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Jim,

We are able to provide comments on the availability of T&D in both the London/European market and the US.

From a London / European market approach:

1) Commercial Insurance Market

- There continues to be a primary market for T&D coverage – with rates being charged of circa 33% rate on line.
  - A Primary $20M policy would have a premium cost of approximately $6.6M (100%) – with the policy limit being an annual aggregate.
- For CenterPoint – due to their operating area, we do not believe that there would be more than $50M (annual aggregate) of capacity available – with the rate online for the capacity all being in the range of 33%.

Rates are not economically feasible for relatively low limits of liability.

2) Parametric Product

- The Parametric markets have matured over the last several years and can now offer programs that are more attractive than they historically were – with an Insured being able to purchase coverage for certain groups of designated assets, rather than their entire schedule of assets.
- The Parametric coverage will also be charged on a rate on line, with the rate charged being highly dependent on the group of assets and the excess point for coverage to be triggered.
- The potential lowest rate on line for Parametric coverage could be 5%, but in order to achieve this level of rating, CenterPoint's attachment point for the coverage will need to be a significant and would result in a very large loss being incurred by CenterPoint before any potential amount would be recoverable under a Parametric coverage.
- Limits for these types of products are in the $100M to $200M range.

  Rates are not economically feasible and require a high self insured retention.
  Low severity on prior losses does not support the high premium
  Proceeds from recovery aren't always parallel with actual losses
  Alternative recovery / restoration bonds remain a viable option to support losses

3) Captive Reinsurance

- An Insured could elect to Insure their T&D system via a Captive.
- Reinsurance solutions exist to protect the Captive that will be similar to 1) and 2) – except that the T&D exposures could be packaged with other lines of Insurance to make the high rate on line more acceptable and this could potentially result in tax efficiencies.

  CNP does not currently have a captive insurance company. Capitalization requirements for a captive insurance company for T&D exposure could exceed $100m

US Market Approach:
Limited domestic market appetite. Available market would be offering the coverage on a named (scheduled) line basis at extremely small limits as it would be net capacity. The rate on line would be similar to London in the 30% range.

Rates are not economically feasible for relatively low limits of liability.

Please let us know if you need any additional information.

Sheryl Winslett, CIC
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PUC DOCKET NO. 56211

APPLICATION OF CENTERPOINT	**§**	**PUBLIC UTILITY COMMISSION**
ENERGY HOUSTON ELECTRIC, LLC	**§**	
FOR AUTHORITY TO CHANGE RATES	**§**	**OF TEXAS**

DIRECT TESTIMONY

OF

DR. J. STUART MCMENAMIN

ON BEHALF OF

CENTERPOINT ENERGY HOUSTON ELECTRIC, LLC

MARCH 2024

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EXECUTIVE SUMMARY - LOAD STUDIES & WEATHER NORMALIZATION

DR. J. STUART MCMENAMIN

My testimony explains how hourly data from the CenterPoint Energy Houston Electric, LLC ("CenterPoint Houston") advanced metering system is used to adjust daily and monthly energy usage and billing determinants in order to ensure that its rates are set on data that reflect normal weather, as contemplated by the Public Utility Commission's rate filing package instructions. The weather adjustment method used is reasonable and necessary when preparing rates. Specifically, I address:

- weather adjustment models for daily energy;
- weather adjustment models for class peaks and CP values;
- weather adjustment models for customer maximum demand and billing demand;
- calculation of normal weather;
- unadjusted test year load data;
- adjusted test year load data; and
- adjusted revenue month energy, customer demand and billing demand.

Utilities make weather adjustments to ensure that rates are set to meet revenue requirements in a year with normal weather. By looking at weather data from recent years, we can construct a test year weather pattern that is representative of typical weather conditions. This ensures that rates are not based upon the specific and possibly uncharacteristic weather pattern that occurred in one particular year. The weather adjustment methods summarized in my testimony are consistent with industry practice and the weather adjustment results provide accurate estimates of the impact of weather deviations from normal for the test year ending December 31, 2023. Schedules related to the weather adjustment of energy, class peak, class coincident loads, and customer demand are attached to my testimony.

I. INTRODUCTION

Q. PLEASE STATE YOUR NAME, EMPLOYER, POSITION, AND BUSINESS ADDRESS.

A. My name is John Stuart McMenamin. I am Director of Forecasting at Itron Inc. ("Itron"), 10875 Rancho Bernardo Road, Suite 100, San Diego, CA 92127.

Q. WHAT ARE YOUR RESPONSIBILITIES AS THE DIRECTOR OF FORECASTING AT ITRON?

A. For the last 22 years, I have been employed by Itron as Director of the Forecasting Solutions group. During this period, I have been in charge of development for our Automated Forecasting System which is used by many large system operators, like the California ISO, Midwest ISO, and ERCOT. Also, I am responsible for Itron products and services related to financial forecasting, including the Itron statistical package (MetrixND) which is used by utilities (like CenterPoint Houston, Oncor, CPS Energy, Texas New Mexico Power Company ("TNMP"), Xcel Energy, and Entergy) to analyze and forecast customer growth, sales, revenues, and hourly loads. In addition to product design and algorithm development, I direct or contribute to consulting projects related to forecasting and load research for utilities. For the last 20 years, I have been working with utilities in North America to help them improve analysis and forecasting processes using advanced metering system (AMS) data. The work that was conducted for CenterPoint Houston is an example of this type of work.

Q. PLEASE DESCRIBE YOUR EDUCATIONAL BACKGROUND, PROFESSIONAL QUALIFICATIONS, AND PREVIOUS WORK EXPERIENCE.

A. I received my undergraduate degree in Mathematics and Economics from Occidental College in Los Angeles, California in 1971. My post graduate degree is a Ph.D. in Economics from the University of California, San Diego in 1976. I have worked in the fields of energy forecasting and load research since 1976 and have consulted with many of the major electric and gas utilities in North America. In the 1980's and early 1990's, my work focused on end-use modeling, and I was the principal investigator for the Electric Power Research Institute end-use modeling programs. More recently, my work has focused on methods that combine econometric and end-use concepts. For the last 22 years, I have been employed by Itron, and I am currently Director of the Forecasting Solutions group at Itron. Additional details are available in my resume, which is attached to this testimony as Exhibit JSM-1.

Q. ON WHOSE BEHALF ARE YOU TESTIFYING IN THIS PROCEEDING?

A. I am testifying on behalf of CenterPoint Houston.

Q. HAVE YOU PREVIOUSLY SPONSORED TESTIMONY BEFORE THE PUBLIC UTILITY COMMISSION OF TEXAS ("COMMISSION") OR OTHER REGULATORY AUTHORITIES?

A. Yes. I provided weather normalization testimony in 2019 in the CenterPoint Houston rate case, Docket No. 49421, and in 2018 in the TNMP rate case, Docket No. 48401. In 2022, I provided testimony about future test year energy use in the Public Service Company of New Mexico rate case in New Mexico (Case No. 22-00270-UT).

Q. ARE THERE IMPORTANT DIFFERENCES BETWEEN THE WEATHER ADJUSTMENT YOU RECOMMEND IN THIS PROCEEDING AND THOSE MADE IN THE LAST CENTERPOINT HOUSTON RATE CASES?

A. The modeling approach, based on daily AMS data, remains unchanged. Of course, all models are updated to use the most recent data through the end of the test year. Also, it was necessary to introduce some additional variables to account for the impacts of various phases of the Covid pandemic, which drove residential loads upward and business loads downward in the early phases.

In the prior base rate proceeding, my initial direct testimony used 20-year normal weather. Based on subsequent discovery questions, I also provided estimates based on 10-year normal weather. As in the prior proceeding, my direct testimony in this case uses a 20-year normal weather definition and the data have been updated to use the most recent 20-year period (2004 to 2023). Given this updated data, the method used to compute weather impacts remains unchanged.

Q. DO YOU SPONSOR OR CO-SPONSOR ANY SCHEDULES IN THIS PROCEEDING?

A. Yes. I am sponsoring Schedules related to weather adjustment of energy, class peak, class loads coincident with system peaks, maximum customer demand and billing demand. I sponsor or co-sponsor the following Rate Filing Package ("RFP") schedules including the associated workpapers:

> **Schedule II-H-1.2: Monthly Sales Data** – This schedule provides the unadjusted and adjusted test year sales data and provides monthly weather adjustments for each class. My testimony relates to the weather data, modeling, and analysis used to calculate the weather adjustments presented in this schedule and other schedules listed below.

> **Schedule II-H-1.3: Unadjusted Test Year Load Data** – This schedule provides the unadjusted Test Year data at the customer meter and at the source (busbar) by rate class for each month of the Test Year. Data include the following: Energy usage; Sum of customer maximum demands (non-coincident); Class peak demand (non-coincident); Class demand coincident with the CenterPoint Houston system peak demand; Class demand coincident with the ERCOT peak demand; Monthly class coincidence and load factors.

> **Schedule II-H-1.4: Adjusted Test Year Load Data** – This schedule provides the adjusted Test Year data at the meter and at the source (busbar) by rate class for each month of the Test Year. Data include the following: Sum of customer maximum demands (non-coincident); Energy usage; Class peak demand (non-coincident); Class demand coincident with the CenterPoint Houston system peak demand; Class demand

coincident with ERCOT peak demand; Monthly class coincidence and load factors.

Schedule II-H-2.1: Model Information – This schedule provides descriptive information, definitions, and statistics related to statistical models used to estimate weather adjustments to class sales, class peaks, and class demand. The schedule also provides a complete listing of the model spreadsheet files that are provided as exhibits.

Schedule II-H-2.2: **Model Data** – This schedule provides information about the structure of spreadsheet exhibits for the weather adjustment models. There is one file per model, and each file includes a complete listing of all data used in the model as well as model coefficients and statistics, model predicted values and residuals, and model statistics. Schedule II-H-2.2 lists the worksheet tabs in each file and provides a description of the contents of each tab.

Schedule II-H-2.3: Model Variables – This schedule provides additional variable definitions for daily weather variables constructed from daily heating degree and daily cooling degree variables, as well as lagged daily weather variables, and weather variables that are interacted with seasonal variables and day type variables. An extension of this schedule (II-H-2.3-1) provides the weights used for each class to combine low-powered, medium-powered, and high-powered heating degree (HD) and cooling degree (CD) variables into the CDSpline and HDSpline variables used in the daily energy and peak weather adjustment models.

Schedule II-H-4.1: Revenue Impact Data – This schedule provides unadjusted and adjusted billing determinants. These data are on a billing cycle basis and include weather adjustments to revenue month sales (KWh) and customer demand (KVA), customer billing demand (KVA), and customer load at the time of the four ERCOT system peak days.

Schedule II-H-5.1: Weather Station Data – This schedule provides actual and normal monthly Heating Degree Day ("HDD") and Cooling Degree Day ("CDD") values for each of the three National Oceanic and Atmospheric Administration ("NOAA") weather stations used in the weather normalization analysis. It also provides weighted monthly CDD and HDD values for CenterPoint Houston.

Schedule II-H-5.2: Adjusted Weather Station Data – This schedule provides actual and normal monthly Heating Degree Day (HDD) and Cooling Degree Day (CDD) values computed for individual billing cycles in each month and then combined across cycles. The cycle calculations assume equal weight for each cycle.

Q. HOW DOES YOUR TESTIMONY RELATE TO THE TESTIMONY OF OTHER WITNESSES IN THIS PROCEEDING?

A. My testimony explains how CenterPoint Houston adjusts energy usage, class peak demands, and billing determinants to reflect normal test-year weather. Company witness John Durland explains how the adjusted weather data are used to design rates.

Q. WAS YOUR TESTIMONY, INCLUDING ASSOCIATED SCHEDULES, WORKPAPERS AND EXHIBITS, PREPARED BY YOU OR UNDER YOUR CONTROL AND DIRECTION?

A. Yes.

II. <u>PURPOSE AND SCOPE OF TESTIMONY</u>

Q. WHAT IS THE PURPOSE OF YOUR DIRECT TESTIMONY IN THIS PROCEEDING?

A. The purpose of my testimony is to present the methods and data that were used to develop weather adjustments for the Company's filing, including adjustments for monthly sales, customer demand, billing demand, class peaks, and class loads at the time of CenterPoint Houston and ERCOT peaks. The estimates were developed using AMS data for the CenterPoint Houston population of metered customers. My testimony describes the organization and processing of the 15-minute AMS data, as well as the modeling and weather adjustment calculations.

Q. WHY DO UTILITIES MAKE WEATHER ADJUSTMENTS AS PART OF THE RATE CASE FILINGS?

A. Utilities make weather adjustments to normalize energy usage patterns in the test year. By looking at weather data from recent years, a test year weather pattern is constructed that is representative of typical conditions. This ensures that rates are not based upon the specific and possibly uncharacteristic weather pattern that occurred in one particular year. This is especially important in a test year like calendar year 2023 which had extremely warm weather in the summer months.

Q. WHAT IS THE METHOD USED TO MAKE WEATHER ADJUSTMENTS?

A. First normal weather is defined based on the most recent 20 years of historical hourly temperature data (2004 through 2023). A rank and average approach is used to create a daily weather series that represents normal extreme temperatures as well as normal average values. Second, 15-minute interval data are used to construct daily energy and peak demand values for each customer class. Third, the daily weather data and the daily energy and peak data are combined in statistical models to estimate the response of daily energy and peak values to daily weather conditions. Estimated coefficients from these models are then used to calculate the estimated impact of differences between actual weather and normal weather, and these impacts are used to adjust actual energy and demands. The adjusted energy and demand values are estimates of what would have occurred had weather in the test year been normal.

III. UNADJUSTED TEST YEAR DATA

Q. PLEASE EXPLAIN THE SIGNIFICANCE OF UNADJUSTED TEST-YEAR DATA.

A. Unadjusted test-year data is the starting point for weather adjustment calculations. Unadjusted data provide the base values to which weather adjustments are added. Unadjusted data for the test year and earlier years are also used to estimate models that quantify the impact of weather on energy usage and demand.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE UNADJUSTED TEST YEAR LOAD DATA FOR CENTERPOINT HOUSTON AS PROVIDED IN SCHEDULE II-H-1.3.

A. The process starts with 15-minute AMS data for the population of about 2.76 million CenterPoint Houston customers. CenterPoint Houston provided aggregated interval data for each class for 2019 through 2023. In addition to 15-minute consumption, the number of customers included in each 15-minute calculation was provided.

In addition to the AMS data, the Company provided monthly billing data for each class, including the number of customers, billing month energy, actual monthly customer demand, monthly billing demand, and ERCOT monthly 4CP values for the larger IDR classes.

Q. PLEASE DESCRIBE THE STEPS IN PROCESSING THE 15-MINUTE DATA.

A. The 15-minute data for KWh and number of customers were provided for each class for days between the beginning of January 2019 and the end of December 2023. The classes are:

1. RS – Residential
2. SVS – Small secondary voltage
3. SVL – Large secondary voltage
4. SVL_IDR – Large secondary voltage with IDR meter
5. PVS – Primary voltage
6. PVS_IDR – Primary voltage with IDR meter
7. TVS – Transmission voltage with IDR meter
8. SLS – Street lighting secondary voltage
9. MLS – Other lighting secondary voltage

The KWh and customer data series were inspected graphically in line charts to examine trends, shifts, and spikes in the data. Also, the KWh data were aggregated and compared to CenterPoint Houston system load data. As part of this process a small number of historical data anomalies were identified and corrected. Also, abnormal intervals impacted by outages in the middle of February 2021 were marked for exclusion from the estimation process.

Q. PLEASE EXPLAIN ANY ADJUSTMENT TO THE TEST YEAR LOAD DATA.

A. The AMS data for the test year contains 35,040 15-minute interval values for each class. Out of these intervals, replacement values were estimated for 30 intervals for the SVS class in August of 2023, and replacement values were estimated for 8 intervals for the SVL class in September of 2023. For the remaining classes, no modifications were made to the test-year data.

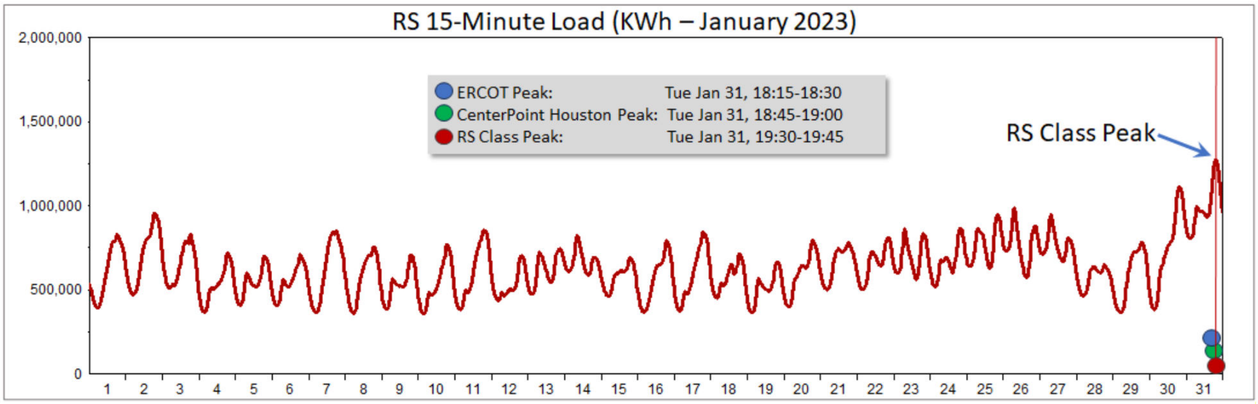
Q. PLEASE DESCRIBE THE AMS AND IDR 15-MINUTE DATA.

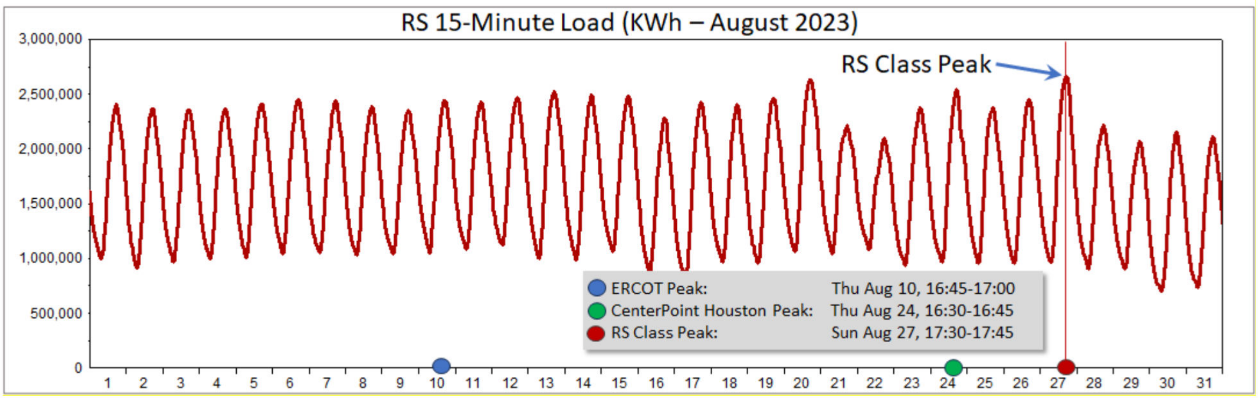
A. 15-minute data were provided for January 2019 through December 2023. These data were used to calculate daily energy, daily class peaks, and class loads coincident with CenterPoint Houston and ERCOT daily peaks. Definitions of the daily variables follow:

> Daily energy. Daily energy was computed by adding the KWh values for the 96 intervals in each day. These totals were divided by 1000 to convert to MWh.
>
> Daily class peaks. For each day, class peaks were identified as the maximum of the 15-minute intervals for that day (in KWh) multiplied by 4 to get a KW equivalent value and divided by 1000 to get a MW equivalent value.
>
> Coincident loads. On each day, the intervals for the CenterPoint Houston system peak and ERCOT peak on that day were identified, and the class loads for those intervals were extracted and multiplied by 4 to get a KW equivalent value and divided by 1000 to get a MW value.

Examples of the data are provided in the following two panels. The first panel shows 15-minute interval data for the Residential class for the month of January, 2023. As shown, the ERCOT Peak, the Company peak and the residential class peak all occur on the evening of the same day (January 31) but at a slightly different time between 6:15 pm and 7:45 pm.

15-Minute Interval Data for RS, January 2023 and August 2023 (Figures 1 and 2)





The second panel shows 15-minute interval data for the residential class in August 2023. As shown, the ERCOT peak, the Company peak and the residential class peaks all occur in the afternoon but on different days.

These 15-minute data are used to compute daily energy, daily class peaks, daily loads at the time of CenterPoint Houston and ERCOT peaks, and monthly load factors and diversity factors. The daily data are also used to estimate weather adjustment models for daily energy, daily class peak loads, and loads coincident with CenterPoint Houston and ERCOT daily peaks.

In addition to the aggregated 15-minute interval data, monthly non coincident customer demand data were provided for each class for the months between January 2021 and December 2023. To compute this value for a month, the maximum 15-minute interval in the month is located for each customer. For each month and customer class, these non-coincident maximum demand values are summed across all customers in the class.

Q. PLEASE EXPLAIN THE DATA USED TO IDENTIFY THE INTERVALS FOR COINCIDENT PEAK CALCULATIONS.

A. ERCOT 15-minute load data were used to identify the time of the ERCOT peak interval each day. Similarly, 15-minute load data for CenterPoint Houston were used to identify the time of the daily peak interval for each day. Once the peak intervals were identified for each day, the load for those intervals was extracted for each of the classes into a daily series for that class.

