  - Collaboration between National Renewable Energy Laboratory and the California Energy Commission
  - Provides EV charging shapes under various assumptions
    - Average Daily Miles
    - Average Ambient Temperature
    - Share All-Electric vs Plug-in Hybrid and Sedans vs SUVs
    - Mix of chargers available
    - Preference for home charging
    - Home and Workplace Charging Strategy

Apply Technology Shapes – Electric Vehicles

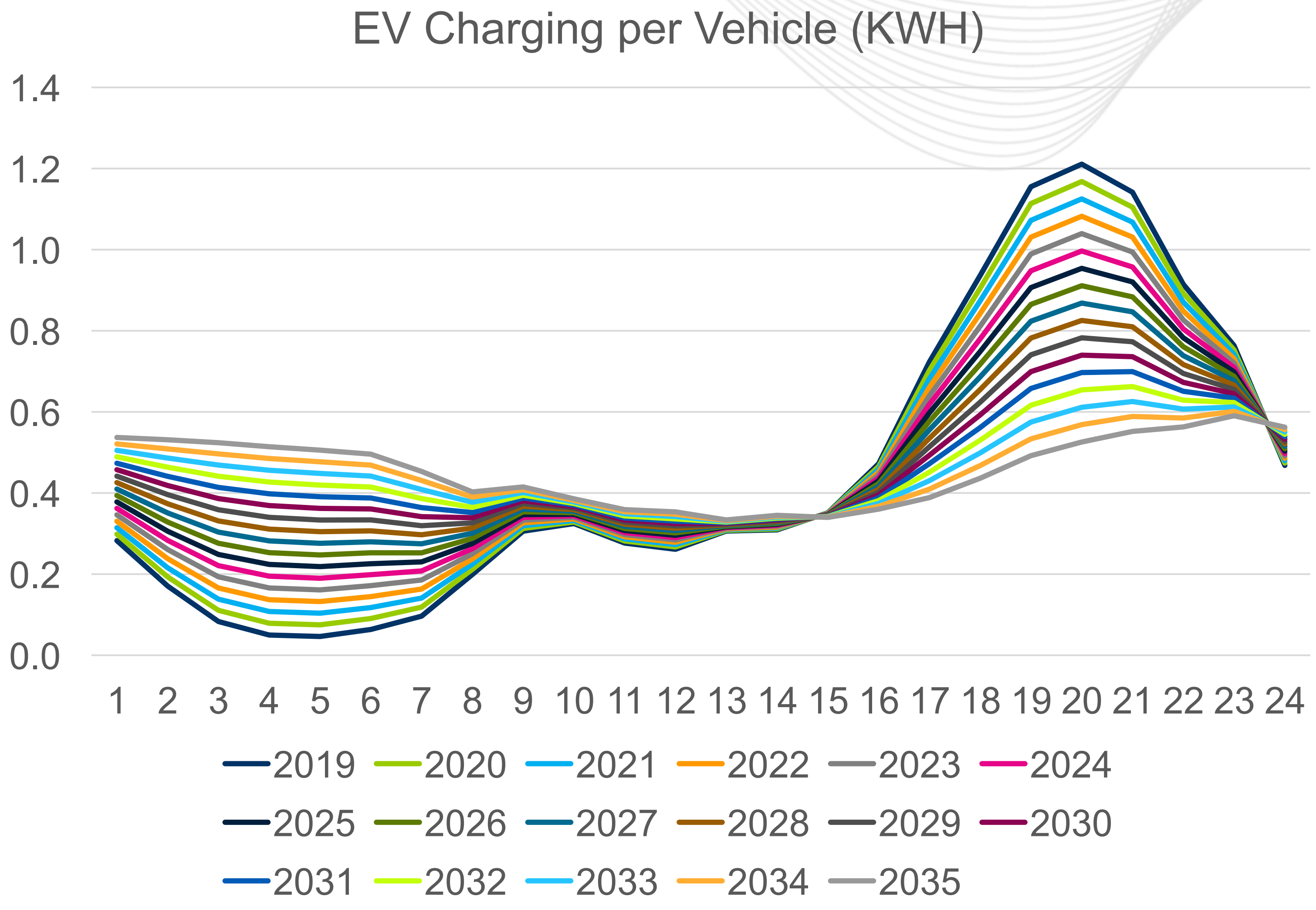
- We pulled 4 charging shapes
  - Shape A: 80% Preference for home charging and charges as fast as possible
  - Shape B: 60% Preference for home charging and levelizes charging
  - Shape C: 60% Preference for home charging and delays all charging to be ready by departure
  - Shape D: 60% Preference for home charging and delays work charging to be ready by departure and home charging to start at midnight

Apply Technology Shapes – Electric Vehicles



- Shape A is not good for the peak
- Shape C and D might be problematic at large penetrations of EVs.
- Shape B reduces peak impact, and takes advantage of overnight valley.

