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EMPIRE DISTRICT ELECTRIC COMPANY FORECAST MODELS FOR 2025 IRP

Submitted to:
Empire District Electric Company
602 S Joplin Ave.
Joplin, MO 64801

Prepared by:
Itron
10875 Rancho Bernardo Road
Suite 200
San Diego, CA 92127

858-724-2620

www.itron.com/forecasting

November 4, 2024

20 CSR 4240-2.135(2)(A)1,5

Denotes Confidential


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1. EMPIRE DISTRICT ELECTRIC COMPANY FORECAST MODELS

In February 2024, Empire District Electric Company (Empire) contracted with Itron to develop its 2025 Integrated Resource Plan (IRP) load forecast. This report presents an overview of the forecasting approach, a description of the forecast models, and the forecast results. Detailed information about the forecast models, calibration method, and results may be viewed in the MetrixND and MetrixLT project files.

The forecast is developed using three modeling processes summarized below.

- **Sales Models.** The sales models use Itron's Statistically Adjusted End-Use (SAE) method for the residential and commercial classes and traditional econometric methods for the remaining classes. The following rate classes are modeled.

  - Residential
  - Small Commercial
  - Large Commercial
  - Industrial
  - Transmission
  - **[redacted]**
  - Lighting
  - Municipal (Lockwood)

  The sales models are based on historical monthly rate class data and include the impacts of historical DSM programs and behind-the-meter photovoltaic (PV) generation.

- **Peak Model.** The peak model forecasts monthly gross system peaks. The peak model is an econometric model and based on the sales forecast.

- **Hourly Load Model.** The system hourly load forecast is developed by aggregating hourly class forecasts and calibrating them to the peak model result. The hourly class forecasts are developed using the sales model forecast scaled for losses and shaped with hourly profile models.

After completing the three modeling processes, the economic and weather scenarios are created by applying different input assumptions into the models.

2. FORECAST METHOD

The 2025 IRP forecast relies on historical monthly billing data, AMI data, weather data, and economic data. The forecast steps are described in this section.

STEP 1. SALES FORECAST

For each class, the monthly sales forecast is developed using an econometric or SAE model. For some classes (e.g., Industrial), external adjustments are used to incorporate known customer additions. The forecast class models and their adjustments are described in Sections 5 through 12. Once the class forecasts are complete, the forecasts are scaled for losses and summed together for the system energy forecast.

The sales forecast models have three key inputs, data, weather, and economics. Historical data are provided by Empire. Weather data are derived from the National Oceanic and Atmospheric Administration (NOAA) data for Springfield, Missouri. Economic data are purchased from Woods and Poole, Inc.

Historical Data. The forecast begins by developing the historical data for modeling. In the 2022 IRP, nine (9) classes were defined mapping individual tariffs to the classes. For instance, the Small Commercial class was comprised of the CB and SH tariffs. In 2022, Empire created a new set of tariffs resulting in significant movement between the existing and new tariffs. To remain consistent with the 2022 IRP class definition, the new tariffs are mapped to the same classes maintaining a consistent historical dataset.

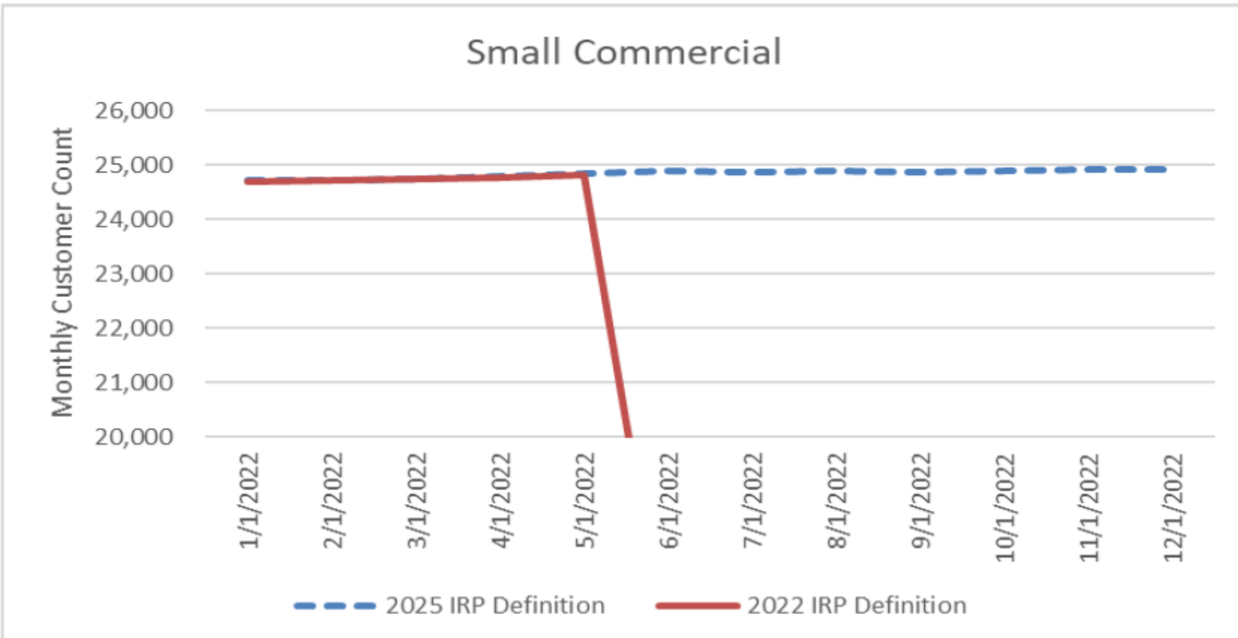
TABLE 1 shows the 2025 IRP tariff to rate classes mapping compared with the 2022 IRP tariff to rate class mapping.

TABLE 1: RATE CLASS MAPPING

Class	2022 IRP	2025 IRP
Residential	All RG Rates	RG, NS-RG, RG WH, RGL, RH, TC-RG, TP-RG, NEB
Small Commercial	CB, SH	CB, SH, NS-GS, PFM, TC-GS, TP-GS, TS-GS
Large Commercial	GP, TEB	GP, TEB, NS-SP, NS-LG, NS-SP TEB, OP GP, TC-SP, NS-SP Oil, TC-LG
Industrial	LP	LP, OP LP
Power Feed Mills	PFM	Customers no longer exist
Transmission	PT	PT, OP PT
Lighting	LS, PL	LS, PL, SPL
[redacted]	**[redacted]**	**[redacted]**
Municipals	Lockwood	Lockwood

FIGURE 1 illustrates the result of the mapping. In this figure, the 2022 IRP Small Commercial class consists of the two (2) tariffs (i.e., CB and SH tariffs) listed in TABLE 1. In April 2022, the class consisted of 24,775 customers. Using the 2022 IRP definition, the class is reduced to 3,080 customers in July 2022. However, these customers have not disappeared, instead they are simply moved to new tariffs. Using the 2025 IRP Small Commercial class definition, the July 2022 customer count is 24,868. FIGURE 1 shows that the rate class mapping maintains a consistent Small Commercial data series which can be used as the basis for the IRP forecast models.

FIGURE 1: SMALL COMMERCIAL HISTORICAL DATA SERIES



Using the revised tariff mapping, the forecast model historical dataset is consistent with the 2022 IRP historical dataset.

Monthly Weather Forecast. Hourly weather for Springfield, Missouri from January 1, 1981, through April 30, 2024, are acquired from NOAA. These data are converted to monthly weather and used to calculate the normal weather forecast. The following steps are used to develop the weather data.

1. **Daily Average Temperature**. Calculate daily average temperatures from the original hourly temperatures. The daily average temperature is the average of the 24-hourly values.
2. **Daily HDD and CDD**. Daily heating and cooling degree days (HDD and CDD) are calculated using different temperature reference points (i.e., 50, 55, 60, 65 degrees) and the daily average temperature.
3. **Monthly HDD and CDD**. Monthly HDDs and CDDs are calculated by summing the daily HDD and CDD values over the calendar month. Monthly HDDs and CDDs are used in the sales models.

4. **Normal Monthly HDD and CDD**. Normal monthly HDDs and CDDs are calculated by averaging historical monthly HDDs and CDDs from 1994 through 2023. The normal HDDs and CDDs are 30-year normal values.

Economic Forecast. The economic forecast drives long-term growth for the customer and sales models. The economic forecast uses a weighted average of the Joplin MSA and Springfield MSA economic forecasts. The Joplin and Springfield MSAs represent 6 of the 21 counties or approximately 60% of Empire's residential customers. While Empire serves additional counties that are not included in the Springfield MSA or Joplin MSAs, the models assume that their economic conditions are driven by their physical proximity to the Joplin and Springfield MSAs.

STEP 2. SYSTEM PEAK FORECAST

The monthly system peak forecast uses an econometric model based on historical monthly peak day events from January 2013 through April 2024. The peak model is described in Section 13.

The key drivers of the peak model are weather and energy growth. Weather data are derived from historical weather conditions on past monthly peak days. The energy growth is derived from the sales models in Step 1. These drivers are described below.

Peak Weather Forecast. Peak weather is obtained by averaging the monthly peak producing weather events. The following steps are used to develop the weather data.