Q. HOW WERE LOSS FACTORS APPLIED TO THE AMS INTERVAL DATA TO DETERMINE ENERGY AND PEAK LOADS AT THE SOURCE?

A. AMS data is measured at the customer meter. To inflate these measured values for transmission and distribution losses, we applied distribution loss factors (DLF) and transmission loss factors (TLF) based on 15-minute loss factor data from ERCOT. The Company has two distribution loss factor categories, one for loads at secondary voltage and one for loads at primary voltage. For both categories, ERCOT calculates distribution loss factors for each 15-minute interval based on the ERCOT load in that interval.

The DLF values were applied to all classes except Transmission. The TLF values were applied to all classes. For all classes except Transmission, the formula for each 15-minute interval is:

$$\text{Load@Source} = \text{Load@Meter} \times (1+\text{DLF}) \times (1+\text{TLF})`$$

For the transmission class, the form is the same but the term with DLF is excluded.

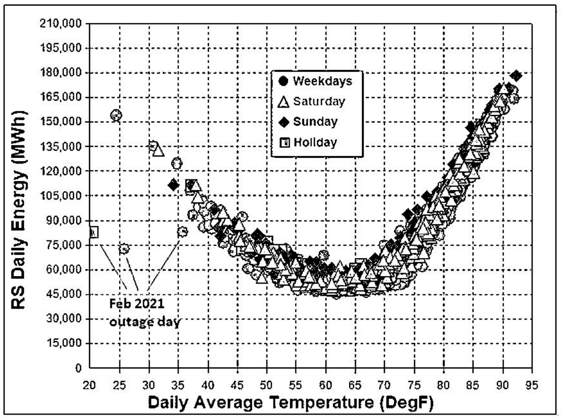
The 15-minute data for Load@Source and the 15-minute data for Load@Meter were then used to compute loss factor multipliers for daily and monthly energy, daily and monthly class peaks, and daily and monthly coincident peaks.

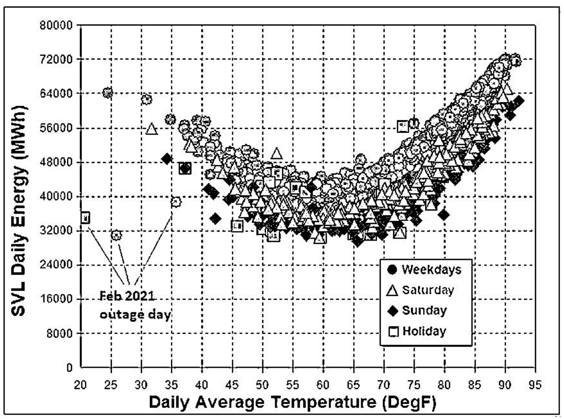
IV. WEATHER ADJUSTMENT MODELS FOR ENERGY

Q. PLEASE EXPLAIN THE MODELING PROCESS USED TO CALCULATE WEATHER ADJUSTMENTS FOR DAILY ENERGY.

A. To adjust test-year energy, we start with models of actual energy usage for each day of the test year. The models are used to calculate daily weather adjustments for each day. The daily adjustments are added across days in the month to get calendar month energy adjustments. The daily adjustments are added across days in monthly billing cycles to get revenue month energy adjustments. The process begins with a review of daily AMS data for each class. As an example, the following figures show scatter plots of daily energy versus daily average temperature for the residential (RS) and large secondary (SVL) classes. These two classes account for more than 90% of the total weather adjustment for the test year.

Daily Energy vs. Daily Average Temperature for RS and SVL (Figures 3 and 4)





In the charts, each point is one day. The charts show daily data for 2019 through 2023, so there are over 1,800 data points in each chart. The Y-axis is daily energy (computed from the 15-minute AMS data) in MWh. The X-axis is daily average temperature, computed from the hourly temperature values for three weather stations in the CenterPoint Houston service area. The points are color coded, with weekdays as blue circles, Saturdays as orange triangles, Sundays as red diamonds, and Holidays as green squares.

The charts show us where weather starts to matter on the warm side (about 65 for RS and about 60 for SVL). It also shows that not all degrees are equal and that the early degrees cause a much weaker lift in daily energy than the more extreme degrees. Finally, it shows a strong heating response on the cold side for RS and SVL classes, starting at about 60 degrees in both cases.

For each class, the modeling process starts by quantifying the nonlinear shape of the weather response using a preliminary regression to determine the relative strength of low-powered, medium-powered, and high-powered degrees for that class. This is accomplished by including multiple Heating Degree and Cooling Degree variables in the preliminary regression. On the cooling side, the coefficients from this regression are then used to construct a cooling degree spline that combines the successive cooling degree variables. On the heating side, the coefficients from this regression are used to construct a heating degree spline that combines the successive heating degree variables. I believe that the use of these spline variables is an effective and accurate method for modeling the nonlinear relationship between weather and customer load and for calculating weather adjustments for daily energy and daily peak loads.

To illustrate this process, consider the following example for the residential model. The preliminary regression for this class provides the following coefficients on the cooling side.

Example of Preliminary Regression and Spline Weight Calculation (Figure 5)

(1) Variable	(2) Coefficient (KWh/Degree)	(3) Standard Error	(4) T Statistic	(5) Spline Weight
CD65-70	0.496	0.048	10.42	20.2%
CD70-75	1.204	0.057	21.22	28.8%
CD75-80	1.948	0.052	37.11	30.2%
CD80+	2.458	0.030	81.15	20.8%

The estimated coefficients in column (2) are the slopes for each successive cooling degree variable. The models are estimated with daily KWh per customer as the Y variable, so the unit of measurement for these slopes is daily KWh per customer per degree. The first variable (CD65-70) is for low powered degrees, and the estimated impact is about .50 KWh per degree. Moving above 70 degrees, this jumps up to 1.20 KWh per degree. Moving above 75 degrees, the impact increases to 1.95 KWh per degree. Finally, moving past 80 degrees, the impact increases to 2.46 KWh per degree. In this case, high powered degrees (above 80) have almost 5 times the impact of low powered degrees (over 65).

The standard errors and T Statistics in columns (3) and (4) show that these slopes are well defined and highly significant. The spline weights in column (5) are computed from these values by dividing the change in the estimated impact by the largest coefficient. If all coefficients are positive, this normalizes the weights to sum to 1.0. For the residential coefficients shown above, the initial cooling variable for degrees above 65 (CD65) has a spline weight of .202 (computed as .496/2.458), indicating that these degrees have about 20% of the impact of the high-powered degrees. The second term (CD70) adds an additional 29% (computed as [1.204-.496]/2.451. Using the same logic, the third and fourth terms add 30% and 21%, respectively.

With these weights, the CD spline variable is computed as:

CDSpline = .202 * CD65 + .288 * CD70 + .302 * CD75 + .208 * CD80

The comparable heating degree spline variable is:

HDSpline = .402 * HD60 + .024 * HD55 + .317 * HD50 + .257 * HD45

Once constructed, the daily HDSpline and CDSpline series provide powerful variables that are nonlinear in temperature and that capture the shape of the weather response. These variables are used to estimate models that explain variations in daily energy use per customer based on daily weather variations. As I will show below, the estimated models are then used to compute daily weather adjustments for the test year.

Q. DO THE MODELS FOR DIFFERENT CLASSES USE THE SAME COOLING DEGREE AND HEATING DEGREE SPLINE VARIABLES?

No. Each class is evaluated separately to determine which HD and CD variables should be included. Generally, as customers get larger, the balance point between heating and cooling moves to the left. For small customers, cooling typically begins to show up at 65 and heating begins to show at 60 degrees. For larger customers, weather effects usually start at lower temperatures. For the largest customers, weather effects can be hard to detect. For example, for the largest CenterPoint Houston class (TVS) there was no detectable heating or cooling activity.

The following table shows the HD and CD weights that were estimated for the different classes for purposes of modeling daily energy use. More details are provided in Schedule II-H-2.3 which provides the weights that were used for energy and peak models.

HD and CD Spline Weights for Daily Energy Models (Figure 6)

	Heating Degree Weights				Cooling Degree Weights				
Class	HD60	HD55	HD50	HD45	CD60	CD65	CD70	CD75	CD80
RS	40.2%	2.4%	31.7%	25.7%		20.2%	28.8%	30.2%	20.8%
SVS	33.6%		66.4%			16.2%	47.7%	36.1%	
SVL	25.3%		58.9%	15.9%	17.8%	10.9%	33.0%	23.9%	14.5%
PVS	34.8%		65.2%		16.2%	8.0%	23.1%	30.5%	22.3%
SVL_IDR		100.0%			41.0%		39.4%	18.5%	1.1%
PVS_IDR		100.0%			35.4%		51.9%		12.6%

Q. PLEASE EXPLAIN THE WEATHER ADJUSTMENT MODELS AND HOW THE SPLINE VARIABLES ARE USED IN THESE MODELS.

For energy and class peak demands, the weather adjustment models are daily models. The models include a constant term and a variety of daily calendar variables as well as the HDSpline and CDSpline variables. The calendar variables are:

-- Monthly binary variables for January through November (December excluded)

-- Day of the week variables for Saturday and Sunday

-- Specific holiday variables for holidays from New Year's Day through Christmas

-- Covid variables for four phases starting in the middle of March, 2020

-- Class specific binary variables to account for irregular data

In addition to the HDSpline and CDSpline variables, additional weather interaction variables are included in some of the models.

-- Two-day weighted lag of HDSpline and CDSpline variables with 85%/15% weights

-- Binary variable for weekend and holidays interacted with HDSpline and CDSpline

-- Spring day variable interacted with HDSpline and CDSpline

-- Fall day variable interacted with HDSpline and CDSpline

-- End shift variable (active in 2022 and 2023) interacted with HDSpline and CDSpline

The full set of estimated models is included in the working papers filed with this testimony. As an example, the following table provides the estimated coefficients for the residential (RS) daily energy model with a first order Autoregressive term (AR1).

The coefficients that matter for the weather adjustment calculations are the last 10 variables, five for heating and five for cooling. These estimated coefficients all give weather responses in units of KWh per customer per full powered heating degree or per full powered cooling degree. For the residential model, the main HDSpline and CDSpline variables have very strong statistical significance (T statistics greater than 50), and the lag and interaction variables are also significant (T statistics greater than 2).

The LagHD and LagCD variables capture the carryover effect of prior day temperatures onto the current day. For example, for the residential model, the lagged effect for heating is .374 KWh per degree, which is about 28% of the same-day coefficient on HDSpline (1.354 KWh per degree). For cooling, the lag effect is .393 KWh per degree, which is about 18% of the same-day coefficient on CDSpline (2.204 KWh per degree).

The weekend interactions (WkEndHD and WkEndCD) allow the weather response to be different for weekend days and holidays than it is for weekdays. For residential heating, the HDSpline slope is estimated to be about .157 KWh per degree smaller on weekend days than it is on weekdays. For residential cooling, the CDSpline slope is estimated to be about .037 KWh per degree bigger on weekend days than it is on weekdays.

Estimated Coefficients for Residential Model with AR1 (Figure 7)

Type	Variable	Coefficient	Standard Error	T Statistic	Units of Measure	Variable Defnintion
Intercept	CONST	22.789	0.322	70.767		Constant term
Month	Jan	-1.233	0.376	-3.282	Binary	Binary = 1 in January
Month	Feb	-1.455	0.380	-3.835	Binary	Binary = 1 in February
Month	Mar	-1.312	0.373	-3.520	Binary	Binary = 1 in March
Month	Apr	-0.408	0.385	-1.060	Binary	Binary = 1 in April
Month	May	1.119	0.409	2.737	Binary	Binary = 1 in May
Month	Jun	1.295	0.466	2.777	Binary	Binary = 1 in June
Month	Jul	0.955	0.497	1.921	Binary	Binary = 1 in July
Month	Aug	0.834	0.502	1.661	Binary	Binary = 1 in August
Month	Sep	0.268	0.445	0.604	Binary	Binary = 1 in September
Month	Oct	0.130	0.377	0.346	Binary	Binary = 1 in October
Month	Nov	-0.944	0.353	-2.672	Binary	Binary = 1 in November
Day	Saturday	0.773	0.121	6.386	Binary	Binary = 1 on Saturday
Day	Sunday	1.630	0.120	13.579	Binary	Binary = 1 on Sunday
Holiday	MLK	2.029	0.547	3.712	Binary	Binary = 1 on M L King Day
Holiday	PresDay	0.651	0.610	1.067	Binary	Binary = 1 on Presidents Day
Holiday	GoodFri	-0.910	0.543	-1.675	Binary	Binary = 1 on Good Friday
Holiday	MemDay	1.381	0.552	2.502	Binary	Binary = 1 on Memorial Day
Holiday	July4th	0.368	0.559	0.658	Binary	Binary = 1 on Independence Day
Holiday	LaborDay	2.445	0.555	4.410	Binary	Binary = 1 on Labor Day
Holiday	Thanks	2.600	0.601	4.329	Binary	Binary = 1 on Thanksgiving Day
Holiday	FriAThanks	-0.149	0.604	-0.247	Binary	Binary = 1 on Friday after Thanksgiving
Holiday	XMasWkB4	0.692	0.379	1.827	Binary	Binary = 1 on week before XMas
Holiday	XMasEve	0.839	0.633	1.325	Binary	Binary = 1 on XMas Eve
Holiday	XMasDay	0.814	0.703	1.158	Binary	Binary = 1 on XMas Day
Holiday	XMasWk	-0.367	0.563	-0.653	Binary	Binary = 1 during week after XMas
Holiday	NYEve	1.110	0.645	1.722	Binary	Binary = 1 on New Years Eve
Holiday	NYDay	1.265	0.652	1.941	Binary	Binary = 1 on New Years Day
Covid	Phase1	2.611	0.424	6.152	Binary	Binary = 1 in Apr and May 2020
Covid	Phase2	1.516	0.282	5.376	Binary	Binary = 1 for June through Nov 2020
Covid	Phase3	0.123	0.323	0.382	Binary	Binary = 1 for Dec 2020 to March 2021
Covid	Phase4	-0.863	0.178	-4.848	Binary	Binary = 1 for April 2021 and beyond
Heating	HDSpline	1.354	0.025	53.295	DegF	Heating Degree Spline
Heating	LagHD	0.374	0.024	15.346	DegF	Two day lagged HD (85/15 weights)
Heating	WkEndHD	-0.157	0.031	-5.001	DegF	Heating Deg Spline on Weekend Days
Heating	FallHD	-0.390	0.064	-6.070	DegF	Heating Deg Spline on Fall Days
Cooling	CDSpline	2.204	0.025	89.913	DegF	Cooling Degree Spline
Cooling	LagCD	0.393	0.022	17.545	DegF	Two day lagged CD (85/15 weights)
Cooling	WkEndCD	0.037	0.014	2.618	DegF	Cooling Deg Spline on Weekend Days
Cooling	SpringCD	-0.275	0.066	-4.163	DegF	Cooling Deg Spline on Spring Days
Cooling	FallCD	-0.183	0.064	-2.871	DegF	Cooling Deg Spline on Fall Days
AR1	AR(1)	0.548	0.02	27.413		

For heating, the FallHD variable allows weather response to be different for months leading into winter, and the estimated coefficient is -.390 KWh per degree, which indicates that Fall responses are about 29% weaker than Winter responses. The SpringHD variable was statistically insignificant and was not included in the final model. For cooling, both SpringCD and FallCD terms indicate that the responses to hot weather are smaller for months before and after the summer months. Although the differences are small, both slope differences are statistically significant.

For the residential model, the HDSpline and CDSpline end-shift variables were not included in the final specification because they were numerically small and not statistically significant (T-Statistics less than 1.0). This indicates that the main weather slopes in 2022 and 2023 were not significantly different than the average slopes over the full estimation period for this class.

The estimated coefficients are used to compute daily weather impacts and weather adjustments. The weather impact is the difference between the model predicted value with actual weather and the model predicted value with normal weather. If the weather impact is positive, this means that actual weather was more extreme than normal, indicating that usage needs to be adjusted downward. If the weather impact is negative, this means that actual weather was less extreme than normal, indicating that usage needs to be adjusted upward.

As an example on the cold side, January of 2023 was extremely mild. As a result, heating energy was less than expected and a positive weather adjustment for heating was required to bring heating energy back up to normal levels in this month.

As an example of hot weather, all the summer months were significantly hotter than normal. As a result, cooling energy was significantly higher than expected and negative weather adjustments were required to bring cooling energy down to normal levels in these months.

Q. AN AUTOREGRESSIVE ERROR TERM HAS BEEN INCLUDED IN THE WEATHER ADJUSTMENT MODELS. DOES THIS MAKE A DIFFERENCE?

A. Before adding the autoregressive term, it is important to build a strong static model to ensure the right functional form exists. Otherwise, the autoregressive term could disguise a specification problem. In the working papers, both the static model results (without the AR1 term) and the dynamic model results (with the AR1 term) are provided. For example, the following provides the residential model coefficient estimates for the HD and CD variables from both specifications.

RS Daily Energy Model Weather Coefficients (Figure 8)

		Static Model (No AR1)			Dynamic Model (with AR1)		
Type	Variable	Coefficient	Std Error	T-Stat	Coefficient	Std Error	T-Stat
Heating	HDSpline	1.374	0.028	48.741	1.354	0.025	53.295
Heating	LagHD	0.366	0.026	13.872	0.374	0.024	15.346
Heating	WkEndHD	-0.120	0.040	-2.959	-0.157	0.031	-5.001
Heating	FallHD	-0.398	0.060	-6.634	-0.390	0.064	-6.070
Cooling	CDSpline	2.236	0.027	83.011	2.204	0.025	89.913
Cooling	LagCD	0.332	0.025	13.305	0.393	0.022	17.545
Cooling	WkEndCD	0.041	0.017	2.503	0.037	0.014	2.618
Cooling	SpringCD	-0.185	0.063	-2.937	-0.275	0.066	-4.163
Cooling	FallCD	-0.055	0.059	-0.924	-0.183	0.064	-2.871

The coefficient pattern from the two specifications is consistent, and in most cases the coefficient estimates from the two specifications are well within two standard errors of each other. For example, the CDSpline coefficient is 2.236 KWh per degree in the static model and 2.204 KWh per degree in the model with the AR1 term. Both parameters are strongly statistically significant (t-statistics > 80). The coefficient standard error in both models is about .025, so the two slopes are basically the same in a practical sense and in a statistical sense. This coefficient stability is the signature of a strong well specified model.

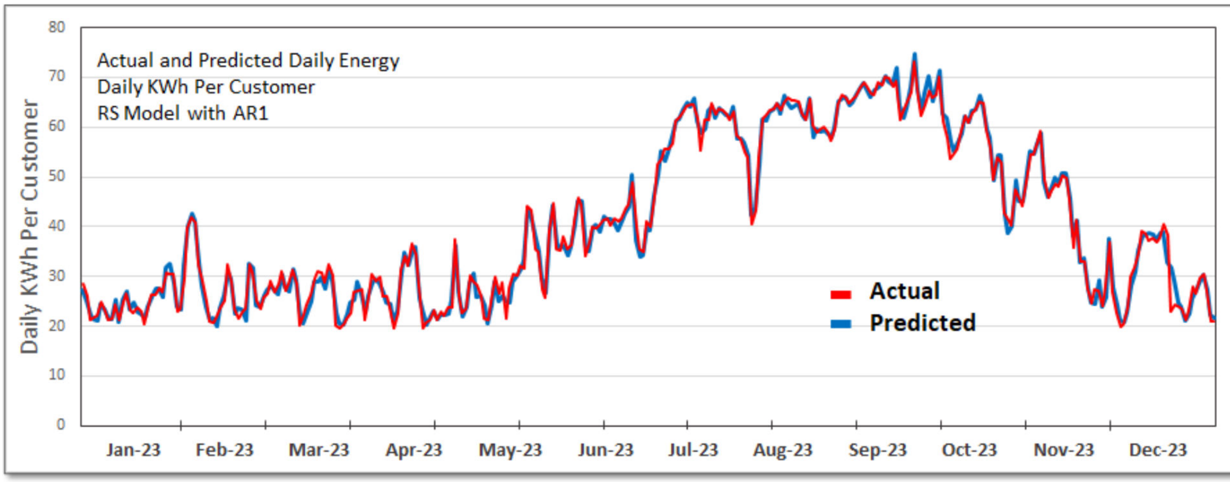
Both sets of models for all classes are included in the working papers filed with this testimony. The weather adjustments presented in the Schedules are from the models with the AR1 terms, but the results would not differ materially if the static models were used.

Q. HOW WELL DO THESE MODELS EXPLAIN THE DAILY VARIATION IN ENERGY?

A. Generally, these models are very strong and explain the daily variations with good accuracy. For example, the following chart shows the actual and predicted daily energy values for the residential model for the test year ending in December 2023.

In the chart, the red line is the actual daily energy computed from the 15-minute AMS data and the blue line is the model predicted values. Clearly the model works extremely well throughout the year.

Actual and Predicted Values for the Test Year– Residential Model with AR1 (Figure 9)



The following provides the residential model statistics for the static (without AR1) and dynamic (with AR1) residential models.

