P.U.C. DOCKET NO. 58964

BEFORE THE PUBLIC UTILITY COMMISSION OF TEXAS

APPLICATION OF
TEXAS-NEW MEXICO POWER COMPANY
FOR AUTHORITY TO CHANGE RATES

PREPARED DIRECT TESTIMONY AND EXHIBITS

OF

DR. J. STUART MCMENAMIN

ON BEHALF OF

TEXAS-NEW MEXICO POWER COMPANY

NOVEMBER 14, 2025

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EXHIBIT JSM-1
EDUCATIONAL BACKGROUND AND BUSINESS EXPERIENCE

I. INTRODUCTION AND QUALIFICATIONS

Q. PLEASE STATE YOUR NAME, BUSINESS ADDRESS, AND PLACE OF EMPLOYMENT.

A. My name is John Stuart McMenamin. I am a Senior Principal Forecasting Consultant at Itron, 10870 Rancho Bernardo Road, Suite 100, San Diego, CA 92127.

Q. ON WHOSE BEHALF ARE YOU TESTIFYING?

A. I am testifying on behalf of TNMP.

Q. PLEASE DESCRIBE YOUR EDUCATIONAL BACKGROUND AND PROFESSIONAL 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's end-use modeling programs. More recently, my work has focused on methods that combine econometric and end-use concepts. I have been employed by Itron, Inc. as the Director of the Forecasting and Load Research Solutions group for 22 years, and now I am the Senior Principal Consultant with the Itron Forecasting group. Additional details are available in my resume, which is attached to this testimony.

Q. PLEASE DESCRIBE YOUR DUTIES AS DIRECTOR OF FORECASTING AT ITRON.

A. From 2002 to 2024, I was the Director of the Forecasting Solutions group at Itron, Inc. In that position I was in charge of development for our Automated Forecasting System, which is used by many large system operators, such as the California ISO, Midwest ISO, and ERCOT. I was also responsible for Itron products and services related to financial forecasting, including the Itron statistical package (MetrixND), used by utilities (like CenterPoint, Oncor, CPS, and TNMP), to forecast and analyze customers, sales, revenues, and hourly loads. In addition to product design and algorithm development, I directed and contributed to consulting projects related to forecasting and load research for utilities. For the last 15 years, I have been working with utilities in North America to help them improve analysis and forecasting processes using AMS data. The analysis I conducted for TNMP and that I describe in this testimony is an example of this work.

Q. HAVE YOU PREPARED ANY EXHIBITS?

A. Yes. I am sponsoring Schedules related to weather adjustment of energy, class peak, class coincident loads, and customer demand. All of the exhibits were prepared by me or at my direction and under my control. The information contained in these schedules and supporting exhibits is true and correct to the best of my knowledge and belief.

II. PURPOSE OF TESTIMONY

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

A. The purpose of my testimony is to present the methods and data that were used to develop load estimates and weather adjustments for the TNMP filing, including estimates and adjustments for monthly sales, customer demand, class peaks, and class loads at the time of TNMP and ERCOT peaks. The estimates and adjustments were developed using AMS data for the TNMP 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. DO YOU SPONSOR ANY SCHEDULES IN THE RATE FILING PACKAGE?

A. Yes. I sponsor or co-sponsor the following Rate Filing Package ("RFP") schedules including the associated workpapers:

Schedule II-H-1.2: Test Year Sales by Month. This schedule provides a summary of the number of customers, monthly sales, and monthly sales adjustments. The sponsor for this form is Stacy Whitehurst, and I am responsible for the weather adjustment values in column (3) of this form.

Schedule II-H-1.3: Unadjusted test year load data – This schedule provides the following unadjusted Test Year data at the source (busbar) and at the meter by rate class for the Test Year and for each month of the Test Year: Sum of customer maximum demands (non-coincident); Class peak demand (non-coincident); class demand coincident with the TNMP system peak demand; class demand coincident with the ERCOT peak demand; energy usage; monthly class coincidence factors and load factors.

Schedule II-H.1.4: Adjusted Test-Year Load Data – This schedule provides the following adjusted Test Year data at the source (busbar) and at the meter by rate class for the Test Year and for each month of the Test Year: Sum of customer maximum demands (non-coincident); class peak demand (non-coincident); class demand coincident with the TNMP system peak demand; class demand coincident with ERCOT peak demand; Energy usage; monthly class coincidence factors 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 for class sales, class peaks, and class demand.

Schedule II-H-2.2: Model Information – This schedule provides information about daily and monthly models used for weather adjustment and provides a description of spreadsheets that document the input data and statistics available for each model.

Schedule II-H-2.3: Model Information – This schedule provides additional data variable definitions and references to a listing of raw data used to construct the model variables listed in Schedule II-H-2.1

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

Schedule II-H-5.2: Adjusted Weather Station Data – This schedule is included for completeness. No adjustments or cycle weighting was required, since daily weather data are used directly in weather adjustment models based on AMS data at the daily level.

III. UNADJUSTED TEST YEAR DATA

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

A. The process starts with 15-minute AMS data for the population of about 278,000 TNMP customers. TNMP provided final settlement data for each ESIID in a set of monthly files covering the period from July 2022 through to the end of the test year ending June 2025. For each month, a second file was provided to map each meter to a TNMP region and to a rate category. The first step was to analyze these data sets and perform calculations that combine the individual customer data into aggregated data by region and rate class.

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

A. Inspection of the data revealed that most customers had a single channel (Channel 4) with 15-minute values for KWh delivered to the customer. A small fraction of the customers had a second channel (Channel 1) with 15-minute KWh received from the customer, indicating on-site generation flowing from the customer back to TNMP. Net energy at the 15-minute level was defined as the difference between these two channels (Delivered – Received). This value is positive when the customer is using more energy than they are generating, and it is negative when they are generating more energy than they are using.

Next, the net energy values for each 15-minute interval were added across customers in each of four TNMP regions and eight rate classes. The four regions are Central, Gulf, North, and West. The eight rate classes are Residential, Secondary Less Than 5 KW, Secondary Greater than 5 KW, Secondary IDR, Primary, Primary IDR, Transmission, and Metered Lighting.

Then, the maximum 15-minute interval in each month was identified for each customer. These monthly maximum values were also aggregated across customers for each area and rate class. The monthly maximum values are reported in the relevant schedules and are input into the monthly models that are used to estimate weather adjustment for customer demand.

Additional interval data were provided for 9 customers in the Primary IDR class who receive power at customer owned substations. The loads for these customers were removed from the Primary IDR totals to support separate calculations for the substation class and for the remaining Primary IDR group.

Finally, interval data were provided for 24 Battery Energy Storage System sites (BESS). Also monthly energy and peak data were provided for three customers in the Wholesale Distribution Service Provider (WDSP) class. These data were combined to report energy and peak statistics for the Wholesale Distribution Line Service (WDLS) class in Schedules II-H-1.3 and II-H-1.4.

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

A. After aggregation, the AMS data are adjusted upward slightly to account for a small number of customers without AMS meters. These adjustments are small, at about 0.04% for the Residential and 0.006% for the Secondary LT5 class.

Q. PLEASE EXPLAIN HOW THE AMS DATA WERE USED IN THE WEATHER ADJUSTMENT MODELS.

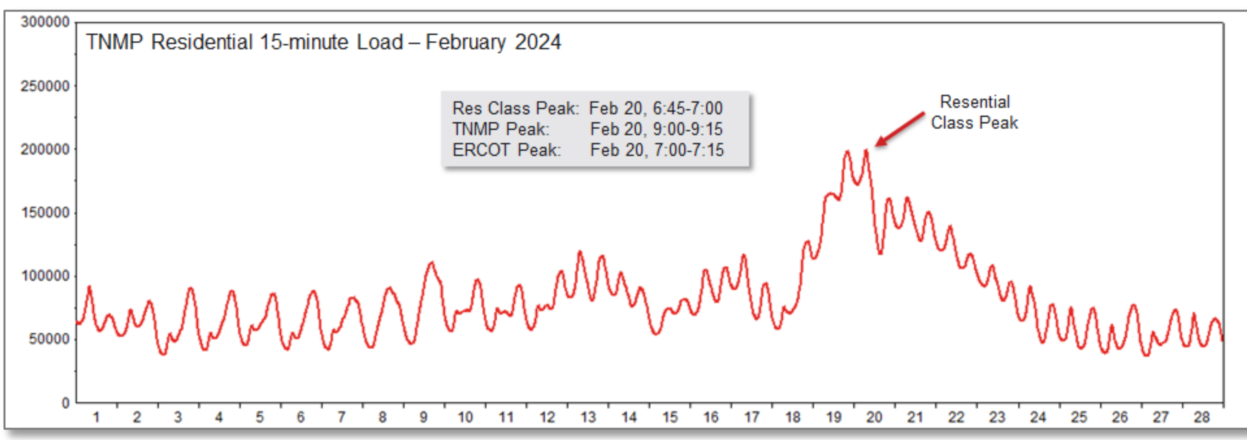
A. For each class, the 15-minute AMS data were aggregated across regions to get 15-minute interval data at the rate-class level. These data were then used to calculate daily energy, daily class peaks, and daily coincident peak loads, which are the dependent variables (Y variables) in the daily weather adjustment models. The Y variable values were calculated as follows:

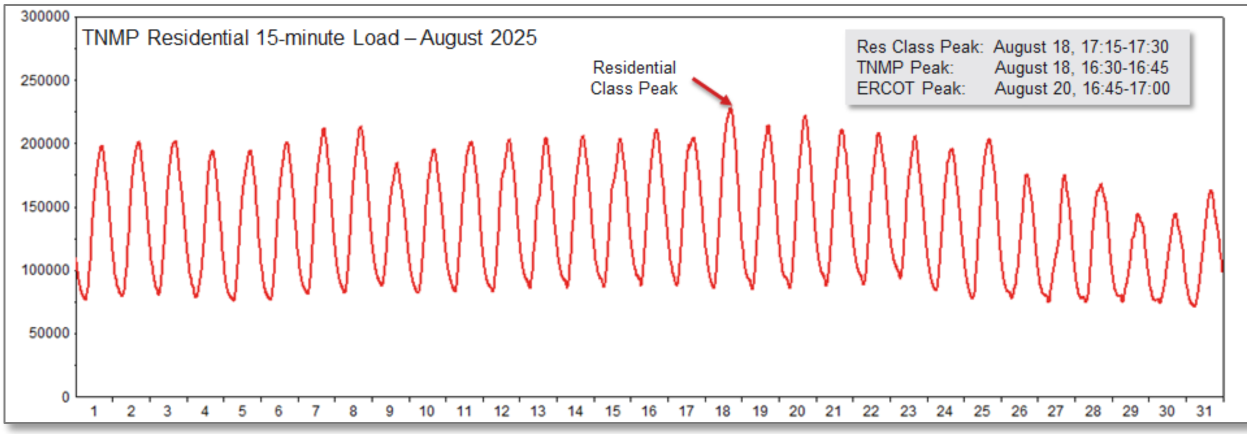
> Daily Energy. Daily energy was computed by adding the 96 intervals for each day.