1. **Monthly Peak Weather Conditions**. Identify the peak producing weather conditions for each month from 2004 through 2024. The weather conditions include the peak day average temperature and the two prior days' average temperatures.
2. **Weighted Average Peak Weather**. The peak temperature is calculated as a three-day weighted average. The weighted average consists of 70% of the current day temperature, 20% of the prior day temperature, and 10% of the two-day prior temperature.
3. **Normal Monthly Peak Weather**. The normal peak weather is the average of historical peak weather conditions over the prior 20 years (or 21 years) calculated as the average from January 2004 through April 2024.
4. **Correct Shoulder Month Weather**. Shoulder month peaks may be driven by hot or cold weather. For instance, April peaks are driven by hot weather in 8 of the 21 historical years. For normal peak weather in April, May and October, the normal weather is modified by removing historical years from the average that do not match the primary weather effect. In April, the predominate peak weather effect is heating. As a result, the cooling peak weather is removed from the April normal weather calculation. May is designated as a cooling month, and October is designated as a heating month.
5. **Correct Seasonal Peak**. Because January and August are the seasonal peaks, their normal values are replaced using the seasonal peak averages.

Peak Growth Drivers. Peak growth is related to the underlying changes in end-use equipment. For example, if electric space heating is growing faster than space cooling, winter peaks should grow at a different rate than summer peaks. This differentiated peak growth is captured by decomposing the sales models into their heating, cooling, and base load components and using these components to drive the winter, summer, and baseload peak growth.

STEP 3. HOURLY LOAD FORECAST

The hourly load forecast is developed using a bottom-up approach, then calibrating the hourly load forecast to the system peak forecast.

The approach begins by developing hourly rate class models based on Empire's hourly AMI load data to forecast the hourly profiles. The hourly profiles are forecast using daily normal weather. Next, the hourly profiles are calibrated to their respective class sales forecasts from Step 1 and scaled for losses to obtain the hourly class loads. The hourly class loads are summed to obtain the hourly system loads and then calibrated to the system peak forecast from Step 2. Finally, independent forecasts for behind-the-meter solar (PV) and electric vehicles (EV) are added to the hourly system load forecast.

The key components in the hourly load forecast are the hourly class models, the normal daily weather, and the PV and EV forecasts. These components are described below.

Hourly Class Models. For each class, hourly load profiles are forecast based on rate class hourly data. The forecast models are developed as hourly econometric models and described in Section 14.

Normal Daily Weather. Normal daily average temperatures are calculated using a 30-year period (1994-2023) and the rank-and-average method. In the forecast period, the rank-and-average results are mapped to the 2003 temperature calendar and scaled to be consistent with the 30-year monthly normal HDDs and CDDs.

PV Model. PV is forecast based on the Energy Information Administration's (EIA) 2023 Annual Energy Outlook (AEO) forecast calibrated to historical Empire solar adoption. The hourly profiles are based on the National Renewable Energy Laboratory's (NREL) PVWatts Calculator for Springfield, Missouri.

EV Model. The EV forecast is based on an estimate of registered EV in Empire's service territory and the EIA's 2023 AEO forecast growth rates. The current number of EVs is derived from the Alternative Fuel Data Center (AFDC) 2022 estimates, modified based on Empire's population relative to the state population, and escalated based on the EIA's 2023 AEO forecast. The hourly profiles are based on AFDC charging profiles assuming a "delayed – finish by departure" charging strategy for resident charging and "immediate" charging strategy for workplaces and fast charging stations.

STEP 4. ECONOMIC SCENARIOS

Two economic scenarios are created to construct reasonable planning bounds around the base forecast. The High and Low scenarios are based on alternative economic scenarios constructed by increasing or decreasing the base economic forecast.

The high and low economic forecasts are developed using the historical and forecast population growth rates. The high economic forecast is calculated based on the ratio of the historical annual average population growth rate to the forecast annual average population growth rate.

For example, the 2004-2023 annual average population growth rate is 0.77%. The 2023-2054 forecast annual average population growth rate is 0.50%. The ratio of historical growth to forecast growth is 1.54. The high economic forecasts drivers are created by scaling the base forecast by 1.54. The low economic forecasts mirror the difference between the base forecast and high case. FIGURE 2 and FIGURE 3 show the total employment and households drivers for the base, high, and low scenarios.

FIGURE 2: SCENARIOS: TOTAL EMPLOYMENT

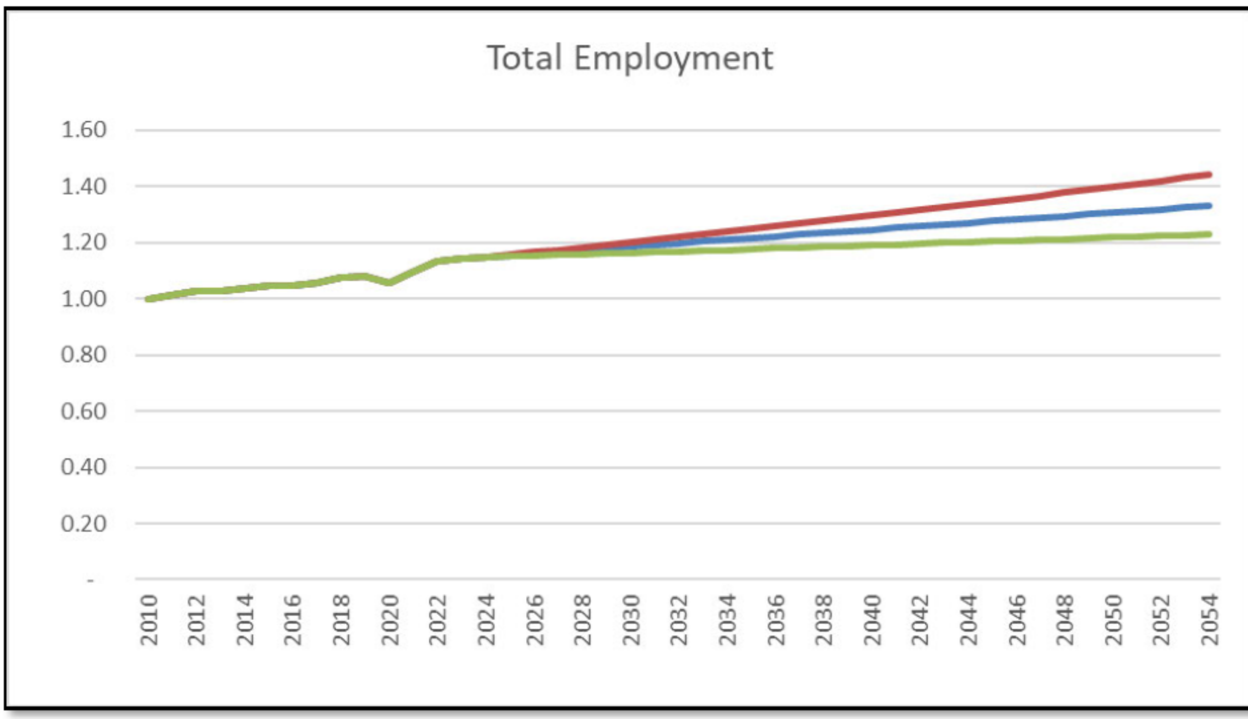
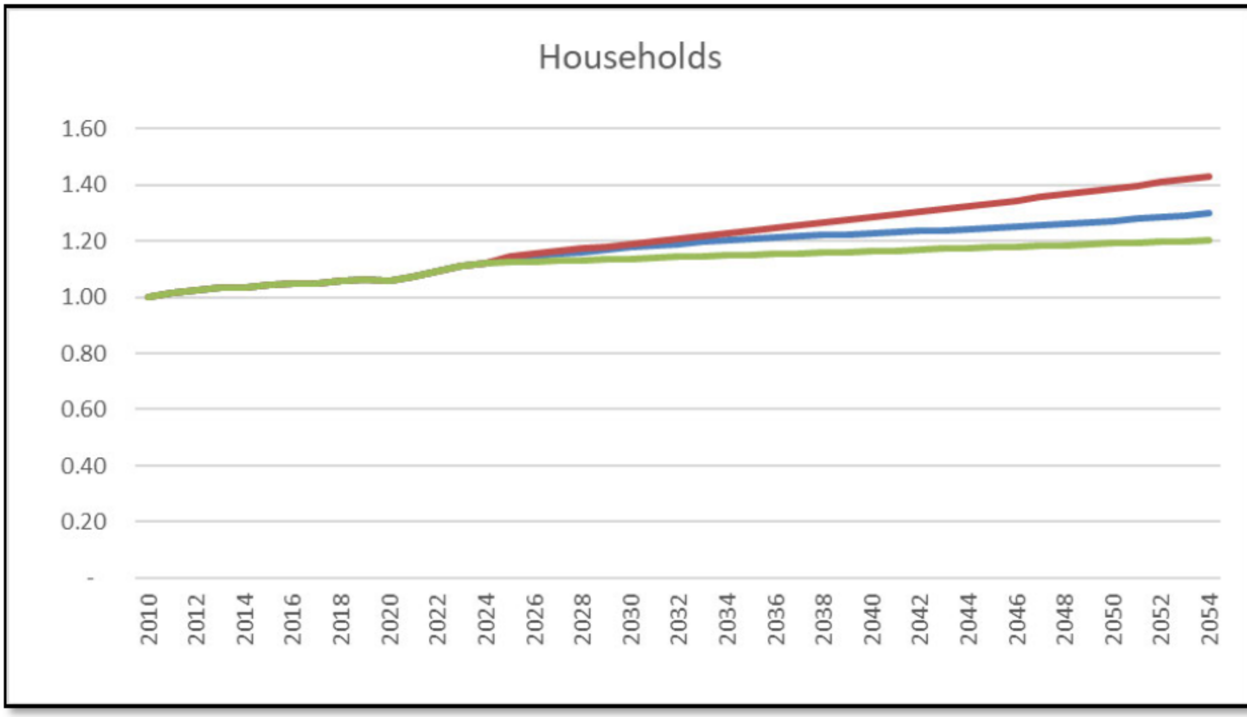


FIGURE 3: SCENARIOS: HOUSEHOLDS



STEP 5. WEATHER SCENARIOS

The mild and extreme weather scenarios are created to capture the uncertainty associated with weather conditions. These scenarios are developed using the same historical weather data as the base case but identify a 1-in-10 scenario above and below the base forecast normal temperatures.