RS Energy Model Statistics (Figure 10)

Residential (RS) Daily Energy Model Statistics	Static Model (No AR1)	Dynamic Model (With AR1)
Adjusted Observations	1,820	1,819
Deg. of Freedom for Error	1,779	1,777
R-Squared	0.987	0.991
Adjusted R-Squared	0.986	0.990
AIC	1.010	0.664
BIC	1.134	0.791
Std. Error of Regression	1.639	1.378
Mean Abs. Dev. (MAD)	1.282	1.039
Mean Abs. % Err. (MAPE)	3.82%	3.18%
Durbin-Watson Statistic	0.927	1.991

The quality of the model fit is excellent with mean absolute percent error (MAPE) values of 3.82% for the static model and 3.18% for the dynamic model. The Durbin-Watson statistic provides an indicator of first order autocorrelation. This statistic ranges from 0 to 4 and values that are near 2.0 indicate absence of first order autocorrelation. As values decline toward 0.0, this provides increasing evidence of positive autocorrelation. As values rise toward 4.0, this provides increasing evidence of negative autocorrelation. For the static model, the value of .93 indicates strong positive autocorrelation. With the AR1 correction there is no indication of first order autocorrelation (as indicated by the Durbin-Watson statistic of 1.99).

The following table provides the daily energy model summary statistics for all weather sensitive classes. As this shows, the model fit for all classes is strong, with mean absolute percentage error (MAPE) values ranging between 1.2% and 3.2%.

Model Statistics for Daily Energy Models with AR1 (Figure 11)

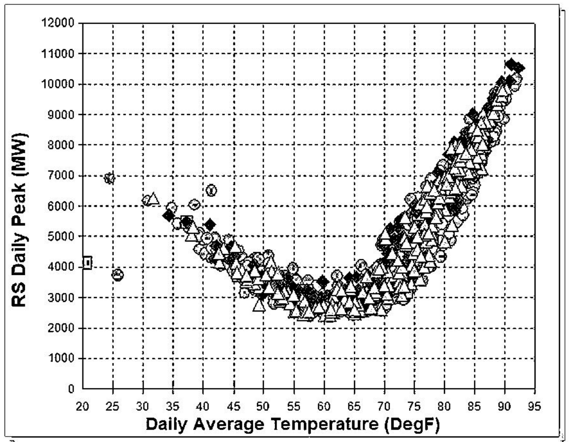
Daily Model Statistic	(RS) Residential	(SVS) Small Secondary	(SVL) Large Secondary	(SVL_IDR) Large Secondary IDR	(PVS) Primary	(PVS_IDR) Primary IDR
Adjusted Observations	1,819	1,811	1,799	1,817	1,692	1,811
Deg. of Freedom for Error	1,777	1,769	1,757	1,776	1,650	1,771
R-Squared	0.991	0.970	0.984	0.976	0.972	0.956
Adjusted R-Squared	0.990	0.969	0.984	0.976	0.972	0.955
AIC	0.664	-2.493	4.292	10.831	8.071	12.148
BIC	0.791	-2.366	4.420	10.955	8.206	12.270
Std. Error of Regression	1.38	0.28	8.45	222.37	55.88	429.69
Mean Abs. Dev. (MAD)	1.04	0.20	6.03	153.60	40.66	321.91
Mean Abs. % Err. (MAPE)	3.18%	1.18%	1.83%	1.63%	2.22%	1.84%
Durbin-Watson Statistic	1.991	2.100	2.008	1.921	2.118	1.988

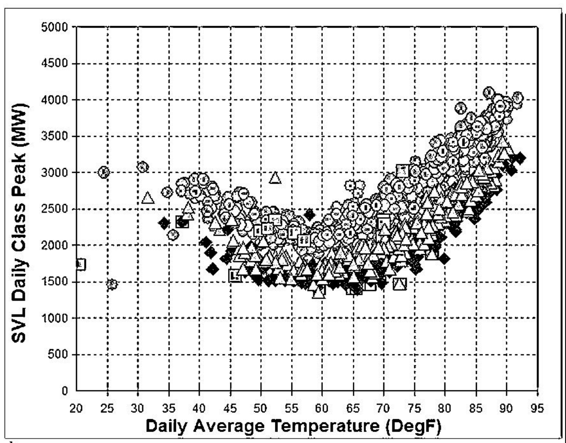
V. <u>WEATHER ADJUSTMENT MODELS FOR CLASS PEAKS</u>

Q. PLEASE EXPLAIN THE MODELING PROCESS USED TO CALCULATE WEATHER ADJUSTMENTS FOR CLASS PEAK MODELS.

A. In addition to adjusting energy data to reflect normal weather, it is important to understand the impacts of weather on peak loads for each customer class (class peaks), and to know about class loads at the time of overall system peak loads (coincident peak (CP) values). The daily class peak models are similar to the daily energy models, except daily class peak load is the variable that is explained instead of daily energy. As examples, the following figures show scatter plots of daily class peak vs daily average temperature for the residential (RS) and large secondary (SVL) classes.

Daily Class Peak vs. Daily Average Temperature for RS and SVL (Figures 12 and 13)





These graphs show weather response patterns for daily class peaks that are similar to the daily energy patterns. However, there are some differences, and as a result, we estimated a different set of HD and CD weights for the class peak and coincident peak models. These weights are shown in the following table.

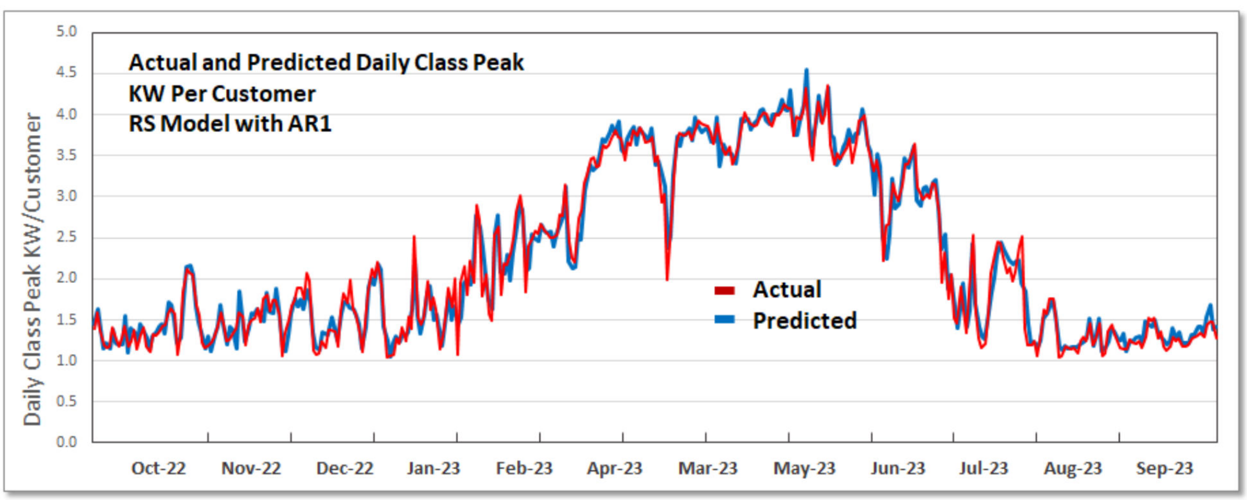
HD and CD Spline Weights for Class Peak Models (Figure 14)

Class	Heating Degree Weights				Cooling Degree Weights				
	HD60	HD55	HD50	HD45	CD60	CD65	CD70	CD75	CD80
RS	48.4%		51.6%			37.6%	12.9%	33.2%	16.3%
SVS	21.9%		78.1%			27.9%	26.6%	21.8%	23.8%
SVL	19.4%	29.9%	50.7%		43.9%		27.6%	28.5%	-4.8%
PVS	59.4%		40.6%		29.8%		25.1%	18.9%	26.1%
SVL_IDR		100.0%			52.9%		22.2%	24.9%	-17.4%
PVS_IDR		100.0%			49.8%		35.1%		15.1%

The class peak models contain the same set of explanatory variables discussed above for the daily energy models. The working papers filed with this testimony contain spreadsheets that show the data used in the models as well as estimated coefficients, model statistics, and actual and predicted values. Spreadsheets are provided for static models and for dynamic models with AR1 adjustments. The models with AR1 adjustments are used to compute the weather adjustments presented in the Schedules.

Like the daily energy models, the class peak models are very strong and explain most of the variation in daily class peaks. For example, the following chart shows the actual and predicted values for the residential daily class peaks in the test year.

Actual and Predicted Daily Class Peak – Residential Model with AR1 (Figure 15)



The class peak models have errors that are slightly larger than for the energy models. The mean absolute percent errors for these models range from 1.4% (Small

Secondary (SVS)) to 6.4% (Residential). As with the energy models, weather slopes are well defined and strongly significant.

Q. HOW DO THE COINCIDENT PEAK (CP) MODELS DIFFER FROM THE CLASS PEAK MODELS?

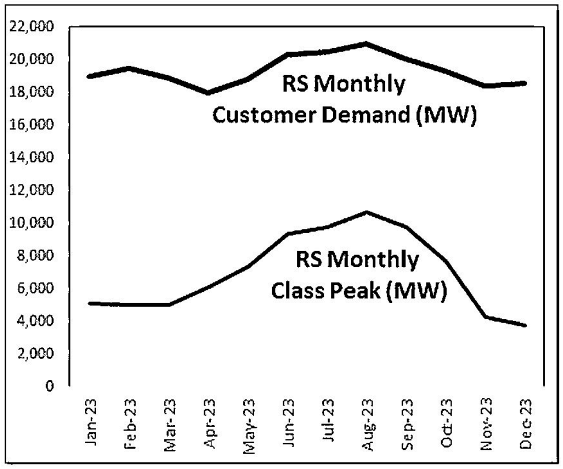
A. Two sets of daily CP models are estimated, one using loads at the time of the daily CenterPoint Houston peaks and the other using loads at the time of the daily ERCOT peaks. The CP models use the same set of weather variables and the same model specifications that are used in the daily class peak models. The model estimation results for the CP models are not as strong as the results for the NCP models reflecting the differences in timing for the daily CP values. MAPE values for the CenterPoint CP models range from 3.6% (PVS_IDR) to 8.7% (SVS). MAPE values for the ERCOT CP models range from 3.5% (PVS_IDR) to 9.4% (SVS). The full set of model results with and without AR1 terms is included in the working papers filed with this testimony.

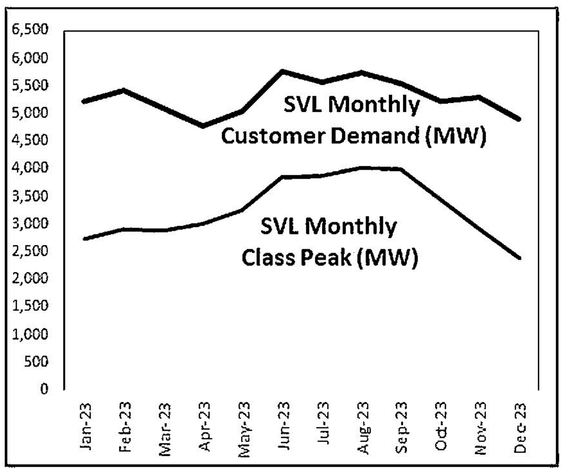
VI. <u>WEATHER ADJUSTMENT MODELS FOR CUSTOMER DEMAND</u>

Q. PLEASE EXPLAIN THE MODELS USED TO ADJUST CALENDAR MONTH CUSTOMER DEMAND.

Customer demand for a calendar month is the sum of the individual customer maximum demands in the month. Customer demand differs from class peak demand since individual customers have maximum demand values on different days in the month and at different times of day. This load diversity implies that customer demand in a month is a bigger number than the class peak demand in the month. The following shows the monthly customer demand and class peak data for the residential (RS) and large secondary (SVL) classes for the months in the test year.

Monthly Class Peak and Customer Demand for RS and SVL (Figures 16 and 17)





For the residential (RS) class, the sum of the monthly customer demand values is almost three times as large as the sum of the monthly class peaks. For the large secondary (SVL) class, the sum of the individual customer demands is about 62% larger than the class peaks. Despite the larger scale, of the customer demands, there is less variation from month to month in the sum of the customer demands. This indicates that the sum of the maximum customer demands is less sensitive to weather than the class peaks. As a result, we expect to find lower percentage weather adjustments for the customer demands.

The models for customer demand are relatively simple and use only the data from January 2021 to December 2023. For the heating side, the models include the largest value of HD55 in each month, representing the coldest day. For the cooling side, the models include the largest value of CD70 for each month, representing the hottest day. The models also include a variable for the number of customers to account for growth over time.

The estimated model coefficients are shown below. The estimated coefficients are statistically significant in most cases, as indicated by T-statistics greater than 2.0. The exceptions are SVL_IDR and PVS_IDR, both of which have weak weather sensitivity on the cold side. For PVS_IDR, the cold side variable was strongly insignificant (T-statistic less than 1.0) and was excluded from the equation. The slopes are in terms of MW per degree, and as expected the largest slopes are for the residential (RS) class, which has a hot side slope of 168.2 MW per degree, and the large secondary (SVL) class, which has a hot side slope of 50 MW per degree.

Estimated Coefficients from Calendar Month Demand Models (Figure 18)

	Coldesd Day (MaxHD55)			Hottest Day (MaxCD70)		
Rate Class	Coefficient	Std Error	T-Stat	Coefficient	Std Error	T-Stat
Residential (RS)	98.80	11.70	8.45	166.19	15.83	10.50
Secondary Voltage Small (SVS)	1.51	0.16	9.65	2.15	0.28	7.55
Secondary Voltage Large (SVL)	33.08	4.11	8.05	49.47	5.01	9.88
Secondary Voltage Large IDR (SVL-IDR)	1.78	1.46	1.22	30.59	2.64	11.58
Primary Voltage Service (PVS)	0.57	0.10	5.74	0.82	0.20	4.17
Primary Voltage Service IDR (PVS-IDR)	0.00	0.00		6.35	0.77	8.23

Although the models are simple, they explain customer demand very well with mean absolute percent errors ranging from 1.24% for the SVS class to 4.01% for the PVS class.

In the working papers, we have provided spreadsheets that contain the data used to estimate these models as well as the estimated coefficients, model statistics, and actual and predicted values.

To calculate weather adjustments for calendar month customer demand, the estimated models are used to simulate predicted customer demands using normal values of HD55 for the coldest day in each month and the normal values of CD70 for the hottest day in each month. The difference between the model predicted value with actual inputs and the model simulated value with normal inputs is the weather impact for each calendar month. These impacts are subtracted from the actual demands to give the weather adjusted calendar month demand estimates.

Q. PLEASE EXPLAIN MODELS USED TO WEATHER ADJUST REVENUE MONTH CUSTOMER DEMAND.

A. Revenue month customer demand models explain monthly demand values from customer billing data. These values are measured in kilo-volt amperes or kVA. Models are estimated for only two classes, large secondary (SVL) and primary (PVS). These are the only two classes that use actual customer maximum demand during a billing cycle as a billing determinant.

The maximum demand value in a revenue month for a customer corresponds to the largest load that occurs during the days of the billing cycle to which the customer is assigned. Not only are the individual customer demands occurring on different days and at different times, but the set of days included is different for each of the 21 billing cycles. In addition, the number of billing cycles included in a revenue month can vary. For example, in 2023, the March and August billing months included 23 cycles. In contrast, the April billing month included only 19 cycles. A difference of 4 cycles would imply an expected 19% variation in monthly class sales and monthly demand if customers are evenly distributed across the 21 cycles.

The demand models are estimated using billing data from 2019 through 2023. To account for customer growth, the models are estimated based on billing demand per customer. To account for the difference in the number of cycles contributing to each month, the demand per customer values are further normalized to represent 21 full cycles. In equation form, the Y variable in the revenue month demand equation for a class is:

$$Y(m) = (DemandKVA(m)/Customers(m)) * (21/NCycles(m))$$

In this expression DemandKVA(m) is the sum of the customer maximum demand values in KVA and NCycles(m) is the number of billing cycles contributing to revenue in each billing month (m).

As with the sum of the calendar month customer demands computed from AMS data, the sum of the actual demand values for a revenue month is larger than the monthly class peak values, reflecting the diversity in the timing of the individual customer peaks. For example, for the large secondary (SVL) class, the monthly class peaks in the test year averaged 3,270 MW, whereas the average of the actual demand values in the revenue months averaged close to 6,000 MVA.

The models explain variations in billing demand based on variations in monthly class peak values. To implement this strategy, it is necessary to align the monthly class peaks to account for billing cycle timing. For example, in January, typically about half of the cycle energy comes from days in December and half comes from days in January. To reflect this, explanatory variables for a month are calculated as a weighted average of the current and prior month values with 50/50 weights. The first explanatory variable is the monthly class peak normalized by the number of customers in each month. The weighted variable is:

Wgt_NCP_PerCust(m) = .5 * NCP_PerCust(m) + .5 * NCP_PerCust(m-1)

The model is estimated with the actual weighted class peak values as explanatory factors and is later simulated with the weather adjusted weighted class peak values.

The customer demands are not necessarily expected to be explained completely by the class peak values, so direct weather variables are also included. To represent the impact of the coldest day in each month, the maximum value of the heating degree variable with base temperature 55 is included. The two-month weighted value is computed as follows:

Wgt_MaxHD55(m) = .5 * MaxHD55(m) + .5 * MaxHD55(m-1)

where MaxHD55(m) is the largest of the daily HD55 values in month m.

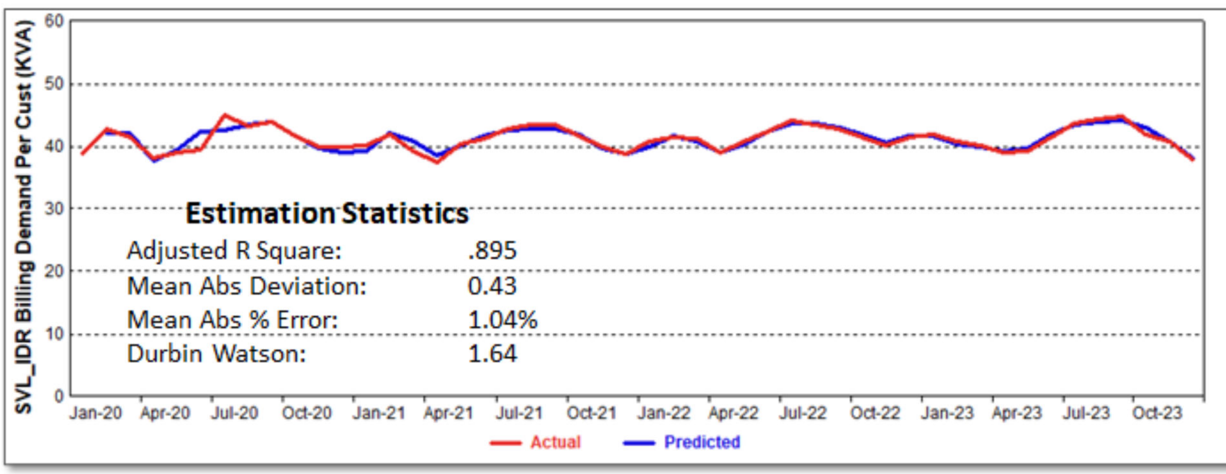
Similarly, to represent the impact of the hottest day in each month, the maximum value of the cooling degree variable with base temperature 70 is included. The two-month weighted value is computed as follows:

Wgt_MaxCD70(m) = .5 * MaxCD70(m) + .5 * MaxCD70(m-1) where MaxCD70(m) is the largest of the daily CD70 values in month m.

The estimated model for the large secondary (SVL) class is shown below. Actual and predicted values from the monthly model are also shown along with key model statistics. The slope value on the class peak (NCP) variable is .497, which will cause about 50% of the weather impact estimated for the weighted NCP variable to be passed on to the customer demand. Additional impacts for extreme cold and hot weather will augment or reduce this NCP pass-through effect.

Revenue Month Demand Model for SVL (Figures 19 and 20)

Variable	Coefficient	Standard Error	T Statistic	Units	Definition
CONST	30.727	1.915	16.049		Constant Term
Phase1	-4.491	0.602	-7.458	Binary	= 1 in Apr and May 2020 -- Covid Phase 1
Phase2	-3.633	0.537	-6.759	Binary	= 1 for June through Nov 2020 -- Covid Phase 2
Phase3	-2.990	0.541	-5.524	Binary	= 1 for Dec 2020 to March 2021 -- Covid Phase 3
Phase4	-3.094	0.461	-6.713	Binary	= 1 for April 2021 and beyond -- Covid Phase 4
SVL_Wgt_NCP	0.497	0.113	4.386	MW	Two-month weighted class peak per customer
Wgt_MaxHD55	0.154	0.020	7.656	DegF	Two-month weighted maximum HD55
Wgt_MaxCD70	0.141	0.070	2.019	DegF	Two-month weighted maximum CD70
AR(1)	-0.041	0.131	-0.312		



The model for the primary (PVS) class is similar but excludes MaxCD and MaxHD variables. The slope value on the class peak (NCP) variable for this class is 1.028, which will cause the weather impact estimated for the weighted NCP variable to be amplified slightly for the customer demand. Although slightly amplified, these impacts will be a smaller percentage of the customer revenue month demand values, which are significantly larger than the class NCP values.

In the working papers, spreadsheets are provided for the static and dynamic versions of the model for SVL and PVS classes. The spreadsheets contain all data used to estimate these models as well as the estimated coefficients, model statistics, and actual and predicted values. Although the models are very simple, they have strong predictive power, with mean absolute percent errors of 1.04% for SVL and 5.07% for PVS.

To calculate weather adjustments for the revenue month demands, the models are used to simulate predicted demands using weather adjusted values of the current and prior month class peaks and normal values for the current and prior month weather variables. The differences between the model predicted values with actual inputs and the model simulated values with normal inputs are the weather impacts. These impacts are subtracted from the actual values to give the weather adjusted revenue month demand estimates.

Q. PLEASE EXPLAIN THE APPROACH USED TO ESTIMATE WEATHER IMPACTS FOR REVENUE MONTH BILLING DEMAND.

For the SVL class, billing demand is the same as customer demand (there is no ratchet), so the billing demand weather impacts are the same as the customer demand impacts discussed above.