Apply Technology Shapes – Electric Vehicles



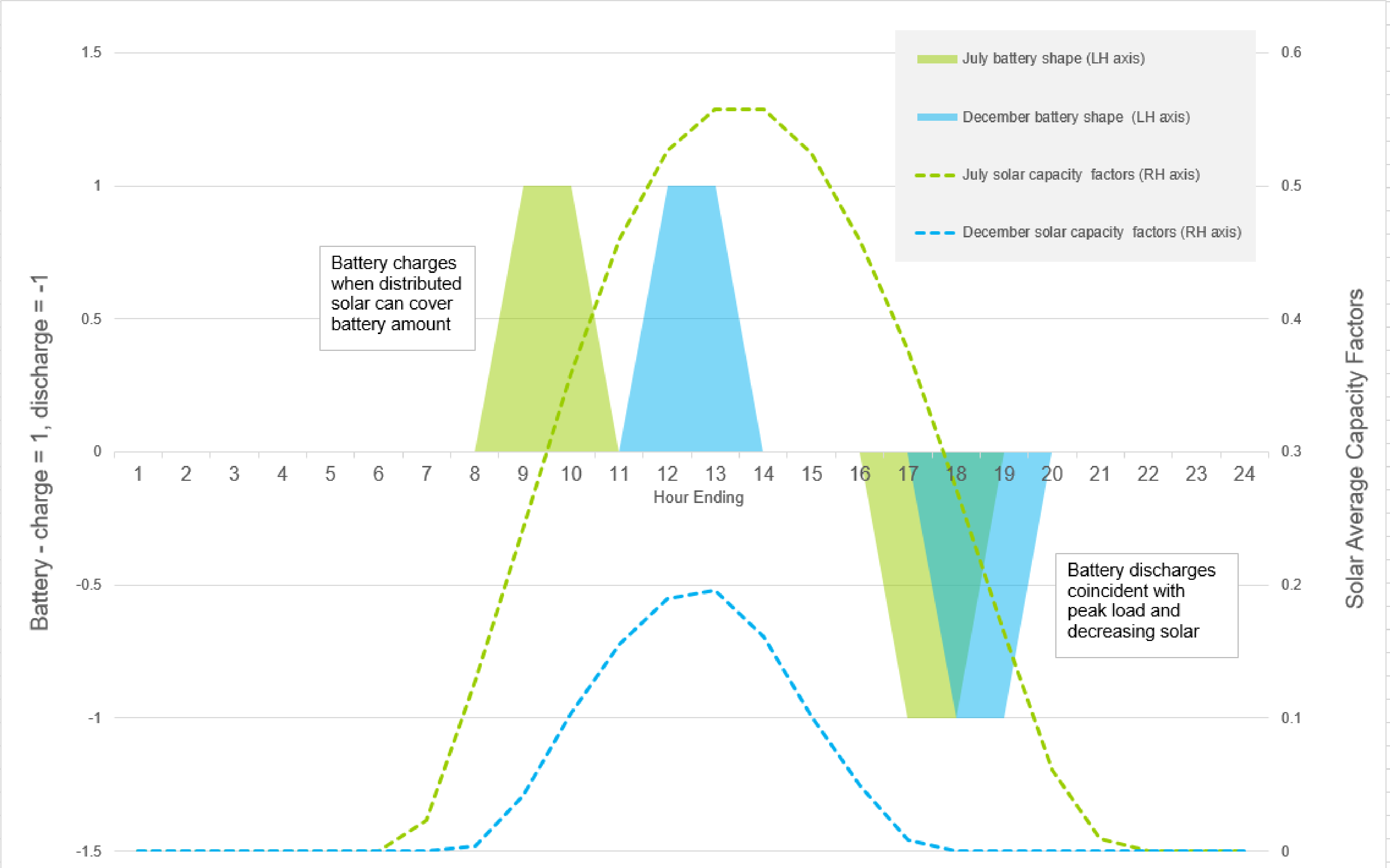
- Over time blend charging strategy away from un-managed charging (Shape A) towards a more levelized charging (Shape B) that mitigates peak impact

- This is akin to current practice used in the 2022 Load Forecast to assume that steps will be taken to reduce the future peak impact of EVs.

Apply Technology Shapes – Battery Storage

- Behind the meter batteries are assumed to be used in conjunction with distributed solar.
- Batteries will charge when there is enough solar production to cover the battery charge and discharge at peak when solar production is lower (later in the day)
- We are assuming behind the meter batteries are 2 hour duration
- Hourly shape is constructed on a monthly basis by looking at average hourly capacity factors from distributed solar and typical peak hours.

Apply Technology Shapes – Battery Storage



- Results from model simulation (gross load and solar) are combined with EV, storage, and any identified forecast adjustment load (such as data centers) to get to final hourly zonal loads.

- Zone are aggregated to RTO and LDAs.

- Peaks (50/50, 90/10) and Energy results are calculated in a similar manner to what we currently do.

Next Steps

- October 18th LAS
  - Further evaluation of recommendations
  - Discussion of plan for 2023 Load Forecast

- November 29th LAS
  - Preliminary 2023 Load Forecast

- December 6th Planning Committee
  - Preliminary 2023 Load Forecast

- End of December 2022
  - Final 2023 Load Forecast
  - 2023 Load Forecast Supplement (December 2022/January 2023)

Contact

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Load Forecast Model Development

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