Two types of weather are developed to create the mild and extreme scenarios. Monthly weather is developed and used in the sales models. Peak weather is developed and used in the peak model. The development of these scenarios is discussed below.

Monthly Weather Scenarios. Monthly HDD and CDD scenarios are created by ranking 30 years of historic annual HDD and CDD values (base 65 degrees) from lowest to highest values. The mild case is determined by using the 3rd lowest year in the ranked list (i.e., 1 in 10 occurrences). The extreme case is determined by using the 3rd highest year in the ranked list. FIGURE 4 and FIGURE 5 show the ordered annual HDD and CDD with the mild and extreme scenarios. TABLE 2 shows the annual HDD and CDD values for the base, mild, and extreme scenarios.

FIGURE 4: SCENARIOS: ANNUAL HDD BASE 65

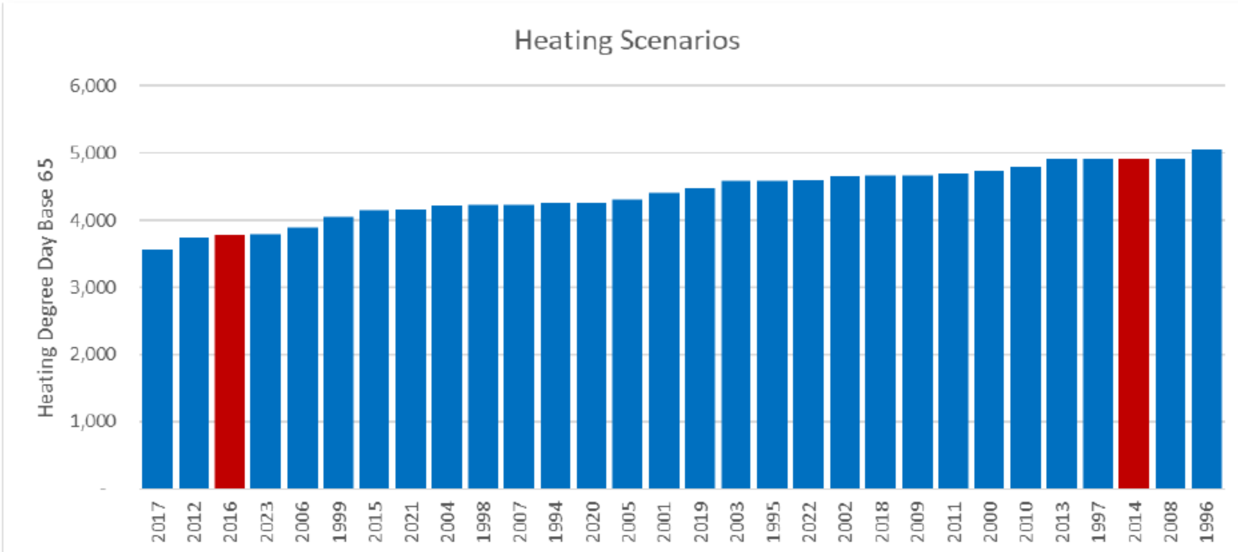


FIGURE 5: SCENARIOS: ANNUAL CDD BASE 65

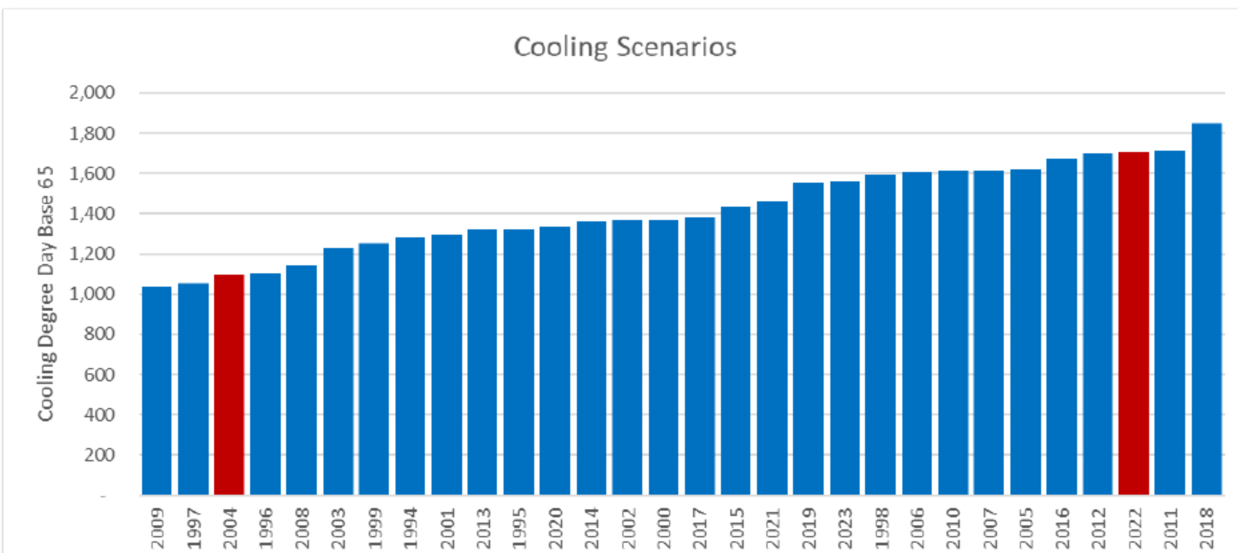


TABLE 2: SCENARIOS: ANNUAL DEGREE DAYS

Scenario	HDD65	CDD65
Base	4,403	1,420
Mild	3,793	1,081
Extreme	4.934	1,682

After determining the annual HDD and CDD scenario, monthly HDD and CDD values are calculated by distributing the annual HDD and CDD values based on the base case normal monthly pattern.

Peak Weather Scenarios. The mild and extreme peak scenarios are derived based on 21 years of historical (2004 to 2024) peak producing weather. The extreme cases are obtained by selecting the 2nd lowest average temperatures in the winter months and the 2nd highest average temperatures in the summer months. The mild case is obtained by selecting the 2nd highest average temperatures in the winter month and the 2nd lowest average temperatures in the summer months. FIGURE 6 and TABLE 3 show the extreme and mild peak temperature scenarios.

FIGURE 6: SCENARIOS: PEAK TEMPERATURES

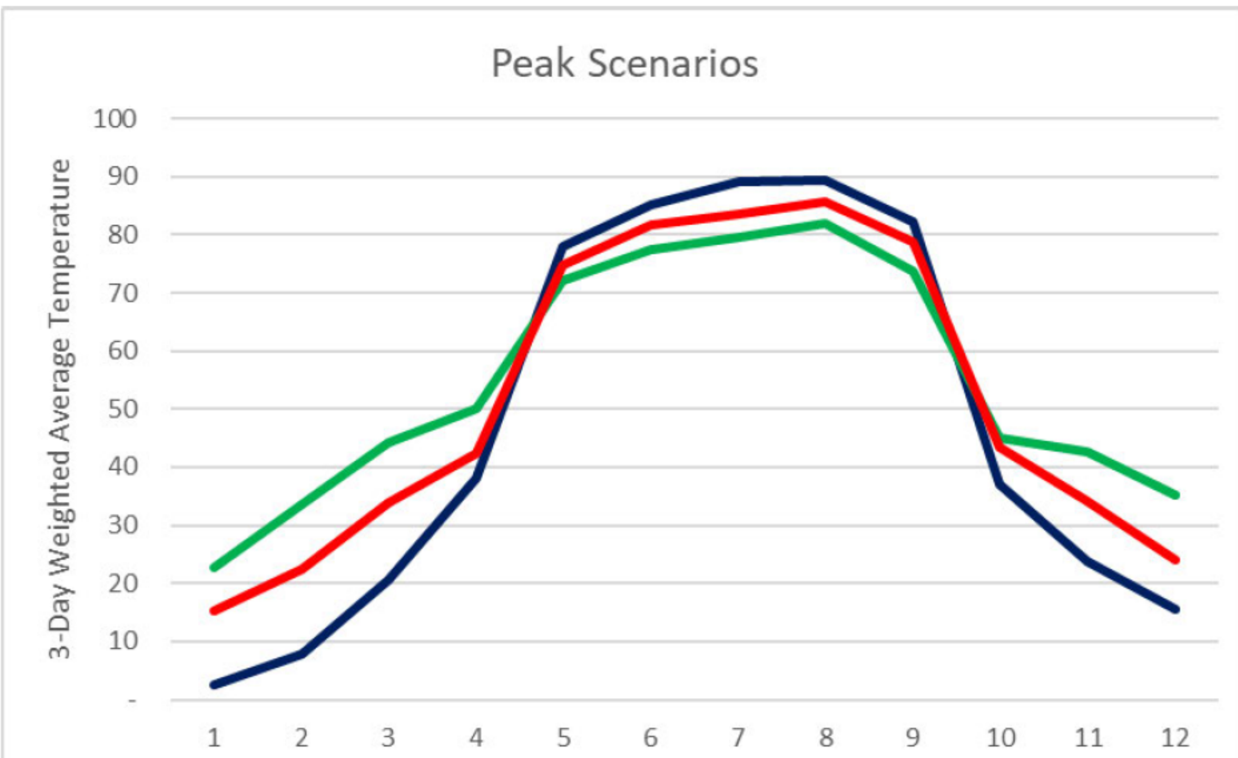


TABLE 3: SCENARIOS: MONTHLY PEAK PRODUCING TEMPERATURES

Month	Base	Extreme	Mild
Jan	15.22	2.64	22.77
Feb	22.33	7.96	33.67
Mar	33.83	20.63	44.10
Apr	42.44	38.24	50.05
May	74.70	77.97	72.01
Jun	81.58	85.00	77.53
Jul	83.55	88.98	79.51
Aug	85.58	89.36	81.97
Sep	78.74	82.14	73.59
Oct	43.55	37.00	45.03
Nov	34.15	23.79	42.67
Dec	24.09	15.68	35.30