For the SVL_IDR class, billing demand and 4CP demand are the billing determinants. For most SVL_IDR customers billing demand is set to equal maximum demand. The billing demand model is discussed below.

For customers in the PVS and PVS_IDR classes, monthly billing demand is often larger than the maximum monthly demand based on a "ratchet" calculation, which sets billing demand to the larger of the maximum demand in a month and 80% of the largest demand in the prior 11 months. For example, in the test year, monthly billing demands for PVS averaged 110.2 MVA, which is about 10% above the average across months of the maximum customer demands for the class.

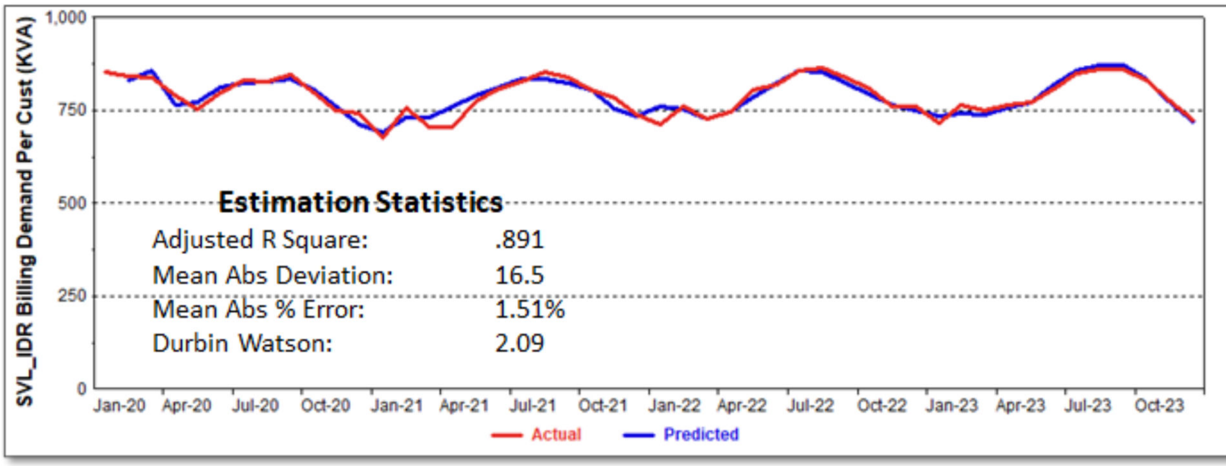
The PVS billing demand model uses the monthly value from the customer demand model described above in addition to the Covid phase variables. The estimated coefficient on customer demand is .916 which will cause 91.6% of the customer demand weather impacts to be passed through to the billing demand.

For the SVL_IDR and PVS_IDR classes, billing demand models use the same specification described above for estimation of actual customer demand. As described above, in addition to Covid phase variables, these models have three inputs that are weighted across the current and prior months. The inputs are (a) the weighted class peak per customer, (b) weighted HD55 for the coldest days, and (c) weighted CD70 for the hottest days. The dependent variable in these models is billing demand per customer adjusted for the number of cycles.

As an example, the coefficients of the estimated model for SVL_IDR are summarized below. The slope value on the class peak (NCP) variable is .55, which will cause 55% of the weather impact estimated for the weighted NCP variable to be passed on to the billing demand. Additional impacts for extreme cold and hot weather will augment or reduce this NCP pass-through effect.

Revenue Month Billing Demand Model for SVL_IDR (Figures 21 and 22)

Variable	Coefficient	Standard Error	T Statistic	Units	Definition
CONST	517.02	72.25	7.156		Constant Term
Phase1	-85.20	17.67	-4.823	Binary	= 1 in Apr and May 2020 -- Covid Phase 1
Phase2	-114.69	12.03	-9.531	Binary	= 1 for June through Nov 2020 -- Covid Phase 2
Phase3	-100.88	13.37	-7.546	Binary	= 1 for Dec 2020 to March 2021 -- Covid Phase 3
Phase4	-107.85	10.22	-10.551	Binary	= 1 for April 2021 and beyond -- Covid Phase 4
SVL_IDR Wgt_NCP	0.55	0.14	4.027	MWh	Two-month weighted class peak per customer
Wgt_MaxHD55	1.18	0.46	2.534	DegF	Two-month weighted maximum HD55
Wgt_MaxCD70	5.65	0.98	5.753	DegF	Two-month weighted maximum CD70
AR(1)	-0.36	0.15	-2.338		



The model for the PVS_IDR is similar with an estimated slope on the class peak (NCP) variable of .708, which will cause about 71% of the weather impact estimated for the weighted NCP variable to be passed on to the billing demand. Additional impacts for extreme cold and hot weather will augment or reduce this NCP pass-through effect.

In the working papers, spreadsheets are provided for the static and dynamic versions of the models for each class. The spreadsheets contain all data used to estimate these models as well as the estimated coefficients, model statistics, and actual and predicted values. Although the models are very simple, they have strong predictive power, with mean absolute percent errors between m 1.5% for SVL_IDR and 2.3% for PVS.

To calculate weather adjustments for the billing demands, the models are used to simulate predicted demands using weather adjusted values of the current and prior month class peaks and normal values for the current and prior month weather variables. The differences between the model predicted values with actual inputs and the model simulated values with normal inputs are the weather impacts. These impacts are subtracted from the actual billing demand values to give the weather adjusted revenue month billing demand estimates.

Q. PLEASE EXPLAIN THE APPROACH USED TO ESTIMATE WEATHER IMPACTS FOR ERCOT COINCIDENT DEMAND (4KVA)

ERCOT coincident demand is a billing determinant for two weather sensitive classes, SVL_IDR and PVS_IDR. 4CP demand charges in 2023 are based on coincident load levels in the four summer months of 2022. As a result, weather adjustments to the test year 4CP values depend on weather outcomes for the previous year.

Daily models of class loads at the time of the ERCOT peak are discussed earlier in the testimony. These models, which are based on AMS interval data, are used to compute daily and monthly ERCOT CP weather adjustments for the test year, and these adjustments are reported on Schedule II-H-1.3. The models are also used to compute daily weather adjustments for all days in 2022, including the days that contribute to the 4CP calculation for months in the test year. These coincident loads and the associated weather adjustments for the 2022 days used in 4CP calculations are shown in the following table.

Summary of ECP Weather Adjustments for 4CP Months (Figure 23)

	ERCOT CP (MVA)		WeatherAdjustment (MVA)		Percent Adjustment	
4CP Days	SVL_IDR	PVS_IDR	SVL_IDR	PVS_IDR	SVL_IDR	PVS_IDR
June, 2022	1,828	512	-29.1	-8.7	-1.59%	-1.70%
July, 2022	1,871	520	-37.2	-11.2	-1.99%	-2.15%
August, 2022	1,853	541	-1.3	-0.4	-0.07%	-0.08%
September, 2022	1,799	518	17.7	5.4	0.99%	1.04%
Average	**1,838**	**523**	**-12.5**	**-3.7**	**-0.67%**	**-0.72%**

The last two columns show percentage weather adjustments for each of the 4CP months. The average weather adjustment percentage across the four 4CP days are

-0.67% for SVL_IDR and -.72% for PVS_IDR. Reflecting these results, test year 4CP values for January through December of 2023 are adjusted downward by these percentages.

The resulting weather adjustments are reported for all months in the test year in the working paper exhibit WP H-4.1 (Weather Adjustments).

VII. <u>NORMAL WEATHER CALCULATIONS</u>

Q. PLEASE DESCRIBE THE DATA AND PROCESS USED TO DEFINE NORMAL WEATHER FOR THE TEST YEAR.

A. To perform daily weather adjustment calculations, it was necessary to define normal weather at the daily level. In order to represent normal weather for both energy and peak calculations, the "rank and average" approach was used. The calculations are based on hourly weather data for the 20-year period between 2004 and 2023.

Steps in the approach to define normal weather are as follows:

1. Compute daily average temperature for each station and historical day as the average of the hourly values for that day. Stations are Houston Intercontinental, Houston Hobby, and Sugarland.
2. Compute daily heating degree (HD) and cooling degree (CD) values for each station and each temperature base using the daily average temperature value for each historical day.
3. Combine average temperature, HD, and CD variables across stations using equal weights. The remaining operations are applied to the combined data.
4. Rank the daily data for each historical month and year by sorting the data from hottest to coldest based on the combined daily average temperature.

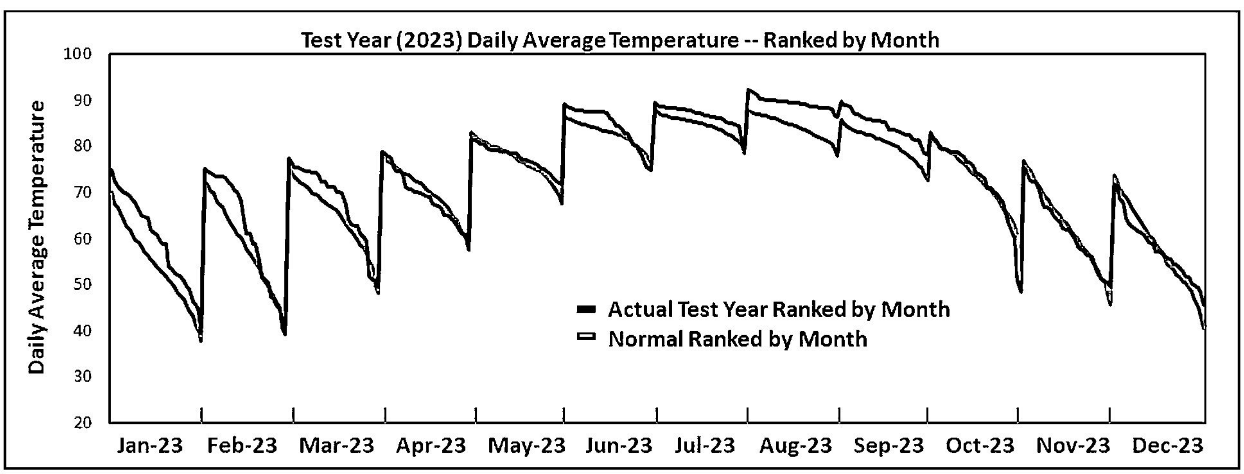
5. For each month, average the ranked data across the 20-year historical period. This gives an average hottest day, an average second hottest data, and so on through to an average coldest day for each month.

6. Repeat the rank and average process by season to identify the typical hottest day in summer and the typical coldest day in winter. Replace the coldest day in January from the calculations by month with the coldest day for the winter season. Replace the hottest day in August from the calculations by month with the hottest day for the summer season.

7. Assign the rank-and-average results to days in the test year based on the weather order that actually occurred in 2023. For example, the coldest day in February 2023 is assigned the value for the typical coldest day in February. Similarly, the hottest day in July 2023 will be assigned the value for the typical hottest day in July.

The results after the rank and average calculation (step 5 above) are shown in the following chart. This chart shows the result of the process applied to daily average temperatures. The green line shows the 10-year rank and average values. The red line shows the actual data for the test year sorted from highest to lowest within each month.

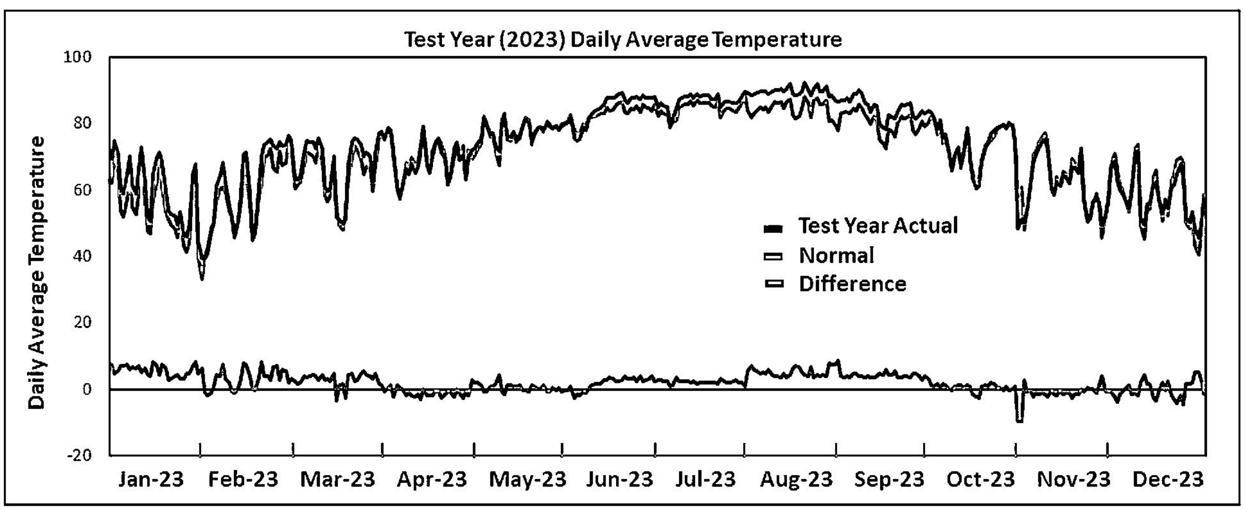
Rank and Average Results for Test Year Daily Average Temperature (Figure 24)



This chart provides a clear picture of how actual and normal weather compare within each month. For example, January of 2023 was warmer than normal for all ranked values. In contrast, April was slightly colder than normal and May, October, and November were close to normal. Most notably, almost all days in June through September were well above normal, and this will lead to significant downward adjustments of energy and demand in these summer months.

The following chart shows the data for the test year after Step 7, in which normal values are assigned to days based on the actual test year weather pattern. As before, the red line shows actual daily average temperatures, and the green line shows the assigned normal values. The blue line shows the daily deviations. A negative value for the blue line occurs when a day is colder than normal. A positive value for the blue line occurs when a day is warmer than normal. This is the way the daily modeling process sees the data for observations in the test year. The actual data (red line) are used to estimate models and to compute daily predicted values with actual weather. The normal data (green line) are used to simulate daily predicted values with normal weather.

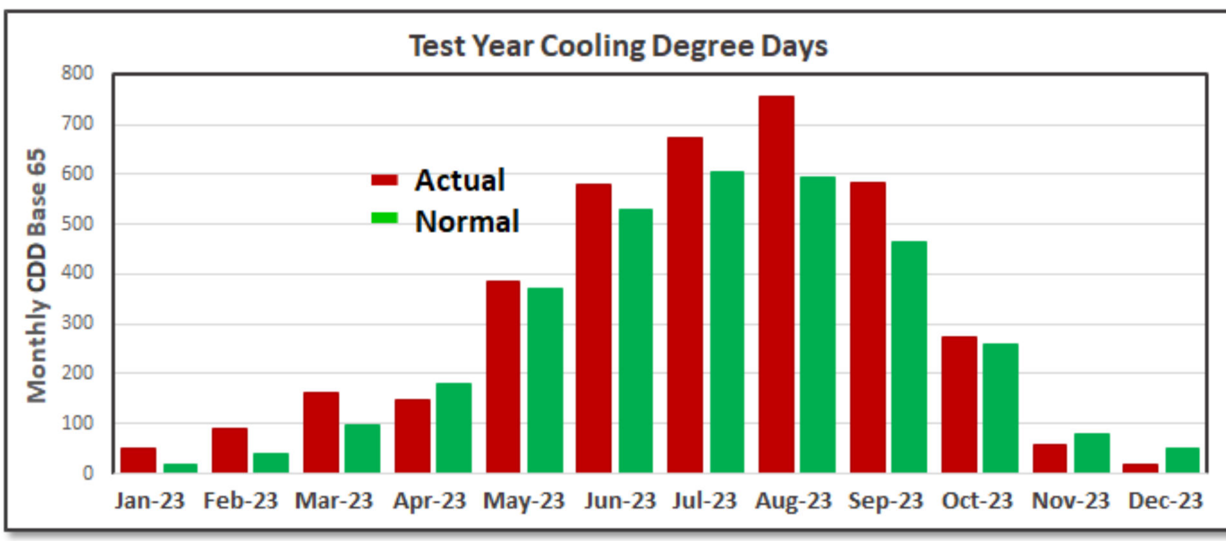
Rank and Average Results Sorted by Daily Weather Pattern (Figure 25)



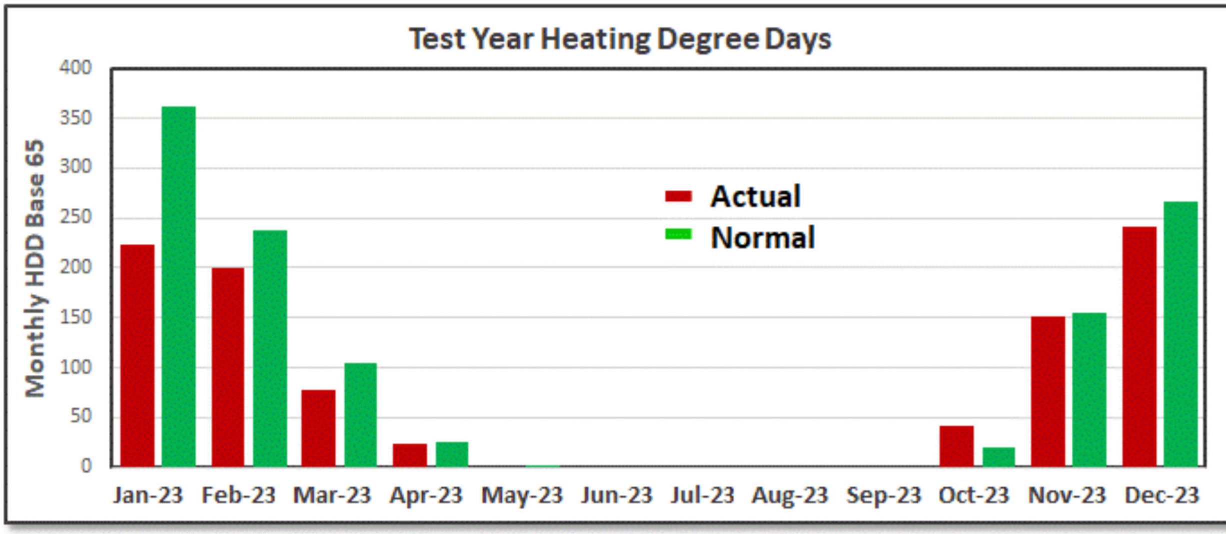
As described earlier, the models are based on heating degree (HD) and cooling degree (CD) values for various base temperatures. The following charts show the monthly sum of the daily HD values, called Heating Degree Days (HDD) and the monthly sum of the daily CD values, called Cooling Degree Days (CDD). Both HDD and CDD monthly sums are shown with a base temperature of 65 degrees.

The CDD chart shows that the months of May through September all had more than normal cooling degrees, with significant deviations in June, July, August, and September. The HDD chart shows that January, February and March had significantly less cold weather than normal. October is the only month in the test year with more cold weather than normal. Not shown in the charts is December of 2022, which had some extremely cold weather toward the end of the month. Although this event does not impact calendar month energy usage in the test year, it will have a noticeable impact on January 2023 billing energy and demand, since the December cold weather impacts are included in most of the January billing cycles.

Actual and Normal Monthly Cooling Degree Days (CDD Base 65) (Figure 26)



Actual and Normal Monthly Heating Degree Days (HDD Base 65) (Figure 27)



The following figure shows normal and test year annual degree day values for all of the CD base temperatures and HD base temperatures that are used in the weather adjustment models.

The test year CDD sums are well above normal values for all base temperatures, and the percentage difference is very large for the high powered degrees (degrees above 80). This will cause cooling loads well above normal levels, implying that cooling energy use should be adjusted downward significantly to represent normal conditions.

On the other side, test year HDD sums are well below normal for all base temperatures. This will cause lower than normal heating loads, implying that heating energy use should be adjusted upward to represent normal conditions.