Daily Class Peaks (NCP). 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. These values are used in the class peak (NCP) models.

Coincident Peak Loads (CP). For each day, the intervals for the TNMP peak and ERCOT peak on that day were identified, and the class loads for those intervals were extracted and multiplied by 4 to get KW equivalent values. These values are used in the TNMP and ERCOT daily coincident peak models.

An example of the data is provided in the following two panels. The first panel shows data for the Residential class in February 2025, the month of the ERCOT winter peak. The date and time for the ERCOT peak interval, the TNMP peak interval, and the Residential Class Peak are identified. The second panel shows comparable data for August 2024, the month of the ERCOT summer peak. For the winter loads in February, the Class and TNMP peak occur on the same day as the ERCOT peak but at different times. For the summer loads in August, the Class and TNMP peak occur on a different day than the ERCOT peak.





These 15-minute data at the class and system level support calculation of daily class energy (the sum of intervals for a day), noncoincident class peaks (the maximum of the interval values for a day), and load values at the time of the ERCOT and TNMP system peaks on each day. These daily values provide the foundation for estimation of daily energy, NCP, and CP models that are used to compute weather adjustments.

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. TNMP 15-minute system load data from ERCOT were used to identify the time of the daily peak interval for the TNMP system on each day. Once the peak intervals are identified for each day, the load for those intervals is 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 loss factors, we applied distribution loss factors (DLF) and transmission loss factors (TLF) based on 15-minute loss factor data from ERCOT. TNMP has five distribution loss factor categories labeled A through E based on geographic location and an urban/rural designation. For each category, formulas are used to calculate distribution loss factors for each 15-minute interval based on the ERCOT load in that interval. For regions that contain both urban and rural areas, the urban and rural loss are combined with weights for each class based on the Urban/Rural sales mix for that class in each region. The result is a series of 15-minute loss factor values series for each class in each region.

The distribution loss factors (DLF) were applied to all classes except Transmission. The transmission loss factors (TLF) were applied to all classes. For all classes except Transmission, the formula for each 15-minute interval is:

Load@Source = Load@Meter * (1+DLF) * (1+TLF)

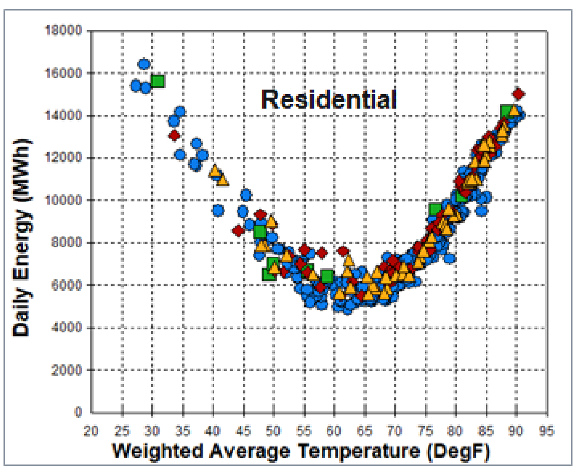
For the transmission class, the form is the same but the term with DLF is excluded.

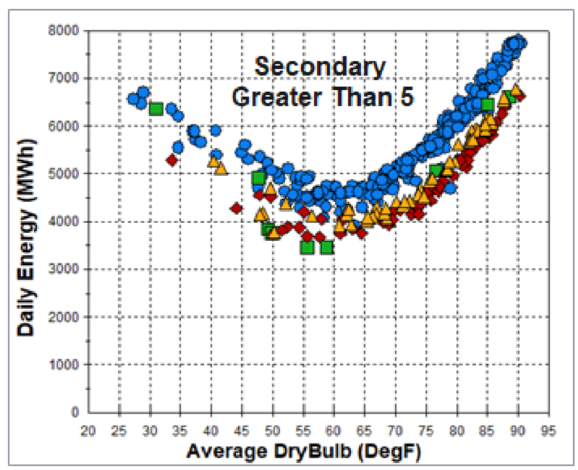
The 15-minute data for Load@Meter is used to complete tables in the rate case Schedules for energy and peak loads at the customer meter. The 15-minute data for Load@Source is used to complete tables in the rate case Schedules for energy and peak loads at the generation source.

IV. WEATHER ADJUSTMENT MODELS FOR ENERGY

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

A. 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 (Res) and Secondary Greater Than 5 KW (SecGT5) classes. These two classes account for more than 90% of the total weather adjustment for the test year.





In the charts, each point is one day. The Y-axis is daily energy (computed from the AMS data) in MWh. The X-axis is daily average temperature. There are 365 observations for the days in the test year (the 12 months ending June 2025). 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 Res and about 60 for SecGT5). 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 very strong heating response on the cold side for residential and a significant heating response on the cold side for SecGT5.

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. Based on my experience, 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.

(1) Variable	(2) Estimated Coefficient	(3) Standard Error	(4) T Statistic	(5) Slope (MWh/Degree)	(6) Spline Weight
CD65	114.6	21.45	5.34	114.6	0.255
CD70	182.7	36.04	5.07	297.3	0.406
CD75	65.2	30.67	2.13	362.5	0.145
CD80	87.4	20.00	4.37	449.9	0.194
Total	449.9				1.000

The estimated coefficients in column (2) are the slopes for each successive cooling degree variable. The unit of measurement for these slopes is daily megawatt hours (MWh) per degree. The first variable CD65 adds about 115 MWh per degree. Moving above 70 degrees, this jumps up by an additional 183 MWh per degree (for a total slope of 297). Moving above 75 degrees, we gain an additional 65 MWh per degree (for a total slope of 362). Finally, moving past 80 degrees, we gain an additional 87 MWh per degree (for a total slope of 450). The spline weights are computed from these values by taking each estimated coefficient and dividing by the total slope for the highest power degrees (450 in this case). So the initial degrees above 65 have a weight of .255 (computed as 114.6/449.9), indicating that these degrees have about 25% of the power of the highest power degrees. With these numbers, the CD spline variable is computed as:

CDSpline = .255 * CD65 + .405 * CD70 + .145 * CD75 + .194 * CD80

The comparable heating degree spline variable is:

HDSpline =.271 * HD60 + .270 * HD55 + .459 * 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 first used to estimate models that explain variations in daily energy use based on actual daily weather values. As discussed later in the testimony, these variables are also utilized to compute weather adjustments for the test year data based on normal daily weather values.

Q. DO THE MODELS FOR DIFFERENT CLASSES USE THE SAME COOLING DEGREE AND HEATING DEGREE 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 degrees and heating begins to show at 60 degrees. For larger customers, weather effects usually start at lower temperatures. Additionally, for the largest customers, weather effects can be hard to detect. For example, for the Secondary IDR class and the Primary IDR Substation class, it was possible to identify cooling effects but not heating effects. For Primary, Primary IDR, and Transmission classes, neither cooling nor heating effects could be identified. 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 a full list of variables used in the weather adjustment models.

Class	Heating Degree Weights				Cooling Degree Weights					
	HDD60	HDD55	HDD50	HDD45	CDD55	CDD60	CDD65	CDD70	CDD75	CDD80
Residential	0.271	0.270		0.45937			0.255	0.406	0.145	0.194
Secondary LT 5	0.370		0.630				0.279		0.721	
Secondary GT 5	0.273		0.727			0.233		0.414	0.209	0.144
Secondary IDR		1.000			0.376		0.314		0.310	
Primary IDR Sub	1.000						0.346		0.654	

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 Monday through Sunday (Wednesday excluded)

-- Specific holiday variables for individual holidays.

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 80%/20% 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

The estimated models are documented in the working papers filed with this testimony. As an example, the following table provides the estimated coefficients for the Residential daily energy model with a first order Autoregressive term (AR1).