STEP 6. ADDITIONAL SCENARIO

In addition to the four required scenarios (e.g., high, low, extreme, and mild), an additional scenario is created for this forecast. The scenario combines the high economic scenario with a high electric vehicle forecast and is named the “high-high” scenario.

In the base case, the electric vehicle forecast is developed based on the EIA’s 2023 AEO forecast of electric vehicle growth adjusted to the expected EV count in Empire’s service territory. The base forecast results in electric vehicle saturations (e.g., electric vehicles divided by residential customers) increasing from approximately 2.1% in 2024 to 18.6% in 2055.

The high electric vehicle forecast included in the high-high scenario assumes that 100% of new vehicle purchases are electric by 2045. This forecast considers the current mandates for 100% vehicle purchases to be electric by 2035 but delays the implementation to 2045 allowing a 20-year transition from the beginning of the forecast period. While there are no specific goals or mandates that target 2045, the scenario imagines that the current electric vehicle policy environment will ultimately succeed but in a delayed form.

The high forecast results in electric vehicle saturations increasing from approximately 2.1% in 2024 to 96.1% in 2055. FIGURE 7 compares the base and high electric vehicle scenarios and TABLE 4 presents estimated electric vehicle counts and saturations.

FIGURE 7: SCENARIOS: ELECTRIC VEHICLE SCENARIOS

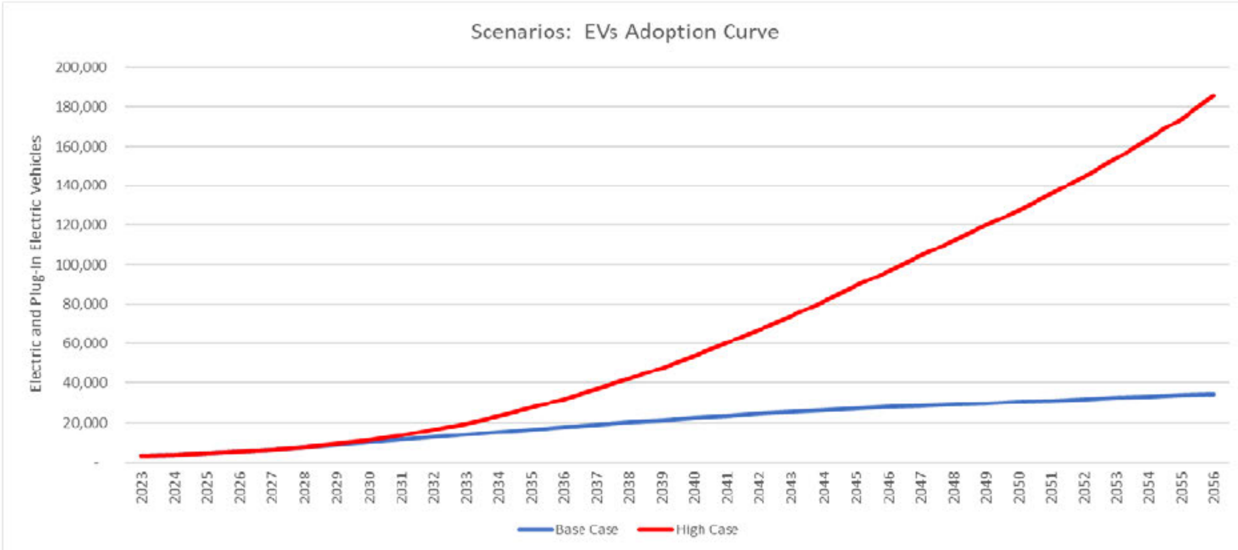


TABLE 4: SCENARIOS: ELECTRIC VEHICLE ESTIMATED SATURATIONS

Year	Base Count	Base Saturation	High Count	High Saturation
2024	3,313	2.1%	3,313	2.1%
2025	4,133	2.6%	4,133	2.6%
2030	9,729	5.9%	10,941	6.7%
2035	16,257	9.7%	27,283	16.2%
2040	22,303	13.0%	53,660	31.4%
2045	26,940	15.5%	89,143	51.3%
2050	30,453	17.2%	127,708	72.2%
2055	33,776	18.6%	174,129	96.1%

3. BASE FORECAST SUMMARY

Total system energy grows from **[redacted].** The summer and winter peaks (net system peaks) move consistently with the energy forecast with average annual growth rates of **[redacted]** Annual forecast values are shown in TABLE 5.

TABLE 5: SYSTEM FORECAST SUMMARY

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[redacted]

FIGURE 8 shows the system energy forecast compared with recent history. In this figure the net forecast (green) is compared with the system forecast excluding new PV and EV (yellow).

FIGURE 8: SYSTEM ENERGY FORECAST

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[redacted]

FIGURE 9 show the system peak forecasts (including the PV and EV forecasts) for the summer and winter seasons. This figure shows that Empire is expected to remain a predominately winter peaking utility.

FIGURE 9: SYSTEM SUMMER AND WINTER PEAK FORECAST

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[redacted]

4. SCENARIO FORECAST SUMMARY

After the base forecast is complete, the forecast models are applied to the High and Low economic scenario inputs, the Mild and Extreme weather scenario inputs, and the additional High-High scenario inputs. TABLE 6 and TABLE 7 compare the scenario forecasts for energy and peaks. FIGURE 10 and FIGURE 11 show the scenarios relative to the base case.

As expected, the extreme, mild, high, and low scenarios create upper and lower bounds around the base case that capture demand risk. The high-high scenario creates a new upper energy bound due to the quantity of charging required by the increased number of vehicles. However, the high-high scenario does not show a similar peak impact. Electric vehicle charging has a diverse load profile and the forecast assumes that most vehicle charging is residential which occurs during the night hours. As a result, vehicle charging has a minor impact during the time of the winter peak.

TABLE 6: SCENARIOS: ENERGY FORECASTS (MWH)

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[redacted]

FIGURE 10: SCENARIOS: SALES FORECAST COMPARISON

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TABLE 7: SCENARIOS: BASE, MILD, EXTREME, HIGH, AND LOW GROSS PEAK FORECAST (MW)

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[redacted]

TABLE 7 (CONT'D): SCENARIOS: BASE, MILD, EXTREME, HIGH, AND LOW GROSS PEAK FORECAST (MW)

[redacted]

FIGURE 11: SCENARIOS: PEAK FORECAST COMPARISON

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[redacted]

5. RESIDENTIAL SALES MODEL

Residential electric sales consist of all customers with residential rates. The class is modelled with two models, a Customer Model and an average use (UPC) model. The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total sales in each month. Using two models captures both the class growth based on the changing number of customers (Customer Model) and usage changes based on end-use information (UPC Model). After modelling, the forecast is adjusted for EV and PV growth.

CUSTOMER MODEL

The Customer Model is a regression model estimated with historical data from January 2012 through March 2024. TABLE 8 shows the Customer Model specification and TABLE 9 shows the Customer Model statistics.

TABLE 8: RESIDENTIAL CUSTOMER MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	6066.161	4473.484	1.356
Household Index	133525.640	4398.696	30.356
Year2017Plus	1279.096	146.078	8.756
Year2021Plus	2851.052	215.147	13.252
Oct2019toMar2020	1498.130	200.076	7.488
Apr2020toDec2020	2753.007	203.213	13.547
MA(1)	0.946	0.080	11.838
MA(2)	0.431	0.080	5.362

TABLE 9: RESIDENTIAL CUSTOMER MODEL STATISTICS

Statistics	Residential Customer Model
Estimation	1/2012 – 3/2024
R^2	0.997
Adj. R^2	0.997
MAPE	0.14%
DW	1.823

Model Variables. The residential model is driven by households and incorporates adjustments for Covid and the recent acceleration of residential customer formation. The variables included in the model are described below.

- **Household Index.** This variable is the household forecasts for the Springfield and Joplin MSAs.
- **Year2021Plus**. This binary variable captures the post-Covid acceleration of customer formation.
- **Year2017Plus**. This binary variable captures a minor acceleration in customer formation prior to Covid.
- **Covid.** Four model adjustments are included to capture the Covid impact. Two binary variables (**Oct2019toMar2020** and **Apr202toDec2020**) and two MA terms. These adjustments correct for the conversion of annual to monthly households' data and the timing of the Covid impact.