Comparison of Test Year and Normal Annual Degree Days (Figure 28)

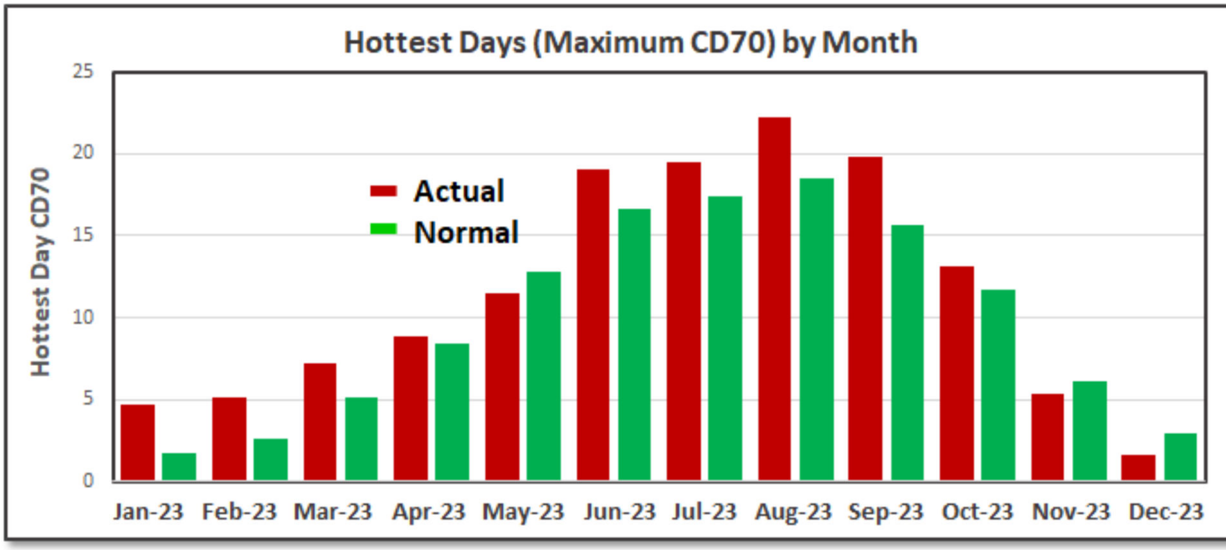
	Cooling Degree Days (CDD)			
	Test Year	Normal	Difference	% Diff
CDD60	5,165	4,596	568	12.4%
CDD65	3,775	3,247	528	16.3%
CDD70	2,550	2,078	471	22.7%
CDD75	1,542	1,132	411	36.3%
CDD80	800	437	363	83.1%
	Heating Degree Days (HDD)			
	Test Year	Normal	Difference	% Diff
HDD65	957	1,189	(232)	-19.5%
HDD60	521	713	(192)	-26.9%
HDD55	246	381	(136)	-35.6%
HDD50	75	175	(100)	-57.4%
HDD45	18	72	(55)	-75.5%

Q. PLEASE DESCRIBE THE DATA AND PROCESS USED TO DEFINE NORMAL WEATHER FOR MODELING CUSTOMER PEAK DEMANDS.

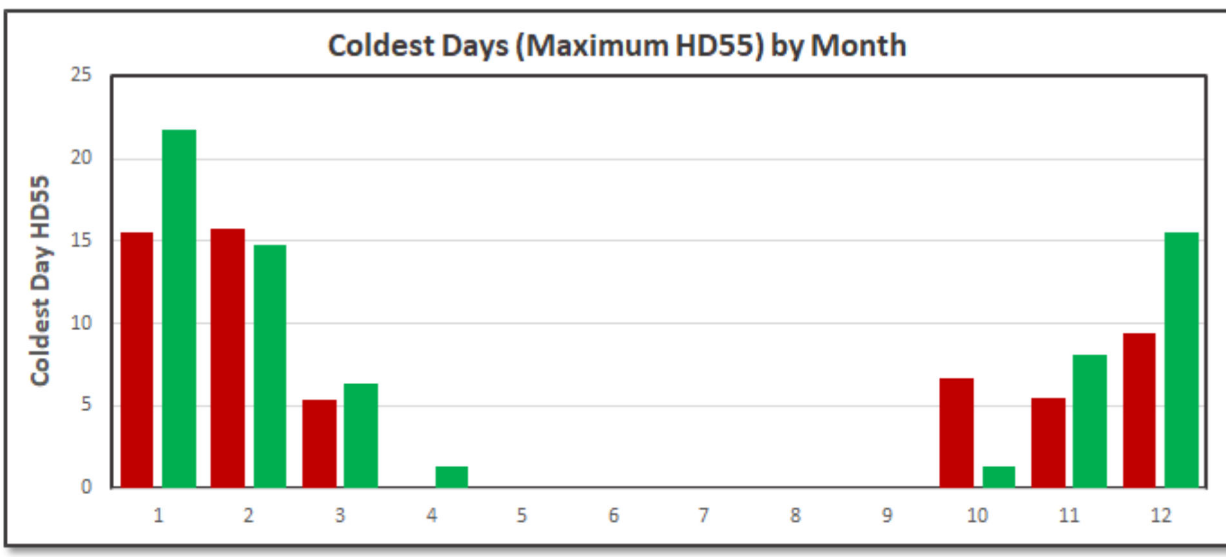
For modeling class peaks and customer peaks, it is useful to understand how the most extreme weather in each month compares to the normal extreme values. The rank and average calculation gives us a typical hottest day in each month and a typical coldest day in each month. The following charts show the comparison of these typical extremes and the actual hottest and coldest days in each month of the test year.

Understanding these charts helps to explain some of the results that are seen in the demand models. For example, we can expect to see very weak demand from heating in both January and December since both months have relatively mild coldest days in the test year. On the cooling side, we expect extra demand in all the summer months, since the hottest days are 1 to 4 degrees hotter than the normal monthly extreme values in these months.

Actual and Normal Hottest Days (CD70) (Figure 29)



Actual and Normal Coldest Days (HD60) (Figure 30)



More details on weather data are presented in Schedule II-H-5.1 and II-H-5.2.

VIII. SCHEDULES FOR TEST-YEAR SALES DATA

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS REPORTED FOR TEST YEAR MONTHLY SALES IN SCHEDULE II-H-1.2.

A. Weather adjustments to test year energy are computed using daily energy models based on AMS data. Daily energy models are discussed earlier in the testimony and include CD spline and HD spline variables that embody the nonlinear relationship between temperature and daily energy. These variables appear in the models directly and they also appear interacting with weekend variables and seasonal variables that allow the weather response to be different on different types of days.

Daily energy models are estimated with actual daily weather from 2019 to 2023. The estimated models are used to recalculate what daily energy would have been with normal weather on each day. The difference between predicted values with actual weather and predicted values with normal weather is the weather impact. The weather impact is subtracted from actual sales to get adjusted daily sales.

The daily weather impacts from the daily energy models are used to adjust billed sales as reported on Schedule II-H-1.2. Billed sales data represent customer usage over the billing cycles that contribute to each revenue month. For each cycle that contributes to a revenue month, the daily weather impacts are summed across the days in that cycle. These sums are then combined across cycles by assigning an equal weight (1/21) to each cycle. In a revenue month that includes exactly 21 cycles, these weights sum to one. In revenue months with less than 21 cycles, the weights sum to less than one. In revenue months with more than 21 cycles, the weights sum to more than one.

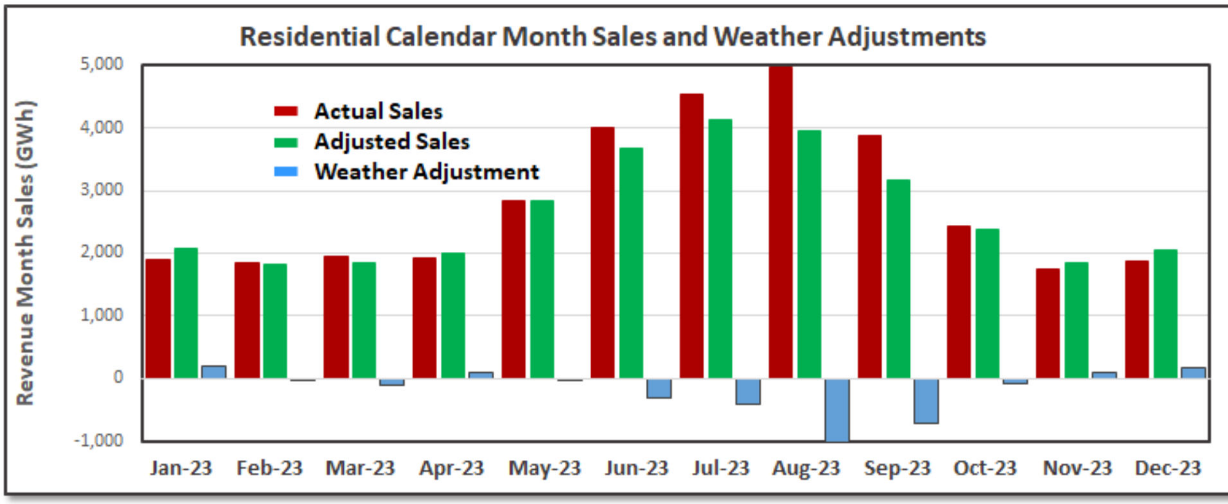
Q. HOW DO THE REVENUE MONTH WEATHER ADJUSTMENTS IN II-H-1.2 COMPARE TO THE CALENDAR MONTH WEATHER ADJUSTMENTS FOR ENERGY IN II-H-1.3?

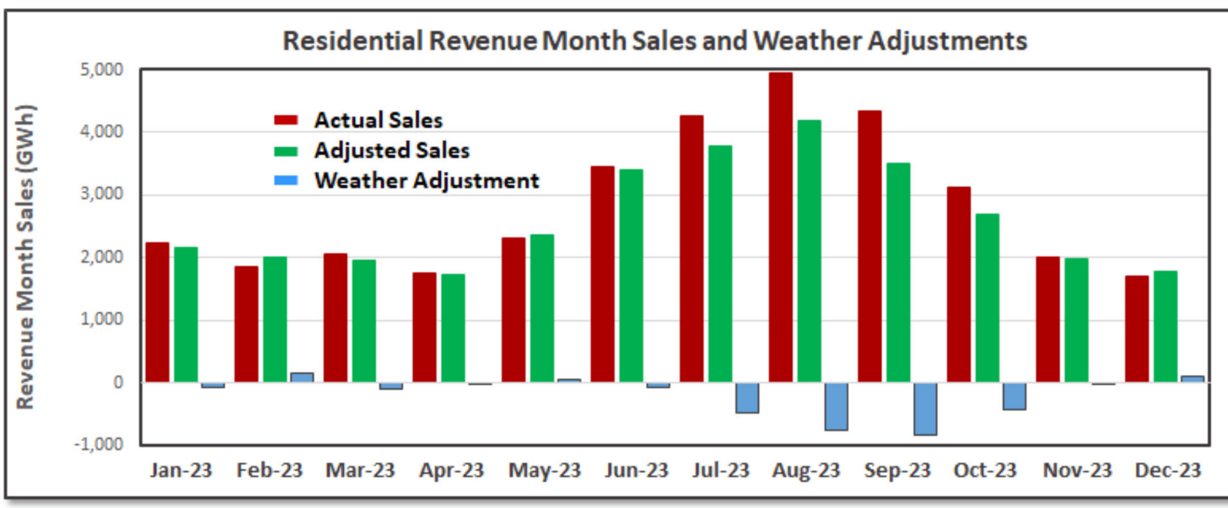
A. The calculation of revenue month adjustments and calendar month adjustments are both based on the daily weather impact estimates. As a result, the revenue month and calendar month weather adjustments follow similar patterns overall, but there are some differences at the monthly level reflecting the timing of billing cycles. The monthly adjustments for the residential class are shown in the following two figures. The top figure shows the calendar month weather adjustments. The bottom figure shows the revenue month weather adjustments, based on weather impacts for the days that fall within each of the billing cycles that contribute to billed sales for each month.

The biggest difference between the revenue month and calendar month estimates occurs in January. As discussed earlier in the testimony, the days in the calendar month January were all warmer than normal. Although this may have resulted in more cooling energy for some of the classes, the main impact for the residential class was reduced heating loads. The result is a positive weather adjustment of 184 GWh, which is a 9.8% upward adjustment. In contrast, on a billing cycle basis, the January revenue adjustment is -72 GWh, which is a 3.2% downward adjustment. This reflects extremely cold weather in late December of 2022, which created a significant spike in heating energy use. This positive heating impact impacted January billed sales, since most of the January cycles included the impact of this extreme cold event.

Focusing on the summer months, the sales adjustments are consistently strong and negative, reflecting the fact that almost all days in the summer of 2023 were warmer than normal, and the downward adjustments are needed to represent the lower cooling levels that would go with normal weather. On a calendar month basis, the biggest impact is in August which has a downward adjustment of 966 GWh (19.5%). On a cycle month basis, a good share of the impacts on August days is registered in the September billing cycles. As a result, September has the largest revenue month downward adjustment of 830 GWh -19.1%).

RS Calendar Month (Figure 29) and Revenue Month (Figure 31) Weather Adjustments





For the most part, these timing differences cancel out over a 12-month period. Annual weather adjustments are summarized in the figure below. The GWh columns give the size of the weather adjustments, and the Percent columns give the adjustments as a percent of the actual sales values. The adjustments for energy are negative for all classes for both the calendar year and the revenue year. The overall adjustments are -3,106.6 GWh (-3.97%) for the calendar year and -3,485 GWh for the revenue year (-3.38%). The revenue year impacts are larger mainly because of the spillover of cold weather impacts in the end of December into the January billing cycles.

Summary of Annual Weather Adjustments for the Test Year (Figure 32)

Rate Class	Weather Adjustment (GWH)		Adjustment % of Sales	
	Calendar Year	Revenue Year	Calendar Year	Revenue Year
Residential (RS)	-2,282.4	-2,549.0	-6.74%	-7.48%
Secondary Voltage Small (SVS)	-10.7	-12.5	-1.20%	-1.42%
Secondary Voltage Large (SVL)	-503.5	-589.3	-2.74%	-3.20%
Secondary Voltage Large IDR (SVL-IDR)	-245.3	-264.5	-1.76%	-1.89%
Primary Voltage Service (PVS)	-8.3	-9.6	-2.29%	-2.47%
Primary Voltage Service IDR (PVS-IDR)	-56.0	-59.3	-1.28%	-1.37%
Transmission Service (TVS)	0.0	0.0	0.00%	0.00%
Lighting Services (SLS & MLS)	0.0	0.0	0.00%	0.00%
Total All Classes	-3,106.2	-3,484.2	-2.97%	-3.38%

The weather adjustments are largest for the residential (RS) class and the large secondary (SVL) class. These classes account for about 90% of the total impact in both cases. The residential impact is largest in both absolute and percentage terms at -6.7% for the calendar year and -7.5% for the revenue year.

IX. SCHEDULES FOR TEST-YEAR PEAK LOAD DATA

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE VALUES FOR CALENDAR MONTH ENERGY USAGE AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.

A. Energy usage at the meter is computed from the AMS and IDR 15-minute interval data. For each day, energy is summed across the 96 intervals that contribute to that day. Daily data are summed across days to give the calendar month energy sum.

Energy usage at the source is computed from the AMS and IDR 15-minute interval data. For each interval, energy use is scaled upward for the distribution and transmission loss factor for that interval. The scaled values are then summed across the 96 intervals that contribute to each day, and the daily values are summed across days in each month. The result is calendar month energy by class at the source. The monthly loss multiplier for energy can then be calculated as the ratio of the energy sum with losses to the energy sum without losses.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE VALUES FOR CUSTOMER MAXIMUM DEMAND AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.

Customer maximum demand at the meter is computed from the AMS and IDR 15-minute interval data for each customer. The maximum 15-minute MWh value for each customer is multiplied by 4 and these hourly MWh values are then added across customers to get the actual demand sum for each class in each calendar month.

Because the individual customer demand values come from different days and different hours on those days, there is not a specific loss multiplier that is appropriate to compute demand values at the source. The values at the source on Schedule II-H-1.3 were computed using the distribution and transmission loss multipliers for monthly energy.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE MONTHLY VALUES FOR CLASS PEAK DEMAND AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.

Class peak demand at the meter is computed directly from the 15-minute interval data summed across customers in each class. Class peak demand at the source is computed from class peak demand at the meter adjusted upward for distribution and transmission loss factors. For each class, the loss factor for a month is the 15-minute loss factor for the class peak interval in that month.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE MONTHLY VALUES FOR CLASS LOAD AT CENTERPOINT HOUSTON PEAK PROVIDED IN SCHEDULE II-H-1.3.

A. CenterPoint Houston peak intervals are determined from 15-minute load data for the CenterPoint Houston system. In each month, the class load in the peak interval is extracted from the 15-minute interval data for that class. This is the class coincident load at the meter.

Class load at the CenterPoint Houston peak interval at the source is computed from the class load at the meter adjusted upward for distribution and transmission loss factors. The loss factors for a month are the 15-minute loss factors that apply to each class at the time of the CenterPoint Houston peak in that month.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE VALUES FOR CLASS LOAD AT ERCOT PEAK PROVIDED IN SCHEDULE II-H-1.3.

A. ERCOT peak intervals are determined based on 15-minute ERCOT load data published by ERCOT. In each month, the class load in the peak interval is extracted from the 15-minute AMS data for that class. This is the class coincident load at the meter.

Class load at the ERCOT peak interval at the source is computed from the class load at the meter adjusted upward for distribution and transmission loss factors. The loss factors for a month are the 15-minute loss factors that apply to each class at the time of the ERCOT peak in that month.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE VALUES FOR CLASS COINCIDENCE FACTORS AND CLASS LOAD FACTORS PROVIDED IN SCHEDULE II-H-1.3.

A. Class coincidence factors are computed directly from the 15-minute AMS data. For each class, the class peak in a month is identified as the maximum 15-minute value in the month.

Class loads at the time of the ERCOT peak are extracted from the AMS data for the 15-minute interval in which the ERCOT peak occurs.

The value reported as the coincidence factor is the ratio of the class load at the time of the ERCOT peak in each month to the class peak in each month. This value is 100% in months when the class peak occurs exactly at the same interval as the ERCOT peak. Otherwise, it is less than 100%.

Class load factors are also computed directly from the AMS data. For each calendar month, AMS energy is computed as the sum of the class load data for 15-minute intervals that fall in that month. The class peak in a month is identified as the maximum 15-minute value in the month. The load factor is the ratio of the average hourly energy value in a month to the class peak in that month.

X. SCHEDULES FOR ADJUSTED ENERGY AND PEAKS

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS REPORTED IN SCHEDULE II-H-1.3.1 AND THE WEATHER ADJUSTED ENERGY AND LOAD DATA REPORTED IN SCHEDULE II-H-1.4.

A. Weather adjustments for calendar month energy and class demands are reported for all classes in Schedule II-H-1.3.1 at the meter and at the source. Adjusted energy and demand values are reported in Schedule II-H-1.4 for all classes. At a high level, the method is the same for all energy and demand concepts. The actual value is calculated from AMS or IDR interval data. The adjustments are computed using statistical models of the daily or monthly data to estimate the impacts of weather deviations from normal. The adjusted values at the meter are computed as the actual value minus the estimated abnormal weather impact.

To compute weather adjusted values at the source, the weather adjusted values at the meter are scaled upward for distribution and transmission loss factors. The loss factors applied to the adjusted loads are the same as the loss factors applied to the actual loads.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENT RESULTS FOR ENERGY USAGE AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.1

A. Weather adjustments to calendar month energy are computed using the daily energy models. Daily energy models are discussed earlier in the testimony and include CD spline and HD spline variables that embody the nonlinear relationship between temperature and daily energy. These variables appear directly in the models and they also appear interacting with weekend variables and seasonal variables that allow the weather response to be different on different types of days.

Daily energy models are estimated with actual daily weather data. The estimated models are then used to recalculate what daily energy would have been with normal weather on each day. The difference between the predicted daily energy with actual weather and simulated daily energy with normal weather is the weather impact for a day. Daily weather impacts are summed across days in the calendar month. The monthly weather adjustment values reported on Schedule II-H-1.3.1 are the inverse of the monthly weather impact values. The monthly weather impacts are subtracted from actual monthly energy values and the result is further adjusted for customer growth, giving the weather adjusted monthly energy at the meter reported on Schedule II-H-1.4.

To derive weather adjusted energy at the source, distribution and transmission loss factors for actual monthly energy in a month are applied to the weather adjusted value at the meter.

Annual weather adjustments at the meter for the 2023 calendar test year are summarized in the following figure. About 90% of the weather adjustment comes from the residential (RS) and secondary voltage large (SVL) classes.

Annual Weather Adjustments for the 2023 Calendar Test Year (Figure 33)

Rate Class	Calendar Year Energy (GWh)	Annual Weather Adjustment (GWh)	Annual Percent Adjustment
Residential (RS)	33,875.4	-2,282.4	-6.74%
Secondary Voltage Small (SVS)	899.0	-10.7	-1.19%
Secondary Voltage Large (SVL)	18,376.7	-503.5	-2.74%
Secondary Voltage Large IDR (SVL-IDR)	13,929.2	-245.3	-1.76%
Primary Voltage Service (PVS)	360.8	-8.3	-2.29%
Primary Voltage Service IDR (PVS-IDR)	4,389.7	-56.0	-1.28%
Transmission Service (TVS)	32,673.5	0.0	0.00%
Lighting Services (SLS & MLS)	223.2	0.0	0.00%
Total All Classes	104,727.5	-3,106.2	-2.97%

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS FOR CUSTOMER MAXIMUM DEMAND AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.1.

A. The calendar month demand models are discussed earlier in the testimony and include variables for the hottest day (maximum CD70) and the coldest days (maximum HD55) in each month. The models are estimated using monthly data for the most recent three years (2021 to 2023).

The estimated models are used to simulate demand values with normal extreme weather inputs. The difference between model predicted values with actual extreme weather and simulated values with normal extreme weather are the weather impacts. The weather adjustment values are the inverse of the impact values, and are reported on Schedule II-H-1.3.1. The impacts are subtracted from the actual demand values and the result is further adjusted for customer growth to give adjusted calendar month customer demands at the meter reported on Schedule II-H-1.4.

For each class, adjusted customer demand at the meter is converted to adjusted customer demand at the source by applying distribution and transmission loss factors computed for monthly energy. These are the same loss factors that are applied to the unadjusted demand data.

The following table summarizes the customer demand impacts at the meter. The first column shows the average of the monthly demand values across the 12 months in the test year. The second column shows the average impact of abnormal weather across the months. The negative adjustment values reflect the strong impact of hotter than normal extreme days in all the summer months.

Summary of Test Year Weather Adjustments for Maximum Demand (Figure 34)

Customer Class	Calendar Month Average Maximum Demand (MW)	Average MW Weather Adjustment	Percent Weather Adjustment
Residential (RS)	19,371.45	-166.29	-0.86%
Secondary Voltage Small (SVS)	292.13	-1.93	-0.66%
Secondary Voltage Large (SVL)	5,304.25	-46.20	-0.87%
Secondary Voltage Large IDR (SVL-IDR)	2,850.31	-45.35	-1.59%
Primary Voltage Service (PVS)	86.86	-0.74	-0.85%
Primary Voltage Service IDR (PVS-IDR)	878.79	-9.75	-1.11%
Transmission Service (TVS)	5,152.67	0.00	0.00%

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS FOR CLASS PEAK DEMAND AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.1.