Estimated Coefficients for Residential Model with AR1

Type	Variable	Coefficient	StdErr	T-Stat	Units	Definition
	CONST	5438.69	57.20	95.091		Constant term
Month	Jan	173.05	72.35	2.392	Binary	Binary = 1 in January
Month	Feb	-249.67	74.70	-3.342	Binary	Binary = 1 in February
Month	Mar	-487.45	74.03	-6.585	Binary	Binary = 1 in March
Month	Apr	-316.07	74.57	-4.239	Binary	Binary = 1 in April
Month	May	-91.13	79.94	-1.140	Binary	Binary = 1 in May
Month	Jun	333.02	97.93	3.401	Binary	Binary = 1 in June
Month	Jul	168.37	110.34	1.526	Binary	Binary = 1 in July
Month	Aug	109.90	112.34	0.978	Binary	Binary = 1 in August
Month	Sep	-37.79	91.66	-0.412	Binary	Binary = 1 in September
Month	Oct	-269.68	75.98	-3.549	Binary	Binary = 1 in October
Month	Nov	-309.78	71.74	-4.318	Binary	Binary = 1 in November
Day	Monday	104.77	29.22	3.585	Binary	Binary = 1 on Monday
Day	Tuesday	-15.75	24.01	-0.656	Binary	Binary = 1 on Tuesday
Day	Thursday	-5.33	24.12	-0.221	Binary	Binary = 1 on Thursday
Day	Friday	-24.45	28.89	-0.846	Binary	Binary = 1 on Friday
Day	Saturday	224.25	37.12	6.041	Binary	Binary = 1 on Saturday
Day	Sunday	498.41	36.81	13.541	Binary	Binary = 1 on Sunday
Holiday	MLK	414.83	164.53	2.521	Binary	Binary = 1 on M L King Day
Holiday	PresDay	-170.29	145.40	-1.171	Binary	Binary = 1 on Presidents Day
Holiday	MemDay	553.33	146.57	3.775	Binary	Binary = 1 on Memorial Day
Holiday	July4th	375.64	157.93	2.379	Binary	Binary = 1 on Independence Day
Holiday	LaborDay	662.73	147.27	4.500	Binary	Binary = 1 on Labor Day
Holiday	Thanks	482.09	150.27	3.208	Binary	Binary = 1 on Thanksgiving Day
Holiday	FriAThanks	-267.60	160.15	-1.671	Binary	Binary = 1 on Friday after Thanksgiving
Holiday	XMasWkB4	-220.83	171.35	-1.289	Binary	Binary = 1 on week before XMas
Holiday	XMasEve	-5.14	229.34	-0.022	Binary	Binary = 1 on XMas Eve
Holiday	XMasDay	23.28	158.72	0.147	Binary	Binary = 1 on XMas Day
Holiday	XMasWk	415.89	161.58	2.574	Binary	Binary = 1 during week after XMas
Holiday	NYEve	129.58	271.61	0.477	Binary	Binary = 1 on New Years Eve
Holiday	NYDay	-245.98	180.68	-1.361	Binary	Binary = 1 on New Years Day
Other	Beryl	-1823.77	178.55	-10.214	DegF	Binary = 1 for Hurricane Beryl in 7/2024
Other	TimeTrend	94.26	17.21	5.478	DegF	Linear time trend gains 1/365 each day
Heating	HDSpline	343.69	5.63	61.076	DegF	Heating Degree (HD) Spline
Heating	LagHD	101.64	5.02	20.260	DegF	Two day lagged HD (80/20 weights)
Heating	WkEndHD	-5.96	5.89	-1.011	DegF	Heating Degree Spline on Weekend Days
Heating	SpringHD	3.13	13.34	0.235	DegF	Heating Degree Spline on Spring Days
Heating	FallHD	-95.12	30.07	-3.164	DegF	Heating Degree Spline on Fall Days
Cooling	CDSpline	422.89	6.24	67.764	DegF	Cooling Degree Spline
Cooling	LagCD	36.09	6.03	5.988	DegF	Two day lagged CD (80/20 weights)
Cooling	WkEndCD	3.96	2.95	1.342	DegF	Cooling Degree Spline on Weekend Days
Cooling	SpringCD	-72.55	16.95	-4.280	DegF	Cooling Degree Spline on Spring Days
Cooling	FallCD	-2.67	15.91	-0.168	DegF	Cooling Degree Spline on Fall Days
AR1	AR(1)	0.451	0.028	15.994		First order autoregressive term

The coefficients that matter for the weather adjustment are the last 10 variables, five for heating and five for cooling. These estimated coefficients all give weather responses in units of MWh per full powered heating degree or per full powered cooling degree. For the residential model, the main weather slopes are the HDSpline and CDSpline variables which are well identified and are strongly significant statistically, with T-Statistics above 60 (a value greater than 2.0 is generally considered to be statistically significant).

The LagHD and LagCD variables capture the carryover effect of prior day temperatures onto the current day. The estimated slopes for these variables are also statistically significant. The lagged effect for heating is 102 MWh per degree, which is about 30% of the same day parameter (344 MWh per degree). For cooling, the lag effect is 36 MWh per degree, which is about 9% of the same day effect (423 MWh 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. These slope modifiers are numerically small and are not statistically significant.

For heating, the FallHD variable allows weather response to be different for months leading into winter, and the SpringHD variable allows weather response to be different for the months following winter. The estimated coefficient for Spring is small and statistically insignificant. The estimated coefficient for Fall is large and significant, indicating that the response to cold weather in Fall is about 95 KWh per degree (28%) weaker than the full winter response.

For cooling, the SpringCD variable allows weather response to be different for months leading into summer, and the FallCD variable allows weather response to be different for the months following summer. The estimated coefficient for Fall is small and statistically insignificant. The estimated coefficient for Spring is large and significant, indicating that the response to hot weather in Spring is about 73 KWh per degree (17%) weaker than the full summer response.

These coefficients are used to compute the daily weather adjustment, which is the difference between the model predicted value with normal daily weather and the model predicted value with actual daily weather.

When actual weather is milder than normal weather, the predicted value with actual weather is below the predicted value with normal weather and the weather adjustment will be positive. In this case we need to add to sales since actual weather was relatively weak. This would be the case, for example, in a winter month with warmer (weaker) than normal weather.

When actual weather is more extreme than normal, the predicted value with actual weather is above the predicted value with normal weather and the weather adjustment is negative. In this case we need to subtract from sales since actual weather was relatively strong. This would be the case, for example, in a summer month with hotter (stronger) than normal weather.

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

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

		Static Model (No AR1)			Model with AR1		
Type	Variable	Coefficient	StdErr	T-Stat	Coefficient	StdErr	T-Stat
Heating	HDSpline	342.63	5.67	60.420	343.69	5.63	61.076
Heating	LagHD	99.84	4.94	20.226	101.64	5.02	20.260
Heating	WkEndHD	-1.16	6.39	-0.182	-5.96	5.89	-1.011
Heating	SpringHD	19.40	10.77	1.802	3.13	13.34	0.235
Heating	FallHD	-74.80	22.96	-3.258	-95.12	30.07	-3.164
Cooling	CDSpline	415.96	6.36	65.399	422.89	6.24	67.764
Cooling	LagCD	39.53	6.18	6.393	36.09	6.03	5.988
Cooling	WkEndCD	4.80	3.18	1.509	3.96	2.95	1.342
Cooling	SpringCD	-55.07	14.49	-3.801	-72.55	16.95	-4.280
Cooling	FallCD	4.913	12.77	0.385	-2.67	15.91	-0.168

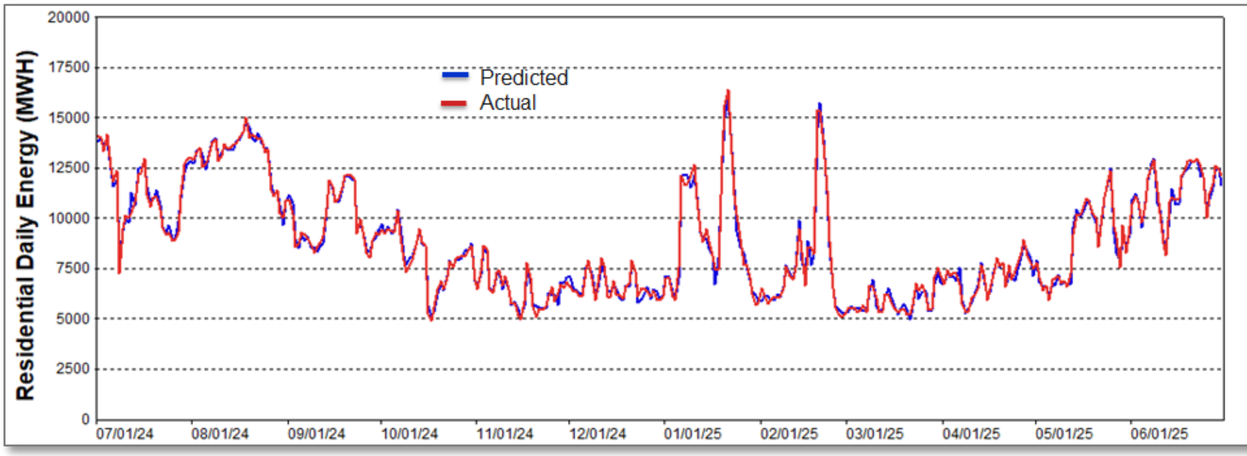
The coefficient pattern from the two specifications is consistent, and all coefficient estimates are within two standard errors between the two specifications. For example, the CDSpline coefficient is 416 MWh per degree in the static model and 422 MWh per degree in the model with the AR1 term. The standard error in both models is about 6, so the two slopes are basically the same in a practical and statistical sense. Both parameters are strongly statistically significant (t-statistics of > 60) and the difference between them is not statistically significant. This is the signature of a strong and well specified model.

Both sets of models 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 we used the static models.

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 in the Test Year.

Actual and Predicted Daily Energy – Residential Model with AR1



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 value. Clearly the model works extremely well throughout the year.

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

Residential Energy Model Statistics	Static Model (No AR1)	Dynamic Model (With AR1)
Adjusted Observations	1096.00	1095.00
R-Squared	0.991	0.993
Adjusted R-Squared	0.991	0.993
AIC	11.328	11.117
BIC	11.525	11.318
F-Statistic	2804.8	3392.6
Prob (F-Statistic)	0.000	0.000
Std. Error of Regression	282.88	254.35
Mean Abs. Dev. (MAD)	211.00	186.10
Mean Abs. % Err. (MAPE)	2.60%	2.30%
Durbin-Watson Statistic	1.139	2.000

The quality of the model fit is excellent with mean absolute percent error (MAPE) values of 2.60% for the static model and 2.30% for the dynamic model. The Durbin-Watson statistic provides an indicator of first order autocorrelation of the model residuals. 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 1.14 indicates moderate positive autocorrelation. With the AR1 correction there is no indication of first order autocorrelation (as indicated by the Durbin-Watson statistic of 2.00).

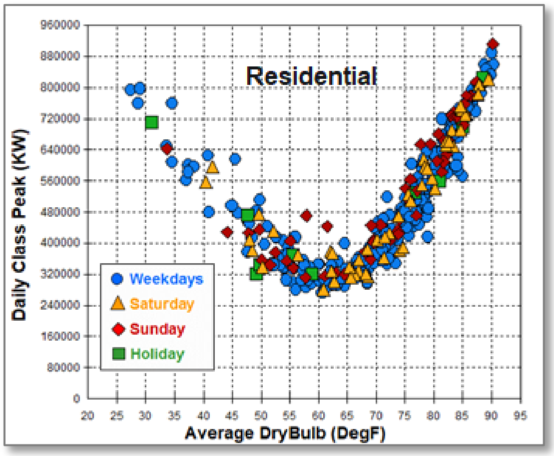
The following table provides the daily energy model summary statistics for all the weather sensitive classes. As this shows, the model fit for all classes is strong, with MAPE values in the 1.1% to 3.0% range.