UPC MODEL

The UPC Model is an SAE model estimated with historical data from January 2012 through March 2024. TABLE 10 shows the UPC Model specification and TABLE 11 shows the UPC Model statistics.

Residential SAE Model Summary. The SAE model contains end-use information for heating, cooling, and base load technologies from Itron's 2023 SAE West North Central region. The following data are included in the model.

- **End-Use Efficiencies.** End-use efficiencies by technology type are based on EIA data.
- **End-Use Saturations and Intensities.** End-use saturations and intensities by technology type are based on EIA data calibrated to Empire's 2008 Potential Study, 2015 Saturation Survey, and 2021 Market Research study. End-use intensities are modified to account for Empire's historical demand-side management (DSM) programs.
- **Economic data.** Historic and forecasted population and household income are based on Woods and Poole's forecasts for the Springfield and Joplin MSAs.
- **Energy Prices.** Class energy prices are based on historical revenues and energy consumption. The energy price forecast is held constant in real dollars.

TABLE 10: RESIDENTIAL UPC MODEL

Variable	Coefficient	StdErr	T-Stat
XHeat	1.103	0.025	44.971
XCool	1.103	0.027	41.366
XOther	1.109	0.028	39.115
ResSolar_UPC_Hist	-2.635	0.587	-4.490
Apr2020toFeb2021	49.436	21.398	2.310
Mar2021	-349.419	66.402	-5.262
Year2023Plus	48.709	23.173	2.102

TABLE 11: RESIDENTIAL UPC MODEL STATISTICS

Statistics	Residential UPC Model
Estimation	1/2012 – 3/2024
R2	0.942
Adj. R2	0.939
MAPE	4.76%
DW	2.220

Model Variables. The UPC Model includes the SAE variables (XHeat, XCool, and XOther), a behind-the-meter solar variable, and Covid adjustment variables.

- **XHeat.** XHeat is an SAE variable and captures the heating response. The response includes the effects of heating technology efficiencies, saturations, thermal shell, weather, price, income, and household size. Heating intensities are adjusted for historic DSM programs.
- **XCool.** XCool is an SAE variable and captures the cooling response. The response includes the effects of cooling technology efficiencies, saturations, thermal shell, weather, price, income, and household size. Cooling intensities are adjusted for historic DSM programs.
- **XOther.** XOther is an SAE variable and captures the baseload response for all non-heating and non-cooling technologies. The response includes the effects of hours of light, price, income, and household size. Baseload intensities are adjusted for historic DSM programs.
- **ResSolar_UPC_Hist.** This variable captures the historical impact of behind-the-meter solar installations based on Empire's solar rebate program. The historical installed capacity is converted to monthly generation using monthly load factors and then divided by customers to obtain solar generation per customer. The model assumes no changes in solar generation in the forecast. New solar installations are forecast externally and added to the final forecast after the statistical modelling is complete.

- **Covid Adjustments**. Three variables are used to capture variations in usage through the Covid period. The **Apr2020toFeb2021, Mar2021** and **Year2023Plus** model minor changes in usage with slightly higher average use after the Covid period**.**

RESIDENTIAL BASE SALES FORECAST

The residential sales forecast is developed as the product of the customer and UPC forecasts and then adjusted for EV and PV growth. The annual sales forecast, customer forecast, and use-per-customer forecast are shown in FIGURE 12, FIGURE 13, and FIGURE 14.

EV Growth. Electric vehicle growth includes all future EV additions with at-home charging. Future EV additions are based on the EIA's 2023 AEO forecast of electric vehicle growth adjusted to the expected EV count in Empire's service territory. At-home charging constitutes 88% of all EV electric consumption based on Empire's 2021 Market Survey.

PV Growth. Behind-the-meter solar growth includes all future PV additions. Future residential PV additions are based on the EIA's 2023 AEO forecast of PV growth and includes a portion of the future planned community solar and distributed solar additions. The residential portion is based on the current mix of solar customers and historical subscription rates of community solar.

Forecast. FIGURE 12 shows the annual sales with and without the EV and PV adjustments. FIGURE 13 shows the customer count forecast and FIGURE 14 shows the average use forecast including EV and PV adjustments.

TABLE 12 shows the annual sales, customer, and average use forecast with average growth rates inclusive of the EV and PV adjustments.

FIGURE 12: RESIDENTIAL SALES FORECAST (ACTUAL, NORMALIZED, AND FORECAST)

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[redacted]

FIGURE 13: RESIDENTIAL CUSTOMER FORECAST (ACTUAL AND FORECAST)

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FIGURE 14: RESIDENTIAL UPC FORECAST (ACTUAL AND FORECAST)

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[redacted]

TABLE 12: RESIDENTIAL SALES FORECAST SUMMARY

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[redacted]

TABLE 12 (CONT'D): RESIDENTIAL SALES FORECAST SUMMARY

[redacted]

6. SMALL COMMERCIAL SALES MODEL

The Small Commercial class consists of customers with the CB, SH, NS-GS, PFM, TC-GS, TP-GS, and TS-GS rates. This class is modeled with two models, a Customer Model and a UPC Model. These models capture both class growth based on the number of customers and changing usage patterns based on end use information. The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month. After modelling, the forecast is adjusted for EV and PV growth.

CUSTOMER MODEL

The Customer Model is a regression model estimated with historical data from January 2012 through March 2024. TABLE 13 shows the Customer Model specification and TABLE 14 shows the Customer Model statistics.

TABLE 13: SMALL COMMERCIAL CUSTOMER MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	6514.732	282.468	23.064
Total Employment	16580.550	269.347	61.558
Apr2020toDec2020	258.084	35.026	7.368
Jan2021toSep2021	209.881	34.317	6.116
Oct2019	1978.181	39.552	50.015
MA(1)	0.809	0.078	10.354
MA(2)	0.504	0.078	6.463

TABLE 14: SMALL COMMERCIAL CUSTOMER MODEL STATISTICS

Statistics	Small Commercial Customer Model
Estimation	1/2012 – 3/2024
R^2	0.994
Adj. R^2	0.993
MAPE	0.17%
DW	1.698

Model Variables. The customer model growth is driven by total employment. The additional variables capture an errant historical data point and Covid impacts. The variables are described below.

- **Total Employment Index.** The total employment index is the historical and forecast employment for the Springfield MSA and Joplin MSA.
- **Covid.** Four model adjustments are included to capture the Covid impact. Two binary variables (**Apr202otoDec2020** and **Jan2021toSep2021**) and two MA terms. These adjustments correct for the conversion of annual to monthly employment data and the timing of the Covid impact.
- **Dummy Variable.** This binary variable (**Oct2019**) removes outlier data.

UPC MODEL

The UPC Model is an SAE model estimated with historical data from January 2012 through March 2024. The SAE model applies the same theoretical foundation as the residential SAE model but modified for commercial end-use information.

TABLE 15 shows the UPC Model specification and TABLE 16 shows the UPC Model statistics.

Commercial SAE Model Summary. The Small Commercial SAE model contains end-use information for heating, cooling, and base load technologies from Itron's 2023 SAE West North Central region. The model includes the following data.

- **End-use Saturations and Efficiencies.** End-use saturations and efficiencies by technology type are based on EIA data and adjusted for historical DSM programs.
- **Economic data.** Historical and forecast employment trends are based on Woods and Poole's forecast for the Springfield and Joplin MSA.
- **Energy Prices.** Price is based on historical revenue and energy consumption. Energy prices are held constant in real dollars through the forecast period.

TABLE 15: SMALL COMMERCIAL UPC MODEL

Variable	Coefficient	StdErr	T-Stat
XHeat	0.911	0.043	20.965
XCool	0.651	0.025	25.986
XOther	0.020	0.000	56.836
SComSolar_UPC_Hist	-1.889	0.924	-2.044
Feb	-85.958	32.503	-2.645
Sep	95.073	28.870	3.293
OctNov2020	121.344	27.748	4.373

TABLE 16: SMALL COMMERCIAL UPC MODEL STATISTICS

Statistics	Small Commercial UPC Model
Estimation	1/2012 – 3/2024
R2	0.867
Adj. R2	0.860
MAPE	4.33%
DW	1.896

Model Variables. The UPC Model includes SAE variables (XHeat, XCool, and XOther), a behind-the-meter solar variable, and binary variables. These variables are described below.

- **XHeat. XHeat** captures the heating response. The variable includes heating technology efficiencies, heating technology saturations, building types, weather, price, and employment. Heating intensities are adjusted for historical DSM programs.
- **XCool. XCool** captures the cooling response. The variable includes cooling technology efficiencies, cooling technology saturations, building types, weather, price, and employment. Cooling intensities are adjusted for historical DSM programs.
- **XOther. XOther** captures the non-heating and cooling technology impacts. The variable includes baseload technology efficiencies, baseload technology saturations, building types, price, and employment. Baseload intensities are adjusted for historical DSM programs.
- **Behind-the-Meter Solar. SComSolar_UPC_Hist** models the historical impact of behind-the-meter solar generation based on Empire's solar rebate program. Historical installed capacity is converted to monthly generation using monthly load factors and then divided by customers to obtain solar generation per customer. The model assumes no changes in solar generation in the forecast. New solar installations are forecast externally and added to the final forecast after the statistical modelling is complete.
- **Monthly Binaries**. Two monthly binary variables (**Feb** and **Sep**) are included to capture additional seasonality.
- **Binary Variables**. The **OctNov2020** binary variable captures billing data errors in the historical dataset.