A. Weather adjustments to monthly class peaks are computed using the daily class peak models. Daily class peak models are discussed earlier in the testimony and include CD spline and HD spline variables that embody the nonlinear relationship between temperature and daily class peak. These variables appear in the models directly and also appear interacting with weekend variables and seasonal variables that allow the weather response to be different on different types of days.

Daily class peak models are estimated with actual daily weather data. The estimated models are used to recalculate what daily class peaks would have been with normal weather on each day. For each month, the difference between the maximum predicted class peak with actual weather and the maximum simulated class peak with normal weather is the class peak weather impact for the month. The weather adjustment values reported on Schedule II-H-1.3.1 are the inverse of the impact values, and are reported on Schedule II-H-1.3.1. The impacts are subtracted from the actual class peaks, and the result is further adjusted for customer growth, giving the adjusted class peak at the meter reported on Schedule II-H-1.4.

To derive weather adjusted class peak values at the source, distribution and transmission loss factors for the actual class peak interval in each month are applied to the weather adjusted value at the meter.

The following table summarizes the weather adjustments for class peaks at the meter. The first column shows the average of 12 monthly class peak values. The second column shows the average weather adjustment across the months. The negative values reflect the strong impact of hotter than normal extreme days in all the summer months.

Summary of Test Year Weather Adjustments for Monthly Class Peaks (Figure 35)

Rate Class	Average Class Peak (MW)	Average Weather Adjustment (MW)	Average Percent Adjustment
Residential (RS)	6,984.3	-291.0	-4.17%
Secondary Voltage Small (SVS)	135.2	-0.7	-0.52%
Secondary Voltage Large (SVL)	3,269.9	-55.4	-1.69%
Secondary Voltage Large IDR (SVL-IDR)	2,225.3	-43.5	-1.95%
Primary Voltage Service (PVS)	58.6	-0.8	-1.31%
Primary Voltage Service IDR (PVS-IDR)	614.7	-9.7	-1.57%
Transmission Service (TVS)	4,086.1	0.0	0.00%
Lighting Services (SLS & MLS)	51.9	0.0	0.00%

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS FOR CLASS LOAD AT THE TIME OF CENTERPOINT HOUSTON PEAK PROVIDED IN SCHEDULE II-H-1.3.1

A. Weather adjustment to class loads at the time of CenterPoint Houston monthly peak are computed using models of daily class coincident loads. Daily loads at the time of CenterPoint Houston peak are computed directly from the 15-minute AMS data based on the time of the Company's peak on each day. Daily coincident load models are discussed earlier in the testimony and include CD spline and HD spline variables. These variables appear in the models directly and they also appear interacting with weekend variables and seasonal variables that allow the weather response to be different on different types of days.

Daily coincident load models are estimated with actual daily weather data. The estimated models are used to recalculate what daily coincident class loads would have been with normal weather on each day. On the Company's peak day in each month, the difference between predicted coincident class load with actual weather and simulated coincident class load with actual weather is the class load weather impact for that month. The weather adjustment values are the inverse of the impact values and are reported on Schedule II-H-1.3.1. The impacts are subtracted from the actual coincident load values, and the result is further adjusted for customer growth, giving the weather adjusted class coincident load at the meter reported on Schedule II-H-1.4.

To derive adjusted values at the source, distribution and transmission loss factors for the interval of the CenterPoint Houston monthly peak are applied to the adjusted value at the meter.

The following table summarizes the weather adjustments for class loads at the meter at the time of the CEHE system peak. The first column shows the average of 12 monthly CP values. The second column shows the average weather adjustment across the months. The negative values reflect the strong impact of hotter than normal extreme days in all the summer months.

Summary of Weather Adjustments for CEHE Coincident Peaks (Figure 36)

Rate Class	Average CEHE CP (MW)	Average Weather Adjustment (MW)	Average Percent Adjustment
Residential (RS)	6,569.3	-341.4	-5.20%
Secondary Voltage Small (SVS)	110.5	-1.4	-1.27%
Secondary Voltage Large (SVL-Non IDR)	3,063.2	-69.7	-2.28%
Secondary Voltage Large (SVL-IDR)	1,853.6	-27.8	-1.50%
Primary Voltage Service (PVS-Non IDR)	53.2	-1.0	-1.94%
Primary Voltage Service (PVS-IDR)	547.9	-7.0	-1.27%
Transmission Service (TVS)	3,795.8	0.0	0.00%
Lighting Services (SLS & MLS)	4.3	0.0	0.00%
Total All Classes	15,997.8	-448.3	-2.80%

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS FOR CLASS LOAD AT THE TIME ERCOT PEAK PROVIDED IN SCHEDULE II-H-1.3.1.

A. Weather adjustment to class loads at the time of ERCOT monthly peak are computed using models of the ERCOT coincident loads for each class. Daily loads at the time of ERCOT peak are computed directly from the 15-minute AMS data based on the time of the ERCOT peak on each day. Daily coincident load models are discussed earlier in the testimony and include CD spline and HD spline variables. These variables appear in the models directly and they also appear interacting with weekend variables and seasonal variables that allow the weather response to be different on different types of days.

Daily coincident load models are estimated with actual daily weather data. The estimated models are used to recalculate what daily coincident class loads would have been with normal weather on each day. On the ERCOT peak day in each month, the difference between predicted class coincident load with actual weather and simulated class coincident load with normal weather is the weather impact for that month. The weather adjustment values are the inverse of the impact values and are reported on Schedule II-H-1.3.1. The impacts are subtracted from the coincident load value for the month, and the result is further adjusted for customer growth, giving the adjusted class coincident load at the meter reported on Schedule II-H-1.4.

To derive adjusted values at the source, distribution and transmission loss factors for the interval of the ERCOT monthly peak are applied to the adjusted value at the meter.

The following table summarizes the weather adjustments for class loads at the meter at the time of the ERCOT monthly system peaks during the test year. The first column shows the average of 12 monthly CP values. The second column shows the average weather adjustment across the months. The negative values reflect the strong impact of hotter than normal extreme days in all the summer months.

Summary of Weather Adjustments for ERCOT Coincident Peaks (Figure 37)

Rate Class	Average ERCOT CP (MW)	Average Weather Adjustment (MW)	Average Percent Adjustment
Residential (RS)	6,551.2	-288.6	-4.41%
Secondary Voltage Small (SVS)	113.5	-2.4	-2.10%
Secondary Voltage Large (SVL)	2,963.9	-23.8	-0.80%
Secondary Voltage Large IDR (SVL-IDR)	1,776.6	-5.3	-0.30%
Primary Voltage Service (PVS)	50.3	-0.6	-1.17%
Primary Voltage Service IDR (PVS-IDR)	530.3	-3.3	-0.63%
Transmission Service (TVS)	3,662.5	0.0	0.00%
Lighting Services (SLS & MLS)	10.1	0.0	0.00%
Total All Classes	15,658.3	-324.0	-2.07%

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR ADJUSTED CLASS COINCIDENCE FACTORS AND ADJUSTED CLASS LOAD FACTORS PROVIDED IN SCHEDULE II-H-1.4.

A. Adjusted class coincidence factors are computed from the weather adjusted ERCOT coincident load values and the weather adjusted class peak values, both of which are discussed above.

Adjusted class load factors are computed from the weather adjusted calendar month energy values and the weather adjusted monthly class peak values, both of which are discussed above.

XI. SCHEDULES FOR REVENUE MONTH DEMAND

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENT FOR REVENUE MONTH CUSTOMER DEMAND (KVA) PROVIDED IN WORKING PAPER EXHIBIT WP H-4.1.

A. Revenue month customer demand is the sum of maximum customer demands for each billing cycle that contributes to the revenue month. The only classes that have demand as a billing determinant are large secondary (SVL) and primary (PVS). As discussed earlier in the testimony, monthly demand data from 2019 through 2023 are used to estimate models that use two-month weighted explanatory variables.

The explanatory variables are monthly class peaks, maximum values of HD55 for extreme cold weather, and maximum values of HD70 for extreme warm weather.

These estimated models are used to simulate what demands would be with normal values for class peaks, maximum HD55, and maximum HD70. For each month, the difference between the predicted value with the actual inputs and the simulated value with the normal inputs is the weather impact. The weather impact for each month is subtracted from the demand value and is further adjusted for customer growth, giving the adjusted revenue month demand value. The unadjusted values, the weather adjustment, and the adjusted monthly values are presented in Schedule WP-H-4.1.

Maximum Demand Values and Weather Adjustments for SVL and PVS (Figures 38)

Year	Month	Revenue Month Maximum Demand (MVA)		Weather Adjustment (MVA)		Percent Weather Adjustment	
		SVL	PVS	SVL	PVS	SVL	PVS
2023	1	5,850.5	91.4	-150.2	-0.9	-2.57%	-0.98%
2023	2	5,659.6	88.6	91.6	2.8	1.62%	3.20%
2023	3	6,386.6	91.2	-74.1	-0.6	-1.16%	-0.70%
2023	4	5,139.9	76.7	-46.6	-0.8	-0.91%	-1.00%
2023	5	5,970.7	82.7	20.9	0.7	0.35%	0.82%
2023	6	6,333.0	93.7	-52.2	-1.2	-0.82%	-1.29%
2023	7	6,075.9	144.9	-135.2	-3.0	-2.22%	-2.08%
2023	8	7,116.3	130.3	-197.9	-4.8	-2.78%	-3.72%
2023	9	6,264.8	122.1	-228.0	-5.5	-3.64%	-4.49%
2023	10	6,414.5	128.2	-227.4	-3.6	-3.54%	-2.79%
2023	11	5,683.0	75.6	-36.2	-0.1	-0.64%	-0.19%
2023	12	5,034.0	74.8	153.7	1.9	3.05%	2.53%
Test Year	Average	5,994.1	100.0	-73.5	-1.3	-1.23%	-1.26%

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENT FOR MONTHLY BILLING DEMAND (KVA) PROVIDED IN WORKING PAPER EXHIBIT WP H-4.1.

A. For SVL and SVL_IDR classes, billing demands are the same as the customer demand. As a result, the billing demand weather adjustments are the same as the customer demand adjustments for SVL and an equivalent model is applied to the billing demand data for SVL_IDR.

For PVS a and PVS_IDR classes, the billing demand includes an 80% ratchet calculation that sets billing demand to the larger of the current month demand or 80% of the largest demand in the prior eleven months. As discussed earlier in the testimony, monthly demand data from 2019 through 2023 are used to estimate billing demand models.

These models are simulated using weather adjusted values and normal weather values. For each month, the difference between the predicted value with the actual inputs and the simulated value with the normal inputs is the weather impact. The weather impact for each month is subtracted from the billing demand value and is further adjusted for customer growth, giving the adjusted billing demand value. The adjusted and unadjusted monthly values, the weather adjustment, and the adjusted monthly values are presented in working paper exhibit WP H-4.1.

The following figure provides a summary of the weather adjustment results. The estimated weather impacts are all negative reflecting the extremely warm weather in the summer of 2023. As a result, normalized billing demands are adjusted downward, and these adjustments range from -1.05% for PVS_IDR to -2.00% for SVL_IDR.

Billing Demand Values and Weather Adjustments (Figure 39)

		Billing Demand (MVA)				Weather Adjustment (MVA)				Percent Weather Adjustment			
Year	Month	SVL	SVL_IDR	PVS	PVS_IDR	SVL	SVL_IDR	PVS	PVS_IDR	SVL	SVL_IDR	PVS	PVS_IDR
2023	1	5,851	2,691	100.6	908	-150.2	-100.4	-0.8	-22.6	-2.57%	-3.73%	-0.83%	-2.49%
2023	2	5,660	2,874	100.9	995	91.6	-92.5	2.6	-12.3	1.62%	-3.22%	2.58%	-1.24%
2023	3	6,387	3,248	104.8	1,112	-74.1	-105.5	-0.6	-18.9	-1.16%	-3.25%	-0.56%	-1.70%
2023	4	5,140	2,738	89.8	919	-46.6	-40.8	-0.7	-0.2	-0.91%	-1.49%	-0.78%	-0.02%
2023	5	5,971	3,203	94.6	1,097	20.9	19.7	0.6	8.0	0.35%	0.62%	0.67%	0.73%
2023	6	6,333	3,364	99.7	1,123	-52.2	-21.2	-1.1	-6.3	-0.82%	-0.63%	-1.11%	-0.56%
2023	7	6,076	3,216	152.8	1,014	-135.2	-77.7	-2.8	-15.3	-2.22%	-2.42%	-1.81%	-1.50%
2023	8	7,116	3,773	137.1	1,221	-197.9	-118.9	-4.4	-22.5	-2.78%	-3.15%	-3.23%	-1.84%
2023	9	6,265	3,281	128.4	1,039	-228.0	-138.9	-5.0	-24.0	-3.64%	-4.23%	-3.91%	-2.31%
2023	10	6,414	3,505	136.2	1,162	-227.4	-114.9	-3.3	-22.3	-3.54%	-3.28%	-2.41%	-1.92%
2023	11	5,683	2,973	86.5	1,022	-36.2	-8.5	-0.1	-2.4	-0.64%	-0.29%	-0.15%	-0.24%
2023	12	5,034	2,631	91.1	979	153.7	50.1	1.7	15.4	3.05%	1.90%	1.90%	1.57%
Test Yr	Avg	5,994	3,125	110.2	1,049	-73.5	-62.5	-1.2	-10.3	-1.23%	-2.00%	-1.05%	-0.98%

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENT FOR ERCOT COINCIDENT DEMAND (4KVA) PROVIDED IN WORKING PAPER EXHIBIT WP H-4.1.

ERCOT coincident demand is a billing determinant for two weather sensitive classes, SVL_IDR and PVS_IDR. The 4CP values observed in the months of the test year reflect coincident demand levels in the summer of 2022 (which determine the 4CP charges in 2023).

As discussed earlier in the testimony, the 15-minute AMS data are used to identify class loads at the time of the ERCOT system peak on each historical day. Models of these daily CP values are then used to compute daily weather adjustments. 4CP weather adjustment percentages for each year are then developed for each class based on the daily weather adjustments on the four 4CP days in the year. As discussed earlier in the testimony, the estimated weather adjustments for the 2022 4CP days are small downward adjustments of -0.67% for SVL_IDR and -0.72% for PVS_IDR. These percentage impacts are applied to the actual 4CP values in all months in the 2023 test year.

The following figure provides a summary of the 4CP demand adjustments for the test year.

ERCOT 4CP Demand Values and Weather Adjustments (Figure 40)

Year	Month	4CP Demand (MVA)		Weather Adjustment (MVA)		Percent Weather Adjustment	
		SVL_IDR	PVS_IDR	SVL_IDR	PVS_IDR	SVL_IDR	PVS_IDR
2023	1	2,036.5	536.4	-13.56	-3.88	-0.67%	-0.72%
2023	2	2,289.8	586.7	-15.25	-4.24	-0.67%	-0.72%
2023	3	2,498.0	639.0	-16.63	-4.62	-0.67%	-0.72%
2023	4	2,075.6	537.1	-13.82	-3.88	-0.67%	-0.72%
2023	5	2,396.7	604.4	-15.96	-4.37	-0.67%	-0.72%
2023	6	2,390.5	618.8	-15.92	-4.47	-0.67%	-0.72%
2023	7	2,179.6	543.2	-14.51	-3.93	-0.67%	-0.72%
2023	8	2,493.1	663.6	-16.60	-4.80	-0.67%	-0.72%
2023	9	2,145.0	531.9	-14.28	-3.84	-0.67%	-0.72%
2023	10	2,400.9	622.7	-15.99	-4.50	-0.67%	-0.72%
2023	11	2,133.9	528.9	-14.21	-3.82	-0.67%	-0.72%
2023	12	2,058.7	537.9	-13.71	-3.89	-0.67%	-0.72%
Test Year	Average	2,258.2	579.2	-15.04	-4.19	-0.67%	-0.72%

These weather impacts are also reported in the working paper exhibit WP H-4.1 (Weather Adjustments).

XII. SUMMARY AND CONCLUSION

Q. ARE THE TYPES OF WEATHER ADJUSTMENTS YOU DISCUSS IN YOUR TESTIMONY TYPICAL FOR UTILITIES IN RATE CASES?

A. Yes. CenterPoint Houston and other utilities use weather adjustments, including adjustments for monthly sales, customer demand, billing demand, class peaks, and class loads at the time of Company and ERCOT peaks, when designing proposed rates. These adjustments are reasonable and necessary to prepare rates based on energy usage patterns that reflect typical conditions.

Q. DOES THIS CONCLUDE YOUR DIRECT TESTIMONY?

A. Yes, it does.

Exhibit JSM-01: Educational Background and Business Experience

Dr. J. Stuart McMenamin

Education

- Ph.D., Economics, University of California, San Diego, 1975
- B.A., Mathematics and Economics, Occidental College, 1971

Employment History

- Director of Forecasting Solutions, Itron, Inc., 2002-present
- Senior Vice President, Regional Economic Research, Inc., 1986-2002
- Vice President, Criterion Inc., 1979-1985
- Senior Economist, President's Council on Wage and Price Stability, 1978-1979
- Lecturer in Economics, University of California, San Diego, 1976-1989
- Research Director, Econometric Research Associates, 1975-1978
- Senior Consultant, Institute for Policy Analysis, 1973-1975

Research Experience

Dr. McMenamin is a nationally recognized expert in the field of energy forecasting. Over the last 45 years, he has specialized in the following areas: end-use modeling, energy technology data development, end-use load shape modeling, system load forecasting, price forecasting, retail load forecasting, financial forecasting, load research data analysis, and smart grid data analytics. In addition to his work in the energy area, Dr. McMenamin has completed numerous studies in the areas of telecommunications markets, regional economic modeling, and statistical analysis of employment practices.

Prior to joining Itron, Dr. McMenamin was the principal investigator for the development of the EPRI end-use models (REEPS, COMMEND, and INFORM) which were the primary end-use modeling tools in North America in the 1980s and 1990's. Since joining Itron in 2002, Dr. McMenamin has directed the development of Itron's forecasting software products (MetrixND, MetrixLT, Forecast Manager, and the Itron Load Research System). These products are used by most of the major utilities and ISOs in North America for short-term forecasting and financial forecasting.

In the area of data development, Dr. McMenamin has directed numerous market research studies involving residential, commercial, and industrial customers. These studies have included large on-site survey projects in all sectors, decision-maker studies, vendor surveys, panel of experts studies, and conjoint studies. Results from these studies have been used to construct comprehensive market assessments involving the modeling of customer purchase actions and customer decision processes.

Over the last two decades, Dr. McMenamin has spearheaded the development of the Statistically Adjusted End-Use modeling framework, which has been adopted by a growing list of major utilities for long-term forecasting. More recently, Dr. McMenamin has focused on analysis of smart meter data and applications of these data to forecasting, weather normalization, and variance analysis.

Teaching Experience

Undergraduate courses taught at the University of California, San Diego (1976-1989).

- Topics in Economics
- Principles of Microeconomics
- Money and Banking
- International Finance

Selected Reports and Papers

Daily Sales Tracking using AMI Data, presented at AEIC Load Research Committee Meeting, June, 2017

Weather Normalization of VPP Hourly Usage, presented at AEIC/WLR Annual Meeting, August, 2015

Incorporating Energy Efficiency into Western Interconnection Transmission Planning, with Galen Berbose, Alan Sanstad, Charles, Goldman, Andy Sukenik, LBNL-6578E, February, 2014

Weather Normalization by Time of Use, with Rob Zacher, AEIC/WLR Annual Meeting, September 2014.

Modeling an Aggressive Energy-Efficiency Scenario in Long-Range Load Forecasting for Electric Power Transmission Planning, with Alan Sanstad, Galen Barbose, Charles Goldman, and Andrew Sukenik, Applied Energy, Sept 2014.

Forecasting Accuracy Survey and Energy Trends, presented at Energy Forecasting Group annual meeting, April 2014.

Leveraging Meter Data for Distributed Energy Load Forecasting, presented at Analytics for Integration of Distributed Energy Resources panel, IEE Power & Energy Society meeting, July 2013.

Exploratory Data Analysis using Neural Networks, presented at Global Energy Forecasting Competition panel, IEE Power & Energy Society meeting, July 2013.

Smart Grid Analytics, presented at AEIC Load Research Workshop, April, 2013.

Using AMI Data to Improve Forecasting and Financial Analytics, presented at Western Load Research Association, October, 2012.

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Impact of AMI on Forecasting and Load Research, presented at Western Load Research Association, March, 2008. Also Itron white paper available at www.Itron.com.

Defining Normal Weather for Energy and Peak Normalization, Itron white paper, September, 2009. Available at www.Itron.com

Weather Normalization Best Practices Survey, presented at Association of Edison Illuminating Companies, Load Research Workshop, April, 2006.

Using Load Research Data to Estimate Unbilled Revenues, presented at Western Load Research Association, September, 2004

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The Technical Side of ERCOT Profile Models, presented at Western Load Research Association, April, 2001.

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Comparison of Statistical Approaches to Electricity Price Forecasting, with F. Monforte. In *Pricing in Competitive Electricity Markets*, Kluwer Academic Publishers, A. Faruqui and K. Eakin, eds, April, 2000.

Long-term and Short-term Hourly Profile Forecasting Methods. Western Load Research Association Conference, October, 1999.

Load Forecasting for Retail Sales, with F. Monforte. EPRI 12th Forecasting Symposium, April, 1999.