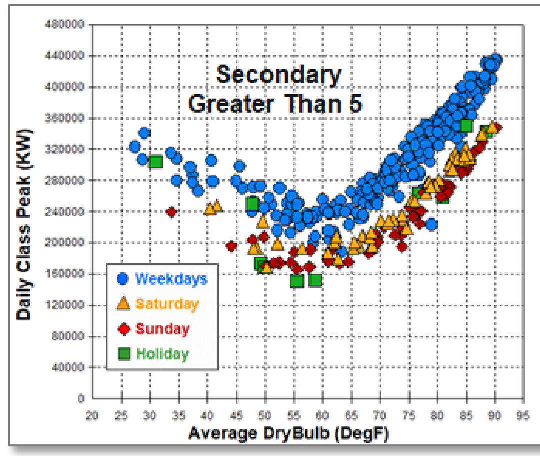
Daily Energy Model Statistics	Residential	Secondary Less Than 5	Secondary Greater Than 5	Secondary IDR	Primary IDR Substation
Adjusted Observations	1095.00	1095.00	1095.00	1095.00	546.00
R-Squared	0.993	0.966	0.990	0.972	0.845
Adjusted R-Squared	0.993	0.965	0.989	0.971	0.834
AIC	11.117	2.002	9.368	6.852	5.650
BIC	11.318	2.198	9.569	7.025	5.930
F-Statistic	3392.6	712.9	2385.3	991.1	79.4
Prob (F-Statistic)	0.000	0.000	0.000	0.000	0.000
Std. Error of Regression	254.35	2.67	106.08	30.23	16.32
Mean Abs. Dev. (MAD)	186.10	1.56	75.32	21.79	12.37
Mean Abs. % Err. (MAPE)	2.30%	1.08%	1.45%	2.07%	2.96%
Durbin-Watson Statistic	2.000	2.085	2.071	1.950	2.066

V. WEATHER ADJUSTMENT MODELS FOR CLASS PEAKS

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

A. The class peak models explain variations in daily class peak values using the same types of explanatory variables that are used in the daily energy models. As examples, the following figures show scatter plots of daily class peak versus daily average temperature for the residential (Res) and Secondary Greater Than 5 KW (SecGT5) classes.





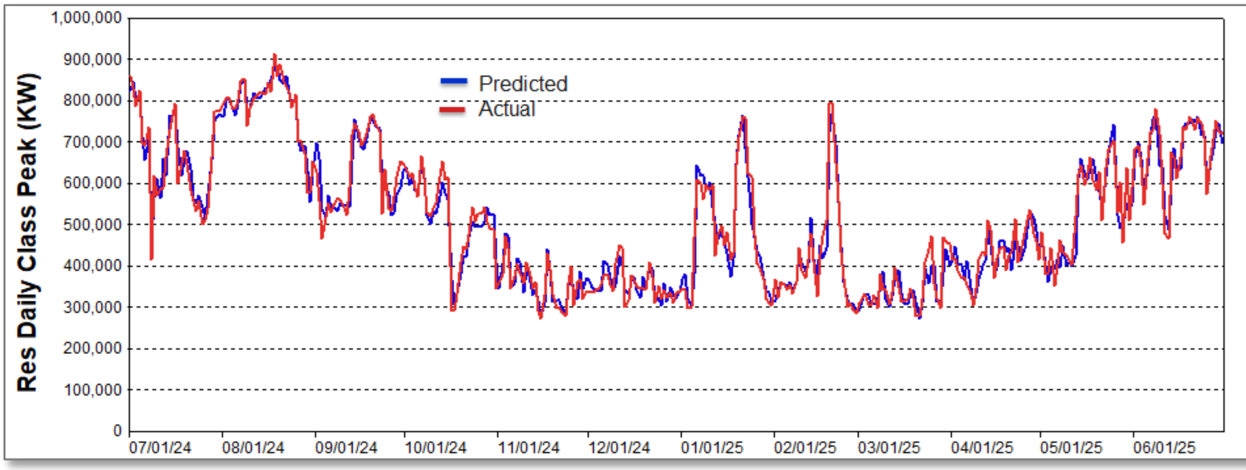
These graphs show weather response patterns for daily class peaks that are similar in appearance to the patterns for daily energy. However, there are some differences, and as a result, we estimated a different set of HD and CD weights for the class peak and coincident peak models. These weights are shown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

Class					Cooling Degree Weights					
	HDD60	HDD55	HDD50	HDD45	CDD55	CDD60	CDD65	CDD70	CDD75	CDD80
Residential	0.519		0.431	0.05			0.401	0.288		0.311
Secondary LT 5	0.258		0.742				0.417		0.583	
Secondary GT 5		1.000				0.408		0.364		0.228
Secondary IDR		1.000			0.437		0.144		0.419	
Primary IDR Sub	1.000						0.558		0.442	

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 all 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 daily variation in class peaks. For example, the following chart shows the actual and predicted values for the residential daily class peaks.

Actual and Predicted Daily Class Peak – Residential Model with AR1



The class peak models have errors that are slightly larger than the energy model errors. The mean absolute percent errors for these models range from 1.3% (Secondary LT 5) to 4.5% (Residential). As with the energy models, weather slopes are well defined and strongly significant.

Q. HOW DO THE COINCIDENT LOAD MODELS DIFFER FROM THE CLASS PEAK MODELS?

A. Two sets of coincident load models are estimated, one explaining loads at the time of the daily TNMP peak and the other explaining loads at the time of the daily ERCOT peak. The models are similar to the daily class peak models in terms of weather parameters and model fit statistics. The full set of model results with and without AR1 terms is included in the working papers filed with this testimony.

Q. HOW DO MODELS USED TO WEATHER ADJUST ACTUAL CUSTOMER DEMAND DIFFER FROM THE CLASS PEAK MODELS?

Actual customer demand differs from class peak demand since in a month the customer demand values come from many different days and times of day. The sum of the maximum customer demands in a month is a larger number than the class peak, reflecting the diversity in timing of the individual customer peak values. For example, for the SecGT5 class, the monthly class peaks in the test year averaged about 351 MW, whereas the average monthly customer demand values were about 74% larger at 611 MW.

Because the maximum demand for a customer can occur on any day of the month for reasons specific to the behavior of that customer, there is not a strong correlation between the maximum demand in a month and daily weather data on any specific day within the month. Further, the monthly maximum demand values are less variable, or more stable, than class NCP or CP values. For example, for the residential class the maximum monthly NCP value in the test year is over 100% larger than the minimum monthly NCP value. In contrast, the largest monthly maximum demand sum is only 20% larger than the smallest monthly maximum demand sum. As a result, weather adjustments for maximum demand are expected to be smaller on a percentage basis than the adjustments for class peaks (NCP).

For all classes, the monthly maximum demand values are modeled in regressions that explain customer demand as a function of heating degrees base 60 and cooling degrees base 65. These simple monthly regressions are estimated with months of data from July 2023 to June 2025.

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. These results are included only for the weather-sensitive classes (Residential, Secondary, and Primary Substation). Although the models are very simple, they have strong explanatory power. For example, for the two main weather sensitive classes, the mean absolute percent error values are 2.0% for Residential and 2.8% for Secondary GT5.

To calculate weather adjustments, the estimated models were used to calculate predicted maximum demand sums with normal monthly CDD and HDD values. The difference between the predicted maximum demand with normal monthly weather and the predicted maximum demand with actual monthly weather is the weather adjustment for the class demand in each month.

VI. NORMAL WEATHER CALCULATIONS

Q. PLEASE DESCRIBE THE PROCESS USED TO DEFINE NORMAL WEATHER FOR PURPOSES OF ENERGY ADJUSTMENT CALCULATIONS

Normal values are calculated from the most recent ten years of historical hourly weather data (2015 to 2024). For daily energy adjustments the normal values are calculated using an "average-by-date" approach. Steps in this approach are as follows:

A. For each weather station, compute daily average temperature for each historical day as the average of the hourly values for that day.

1. For each weather station, compute daily heating degree (HD) and cooling degree (CD) values for each temperature base using the daily average temperature value for each historical day.

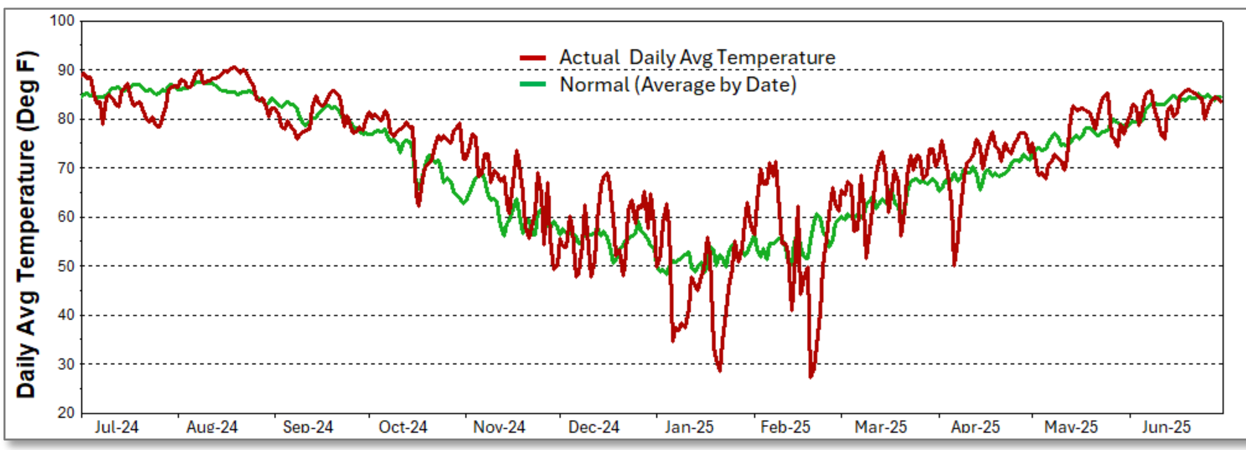
2. Weight the station daily values (average temperature, HD, and CD) across stations to generate historical values for the TNMP system. The temperature weights reflect shares of residential and commercial energy sales over the most recent three years.

A. For each date (Jan 1, Jan 2, …) and concept (average temperature, HD, and CD), compute the average of the 10 values for that date across the 10-year historical period.