SMALL COMMERCIAL BASE SALES FORECAST

The small commercial sales forecast is developed as the product of the customer and UPC forecasts and then adjusted for EV and PV growth. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in FIGURE 15, FIGURE 16, and FIGURE 17.

EV Growth. Electric vehicle growth includes all future EV additions and assumes a portion of the charging takes place at public chargers. Future EV additions are based on the EIA's 2023 AEO forecast of electric vehicle growth adjusted to the expected EV count in Empire's service territory. Based on Empire's 2021 Market Survey, 88% of charging takes place "at-home" and 12% take place at "public chargers". The small commercial class forecast assumes half of the public charging (6%) takes place at commercial businesses.

PV Growth. PV growth includes all future PV. Future small commercial PV additions are based on the EIA's 2023 AEO forecast of PV growth and include a portion of the planned community solar and distributed solar additions. The small commercial portion is based on the current mix of customer solar customers and historical subscription rates of community solar.

Forecast. FIGURE 15 shows the annual sales with and without the EV and PV adjustments. FIGURE 16 shows the customer count forecast and FIGURE 17 shows the average use forecast including EV and PV adjustments. TABLE 17 shows the annual sales, customer, and average use forecast with average growth rates inclusive of the EV and PV adjustments.

FIGURE 15: SMALL COMMERCIAL SALES FORECAST (ACTUAL, NORMALIZED, AND FORECAST)

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FIGURE 16: SMALL COMMERCIAL CUSTOMER FORECAST (ACTUAL AND FORECAST)

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FIGURE 17: SMALL COMMERCIAL UPC FORECAST (ACTUAL AND FORECAST)

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TABLE 17: SMALL COMMERCIAL SALES FORECAST

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7. LARGE COMMERCIAL SALES MODEL

The Large Commercial class consists of customers with the GP, TEB, NS-SP, NS-LG, NS-SP TEB, OP GP, TC-SP, NS-SP Oil, and TC-LG rates. This class is modeled with two models, a Customer Model and a UPC Model. These models capture both class growth based on the number of customers and changing usage patterns based on end use information. The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month. After modelling, the forecast is adjusted for electric vehicle (EV) and behind-the-meter photovoltaic (PV) growth.

CUSTOMER MODEL

The Customer Model is a regression model estimated with historical data from January 2012 through March 2024. TABLE 18 shows the Customer Model specification and TABLE 19 shows the Customer Model statistics.

TABLE 18: LARGE COMMERCIAL CUSTOMER MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	1790.268	48.701	36.761
Total Employment	1177.443	45.767	25.727
Apr2013Dec2013	54.198	6.204	8.736
Apr2020Dec2020	34.433	5.847	5.890
Year2014	-87.871	5.578	-15.753
Year2015	-59.782	5.447	-10.975
Year2016	-28.205	5.328	-5.294
MA(1)	0.437	0.078	5.629

TABLE 19: LARGE COMMERCIAL CUSTOMER MODEL STATISTICS

Statistics	Large Commercial Customer Model
Estimation	1/2012 – 3/2024
R^2	0.965
Adj. R^2	0.963
MAPE	0.28%
DW	1.659

Model Variables. The Customer Model growth is driven by the total employment index. The additional variables capture short-term data shifts and address serial correlation. The variables are described below.

- **Total Employment Index.** The total employment index is the historical and forecast employment for the Springfield MSA and Joplin MSA.
- **Binary Variables.** Five binary variables capture short-term shifts in the number of customers. The **April2013Dec2013** and **April2020Dec2020** binary variables capture 9 month shifts in the customer counts. **Year2014**, **Year2015**, and **Year2016** capture 12 month shifts in the customer counts.
- **MA1.** The MA1 term corrects serial correlation in the model and clarifies the employment index driver.

UPC MODEL

The UPC Model is an SAE model estimated with historical data from January 2012 through March 2024. The SAE model uses the same SAE inputs as the Small Commercial SAE model. TABLE 20 shows the UPC Model specification and TABLE 21 shows the UPC Model statistics.

Commercial SAE Model Summary. The Large Commercial SAE model contains end-use information for heating, cooling, and base load technologies from Itron's 2023 SAE West North Central region. Included in the model are the following data.

- **End-use Saturations and Efficiencies.** End-use saturations and efficiencies by technology type are based on EIA data and adjusted for historical DSM programs.
- **Economic data.** Historical and forecast employment trends are based on Woods and Poole's forecast for the Springfield and Joplin MSA.
- **Energy Prices.** Price is based on historical revenues and energy consumption. The energy prices are held constant in real dollars through the forecast period.

TABLE 20: LARGE COMMERCIAL UPC MODEL

Variable	Coefficient	StdErr	T-Stat
XHeat	9.713	0.756	12.848
XCool	11.573	0.494	23.419
XOther	0.543	0.007	75.747
Apr2020toJul2020	-2389.941	852.955	-2.802
LComSolar_UPC_Hist	-0.355	1.108	-0.321
SepOct2019	2725.318	1174.431	2.321
OctNov2020	3822.864	1172.609	3.260
Year2016	1241.267	516.233	2.404
Year2015	2158.178	529.279	4.078

TABLE 21: LARGE COMMERCIAL UPC MODEL STATISTICS

Statistics	Large Commercial UPC Model
Estimation	1/2012 – 3/2024
R2	0.836
Adj. R2	0.826
MAPE	3.53%
DW	1.223

Model Variables. The UPC Model includes SAE variables (XHeat, XCool, and XOther), a behind-the-meter solar variable, a Covid adjustment variable, and binary variables. These variables are described below.

- **XHeat. XHeat** captures the heating response. The variable includes heating technology efficiencies, heating technology saturations, building types, weather, price, and employment. Heating intensities are adjusted for historical DSM programs.
- **XCool. XCool** captures the cooling response. The variable includes cooling technology efficiencies, cooling technology saturations, building types, weather, price, and employment. Cooling intensities are adjusted for historical DSM programs.
- **XOther. XOther** captures the non-heating and cooling technology impacts. The variable includes baseload technology efficiencies, baseload technology saturations, building types, price, and employment. Baseload intensities are adjusted for historical DSM programs.
- **Behind-the-Meter Solar.** The **LComSolar_UPC_Hist** variable captures the historical impact of behind-the-meter solar generation based on Empire's solar rebate program. The historical installed capacity is converted to monthly generation using monthly load factors and then divided by customers to obtain solar generation per customer. The model assumes no changes in solar generation in the forecast. New solar installations are forecasted externally and added to the final forecast after the statistical modelling is complete. While this variable is statistically insignificant, it has minimal impact but still captures the correct usage response direction (i.e., negative coefficient).
- **Covid Adjustment Variable.** Covid is captured using a binary variable (**Apr2020toJul2020).**
- **Binary Variables.** Four binary variables short-term data shifts and data errors. The annual binaries (**Year2015**, and **Year2016**) capture higher than expected usage in 2015 and 2016. Two trinary variables (**SepOct2019** and **OctNov2020)** capture offsetting data errors in consecutive months.

LARGE COMMERCIAL BASE SALES FORECAST

The large commercial sales forecast is developed as the product of the customer and UPC forecasts and then adjusted for EV and PV growth. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in FIGURE 18, FIGURE 19, and FIGURE 20.

EV Growth. Electric vehicle growth includes all future EV additions and assumes a portion of the charging takes place at public chargers. Future EV additions are based on the EIA's 2023 AEO forecast of electric vehicle growth adjusted to the expected EV count in Empire's service territory. Based on Empire's 2021 Market Survey, 88% of charging takes place "at-home" and 12% take place at "public chargers". The large commercial class forecast assumes half of the public charging (6%) takes place at DC faster chargers.

PV Growth. Behind-the-meter solar growth includes all future PV. Future large commercial PV additions are based on the EIA's 2023 AEO forecast of PV growth and includes expected large customer solar additions. The large commercial portion is based on the current mix of customer solar customers.

Forecast. FIGURE 18 shows the annual sales with and without the EV and PV adjustments. FIGURE 19 shows the customer count forecast and Figure 20 shows the average use forecast including EV and PV adjustments. TABLE 22 shows the annual sales, customer, and average use forecast with average growth rates inclusive of the EV and PV additions.

FIGURE 18: LARGE COMMERCIAL SALES FORECAST (ACTUAL, NORMALIZED, AND FORECAST)

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FIGURE 19: LARGE COMMERCIAL CUSTOMER FORECAST (ACTUAL AND FORECAST)

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FIGURE 20: LARGE COMMERCIAL UPC FORECAST (ACTUAL AND FORECAST)

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TABLE 22: LARGE COMMERCIAL SALES FORECAST

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8. INDUSTRIAL SALES MODEL

The Industrial class consists of customers with the LP and OP LP rate. This class is modeled using a customer count forecast and a UPC Model. The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month.

CUSTOMER FORECAST

Between January 2012 and March 2024, the class increased from 38 customers to 44 customers. The low number of customers and slow growth cannot be reliability forecast using a statistical model. Instead, the industrial customer forecast is based on known customer expansions and projects. In April 2024, one (1) customer is removed from the forecast. Between May 2024 and December 2024, seven (7) new customers are added to the forecast increasing peak demand by 8.2 MW. Beyond 2024, no new customers are added.