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Benefits of Electrification and End-Use Efficiency. With F. Monforte and P. Sioshansi. *The Electricity Journal*. Volume 10, Number 4, May 1997.

Evaluation of Methods for Estimation of End-Use Load Shapes. Presented at the AEIC Annual Load Research Conference, August, 1997.

Environmental Benefits of Electrification and End-Use Efficiency. Electric Power Research Institute, RP3121-12. January 1996

Integration of DSM Evaluation into End-Use Forecasting. Energy Services Journal, Vol. 1, No.1, 67-79, Lawrence Erlbaum Associates, Inc., 1995 (co-author)

EPRI's Industrial End-Use Forecasting Model - Inform. With F.A. Monforte. Paper presented at EPRI's Ninth Electric Utility Forecasting Symposium, Sept. 1993

Technology Issues in Residential Forecasting and Least-Cost Planning. Proceedings of the Eighth Electric Utility Forecasting Symposium. EPRI TR-100396, 1992

A Statistically Adjusted End-Use Model of Electricity Sales and Peak Demand. With K. Parris. Prepared for Baltimore Gas and Electric Company, November 1988

Commercial End-Use Data Development Handbook. Volume 2: COMMEND Data and Parameter Development Techniques. Electric Power Research Institute. EM-5703, V2. April 1988

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The Role of Fiscal Policy in Financially Disaggregated Macroeconomic Models. With D. Cohen. *Journal of Money, Credit and Banking,* August 1978

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PUC DOCKET NO. 56211

APPLICATION OF CENTERPOINT ENERGY HOUSTON ELECTRIC, LLC FOR AUTHORITY TO CHANGE RATES	§	PUBLIC UTILITY COMMISSION
	§	OF TEXAS
	§	

DIRECT TESTIMONY

OF

JOHN R. DURLAND

ON BEHALF OF

CENTERPOINT ENERGY HOUSTON ELECTRIC, LLC

MARCH 2024

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GLOSSARY OF ACRONYMS AND DEFINED TERMS

Acronym	Definition
80% Ratchet	NCP kVa for the current billing month or 80% of the highest monthly NCP kVa cost in the 11 months preceding the current billing month
4CP	Four-Coincident Peak
AMS	Advanced Metering System
CenterPoint Houston or Company	CenterPoint Energy Houston Electric, LLC
CNP	CenterPoint Energy, Inc.
Commission	Public Utility Commission of Texas
CCOSS	Class Cost of Service Study
Current CCOSS	Current Class Cost of Service Study
DESR	Distribution Energy Storage Resources
DIST	Distribution
ERCOT	Electric Reliability Council of Texas
FERC	Federal Energy Regulatory Commission
FIS	Full Interconnection Study
FSR	Field Service Representative
IDR	Interval Data Recorder
IRA	Inflation Reduction Act of 2022
kV	Kilo-volts
kVa	Kilo-volt amps
MET	Transmission and Distribution Utility Metering System Services
MLS	Miscellaneous Lighting Service
MW	Megawatt
NCP	Non-Coincident Peak
NRG	NRG Texas, LLC
O&M	Operations and Maintenance

Acronym	Definition
PGC	Power Generation Company
Proposed CCOSS	Proposed Class Cost of Service Study
PURA	Public Utility Regulatory Act
PVS	Primary Voltage Service
Retail Tariff	Tariff for Retail Delivery Service
RFP	Rate Filing Package
Rider IRA	Proposed rider to recover or refund changes in the Company's tax obligation under the IRA
RS	Residential Service
Service Company	CenterPoint energy Service Company, LLC
SLS	Street Lighting Service
SRC	System Restoration Charge
SVL	Secondary Voltage Large
SVS	Secondary Voltage Service
TBILL	Transmission and Distribution Utility Billing System Services
TDCS	Transmission and Distribution Utility Customer Services
TEEEF	Temporary Emergency Electric Energy Facilities
Test Year	12 months ending December 31, 2023
TRAN	Transmission
TVS	Transmission Voltage Service
UG	Underground
Unity Return	CenterPoint Houston's proposed total company percentage return for proposed CCOSS
WDCRF	Distribution Service Charge adjusted based on the monthly per unit cost
WDS	Wholesale Distribution Service
WTS	Wholesale Transmission Service

EXECUTIVE SUMMARY – RATE DESIGN AND TARIFFS

(JOHN R. DURLAND)

My testimony addresses four areas: (1) the twelve-month period ending December 31, 2023 Test Year ("Test Year") billing determinants used to design the proposed retail delivery service rates; (2) the allocation of costs among the rate classes; (3) the development of CenterPoint Energy Houston Electric, LLC's ("CenterPoint Houston" or the "Company") proposed retail and wholesale delivery service tariff rate schedules, riders and various charges; and (4) other proposed changes to the Company's retail delivery service tariffs. Specifically, my testimony:

- explains the reasonable and necessary adjustments to the Test Year billing determinants that are necessary to make the Test Year billing and usage data more representative of conditions that are expected to exist once new rates go into effect;
- describes the two class cost of service studies used to allocate costs among the rate classes in accordance with the Federal Energy Regulatory Commission System of Accounts, the Public Utility Regulatory Act, the Public Utility Commission of Texas' rules and rate filing package instructions, and the principles of cost causation;
- explains, for both the retail delivery service tariff and the wholesale delivery service tariff, how each rate schedule applies and how each delivery charge is calculated, and also demonstrates that these rate schedules and riders accurately recover the cost of service as described and supported in the rate filing package;
- describes the Company's proposed additional charges and discretionary service charges and the methodology used to determine the present cost of providing these services; and
- summarizes other proposed changes to the Company's retail tariff and certain customer agreements.

I. INTRODUCTION

Q. PLEASE STATE YOUR NAME, EMPLOYER, POSITION, AND BUSINESS ADDRESS.

A. My name is John R. Durland. I am the Director of Rates for CenterPoint Energy Service Company, LLC ("Service Company"). My business address is 1111 Louisiana St., Houston, Texas 77002.

Q. WHAT ARE YOUR RESPONSIBILITIES AS DIRECTOR OF RATES?

A. My duties include the development and implementation of cost of service, cost allocation, rate design, and tariffs for energy delivery.

Q. PLEASE DESCRIBE YOUR EDUCATIONAL BACKGROUND, PROFESSIONAL QUALIFICATIONS, AND PREVIOUS WORK EXPERIENCE.

A. Exhibit JRD-1, included with this direct testimony, summarizes my education and professional experience.

Q. HAVE YOU PREVIOUSLY SPONSORED TESTIMONY BEFORE THE PUBLIC UTILITY COMMISSION OF TEXAS ("COMMISSION") OR OTHER REGULATORY AUTHORITIES?

A. Yes. I have previously filed testimony at the Commission in several proceedings. A list of these proceedings is provided in Exhibit JRD-1.

Q. ON WHOSE BEHALF ARE YOU TESTIFYING IN THIS PROCEEDING?

A. I am testifying on behalf of CenterPoint Energy Houston Electric, LLC ("CenterPoint Houston" or the "Company").

II. PURPOSE AND SCOPE OF TESTIMONY

Q. WHAT IS THE PURPOSE OF YOUR DIRECT TESTIMONY IN THIS PROCEEDING?

A. The purpose of my testimony is to: (1) sponsor the proposed twelve-month period ending December 31, 2023 ("Test Year") billing determinant adjustments made to energy sales, demands, and year-end customer count; (2) present CenterPoint Houston's Class Cost of Service Study ("CCOSS") in support of the Company's proposed delivery system charges in its Tariff for Retail Delivery Service ("Retail Tariff") and the Company's proposed wholesale transmission rates in its Tariff for Wholesale Delivery Service ("Wholesale Tariff"); (3) support the calculation of the proposed delivery system and discretionary service charges in its Retail Tariff, and the proposed rates in its Wholesale Tariff; (4) explain the policy reasons for any proposed rate design changes for delivery system charges in the Retail Tariff; and (5) support the proposed non-rate changes to various provisions in Chapters 2 and 6 of the Retail Tariff. In my testimony, the terms "delivery system charges" and "discretionary charges" have the respective meanings given for those terms in Section 1 of the Retail Tariff.

Q. HAVE YOU PREPARED ANY EXHIBITS IN CONNECTION WITH YOUR TESTIMONY?

A. Yes. I sponsor the exhibits shown in my list of exhibits. These exhibits were prepared by me or under my direction and supervision. The information contained in these exhibits is true and correct to the best of my knowledge and belief.

Q. DO YOU SPONSOR OR CO-SPONSOR ANY SCHEDULES IN THIS PROCEEDING?

A. Yes. I sponsor or co-sponsor the following Rate Filing Package ("RFP") schedules that relate to and support the Company's Test Year Customer Billing Determinant Data, CCOSS, Class Cost Allocation process, and Rate Design process:

- Schedule I-A: Cost of Service Summary – This schedule summarizes the utility's overall cost of service and revenue requirement used for the determination of the non-bypassable retail delivery charges and wholesale transmission rates, which are the sum of 1) the Total Requested Cost of Service net of Revenue Credits from Schedule I-A-I; 2) the Requested Nuclear Decommissioning from Schedule II-G, if applicable; 3) a Competition Transition Charge, if any, outlined in the supporting schedules described herein; and 4) any other charges the Commission has previously approved as non-bypassable charges (Transition Charges, etc.). Costs associated with identifiable riders are listed as distinct line items, and tie to applicable detailed schedules. This schedule begins with unadjusted Test Year rate revenues for each identified item above, adjustments to Test Year rate revenues, proposed rate revenues, and the requested increase/decrease to adjusted Test Year rate revenues. The total information is composed of wholesale transmission service plus retail delivery service, shown in total by class.

- Schedule II-H-1: Summary of Test Year Adjustments – This schedule provides the following summary of Test Year data by rate class: year-end number of customers, total adjusted kWh sales.

- Schedule II-H-1.1: Test Year Sales Data – This schedule provides the following Test Year data by rate class: average number of customers, year-end number of customers; Test Year kWh (unadjusted sales), increase or decrease in kWh sales due to adjustments for abnormal weather, increase or decrease in kWh sales due to adjustments for changes in customer composition and/or for changes in the number of customers; increase or decrease in kWh sales due to adjustments other than for the effects of weather and customer (e.g. reclassification of customers), reflecting each adjustment separately; and total adjusted kWh sales for the Test Year.

- Schedule II-H-1.2: Monthly Sales Data – This schedule provides the data presented in Schedule II-H-1.1 by month of the Test Year.

- Schedule II-H-3.1: Customer Information – This schedule provides the monthly Test Year number of customers by rate class.

- Schedule II-H-3.2: Customer Adjustments – This schedule presents topics and descriptions of the customer adjustments performed by rate class.

- Schedule II-H-3.3: Customer Adjustment Data – The purpose of this schedule is to provide adjustment data not already presented in Schedule II-H-3.1 above. This schedule is not applicable, CenterPoint Houston has provided all the customer adjustment data above in Schedule II-H-3.1.

- Schedule II-H-4.1: Revenue Impact Data – This schedule provides the Test Year data on revenue impacts of kWh sales and kW/kVA demand adjustments by rate class. The data columns show: revenue associated with any rate annualization adjustments, showing components separately; revenues associated with kWh customer adjustments, showing components separately; revenues associated with kW customer adjustments, showing components separately; revenues associated with kWh weather adjustments, showing components separately; revenues associated with kW weather adjustments, showing components separately; revenues associated with other kWh adjustments, showing the revenue associated with each adjustment individually, listing components separately; revenues associated with other kW adjustments, showing the revenue associated with each adjustment individually, listing components separately.

- Schedule II-I-1: Class Revenue Requirement Analysis – This schedule provides a class revenue requirement analysis for the Test Year and displays the functional revenue requirement allocated to each rate class.

- Schedule II-I-2 Class Allocation Factors – This schedule provides the allocation factors used in each customer class.

- Schedule II-I-3 Functionalized Cost-of-Service Analysis (Non-ERCOT Members) – Because CenterPoint Houston is a member of and operates in the Electric Reliability Council of Texas ("ERCOT") power region, this schedule is not applicable.

- Schedule IV-J-1 Revenue Summary – This schedule provides a summary of the Test Year revenue requirement. The rows of the table display the Test Year revenue requirement by base rate function and approved riders. The columns display the Test Year revenue requirement by rate class.

- Schedule IV-J-2 Proposed Charges for Discretionary Services and Other Services – This schedule provides the proposed charges for each discretionary and other service charge in the Company's tariffs.

- Schedule IV-J-3 Rate Class Definition – This schedule is a catalogue of rate classes and definitions.

- Schedule IV-J-5 Billing Determinants – This schedule imparts the following billing summary for each rate class for each month of the Test Year: Billing Demand, Billing kWh, and Number of Customer Bills. Billing Demand details unadjusted, adjustments, and fully-adjusted total. Billing kWh details unadjusted, adjustments (weather and customer changes, and Energy Efficiency Program) and the total fully-adjusted kWh totals. Number of Customer Bills unadjusted, customer growth adjustment, fully-adjusted total.

- Schedule IV-J-6 Justification for Consumption Level-Based Rates – This schedule is not applicable.

- Schedule IV-J-7 Proof of Revenue Statement – This schedule provides a proof of revenue statement, presents the class cost of service, the billing units, proposed rates, and the resulting base revenue for the existing and proposed rate classes, and any other Commission-approved non-bypassable charges under both current and proposed rates.

- Schedule IV-J-8 Rate Design Analysis Data – This schedule provides estimated billing determinants, without ratchet provisions, for peak and off-peak periods as defined by the utility's proposed tariffs, for all classes for which hourly demand data (or demand data for intervals shorter than one hour) is available for customers collectively accounting for over 50% of class sales.

Q. HOW DOES YOUR TESTIMONY RELATE TO THE TESTIMONY OF OTHER WITNESSES IN THIS PROCEEDING?

A. Company witness J. Stuart McMenamin sponsors the specific weather adjustments made to billing determinant data, and other Company witnesses sponsor costs and revenue requirements that are incorporated into the cost allocation model, the rate design model, and the proposed tariffs. The direct testimony of Company witness Lynnae Wilson will present the list of witnesses in this proceeding that will provide further discussion of the topics.

Q. WAS YOUR TESTIMONY, INCLUDING ASSOCIATED SCHEDULES, WORKPAPERS AND EXHIBITS, PREPARED BY YOU OR UNDER YOUR CONTROL AND DIRECTION?

A. Yes, I have prepared or supervised the preparation of the exhibits and workpapers listed in the table of contents.

III. <u>TEST YEAR BILLING DETERMINANTS</u>

Q. WHAT IS A BILLING DETERMINANT?

A. For purposes of establishing rates, a billing determinant may be the measure of energy consumption (kWh), demand (kVa), customer count or meter count.

Q. ARE YOU SPONSORING THE COMPANY'S PROPOSED TEST YEAR BILLING DETERMINANTS?

A. Yes. I sponsor the proposed billing determinants identified in Schedule IV-J-5.

Q. WHY ARE TEST YEAR BILLING DETERMINANTS ADJUSTED?

A. The Company has made certain adjustments to its billing determinants to make the Test Year billing and usage data more representative of conditions that are reasonably expected to exist once new rates go into effect. The Test Year adjustments are based on known and measurable changes and represent a fair and equitable method to allocate necessary cost recovery, and design rates.

Q. WHAT TYPES OF ADJUSTMENTS WERE MADE TO THE TEST YEAR BILLING DETERMINANTS IN THIS PROCEEDING?

A. Two types of adjustments were made to the Test Year billing determinants: (1) customer adjustments to reflect the number of customers at the end of the Test Year and (2) weather adjustments made to the Test Year load data as presented in

Schedules II-H-2 through II-H-2.3, and Schedules II-H-5 through II-H-5.3, sponsored by Company witness J. Stuart McMenamin. See my Exhibit JRD-2 for a summary of the adjustments to Test Year billing determinants.

Q. WHAT IS THE PURPOSE OF THE CUSTOMER ADJUSTMENTS?

A. The purpose of the customer adjustments is to recognize the change in the number of customers over the course of the Test Year by updating the billing determinants for each rate class to levels consistent with electric usage as if the year-end number of customers had been present the entire Test Year.

Q. PLEASE DESCRIBE THE PROPOSED CUSTOMER ADJUSTMENTS.

A. For the residential service ("RS"), secondary voltage small ("SVS"), secondary voltage large ("SVL") and primary voltage service ("PVS") rate classes, the proposed customer adjustment is accomplished by scaling, either up or down, each month's billing determinants, weather normalized if applicable, to the customer count as of December 31, 2023. Non-metered lighting is adjusted similar to other rate classes, except that the adjustments to Test Year kWh reflect the number of active lamps of each lamp type as of December 2023. Customer adjustments to the Transmission Voltage Service ("TVS") rate class are treated somewhat differently. If a new TVS customer is added during the Test Year, billing determinants are adjusted by restating that customer's usage as if that customer had been present the entire year. Similarly, if an existing customer permanently shuts down operations, billing determinants are adjusted by restating the Test Year to remove all of that customer's usage.

Q. ARE THE COMPANY'S CUSTOMER ADJUSTMENTS REASONABLE AND APPROPRIATE?

A. Yes. The proposed customer adjustments are reasonable and appropriate. The customer adjustments are consistent with those approved by the Commission in the Company's last rate case in Docket No. 49421,[1] and are reflective of electric usage going forward based on the information known and measurable as of the end of the Test Year.

Q. PLEASE EXPLAIN ANY WEATHER ADJUSTMENTS TO THE TEST YEAR LOAD DATA.

A. The direct testimony of Dr. McMenamin will explain the proposed weather adjustments to the Test Year load data.

IV. <u>CLASS COST OF SERVICE</u>

Q. WHAT IS A CLASS COST OF SERVICE STUDY?

A. A CCOSS is a cost-causation analysis of the Company's plant investment, revenues, and expenses that calculates and allocates the cost incurred to provide service to each customer class. The measure of cost assigned to each customer class is derived from unique customer class requirements, demand, energy, and revenue attributes to the investment. A CCOSS is a well-established, fair, and equitable way to allocate reasonable and necessary costs to appropriately design rates.

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[1]Application of CenterPoint Energy Houston Electric, LLC For Authority to Change Rates, Docket No. 49421, Final Order (March 9, 2020).

A. Overview Of Class Cost of Service Study Allocation Process

Q. HOW ARE CENTERPOINT HOUSTON'S COSTS ORGANIZED FOR PURPOSES OF ALLOCATION AMONG RETAIL DELIVERY CLASSES?

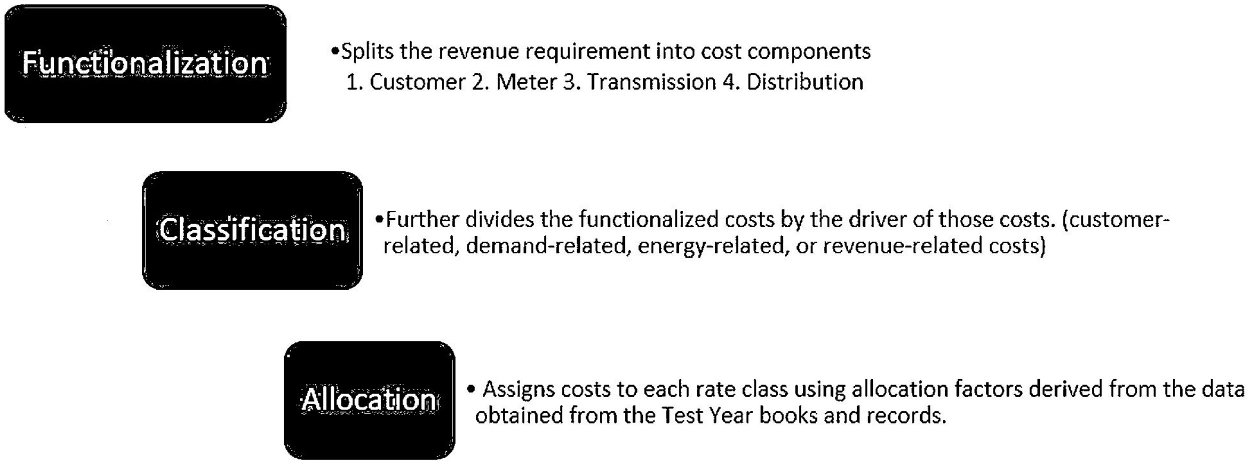
A. CenterPoint Houston follows the FERC Uniform System of Accounts, which provides a numerical system of accounting for revenue, revenue deductions, and plant (assets or investment). The Federal Energy Regulatory Commission ("FERC") Uniform System of Accounts is reflected in Schedules II-B-1 through II-B-12, sponsored by Company witness Kristie L. Colvin. Total revenue includes revenue from electric sales[2] as well as various other revenue items. Revenue deductions include operations and maintenance ("O&M") expense, depreciation and amortization expense, and taxes. Rate base items include plant investment, accumulated depreciation and amortization, and other capital items. Within each FERC account, costs are further functionalized and organized by classification.

Q. PLEASE DESCRIBE HOW THE COMPANY'S CCOSS WAS PREPARED.

A. CenterPoint Houston's CCOSS allocation was prepared using a three-step process: (1) functionalization of expense and revenue of all accounts (see Schedules II-B-1 through II-B-12, as described in the direct testimony of Ms. Colvin); (2) classification of expense, revenue, and rate base accounts; (3)(a) development of allocation factors based on the data obtained from the books and records of the Company for the Test Year; and (b) allocation of the revenue, expense, and rate base accounts to the customer classes based on the allocation factors developed in

[2] Electric sales refers to electric usage measured by the meter(s) at a customer's premise multiplied by the applicable rate.