1. Place the normal values for each date on a Test Year calendar.

The following chart shows the result of the normal weather calculations using the average-by-date method.

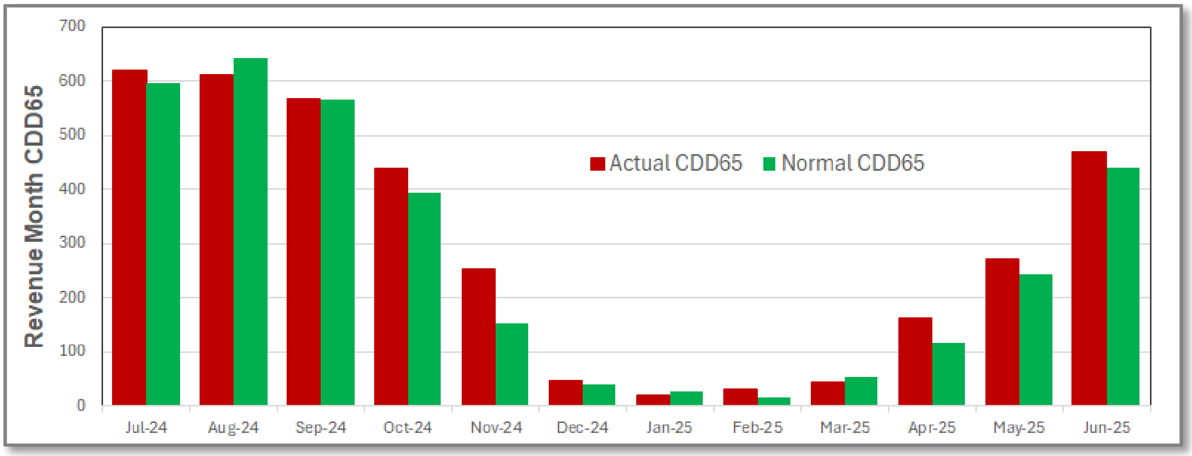
Actual and Normal Daily Average Temperature (Average By Date)



In the chart, the red line is the actual daily average temperature and the green line is the normal daily value from the average-by-date process. The daily chart shows that weather was relatively mild in July, followed by a hot spell in August (the month of the ERCOT summer system peak in the test year). In the winter, the main events were two cold spells in January and one extreme cold event in February, the month of the ERCOT winter system peak. More information about weather data is provided in Schedules II-H.5.1 and II-H.5.2.

The average-by-date method provides daily weather data that are appropriate for use in daily energy adjustment models. Also, these normal daily values can be processed through billing cycles to produce revenue-month heating degree day (HDD) and cooling degree day (CDD) values. These cycle-weighted monthly values are provided here because they help to explain the weather adjustments to billed energy sales presented in Schedule II-H-1.2. As examples, the cycle weighted sums of cooling degrees base 65 and heating degrees base 60 are provided below.

Test Year Values of Actual and Normal Monthly CDD Base 65



As shown, July has slightly higher CDD values than normal. This reflects warm weather in June 2024 (not shown in the daily graphs above) and in the early days of July, which caused the early billing cycles in the month to be hotter than normal. As a result, we expect to see a downward adjustment in July energy sales to remove the impact of these hotter than normal days.

Despite hot weather toward the end of August, the August cycles are slightly cooler than normal, reflecting the impact of relatively cool weather in most of July. As a result, we expect to see an upward adjustment in August energy sales to remove the impact of weaker than normal weather.

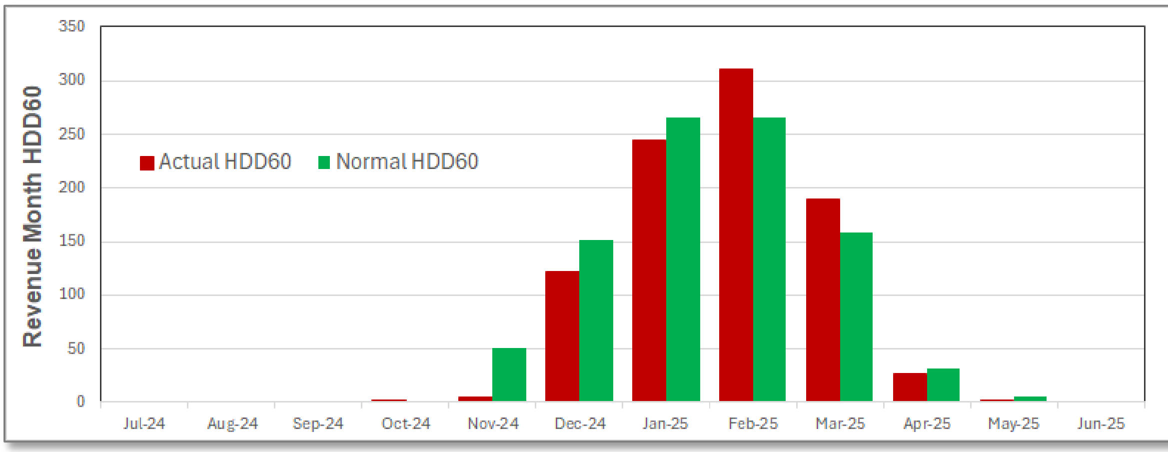
Following a normal September, the remining months in fall (October and November) have hotter than normal weather, as do the spring months (April, May, and June). We expect to see downward adjustments to energy sales in these months to remove the impact of stronger than normal weather.

Since all billing months except August are warmer than normal, we expect the see cooling weather adjustment to be negative for when summed across months of the test year.

For heating adjustments, the following figure shows Test Year values for cycle weighted heating degree day values. December was milder (less cold) than normal, which impacted both the December and January billing cycles. We expect positive weather adjustments in these two months. Reflecting very cold weather in the later part of January and February, both February and March cycles show temperatures that are significantly colder than normal. We expect downward sales adjustments for these months.

Because of the extreme cold weather showing in the February and March cycles, we expect the heating weather adjustment to be negative when we sum across months in the test year.

Test Year Actual and Normal Monthly HDD Base 60



Q. PLEASE DESCRIBE THE PROCESS USED TO DEFINE NORMAL WEATHER FOR PURPOSES OF WEATHER ADJUSTMENT CALCULATIONS FOR PEAK LOADS.

A. A different approach is required for the adjustment of class peaks because these peaks are driven by extreme weather events, and these extremes are not captured using the average-by-date approach. To represent typical extreme weather, the rank-and-average approach is used. This approach is based on the same set of daily historical daily values but uses a different calculation process.

1-3 Steps 1, 2, and 3 are the same as those used in the average-by-date approach.

4. In each historical year, rank the daily data for each month by sorting the data from hottest to coldest based on daily average temperature.

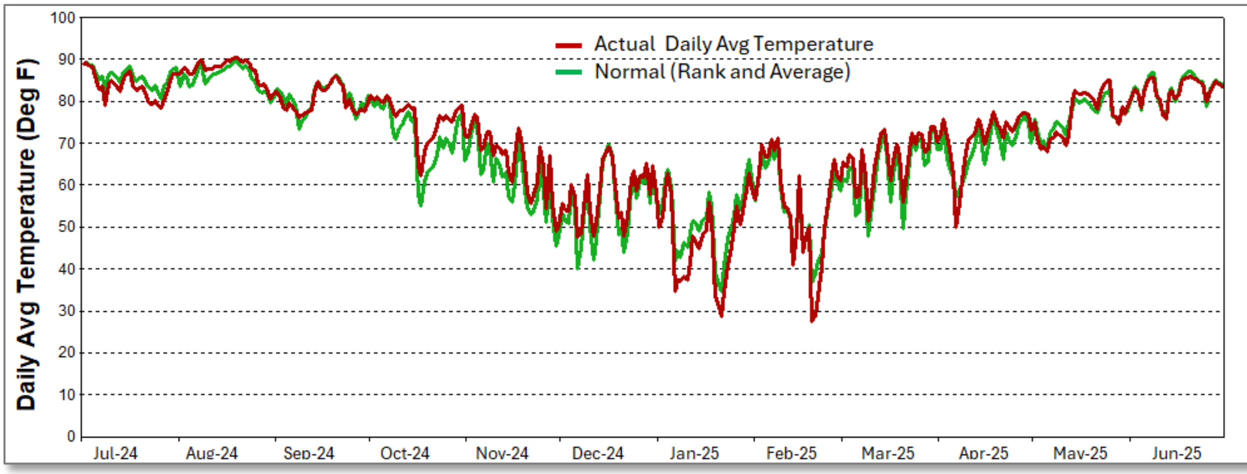
5. For each month, average the ranked data across the 10-year historical period. This gives an average hottest day, an average second hottest data, and so on through to an average coldest day for each month.

6. Assign the rank-and-average results to days in each month of the test year based on the weather order that actually occurred in that month. For example, in August of

2025, the hottest day (August 19) gets assigned the values for the typical hottest day. The second hottest day (Aug 18) gets assigned the values for the typical second hottest day. And so on through to the coldest day.

The following chart shows the results of this process applied to daily average temperature. The red line is the actual daily average temperature and the green line is the normal daily value from the rank-and-average process.

Actual and Normal Daily Average Temperature (Rank and Average)



For the summer months, the extreme weather is a three-day event in August 2024 which had three sequential days with average temperatures above 90 degrees (August 18, 19, and 20). The ERCOT peak occurred on the last of these days, Tuesday August 20. The series of actual average temperatures for these days is 90.2°, 90.4°, and 90.1°. The series of normal values is 89.2°, 89.5°, and 89.1°, each of which is about 1 degree below the actual value. As a result, we expect a negative adjustment for NCP and CP values in August, commensurate with actual temperatures that were 1 degree above normal.

For the winter, the coldest day falls on February 19, 2025 which is also the ERCOT peak day. The actual average temperature on this day was 27.3 degrees, which is 9.4 degrees below the normal coldest day in February at 36.7 degrees. As a result we expect a significant downward adjustment in February peaks for the classes that are sensitive to cold weather. A similar adjustment is expected in January, which had a coldest day that was about 5.9 degrees below the normal extreme day in January.

VII. SCHEDULES FOR TEST-YEAR LOAD DATA

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR CUSTOMER MAXIMUM DEMAND AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3-1.