UPC MODEL

The existing 44 customers' usage is modelled with a UPC model. The model captures the usage patterns after 2021. TABLE 23 shows the UPC Model specification and TABLE 24 shows the UPC Model statistics.

TABLE 23: INDUSTRIAL UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	1486388.637	9747.643	152.487
CDD55	436.363	21.103	20.678
Apr2020toJul2020	-150561.596	36542.465	-4.120
JantoJul 2021Plus	-102965.835	16781.191	-6.136
Year2012	-160090.437	21977.624	-7.284
Year2013	-124252.937	21977.618	-5.654
Year2014	-93299.771	21974.176	-4.246
Oct2018	-559724.534	71543.347	-7.824
Jan2024	1382362.591	72804.642	18.987

TABLE 24: INDUSTRIAL MODEL STATISTICS

Statistics	Industrial UPC Model
Estimation	1/2012 – 3/2024
R2	0.865
Adj. R2	0.857
MAPE	3.52%
DW	1.655

Model Variables. The UPC model forecasts constant usage based on recent usage patterns after accounting for Covid and outlier data impacts. The variables included in the model are described below.

- **CDD55.** The class's weather response is modelled using the CDD variable with a temperature reference point of 55 degrees.
- **Covid Adjustment**. The **Apr2020toJul2020** variable is binary variable from April 2020 to July 2020 and approximates the decline in industrial usage from Covid health care policy orders.
- **JantoJul 2021Plus**. This is a binary variable for January through July beginning in 2021 and continuing through the forecast period. The variable captures a consistent low-level shift in the first half of the year.
- **Binary Variables.** Five binary variables capture the increasing usage from the changing number of customers and remove outlier data points. The **Year2012**, **Year2013** and **Year2014** variables capture the increasing average usage. The **Oct2018** and **Jan2024** binary variables removes the outlier data.

INDUSTRIAL BASE SALES FORECAST

The industrial sales forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in FIGURE 21, FIGURE 22, and FIGURE 23. TABLE 25 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 21: INDUSTRIAL SALES FORECAST (ACTUAL, NORMALIZED, AND FORECAST)

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FIGURE 22: INDUSTRIAL CUSTOMER FORECAST (ACTUAL AND FORECAST)

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FIGURE 23: INDUSTRIAL UPC FORECAST (ACTUAL AND FORECAST)

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TABLE 25: INDUSTRIAL SALES FORECAST

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TABLE 25 (CONT'D): INDUSTRIAL SALES FORECAST

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9. TRANSMISSION SALES MODEL

The Transmission class consists of customers with the transmission rates. This class is modeled using a customer count forecast and a UPC Model. The transmission sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month.

CUSTOMER FORECAST

Between January 2012 and March 2024, the number of customers varies between 13 and 15. The low number of customers cannot be reliability forecast using a statistical model. Since the number of customers has not dramatically changed, the forecast assumes the existing 13 customers continue through the forecast period with no new additions.

UPC MODEL

The existing 13 customers' usage is modelled with a UPC model. The model captures the seasonal usage pattern and annual usage level shifts. TABLE 26 shows the UPC Model specification and TABLE 27 shows the UPC Model statistics.

TABLE 26: TRANSMISSION UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	1145912.151	9692.198	118.230
Jan	-89423.535	20015.987	-4.468
Feb	-105334.425	19392.702	-5.432
Mar	-112699.408	19392.702	-5.811
Apr	-69183.089	20015.987	-3.456
Jul	82661.712	20015.987	4.130
Aug	89591.911	20015.987	4.476
Nov	-99793.666	20764.707	-4.806
Dec	-127524.786	20015.987	-6.371
Year2015	59028.658	18924.713	3.119
Year2019	74456.587	18924.713	3.934
Year2021	49628.334	20612.471	2.408
Year2022	-73561.114	18924.713	-3.887
Oct2021	380769.592	65368.117	5.825
Nov2021	997017.076	64506.066	15.456
Jan2024	241353.720	67755.317	3.562

TABLE 27: TRANSMISSION UPC MODEL STATISTICS

Statistics	Transmission UPC Model
Estimation	1/2012 – 3/2024
R2	0.804
Adj. R2	0.782
MAPE	3.88%
DW	1.640

Model Variables. The UPC Model captures the average usage seasonal pattern. The following variables are used in the model.

- **Binary Variables.** Eight monthly binary variables (**Jan**, **Feb**, **Mar**, **Apr**, **Jul**, **Aug**, **Nov**, and **Dec**) model the seasonal usage pattern.
- **Dummy Variable.** The **Oct2021**, **Nov2021**, and **Jan2024** binary variables remove outlier data from the model estimation.
- **Binary Shift Variable**. Three annual binary shift variables (**Year2015**, **Year2019**, and **Year2021**) capture short-term usage shifts.

TRANSMISSION BASE SALES FORECAST

The Transmission sales forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in FIGURE 24, FIGURE 25, and FIGURE 26. TABLE 28 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 24: TRANSMISSION SALES FORECAST (ACTUAL AND FORECAST)

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FIGURE 25: TRANSMISSION CUSTOMER FORECAST (ACTUAL AND FORECAST)

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FIGURE 26: TRANSMISSION UPC FORECAST (ACTUAL AND FORECAST)

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TABLE 28: TRANSMISSION SALES FORECAST

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TABLE 28 (CONT'D): TRANSMISSION SALES FORECAST

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11. LIGHTING SALES MODEL

The Lighting class consists of customers with the LS, PL and SPL rates. This class is modeled using two models, a Customer Model and a UPC Model. The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month.

CUSTOMER MODEL

The Customer Model is a regression model estimated with historical data from January 2012 through March 2024 and designed to generate a constant forecast.

TABLE 29 shows the Customer Model specification and Table 30 shows the Customer Model statistics.

TABLE 29: LIGHTING CUSTOMER MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	459.991	1.933	237.992
Year2012	110.667	3.337	33.165
Year2013	89.500	3.337	26.822
Year2014	67.667	3.337	20.279
Year2015	50.167	3.337	15.034
Year2016	50.583	3.337	15.159
Year2017	30.667	3.337	9.190
Year2018	18.667	3.337	5.594
Mar	8.147	3.066	2.657
Apr	12.778	3.163	4.040
May	13.361	3.163	4.224
Jun	14.394	3.163	4.550
Jul	7.477	3.163	2.364
Aug	5.061	3.163	1.600
Sep	7.894	3.163	2.496
Year2022Plus	-32.568	2.806	-11.606
Jun2023toDec2023	27.602	4.470	6.175

TABLE 30: LIGHTING CUSTOMER MODEL STATISTICS

Statistics	Lighting Customer Model
Estimation	1/2012 – 3/2024
R^2	0.955
Adj. R^2	0.949
MAPE	1.51%
DW	1.072

Model Variables. The Customer Model is designed to forecast customers at the 2022 through 2024 level and retain the seasonal pattern. The variables in the model are described below.

- **Annual Binary Shift Variables.** The annual binary shift variables (**Year2012**, **Year2013**, … , **Year2018**) model the decline in lighting customers.
- **Monthly Binary Variables**. The monthly binary variables (**Mar**, **Apr**, …, **Sep**) capture the customer seasonality.
- **Annual Shift Variable**. The annual shift variable (**Year2022Plus**) adjusts the forecast to maintain the 2022 through 2024 consumption level.
- **Binary Variable**. The binary variable (**Jun2023toDec2023**) captures an errant short-term data shift.

UPC MODEL

Historical UPC is increasing as customer counts are decreasing. The model captures the recent usage decline and forecasts a constant average use. TABLE 31 shows the UPC Model specification and TABLE 32 shows the UPC Model statistics.

TABLE 31: LIGHTING UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	9458.900	260.894	36.256
Jan	1398.008	87.595	15.960
Feb	965.529	85.033	11.355
Mar	642.837	84.798	7.581
Apr	368.179	87.421	4.212
Aug	343.378	87.424	3.928
Sep	652.732	90.577	7.206
Oct	977.191	87.609	11.154
Nov	1333.629	87.742	15.199
Dec	-3601.096	282.954	-12.727
Oct2018	4092.621	283.687	14.427
Jan2024	-7.501	0.515	-14.574
LightingCustomers	9458.900	260.894	36.256

TABLE 32: LIGHTING MODEL STATISTICS

Statistics	Lighting UPC Model
Estimation	1/2012 – 3/2024
R2	0.945
Adj. R2	0.940
MAPE	2.10%
DW	1.647

Model Variables. The UPC forecasts constant usage based on recent usage patterns and removes outlier data. The model variables are described below.

- **LightingCustomers.** This variable is the historical and forecast number of lighting customers. As lighting customer counts decrease, the average usage increases representing a consolidation of lighting accounts. The forecast assumes a constant number of customers resulting in a constant average use forecast.
- **Monthly Binary Variables**. The monthly binary variables (**Mar**, **Apr**, …, **Sep**) capture the customer seasonality.
- **Dummy Variables.** The **Oct2018** and **Jan2024** binary variables remove outlier data.

LIGHTING BASE SALES FORECAST

The lighting sales forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in FIGURE 28, FIGURE 29, and FIGURE 30. TABLE 33 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 28: LIGHTING SALES FORECAST (ACTUAL AND FORECAST)

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FIGURE 29: LIGHTING CUSTOMER FORECAST (ACTUAL AND FORECAST)

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FIGURE 30: LIGHTING UPC FORECAST (ACTUAL AND FORECAST)

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TABLE 33: LIGHTING SALES FORECAST

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12. MUNICIPAL SALES MODEL

The Municipal class consists of the Lockwood wholesale customer. This class is modeled using total Lockwood sales in each month. Because the Lockwood will no longer be an Empire customer beginning in June 2025, the forecast model is simplified from the prior IPR models and the forecast is set to "0" beginning in June 2025.