(3)(a) above. This process is set forth in the graphic below:



Q. PLEASE DESCRIBE THE FUNCTIONALIZATION PROCESS.

A. Functionalization is the process of assigning costs to a specific business "function" to determine which rate class is responsible for each of the assigned costs. Consistent with the Commission's RFP instructions as defined in 16 TAC § 25.344, the Company has functionalized costs into the following business functions:

Transmission ("TRAN");
Distribution ("DIST");
Transmission and Distribution Utility Metering System Services ("MET");
Transmission and Distribution Utility Billing System Services ("TBILL");
Transmission and Distribution Utility Customer Services ("TDCS").

The Company has combined the TBILL and TDCS functions as permitted by the Commission's RFP instructions. Ms. Colvin sponsors and describes in her testimony how specific revenues and costs were functionalized.

Q. WHAT ARE COST CLASSIFICATIONS AND HOW ARE THEY DETERMINED?

A. Some functionalized costs can be directly assigned to one or more customer rate classes. Other costs involve more than one customer rate class and must be allocated amongst these rate classes. After functionalization, the next step in the allocation process is to classify the costs as being customer-related, demand-related, energy-related, or revenue-related costs, or a combination thereof.

Generally, costs characterized as fixed costs are classified as customer-related or demand-related costs and costs characterized as variable cost are classified as energy-related or revenue-related. For example, customer-related costs are those costs that arise as the result of incrementally adding a customer to the system but vary little or not at all with the customer's actual electrical usage. Customer accounting expense, for example, is a customer-related cost because CenterPoint Houston is required to maintain records for each customer due to the customer's existence on the delivery system, regardless of the level of electrical consumption. Therefore, customer accounting expenses are allocated to rate classes based on the number of customers in the class.

Costs classified as demand-related costs are driven by and dependent on the electric demand or load of the customers. For example, distribution facilities are designed and built to carry the maximum expected electrical demand of the system, without respect to the actual number of customers taking service at any given time. Distribution costs have therefore been classified as demand-related costs.

Energy-related costs are generally driven by the energy usage of each rate class. Revenue-related costs are driven by revenues received from each rate class.

Q. AFTER THE COSTS ARE FUNCTIONALIZED AND CLASSIFIED, WHAT IS THE NEXT STEP IN THE ALLOCATION PROCESS?

A. After functionalization and classification, the costs are allocated according to allocation factors.

Q. PLEASE DESCRIBE HOW ALLOCATION FACTORS ARE DEVELOPED.

A. Allocation factors are developed based on an analysis of the distinct characteristics of each rate class. Costs are first functionalized and then assigned to the classified cost categories described above for each rate class. Allocation factors are then assigned to these functionalized and classified costs and used to allocate the costs to the customer classes.

Q. PLEASE DESCRIBE THE ALLOCATION FACTORS USED IN SCHEDULE II-I-2 AND HOW THEY WERE DEVELOPED.

A. The following are the allocation factors categories shown in the II-I-2 Schedules:

- Customer factors were developed using: (1) the number of customers in each rate class at the end of the Test Year, weighted for meter investment; and (2) the total number of customers at the end of the Test Year.
- Demand factors were developed using various rate class demand measurements and an unadjusted Four-Coincident Peak ("4CP")[3] demand allocation methodology.
- Energy factors were developed based on the energy usage of each rate class.
- Revenue factors were developed based on the percentage of revenues received from each rate class.
- Factors for General Plant Accounts were derived based on allocated operating plant costs.

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[3] 4CP is calculated using a rate class's proportionate share of demand during the highest 15 minute demand interval in ERCOT for each month during the 4-month period June through September.

Q. DESCRIBE THE DATA SOURCE USED TO DEVELOP THE ALLOCATION FACTORS.

A. The data to develop the allocation factors originated from three sources: (1) the schedules and workpapers provided in the rate filing package; (2) the accounting books and records of the Company; and (3) special studies performed to acquire specific data. For example, Dr. McMenamin describes how the data from the CenterPoint Houston advanced metering system ("AMS") is used to adjust daily and monthly energy usage and billing determinants to ensure that its rates are set based on data that reflect normal weather, as contemplated by this Commission's rules and RFP instructions.

Q. HAS THE DEMAND AND ENERGY DATA USED FOR ALLOCATION PURPOSES BEEN ADJUSTED?

A. No. There were no adjustments made to the demand and energy data.

Q. WHERE ARE THE ALLOCATION FACTORS IDENTIFIED IN THE COMPANY SCHEDULES?

A. The allocation factors are shown in the II-I-2 Schedules, and the source of all allocation factors are provided in Schedule II-I-Class Allocation Summary.

Q. ARE THE ALLOCATION METHODOLOGIES USED TO DEVELOP THE ALLOCATION FACTORS CONSISTENT WITH WHAT THE COMMISSION APPROVED IN DOCKET NO. 49421?

A. Yes. CenterPoint Houston generally used the same allocation methodology the Commission approved in CenterPoint Houston's previous rate filing proceeding, Docket No. 49421.[4]

Q. WHAT IS THE FINAL STEP IN PREPARING THE CCOSS?

A. The final step in preparing the CCOSS is applying the allocators derived in the previous step, as shown in the II-I-2 Schedules, to all the FERC Account costs, expenses, and other revenues.

B. Demand-related Allocation Methodology

Q. PLEASE DESCRIBE THE METHOD USED TO ALLOCATE CAPACITY-RELATED TRANSMISSION COSTS.

A. CenterPoint Houston proposes to use the unadjusted 4CP allocation factor based on the ERCOT peak summer month periods (i.e., June, July, August, and September) to allocate capacity-related transmission costs. This matches the use of the 4CP allocator the Commission uses for pricing wholesale transmission charges pursuant to Public Utility Regulatory Act ("PURA") § 35.004(d) and is consistent with Commission rules and the Company's approved approach in Docket No. 49421.

Q. PLEASE DESCRIBE THE METHOD USED TO ALLOCATE DEMAND-RELATED DISTRIBUTION COST.

A. The methodology used for the demand-related distribution cost in the Cost of Service Study is based on the Non-Coincident Peak ("NCP") 15-minute aggregated demand on the CenterPoint Houston distribution system for each rate class in the Test Year. This demand data is shown on Schedule II-H-1.3, sponsored by Dr. McMenamin. The allocation factors are determined at two points of service on the

[4] Docket No. 49421, Final Order (March 9, 2020).

distribution system: the substation and the overhead distribution lines. Since some customers are served exclusively on the underground ("UG") line distribution system and do not use the overhead line facilities, having the allocation factors determined at the substation and the overhead distribution line level allows certain costs of the UG line facilities to be allocated exclusively to those classes which have customers served from those facilities.

Q. WHY HAVE YOU ELECTED TO USE THE NCP DEMAND METHODOLOGY FOR DEMAND-RELATED DISTRIBUTION COST?

A. The Company's distribution system is designed to serve the maximum load requirement of each individual retail customer and is strategically constructed to have the capability to reliably serve the maximum load demanded by any or all customers at any time. NCP demand allocation represents the cost required to serve the highest load of each rate class on the distribution system.

Q. PLEASE DISCUSS THE APPROACH USED TO CLASSIFY AND ALLOCATE OVERHEAD DISTRIBUTION POLES, TOWERS & FIXTURES - ACCOUNT 364, AND CONDUCTORS – ACCOUNT 365.

A. As shown in WP - Acct. 364 and WP - Acct. 365, the costs of distribution poles, towers and fixtures, and conductors are classified as either primary voltage-related, or secondary voltage-related prior to the cost allocation process. The costs are then allocated to rate classes using the NCP distribution allocation factors.

Q. PLEASE DISCUSS THE ALLOCATION OF DISTRIBUTION UNDERGROUND CONDUIT – ACCOUNT 366, AND CONDUCTORS – ACCOUNT 367 TO RATE CLASSES.

A. As shown in WP - Acct. 366 and WP - Acct. 367, Underground facilities are divided into four categories for allocation:

- UG Network;
- UG Getaways and Street Dips;
- UG Service from Terminal Poles; and
- Residential UG.

As shown in WP - Acct. 366 and WP - Acct. 367, investment in UG Network is allocated to rate classes based on each class's proportionate contribution to system peak demand. UG Getaways and Street Dips and UG Service from Terminal Poles are allocated to rate classes based on relative rate class demands at the distribution line level. Residential UG facility investment is assigned directly to the residential class.

Q. HOW ARE LINE TRANSFORMERS – ACCOUNT 368, CLASSIFIED AND ALLOCATED?

A. As shown in WP – Acct. 368, investment in line transformers is divided into two components: primary voltage-related and secondary voltage-related. Costs are then allocated to rate classes using the NCP distribution allocation factors.

Q. HOW ARE SERVICES – ACCOUNT 369 ASSIGNED TO THE RATE CLASSES?

A. Distribution service drops, as shown in WP - Acct. 369, are directly assigned to the customer classes served by these facilities.

Q. HOW ARE METERS – ACCOUNT 370 ALLOCATED TO THE RATE CLASSES?

A. As shown in WP - Acct. 370, meters are separated by meter type, consisting of meters and automated meters, and then further separated between meters and transformers by using accounts 370.1 and 370.3. The meter portion is allocated by meter count by class for Interval Data Recorder ("IDR") and non-IDR. The transformer portion is allocated for IDR and non-IDR by transformer count.

Q. HOW IS STREET LIGHTING PLANT – ACCOUNT 373 ALLOCATED WITHIN THE LIGHTING SERVICE RATE CLASS?

A. As shown in WP - Acct. 373, investment in street lighting is directly assigned by type of service using the Company's accounting records of investment – either Street Lighting Service or Miscellaneous Lighting (i.e., security lighting) Service.

Q. HOW ARE RATE CASE EXPENSES ALLOCATED TO THE RATE CLASSES?

A. The proposed rate case expenses were assigned to the rate classes in the same proportion as the cost of service allocators, shown in Schedule IV-J-7-RCE. The cost of service factor for each rate class is based on the percentage of total cost of service amount allocated to each rate class.

Q. HOW ARE OTHER EXPENSES ALLOCATED TO THE RATE CLASSES?

A. Other expenses such as O&M expenses, depreciation expenses, and taxes were functionalized on a cost-causation basis, as shown on Schedule I-A-1, sponsored by Ms. Colvin. The costs were then allocated to the rate classes using the ratios described in the II-I-2 Schedules.

Q. ARE THE ALLOCATIONS AND ALLOCATION METHODOLOGIES DESCRIBED ABOVE REASONABLE AND CONSISTENT WITH THE APPLICABLE RFP REQUIREMENTS?

A. Yes, these methodologies are reasonable and are consistent with the Commission's RFP instructions.

C. Adjustments to Rate Class Revenue Requirements

Q. HAVE YOU MADE ANY ADJUSTMENTS TO THE RATE CLASS REVENUE REQUIREMENTS CALCULATED IN THE CLASS COST OF SERVICE STUDY?

A. No. The total amounts allocated to each customer class are shown in Schedule II-I-Total.

Q. HOW DID YOU ALLOCATE THE REVENUES RESULTING FROM DISCRETIONARY SERVICE CHARGES AND FROM OTHER REVENUES?

A. Revenues from Discretionary Service Charges and from Other Revenue are deducted from the cost of service to arrive at the Company's proposed revenue requirement. These revenues are allocated on a cost-causation basis, as shown on Schedule I-A-1, sponsored by Ms. Colvin. Thereafter, the cost was allocated to the rate classes using the ratios provided in Schedule II-I-2 Class Ratios. See my Exhibit JRD-3, which summarizes the cost allocations performed.

Q. ARE THE REVENUE ADJUSTMENTS REASONABLE AND NECESSARY AND CONSISTENT WITH COMMISSION RULES AND THE APPLICABLE RATE FILING PACKAGE REQUIREMENTS?

A. Yes, these methodologies are reasonable and are consistent with the Commission's rules and RFP requirements.

D. **<u>Class Cost of Service Study Results</u>**

Q. PLEASE SUMMARIZE THE RESULTS OF THE COMPANY'S CCOSS PROCESS.

A. To determine the appropriate level of costs and revenues to be assigned to each rate class, two retail delivery class cost of service studies were performed using the allocation methodologies described above. The Current Class Cost of Service Study (the "Current CCOSS") shows current revenue and relative rates of return by retail delivery class while the Proposed Class Cost of Service Study (the "Proposed CCOSS") shows the proposed revenue at the system-wide average rate of return by class. The mathematical difference between these two studies shows the change in revenue requirement (increase or decrease) by rate class and the corresponding percentage revenue change if CenterPoint Houston's rates are reset based on the costs and revenue requirements supported by this filing. These results are summarized below:

Figure 1

Rate Class Description	Number of Customers	Present Revenues[1] (a)	Proposed Revenues (b)	Change (c) = (b)-(a)	Change Pct (d)/(a)
Residential	2,455,309	$ 901,815,248	$ 975,768,614	$ 73,953,366	8.2%
Secondary <= 10kva	155,776	$ 25,410,421	$ 24,178,448	$ (1,231,973)	-4.8%
Secondary > 10Kva	151,170	$ 578,913,742	$ 520,202,246	$ (58,711,496)	-10.1%
Primary	1,047	$ 41,515,394	$ 48,954,335	$ 7,438,941	17.9%
Transmission	233	$ 27,090,086	$ 24,523,576	$ (2,566,510)	-9.5%
Miscellaneous Lighting	10,660	$ 5,783,740	$ 3,077,136	$ (2,706,604)	-46.8%
Lighting	5,654	$ 70,568,628	$ 71,339,335	$ 770,707	1.1%
Retail Electric Delivery Revenues	2,779,849	$ 1,651,097,259	$ 1,668,043,689	$ 16,946,431	1.0%
WholesaleTransmission Revenue		$ 654,236,818	$ 697,326,740	$ 43,089,922	6.6%
Total Cost of Service		$ 2,305,334,077	$ 2,365,370,429	$ 60,036,353	2.6%

1 Test Year revenues have been adjusted to normalize billing units and adjust for DCRF
*** See schedule IV-J-7 TCRF for TCRF costs**

For the Current CCOSS, Test Year O&M expenses, depreciation expenses, and taxes were allocated, and then other revenue was subtracted to derive the current dollar return by class. Current dollar return was then divided by the allocated rate base to derive a percentage return by class. Percentage return by class was then divided by the total company return to determine relative rates of return. For the Proposed CCOSS, CenterPoint Houston's proposed total company percentage return ("unity return") is multiplied by the rate base allocated to each class to determine the associated dollar return by class. The O&M expenses, depreciation expenses, and taxes allocated to each class are then added to the dollar return for each class to develop the cost of service and revenue requirement by class at the proposed rate level. Schedule II-I-Class Allocation Summary of the rate filing package provides the summary of the cost of service analysis, and Schedule II-I-Class Factors provides the class allocation factors.

Q. ARE ALL RATE CLASSES "IN UNITY"?

A. Yes, as shown in Schedule II-I-Class Allocation Summary, the proposed delivery system charges for all rate classes were developed using cost causation principles, and thus eliminated interclass revenue subsidies so that the relative rates of return are equalized.

V. <u>RETAIL DELIVERY RATE DESIGN</u>

A. <u>Rate Charges by Customer Class</u>

Q. HOW WERE THE PROPOSED RETAIL DELIVERY SYSTEM CHARGES DESIGNED?

A. The proposed delivery system charges were designed using the processes summarized in Schedule IV-J-1 Revenue Summary. The summary shows total cost of service requirements by function and by rate class. The total cost of service or revenue requirement by rate class is divided by total billing determinants to derive a rate per class. The per-class rate calculations are shown on Schedules IV-J-7 Proof of Revenue Summary. The adjusted billing determinants are indicated in Schedule IV-J-5.

Q. PLEASE DESCRIBE THE FORM OF THE DELIVERY SYSTEM CHARGES FOR THE RETAIL DELIVERY RATE CLASSES.

A. The retail delivery rate classes are:

- Residential Service;
- Secondary Service Less than or Equal to 10 kVA;
- Secondary Service Greater Than 10 kVA;
- Primary Service;
- Transmission Service; and
- Lighting Services.

Each rate class schedule, except for Lighting Services, includes a Customer Charge, Metering Charge, Distribution System Charge, and Transmission System Charge. The current and proposed revenue by rate class and the charges by rate class are shown in Exhibits JRD-4 and JRD-5, respectively.

The Customer Charge and Metering Charge include costs that are incurred regardless of system usage. The Company bills the Customer Charge and Metering Charge on a per customer and meter basis, respectively per month to all rate classes except Lighting Services.

The basis for the Distribution and Transmission Charges varies among the different rate classes. For the Residential and Secondary Service Less Than or Equal to 10 kVA rate schedules, both the Transmission and Distribution Delivery Charges are recovered on a per kWh basis. For the Secondary Service Greater Than 10 kVA rate schedule, the Distribution Delivery Charge will be based on Billing Demand, using NCP kVA. With respect to the Primary Service rate schedule, Distribution Delivery Charges will be based on the Billing kVA, which is defined as NCP kVA for the current billing month or 80% of the highest monthly NCP kVA established in the 11 months preceding the current billing month ("80% Ratchet"). Seasonal agriculture customers are exempted from the 80% Ratchet. For Transmission Service, the Distribution Delivery Charges will be based upon 4CP kVA. For the Secondary Service Greater Than 10 kVA and the Primary Service rate schedules, the Transmission Charge billing determinant depends upon the type of meter attributed to the customer. For those customers classified as having IDR meter service using a traditional IDR meter or an IDR capable AMS meter, the charges for retail transmission service are billed using the customer's 4CP kVA demand at the date and time coincident with the ERCOT 4CP. For customers classified as having a non-IDR meter, the Transmission Charge billing determinants are based on the customer's monthly maximum NCP kVA demand. For the Transmission Service rate schedule, the Transmission Charge billing determinants will be 4CP kVA.

Unlike most service under the other rate classes, Lighting Services are unmetered and do not have a Customer Charge or Metering Charge. The distribution and transmission charges for Lighting Services are stated on a per-fixture basis, based on the type of lamp and its configuration.

Q. PLEASE DESCRIBE THE DEVELOPMENT OF THE CUSTOMER CHARGE FOR EACH RETAIL DELIVERY RATE CLASS.

A. The Customer Charge for each rate schedule (other than Lighting Services, which has no Customer Charge) is based on the class revenue requirement for the Customer Service function from the Proposed CCOSS, divided by the total Test Year adjusted annual customer count for each class. The Customer Charge calculation remains generally unchanged, though the ultimate level of the proposed Customer Charge will change based upon the Proposed CCOSS.

Q. PLEASE DESCRIBE THE DEVELOPMENT OF THE METERING CHARGE FOR EACH RETAIL DELIVERY RATE CLASS.

A. The Metering Charge for each rate schedule (other than Lighting Services, which has no Metering Charge) is based on the class revenue requirement for the Metering function from the Proposed CCOSS, divided by the total Test Year adjusted annual meter count for each class. However, for rate classes that have both IDR service and non-IDR meter categories, both the revenue requirement and the annual meter count are calculated separately for each category.

Q. PLEASE DESCRIBE THE DEVELOPMENT OF THE DISTRIBUTION SYSTEM CHARGE FOR EACH RETAIL DELIVERY CLASS.

A. The Distribution System Charge for each rate schedule is based on the class revenue requirement for the Distribution function from the Proposed CCOSS, divided by the total Test Year adjusted annual distribution billing determinants for that class as shown on the following table.

Figure 2

Rate Class	Distribution Billing Determinant
Residential Service	Test Year adjusted kWh
Secondary Service ≤ 10 kVA	Test Year adjusted kWh
Secondary Service > 10 kVA	Test Year billing kVA, defined as NCP kVA
Primary Service	Test Year billing kVA, defined as NCP kVA with a demand ratchet (ratchet is not applicable to seasonal agricultural customers)
Transmission Service	Test Year 4CP kVA
Lighting Service	N/A

Q. IS CENTERPOINT HOUSTON PROPOSING A TRANSMISSION FUNCTION CHARGE?

A. No. In Docket No. 49421 the Company moved its retail transmission cost to the TCRF, and the Company proposes to continue the same methodology that was approved in that docket. It is my understanding that all ERCOT TDUs recover the ERCOT system-wide access fees through the TCRF and no ERCOT TDU has a Transmission Service Charge as a base rate. Therefore, I have removed the Transmission Service Charge from the applicable rate schedules.

B. <u>Rate Schedules</u>

Q. PLEASE DESCRIBE THE RESIDENTIAL SERVICE RATE SCHEDULE.

A. This rate schedule is available to retail customers requesting delivery service for residential purposes. The rate schedule sets forth the Monthly Rate (composed of the Customer Charge, the Metering Charge, the Distribution System Charge, and the Transmission System Charge), the service riders that may apply to the rate schedule, and the Company's general terms of service under this rate schedule.

Q. PLEASE DESCRIBE ANY PROPOSED CHANGES TO THE DELIVERY SYSTEM CHARGES IN THE RESIDENTIAL SERVICE RATE SCHEDULE.

A. CenterPoint Houston is proposing to update the delivery system charges in the Residential Service rate schedule to reflect the revenue requirement by function as described in the Proposed CCOSS. The proposed Residential Service rate schedule is included in Exhibit JRD-9.

Q. PLEASE DESCRIBE THE SECONDARY SERVICE LESS THAN OR EQUAL TO 10 KVA RATE SCHEDULE.

A. This rate schedule is available to retail customers requesting delivery service for non-residential purposes with demands less than or equal to 10 kVA and to retail customers requesting unmetered services other than Lighting Services. The rate schedule sets forth the Monthly Rate (composed of the Customer Charge, the Metering Charge, and the Distribution System Charge and Transmission System Charge), the service riders that may apply to the rate schedule, and the Company's general terms of service under this rate schedule.