A. Customer maximum demand at the Meter is computed directly from the 15-minute interval data for each customer. The customer maximum values in each month are added across customers to get the sum of the maximum values for each class. Maximum demand at the Source is derived by applying loss factors computed at the time of the class peak for each month.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR CLASS PEAK DEMAND AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3-2.

A. Class peak demand at the Meter is computed directly from the 15-minute interval data summed across customers in each class. The aggregated series is used to find the date and time as well as the maximum class load value. This value is called the non-coincident class peak or NCP.

Class peak demand at the Source is computed from class peak demand 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 for the class peak interval in that month.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR CLASS LOAD AT TNMP PEAK PROVIDED IN SCHEDULE II-H-1.3-3.

A. TNMP peak intervals are determined from 15-minute settlements data from ERCOT. 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 load at the Meter coincident with the TNMP peak.

Class load at the TNMP 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 at the time of the TNMP peak in that month.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR CLASS LOAD AT ERCOT PEAK PROVIDED IN SCHEDULE II-H-1.3-4.

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 load at the Meter coincident with the ERCOT peak.

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 at the time of the ERCOT peak in that month.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR ENERGY USAGE AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3-5.

A. Energy usage at the Meter is booked energy based on TNMP billing data. These are the same data that appear in the Booked KWh column in Schedule II-H-1.2. In each month, these values reflect the timing of billing cycles that define the range of days that go into the bill for each customer. As a result, the KWh value for a month will reflect the number of days in each billing cycle as well as the daily weather that occurred during this day range.

Energy usage at the Source is computed from energy usage at the Meter scaled up for distribution and transmission loss factors. The loss factors for each month are computed from the 15-minute AMS data by class and region. First, 15-minute loss factors are applied to the 15-minute AMS loads by class and region. Second, the 15-minute load values are added across intervals in the month, giving monthly energy with and without losses. The monthly loss multiplier for energy is then calculated as the ratio of the energy sum with losses to the energy sum without losses.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR CLASS COINCIDENCE FACTORS AND CLASS LOAD FACTORS PROVIDED IN SCHEDULE II-1.3-6.

A. Class coincidence factors are computed directly from the 15-minute AMS data. Class coincidence factors have two components, the class peak for the month and the class load at the time of the ERCOT peak in each month.

The class peak in a month is identified as the maximum 15-minute value in the month. These are the values reported on Schedule II-H-1.3.2. 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 in a calendar month to the class peak in that month.

VIII. ADJUSTED TEST-YEAR LOAD DATA

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS TO TEST YEAR SALES DATA PROVIDED 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 also interact with weekend variables and seasonal variables that allow the weather response to be different on different types of days.

Daily weather models are estimated based on actual daily weather for days in the estimation period (July 2022 to June 2025). 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 normal weather and predicted values with actual weather are the daily weather adjustments. If actual weather is more extreme than normal weather, the weather adjustment will be negative. If actual weather is milder than normal weather, the weather adjustment will be positive.

For each month, the daily weather adjustments are run through billing cycles to calculate adjustments that match the timing of the booked KWh in each month. The monthly weather adjustment is added to the monthly booked sales value, and the result is further adjusted for customer growth and hurricane effects giving the adjusted class sales at the Meter as reported in Schedules II-H-1.2 and Schedule II-H-1,3-5.

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-1.4-1.

A. Weather adjustments for customer maximum demand are computed using monthly models of maximum demand estimated with AMS data for each calendar month. These models are discussed earlier in the testimony. Variables in the monthly models include average monthly heating degree days base 60 (HDD60) and monthly cooling degree days base 65 (CDD65).

Predicted values for these models are calculated with the normal values for monthly HDD60 and CDD65. The difference between predicted demand with the normal weather and predicted demand with the actual weather is the weather adjustment at the Meter. The weather adjustment is added to the actual customer maximum demand value, giving the adjusted customer maximum demand value at the Meter.

For each class, adjusted customer demand at the Meter is converted to adjusted customer demand at the Source by applying loss factors computed at the time of the class peak for each month.

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-1.4-2.

A. Weather adjustments to monthly class peaks are computed using daily class peak models. Daily class peak values are computed directly from 15-minute AMS data as the maximum interval for the class on each day. 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 interact 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 for the estimation period (July 2022 to June 2025). 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 normal weather and the maximum predicted class peak with actual weather is the class peak weather adjustment for the month. The weather adjustment is added to the actual class peak, giving the adjusted class peak at the Meter.

To derive adjusted class peak values at the Source, distribution and transmission loss factors for the actual class peak interval are applied to the adjusted value at the Meter.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS FOR CLASS LOAD AT THE TIME OF TNMP PEAK PROVIDED IN SCHEDULE II-1.4-3.

Weather adjustment to monthly loads at the time of TNMP peak are computed using models of daily class coincident loads. Daily loads at the time of TNMP peak are computed directly from the 15-minute AMS data based on the time of the TNMP 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 also interact with weekend and seasonal variables, allowing weather response to be different across seasons and day types (weekday vs. weekend). Daily coincident load models are estimated with actual daily weather data for days in the estimation period (July 2022 to June 2025). The estimated models are used to recalculate what daily coincident class loads would have been with normal weather on each day. In each month, the difference between the predicted coincident class load with normal weather and predicted coincident class load with actual weather is the class load weather adjustment for that month. The weather adjustment is added to the actual coincident load value for the month, giving the adjusted class coincident load at the Meter.

To derive adjusted values at the Source, distribution and transmission loss factors for the interval of the TNMP monthly peak are applied to the adjusted value at the Meter.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS FOR CLASS LOAD AT THE TIME ERCOT PEAK PROVIDED IN SCHEDULE II-1.4-4.

A. Weather adjustment to monthly loads at the time of ERCOT peak are computed using models of the class coincident loads. 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 interact 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 for days in the estimation period (July 2022 to June 2025). 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 normal weather and predicted class coincident load with actual weather is the class load weather adjustment for that month. The weather adjustment is added to the actual coincident load value for the month, giving the adjusted class coincident load at the Meter.

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.

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-1.4-5.

A. The adjusted monthly energy values reported on Schedule II-H-1.4.5 at the Meter are the same as those reported on Schedule II-H-1.2 Column (5) labelled Net. These monthly values are Booked KWh in Column (2) adjusted for temperature deviations from normal in Column (3) and hurricane effects in Column (4).

Adjusted energy usage at the Source is computed from adjusted energy usage at the Meter scaled up for monthly distribution and transmission loss factors. The same monthly loss multipliers that are used for unadjusted monthly energy (as discussed for Schedule II-H-1.3.5) are also used for adjusted monthly energy.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR ADJUSTED CLASS COINCIDENCE FACTORS AND ADJUSTED CLASS LOAD FACTORS PROVIDED IN SCHEDULE II-1.4-6.

A. Adjusted class coincidence factors are computed from the adjusted ERCOT coincident load values (reported on Schedule II-H-1.4-4) and the adjusted class peak values (reported on Schedule II-H.4-2).

Adjusted class load factors are computed from the adjusted calendar month energy values and the adjusted monthly class peak value (reported on Schedule II-H-1.4.2). The load factor is the ratio of the average adjusted hourly energy for the month divided by the adjusted class peak. The adjusted calendar month energy values for this calculation are derived using the same adjustment process that is used for Schedule II-H-1.2 applied to AMS data for calendar month energy rather than monthly billed energy.

IX. CONCLUSIONS

Q. PLEASE SUMMARIZE YOUR TESTIMONY AND RECOMMENDATIONS.

A. AMS data provide the opportunity to understand weather adjustments at a deeper level than is possible with monthly billing data alone. The 15-minute interval data also provide exact values for class peak and coincident load calculations. Using these data, it is possible to build daily weather adjustment models that account for the nonlinear relationship between load and weather, and to make adjustments that recognize the difference between low, medium, and high-powered degrees. Further, it is possible to identify seasonal differences in the strength of weather response, allowing Spring and Fall responses to differ from Summer and Winter responses. The result is a set of weather adjustments that are accurate, based on powerful statistical relationships. These results provide a strong foundation for cost allocation and revenue requirement calculations that use weather adjusted billing determinants.

Q. DOES THIS CONCLUDE YOUR DIRECT TESTIMONY?

A. Yes, it does.

AFFIDAVIT

STATE OF CALIFORNIA §
§
COUNTY OF SAN DIEGO §

BEFORE ME, the undersigned authority, on this day personally appeared John Stuart McMenamin, who, upon proving his identity to me and by me being duly sworn, deposes and states the following:

"My name is John Stuart McMenamin. I am of legal age, a resident of the State of California, and have never been convicted of a felony. I certify that the foregoing testimony, offered by me on behalf of Texas-New Mexico Power Company, is true and correct and based upon my personal knowledge and experience."

11/5/2025

Witness

* * * * *

SWORN TO AND SUBSCRIBED before me, Notary Public, on this 5th day of November, 2025, to certify which witness my hand and seal of office.

KI HOON CHOI
COMM. # 2469842
NOTARY PUBLIC • CALIFORNIA
San Diego County
My Commission Expires
December 1, 2027
RSC1 RSC1

NOTARY PUBLIC in and for the
State of California

Printed Name: Ki Hoon Choi

My Commission expires: 12/01/2027

Notary ID# 2469842

SEAL:

Exhibit JSM-1

J. Stuart McMenamin – Educational Background and Business Experience

Education

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

Employment History

- Senior Principal Consultant, Itron Inc., Jan 2025-present
- Director of Forecasting Solutions, Itron Inc., 2002-2024
- 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.

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.

Over the last decade, 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

Hourly Solar Generation Modeling. Itron Brown Bag Seminar, February 2025.

Retrospective on Neural Networks, Itron Brown Bag Seminar reviewing the use of neural networks in energy modeling and forecasting, June 2024.

Regression Methods A to Z. Itron Brown Bag Seminar on regression methods comparing results for Ridge, Lasso, Elastic Net, Quantile, Absolute Deviations, and Support Vector, May 2023.

Decision Trees, Gradient Boosting and Random Forests, Itron Brown Bag Seminar comparing non parametric methods with regression and neural networks, February 2022. Also see *Exploring Decision Tree Regressors.* Itron white paper. December 2023, available at www.Itron.com.