SALES MODELS

The Lockwood sales model is an econometric model that captures recent weather effects and removes outlier data. TABLE 34 shows the Sales Model specification and TABLE 35 shows the Sales Model statistics.

TABLE 34: MUNICIPAL SALES MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	700373.780	12030.340	58.217
wtHDD	282.631	34.284	8.244
wtCDD	1612.146	65.365	24.664
Jan2024	1002888.628	46425.090	21.602
JanFeb2022	-68731.692	31216.427	-2.202
Mar2021	117757.934	44847.570	2.626
Aug2023	-179730.480	46271.713	-3.884
JantoApr2019	95542.600	23848.892	4.006

TABLE 35: MUNICIPAL MODEL STATISTICS

Statistics	Municipal Model
Estimation	1/2012 – 3/2024
R2	0.956
Adj. R2	0.950
MAPE	3.68%
DW	1.914

Model Variables. The sales model utilizes weather and binary variables to capture the seasonality. The variables are described below.

- **Weather Variables**. The **wtHDD** and **wtCDD** variables are heating and cooling degree day variables that capture the weather response. The **wtHHD** uses 55 degrees as its temperature reference point. The **wtCDD** variables is a multipart-spline variable using two temperature reference points, 65 degrees and 75 degrees.
- **Binary Variables**. The model uses 5 binary variables to remove outlier data points and short-term data shifts. These variables are **Jan2024**, **Aug2023**, **JanFeb2022**, **Mar2021**, and **JantoApr2019**.

The municipal sales forecast is shown in FIGURE 31. This figure shows the continued step down of municipal loads (actual loads) with the final step in 2025. Prior to 2021, Empire served four (4) municipal loads. From 2021 through 2024, Empire served one municipal load. The final forecast removes Lockwood in 2025 and sets the forecast to "0".

FIGURE 31: MUNICIPAL SALES FORECAST (ACTUAL AND FORECAST)

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13. SYSTEM PEAK MODEL

The System Peak Model is a regression model that is designed to forecast monthly peaks for the Net System Load (Gross Peaks). Historical monthly peaks are obtained from the historical hourly Net System Loads adjusted to remove historical wholesale customer loads (e.g., Chetopa, Monett, and Mt. Vernon) and restored with estimated curtailments. The model is estimated with data from January 2013 through April 2024. The model is shown in TABLE 36 and the model statistics are shown in TABLE 37.

TABLE 36: SYSTEM PEAK MODEL

Variable	Coefficient	StdErr	T-Stat
Base_Index	58.002	0.695	83.445
HDD40_HeatIndex	13.114	0.680	19.287
CDD65_CoolIndex	8.280	1.310	6.321
CDD75_CoolIndex	16.886	2.532	6.668
Apr2020toMay2020	-117.376	31.043	-3.781
JanFebDec2014	-62.562	28.265	-2.213
Apr15Apr16Apr17	-124.168	25.785	-4.815
WinterPeakTrend2015Plus	43.481	19.070	2.280

TABLE 37: SYSTEM PEAK MODEL STATISTICS

Statistics	Peak Model
Estimation	1/2013 – 4/2024
R2	0.916
Adj. R2	0.911
MAPE	3.73%
DW	1.780

Model Variables. The System Peak Model is driven by the sales forecast and peak producing weather with adjustments for Covid and short-term data shifts. The variables are discussed below.

- **Base_Index. Base_Index** is created using the non-heating and non-cooling sales from class sales models. The sales results are smoothed using a 12-month moving average. This variable is designed to capture the base load contribution to peak growth.
- **HDD40_HeatIndex.** This variable is created as an interaction between the three-day weighted average temperature below 40 degrees and the sales forecast heating component.

The heating component is derived by multiplying the heating variable coefficients from the class sales models by normal heating degree days. The results are smoothed using a 12-month moving average. This variable captures the heating contribution to peak growth.

- **CDD65_CoolIndex.** This variable is created as the interaction between the three-day weighted average temperature above 65 degrees and the sales forecast cooling components. The cooling components are derived by multiplying the cooling variable coefficients from the class sales models by normal cooling degree days. The results are smoothed using a 12-month moving average. This variable is designed to capture the cooling contribution to peak growth.
- **CDD75_CoolIndex.** This variable is the same as the **CDD65_CoolIndex** variable except that the temperature refence point is 75 degrees.
- **Covid Adjustment**. **Apr2020toMay2020** is binary variable from April 2020 to May 2020 and approximates the decline in peak from Covid health care policy orders.
- **WinterPeakTrend2015Plus.** This variable models the seasonal winter peak trend beginning in 2015 and continuing through the forecast horizon. The variable is created by interacting the **HeatIndex** with the seasonal peak month. This variable is designed to capture additional winter peak growth since 2015.
- **Binaries.** Two binary variables are used to capture short-term shifts in the historical data series. The **JanFebDec2014** variable captures errant data for the winter of 2014. The **Apr15Apr16Apr17** variable captures lower than expected April peaks from 2015 through 2017.

Peak Base Forecast Results.

The summer and winter peak forecast compared against actual and normalized data is shown in FIGURE 32 and FIGURE 33. Numerical peak values are shown in TABLE 5. While the peak forecast shows Empire as a winter peaking system, the annual peak may occur in the summer or winter and is sensitive to the peak producing weather.

FIGURE 32: SYSTEM SUMMER PEAK FORECAST

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FIGURE 33: SYSTEM WINTER PEAK FORECAST

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[redacted]

14. HOURLY LOAD FORECAST

The system hourly load forecast is developed using a bottom-up approach, then calibrating the hourly load forecast to the system peak forecast. The process begins with developing nine hourly load profile models, one for each class. Once the hourly load profile models are developed, they are calibrated to the monthly sales forecasts, summed to the system total, and then scaled to the system peak forecast. This section summarizes the hourly profile models and the calibration process.

HOURLY PROFILE MODELS

The hourly profile models are developed as hourly regression models using AMI data. The models are estimated with data from July 2022 through December 2023 to forecast the most recent load shapes. The limited dataset results from the implementation of AMI meters and the new tariff definitions.

While all the models use a similar set of variables, the variables in each class model are adjusted to capture the main load shape drivers. TABLE 38 identifies the variable classes used in each profile model. Definitions of the variable classes are summarized below.

TABLE 38: MODEL VARIABLES BY CLASS

Class	HDD CDD	Day of Week	Month	Year	Holiday	Hours of Light
Residential	X	X	X			
Small Commercial	X	X	X		X	X
Large Commercial	X	X	X	X	X	X
Industrial	X	X	X	X	X	X
Transmission			X	X		
[redacted]			X			
Lighting			X			
Municipal	X	X	X		X	X

- **HDD and CDD Splines.** HDD and CDD spline variables are used to capture the nonlinear load-weather response. The splines are created by examining multiple HDD and CDD variables that use different temperature reference points. Based on the analysis, the temperature splines are weighted together to create weighted average HDD and CDD variables.
- **Day of Week Binaries.** Day of week binary variables capture variations in the profile shape based on the day of the week.
- **Annual Binaries.** Annual binary variables capture load growth changes in the AMI data.

- **Holidays**. Key holidays are identified using this set of binary variables. These holidays capture the unique shape for specific holidays.
- **Monthly Binaries.** Monthly binary variables capture the underlying load shape variation through the seasons of the year.
- **Hours of Light.** Hours of light are calculated based on the sunrise and sunset times in Springfield, Missouri.

CALIBRATION PROCESS

The hourly system loads are calculated by calibrating the class hourly load profiles to the class monthly energy and the system peak forecast. The calibration process ensures that the hourly system loads equal the monthly energy and peak forecasts. The calibration process consists of the following steps.

1. The hourly profile models are forecast through the forecast time horizon using daily normal weather.
2. Each class hourly profile model forecast is calibrated to the class monthly energy (monthly sales scaled for losses) to obtain the class hourly load forecast.
3. The class hourly load forecasts are summed together to obtain the system hourly load forecast.
4. The system hourly load forecast is calibrated to the monthly peak.
5. The system hourly load forecast is adjusted for the behind-the-meter solar and electric vehicles hourly forecasts.

The result of the calibration process is the hourly system load consistent with the monthly peak forecast and energy forecasts adjusted for new solar and EV forecasts.

15. CONCLUSION

The 2025 IRP forecast and scenarios are based on Empire's historical class growth patterns, peak growth patterns, and future electric vehicle and behind-the-meter solar adoption. From **[redacted]** which is consistent with improving technology efficiencies and the penetration of behind-the-meter solar.

The strength of the forecast is its theoretical basis. First, by using the SAE modelling approach for the residential, small commercial, and large commercial classes, the forecast captures the improving efficiencies of existing end-use technologies. Second, the economic drivers represent economic activity in the Joplin and Springfield area which encompasses most of Empire's customers. Third, key uncertainties in behind-the-meter solar and electric vehicle adoption are separated from the statistical models allowing the system shape to change based on technology load profiles. And finally, the statistical models demonstrate strong statistical model fits and variable statistics.

While this report summarizes the forecast models and results from 2025 through 2054, full results are available in the MetrixND and MetrixLT project files, as well as in the associated workpapers.