Support Vector Regression, Itron Brown Bag Seminar, June 2021. Also presented at AEIC/WLR Annual Meeting, September 2021.

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.

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.

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

Forecasting Accuracy Survey and Energy Trends, with Mark Quan, presented at Energy Forecasting Group annual meeting, May, 2012

The Pros, Cons, and Pitfalls of Ratio Estimation, presented at Western Load Research Association, September, 2011.

Links Between Forecasting, Load Research, and Energy Efficiency Analysis, presented at Western Load Research Association, September, 2011.

Incorporating DSM into the Load Forecast, with Mark Quan, Itron white paper, April, 2010, available at www.itron.com

Forecasting in an AMI World, Energy Forecasting Group annual meeting, April, 2010.

Demand Response Analytics and other Applications of Smart Grid Data, presented at Western Load Research Association, March, 2010.

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.

Load Research in Vietnam, presented at Western Load Research Association, March, 2010.

Regression with ARMA Errors and Issues with Lagged Dependent Variables, presented at Itron Brown Bag seminar, December, 2009.

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

Comparison of Load Research Expansion Methods, presented at Itron Brown Bag seminar, April, 2008.

Using Load Research Data to Improve Financial Forecasting Models, presented at Itron Brown Bag seminar, April, 2007.

Statistical Approaches to Electricity Price Forecasting, Itron white paper, January, 2007. Available at www.Itron.com

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

Price Elasticities in Energy Modeling and Forecasting. Itron white paper. January, 2006. Available at www.Itron.com.

Estimating Unbilled Energy. Itron white paper. November, 2006. Available at www.Itron.com.

Weather Normalization, with Eric Fox and Mark Quan, presented at Itron Brown Bag seminar, September 2005. Available at www.Itron.com.

Modeling Humidity Effects, presented at Itron Brown Bag seminar, June 2005.

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

Load Profiling in Belguim, presented at Association of Edison Illuminating Companies Annual Load Research Conference, August, 2003.

Lessons for Load Research Sample Design, presented at Western Load Research Association, April, 2002.

Profiling and Forecasting in Retail Electricity Markets, presented at Advanced Workshop in Regulation and Competition, Center for Research in Regulated Industries, June, 2001.

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

Sample Design for Load Profiling, presented at Association of Edison Illuminating Companies workshop, April, 2001.

Neural Networks, What Goes on Inside the Black Box, presented at EPRI Forecasting Workshop, December, 2000.

Evaluating the Decline in Residential Gas Usage, primary author, prepared for Gas Research Institute, May, 2000.

Comparison of Statistical Approaches to Electricity Price Forecasting, with F. Monforte. Presented at Rutgers Advanced Workshop in Regulation and Competition. Included in *Pricing in Competitive Electricity Markets*, Kluwer Academic Publishers, A. Faruqui and K. Eakin, eds, April, 2000.

Using Neural Networks for Day-Ahead Forecasting, with F. Monforte. Western Economic Association Conference, July, 1999.

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

Retail Forecasting and Profile Modeling, How it Works. Infocast conference on Load Profiling, Forecasting, and Market Settlement, October, 1999.

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

Profiling Withoug Load Research Data (Virtual Load Research), with F. Monforte, C Fordham, M. Quan, AEIC Load Research Conference, July, 1999.

Load Shape Modeling Methods. Presented at EPRI/GRI Workshop on Load Data Analysis, June, 1999.

Short-Term Energy Forecasting with Neural Networks, with F. Monforte, The Energy Journal, Volume 19, Number 4, 1998.

Dynamic Load Profiling: An In-Depth Look. Infocast Conference on Load Profiling, Forecasting, & Market Settlements. September, 1998.

Why Not Π, A Primer on Neural Networks for Forecasting. Forecasting white paper, available at www.Itron.com.

Advanced Methods for Short-term Forecasting. Workshop presented at the IIR Competitive Research and Forecasting Conference, April, 1997.

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

Demographic and Economic Forecasting Model. With F. Monforte and J. Pritchard. Prepared for San Diego Association of Governments. January, 1997.

Next-Day Forecasting Using Time-Series Methods. Presented at Western Load Research Association, September, 1996.

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

Theories and Models of Customer Retention. Workshop presented at the AMA/EEI Electric Utility Customer Research Conference, May, 1996.

NSP Residential Lighting Evaluation Study. With D. Nore. For Northern States Power Company, April 1996

1995 TU Electric Load Shape Disaggragation Study. With D. Nore, E. Fox, C. Fordham. Prepared for TU Electric Company, March 1996

Third Wave of Electricity Growth. With F. Monforte. For Electric Power Research Institute, February 1996

Environmental Benefits of Electrification and End-Use Efficiency. With F. Monforte, E. Fox, D. Nore, I. Rohmund, C. Fordham. Prepared for Electric Power Research Institute, RP3121-12. January 1996

Georgia Power Company Commercial Load Shape and EUI Study. With I. Rohmund, A. Hensleit, L. Werner and R. Ramirez. For Southern Company Services, January 1996

SITEPRO User's Guide. With I. Rohmund, S. Criswell, R. Ramirez and L. Werner. December 1995

Commercial and Small Industrial Survey and Market Profiles. With I. Rohmund, K. Miller, C. Fordham, L. Werner and R. Ramirez. For Interstate Power Company, November 1995

Product Analysis and Forecasting. With F. D. Sebold. Association of Energy Services Professionals' 1995 Workshop Series: Denver, Colorado. October 1995

Demand Forecasting in the Electric Utility Industry. With F. Monforte, D. Nore, I. Rohmund. Editor: C. W. Gellings. October 1995

Application of Evaluation Methods to Non-Residential New Construction Programs. EPRI Non-Residential Impact Evaluation Guidebook. With R. Barnes, P. C. Jacobs, and F. D. Sebold. Prepared for Center for Electric End-Use Data and Electric Power Research Institute: Portland, Oregon. September 1995

1993 PG&E Commercial End-Use Survey. With I. Rohmund and P. Ham-Su. For Pacific Gas and Electric Company, August 1995

Northern States Power 1993 C&I Market Assessment Study. With C. Fordham, K. Miller, F. Monforte, R. Ramirez, I Rohmund, and L. Werner. August 1995.

ASSET User's Guide. With J. Pritchard. Prepared for Southern California Edison, July 1995

Utility Product Forecasting Workshop. 12-day Seminar presented to Southern California Edison, May-July 1995

Market Segmentation and Forecasting. Presented to EEI Economics Committee, May 1995

New England Electric Service C&I Survey, Technology Data, Load Shapes, and Market Profiles. With F. Monforte, I. Rohmund, K. Miller and C. Fordham, and L Werner. March, 1995.

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

DSM Technology Forecasting: Market Transformation and the Dynamic Baseline. With F. Monforte and I. Rohmund. *ACEEE 1994 Summer Study*, Program Design Proceedings, September 1994

Impact of Residential Rate Structure on Equipment Selection and Electricity Demand. With D. Nore and P. Edmundson. Advanced Workshop in Regulation and Public Utility Economics, July 1994

Drivers of Electricity Growth and the Role of Utility Demand-Side Management. With F. Monforte, D. Nore, I. Rohmund and Barakat & Chamberlin, Inc. EPRI TR-102639, August 1993

Commercial End-Use Load Shape Modeling. With P. Bogenrieder, I. Rohmund and ADM Associates, Inc. Report prepared for Pacific Gas & Electric, August 1993

DSM: What's Real, What's Not, and How We Can Tell the Difference. With C. Gellings. Presented at the Aspen Institute, July 1993

Evaluation and Forecasting; Forging the Link. With P Hummel. Proceedings of the International Energy Program Evaluation Conference, 1993

U.S. Electricity Forecast: Results and Decomposition. With F. Monforte, D. Nore and I. Rohmund. Paper presented at *EPRI's* Ninth Electric Utility Forecasting Symposium, September 1993

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

User's Guide for COMMEND. With I. Rohmund. Prepared for Electric Power Research Institute, January 1988, February 1992, August 1993

COOLAID, The Software Solution for Cool Storage Analysis. With I. Rohmund and S. Criswell. PC Software and User's Guide prepared for Electric Power Research Institute, January 1987, December 1988, April 1989, January 1991, March 1993

INFORM 1.2 User's Guide. Prepared for Electric Power Research Institute. With D. Fabizak, and K. Miller. August 1993

Residential Technology Scenario Analysis: Defining the Role of Efficiency Standards, DSM, and Market Forces. With P. Hummel. ACEEE Summer Study, 1992

Commercial Load Shape Disaggregation Studies. With I. Rohmund and P. Bogenrieder. ACEEE Summer Study, 1992

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

BG&E Statistically Adjusted Residential End-Use Model. *Proceedings of the Eighth Electric Utility Forecasting Symposium*. EPRI TR-100396, April 1992

COMTECH™: Commercial Technology Screening Tool. With I. Rohmund and S. Criswell. Software and User's Guide prepared for Electric Power Research Institute, January 1989, September 1990, March 1992

User's Guide for INFORM 1.0: Industrial End-Use Forecasting Model. With F. Monforte. Prepared for Electric Power Research Institute, January 1992

Commercial Sector Regional Data -- 1986 NBECS Market Profiles. With I. Rohmund, S. Criswell, and P. Bogenrieder. Prepared for Energy Information Administration, Office of Energy Markets and End Use, August 1991

FP&L Commercial Equipment Survey and End-Use Load Shapes. With F. Monforte, I. Rohmund, S. Criswell, and P. Bogenrieder. Report for Florida Power & Light, July 1991

REEPS 2.0 User's Guide. With I. Rohmund, J. Pritchard, and D. Fabiszak. Prepared for Electric Power Research Institute, April 1991

WEPCO 1988 Commercial Survey Analysis. With I. Rohmund. Final Report prepared for Wisconsin Electric Power Company, April 1990

Hourly Weather Normalization. With K. Parris. Report for San Diego Gas & Electric Company, January 1990

Commercial End-Use Load Shapes. With I. Rohmund. Report for San Diego Gas & Electric Company, January 1990

Commercial Data Development Project. With I. Rohmund. Final report prepared for New England Power Service Company, January 1990

Houston Lighting and Power 1989 Commercial Sector Survey. With I. Rohmund. Final Report prepared for HL&P, March 1990

Commercial Cooking Market Potential. With I. Rohmund. Prepared for Southern California Edison, April 1989

WEPCO 1987 Commercial Survey Analysis: End-Use Profiles, Technology Data, and Conservation Supply Estimates. With I. Rohmund. Prepared for Wisconsin Electric Power Company, February 1989

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. Final report prepared for the Electric Power Research Institute. EM-5703, V2. April 1988

Commercial End-Use Data Development Handbook. Volume 1: COMMEND Market Profiles and Model Structure. With I. Rohmund. EPRI EM-5703, April 1988

COOLGEN, A Competitive Assessment Tool for Cogeneration/Absorption Systems. With I. Rohmund. Prepared for the Electric Power Research Institute, August 1987

Models of Commercial Sector Equipment and Fuel Decisions for the COMMEND Code: Framework Design and Data Development Plan. With K. Train. EPRI EM-5356, August 1987

End-Use and Econometric Models: Substitutes or Complements. In Forecasting in an Era of Marketing, Conservation and Competition, Proceedings of the Sixth Load-Forecasting Symposium. EPRI EM 5142, April 1987

Analysis Tools for Thermal Energy Storage Evaluation and Marketing. In *Seminar Proceedings: Commercial Cool Storage*. Presented at EPRI Seminar on Commercial Cool Storage. EPRI EM-5454-SR, February 1987

Commercial Sector End-Use Data Development and Forecasts. Prepared for Wisconsin Electric Power Company, December 1986

Commercial Floor Stock: History and Forecasts. Prepared for San Diego Gas and Electric Company, December 1986

A Review of Commercial Sector Energy Use Indexes. With I. Rohmund. Prepared for Electric Power Research Institute, September 1986

Electricity Use in the Commercial Sector. With I. Rohmund. Developed for Electric Power Research Institute, March 1986

Outlook for the U.S. Economy, 1985-2005. November 1985. Regional Economic and Energy Outlook, January 1986. With M. Herndon. Five-Year U.S. Economic Outlook, Developed for San Diego Gas & Electric Company, June 1986

COMMEND Planning System: National and Regional Data and Analysis. With R. Lann, N. Khosla, Q. Looney. EPRI EM-4486, February 1986

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Implementation of Commend in the Ten Department of Energy Regions. With R. Lann, N. Khosla, Q. Looney, and J. Wharton. Forecasting U.S. Electricity Demand, ed. Adela Maria Bolet, Westview Press, 1985

Approaches to Modeling Pay Equity. Evidentia. June 1985

Statistics, Probability, Sample Design, and Econometrics. Seminar for Telecommunications Management Institute. AT&T Training Center and Bell Communications Research, April, July, October 1985

Subscriber Line Usage System Centrex Study Guidelines. With J. Keegan. Bell Communications Research, Special Report, May 1984

An Evaluation of the Subscriber Line Usage System Distribution Analysis Programs. Bell Communications Research. 31230-84-01, February 1984

Using the Nonresidential Building Energy Consumption Survey with COMMEND. Prepared for Electric Power Research Institute, February 1984

User's/Programmer's Guide to COMMEND. EPRI EM-4487, August 1983

Subscriber Line Usage Study Sample Design. Prepared for Pennsylvania Bell Telephone Company, May 1983

Measuring Labor Compensation in Controls Programs. With R. Russell. In The Measurement of Labor Cost, ed. Jack E. Triplett, University of Chicago Press, 1983

Statistics and Demand Analysis in Regulation. Two-day seminar, AT&T Training Center, March, June 1983

Comments on Conservation Policy Analysis and End-Use Models. In EPRI Proceedings: End-Use Models and Conservation Analysis. EA-2509, July 1982

A Model of Commercial Energy Demand. With I. Domowitz. Energy, 6, No. 12, 1981

Statistical Analysis of Initial Placement Practices in Employment Discrimination. With M. Flolid. Evidentia. October 1981

Statistical Analysis to Test for Equal Treatment in Employee Promotion Practices in Employment Discrimination. With M. Flolid. Evidentia. May 1981

Commercial Sector Energy Demand, Electric Peak, and Customer Forecasting Models for CFM III. With C. Chiang and I. Domowitz. Prepared for San Diego Gas & Electric Company, July 1980

A Statistical Analysis of the Man-Hour Requirements for Data Conversion of the Distribution Facilities Information System. Prepared for San Diego Gas & Electric Company, July 1980

Summary and Evaluation of the CEC Commercial Energy Demand Model. With C. Chiang and I. Domowitz. Prepared for San Diego Gas & Electric Company, January 1980

Analysis of 1978 Hourly Loads and Peak Demand Weather Normalization. With C. Chiang. Prepared for San Diego Gas & Electric Company, December 1979

Incremental Cost Analysis for a Multiproduct Firm. With R. Emmerson and I. Domowitz. Prepared for Western Electric Company, October 1979

An Economic and Demographic Forecasting Model for the Texas Power and Light Service Territory. Prepared for Texas Power and Light Company, October 1979

A Study to Identify the Existence of Any Housing Credit Market Differentials Between Urban and Rural Areas and to Identify Causes of Such Differentials: Volume 6: Statistical analysis of Outstanding Mortgage Credit Differences Between Urban and Rural Areas. With R. Emmerson. Prepared for Department of Housing and Urban Development, April 1979

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

Specification and Estimation of Dynamic Demand Systems Incorporating Polynomial Price Response Functions. With J. Pinard. *Journal of Econometrics*, July 1978

Methods for Estimating Transformer Monthly Peak KVA. Prepared for San Diego Gas & Electric Company, May 1978

A Demographic and Economic Forecasting Model for San Diego--Volume I: A Summary; Volume II: Forecasting Model; Volume III: Data Base and Construction; Volume IV: Statistical Estimation; Volume V: Technical Manual;

Volume VI: Simulation and Forecasts; Volume VII: User's Guide to Computer Programs. With R. Emmerson. Prepared for San Diego County, San Diego City, San Diego Gas & Electric Company, and Comprehensive Planning Organization, January 1978

A Residential End-Use Model of Energy Demand for San Diego. Prepared for San Diego Gas & Electric Company, December 1977

Estimation of Conditional Import Demand Systems. With J. Pinard and R. Russell. University of California Discussion Paper 77-20.

A Time Series Monthly Forecasting Model of Electricity and Natural Gas Sales by Rate Schedule. Prepared for San Diego Gas & Electric Company, August 1977

A History of the U.S. Uranium Market. With R. Emmerson. Prepared for General Atomic Corporation, July 1977

Modified Electric Energy Demand Forecasting Model for the San Diego Region. With R. Emmerson. Prepared for San Diego Gas & Electric Company, 1976

Economic Impact Analysis System Model: A Simultaneous Equation Model, A Disaggregated Industry Employment Model, and an Input-Output Model. With R. Emmerson. Prepared for San Diego County, July 1976

Models of Housing Demand and Mortgage Demand and Supply. With R. Emmerson, R. Russell, R. Schmalensee. Prepared for the Department of Housing and Urban Development, July 1976

Electric Energy Demand Forecasting Model for the San Diego Region. With R. Ramanathan. Prepared for San Diego Gas & Electric Company, February 1976

The Effectiveness of Monetary Policy. With D. Cohen. University of California Discussion Paper 76-13.

A Multilateral, Multicommodity Model of World Trade Flows. With J. Pinard, R. Russell, R. Boyce, and J. Hooper. Institute for Policy Analysis, Working Paper 74-3. Prepared for the Central Intelligence Agency.

APPLICATION OF TEXAS-NEW MEXICO POWER COMPANY FOR AUTHORITY TO CHANGE RATES

WORKPAPERS FOR THE DIRECT TESTIMONY OF STUART MCMENAMIN

The information is voluminous and is being provided in electronic format in compliance with RFP General Instruction No. 15. In accordance with RFP General Instruction No. 12(c), below is a list of the files that are being provided electronically:

Testimony Workpapers/McMenamin

- ClassPeak1_Res_Mod.xlsx
- ClassPeak1_Res_ModAR1.xlsx
- ClassPeak2_SLT5_Mod.xlsx
- ClassPeak3_SGT5_Mod.xlsx
- ClassPeak3_SGT5_ModAR1.xlsx
- ClassPeak4_SIDR_Mod.xlsx
- ClassPeak4_SIDR_ModAR1.xlsx
- ClassPeak5_PrimIDRSub_Mod.xlsx
- ClassPeak5_PrimIDRSub_ModAR1.xlsx
- DailyAMS.xlsx
- DailyWeather.xlsx
- Demand1_ResMaxDemand.xlsx
- Demand2_SLT5MaxDemand.xlsx
- Demand3_SGT5MaxDemand.xlsx
- Demand4_SIDRMaxDemand.xlsx
- Demand5_PrimIDRSubMaxDemand.xlsx
- E1_Res_Mod.xlsx
- E1_Res_ModAR1.xlsx
- E2_SLT5_Mod.xlsx
- E2_SLT5_ModAR1.xlsx
- E3_SGT5_Mod.xlsx
- E3_SGT5_ModAR1.xlsx
- E4_SIDR_Mod.xlsx
- E4_SIDR_ModAR1.xlsx
- E5_PrimIDRSub_Mod.xlsx
- E5_PrimIDRSub_ModAR1.xlsx
- ECP1_Res_Mod.xlsx
- ECP1_Res_ModAR1.xlsx
- ECP2_SLT5_Mod.xlsx
- ECP2_SLT5_ModAR1.xlsx
- ECP3_SGT5_Mod.xlsx
- ECP3_SGT5_ModAR1.xlsx
- ECP4_SIDR_Mod.xlsx
- ECP4_SIDR_ModAR1.xlsx
- ECP5_PrimIDRSub_Mod.xlsx
- ECP5_PrimIDRSub_ModAR1.xlsx
- TCP1_Res_Mod.xlsx
- TCP1_Res_ModAR1.xlsx
- TCP2_SLT5_Mod.xlsx
- TCP2_SLT5_ModAR1.xlsx
- TCP3_SGT5_Mod.xlsx
- TCP3_SGT5_ModAR1.xlsx
- TCP4_SIDR_Mod.xlsx
- TCP4_SIDR_ModAR1.xlsx
- TCP5_PrimIDRSub_Mod.xlsx
- TCP5_PrimIDRSub_ModAR1.xlsx