P.U.C. DOCKET NO. ________

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

MAY 30, 2018

TABLE OF CONTENTS

I. INTRODUCTION AND QUALIFICATIONS

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

A. My name is John Stuart McMenamin. I am Managing Director of Forecasting at Itron, 11236 El Camino Real, Suite 210, San Diego, California 92130.

Q. ON WHOSE BEHALF ARE YOU TESTIFYING?

A. I am testifying on behalf of Texas-New Mexico Power Company (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 end-use modeling programs. More recently, my work has focused on methods that combine econometric and end-use concepts. For the last 15 years, I have been employed by Itron, Inc., and I am currently Director of the Forecasting and Load Research Solutions group at Itron. Additional details are available in my resume, which is attached to this testimony as Exhibit JSM-1.

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

A. For the last 15 years, I have been employed by Itron, Inc. 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, Oncor, CPS, and TNMP) to forecast and analyze customers, 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 10 years, I have been working with utilities in North America to help them improve analysis and forecasting processes using AMS data. The work that was conducted for TNMP is an example of this type of 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. Each of these exhibits was prepared by me or under my direction and 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 weather adjustments for the TNMP filing, including adjustments for monthly sales, customer demand, billing demand, class peaks, and class loads at the time of TNMP and ERCOT peaks. The estimates 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-1.3:** 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 and load factors.

Schedule II-H.1.4: Adjusted Test-Year Load Data – This schedule provides the 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 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.

Schedule II-H-2.2: Model Data – This schedule provides additional data variable definitions and references to a listing of the data for variables used directly in the weather adjustment models.

Schedule II-H-2.3: Model Variables – This schedule provides additional data variable definitions and references to a listing of raw data used to construct the model variables covered in Schedule II-H-2.2

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. The schedule also provides references to a listing of daily cooling degree (CD) and daily heading degree (CD) data, which are the data used in the daily weather adjustment models.

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 244,000 TNMP customers. TNMP provided final settlement data for each ESIID in a set of monthly files covering the 2017 test year. 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 and understand how to 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 few hundred customers also 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 data 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, Secondary Greater than 5, Secondary IDR, Primary, Primary IDR, Transmission, and Metered Lighting.

Finally, for each customer, the maximum 15-minute interval in each month was located. These values were also aggregated across customers for each area and rate class.

These values are then used in the monthly models that are used to estimate weather adjustment for customer demand.

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

A. After aggregation, the AMS data were adjusted upward slightly for about 270 customers without AMS meters. Based on 2017 sales data for the excluded customers, adjustment multipliers were computed for four of the classes. The multipliers represent billed energy use for the excluded customers relative to energy use for customers in the AMS population. As shown in the table, the adjustments are less than .1% for all classes except Secondary Less Than 5 KW where it is about .3%.

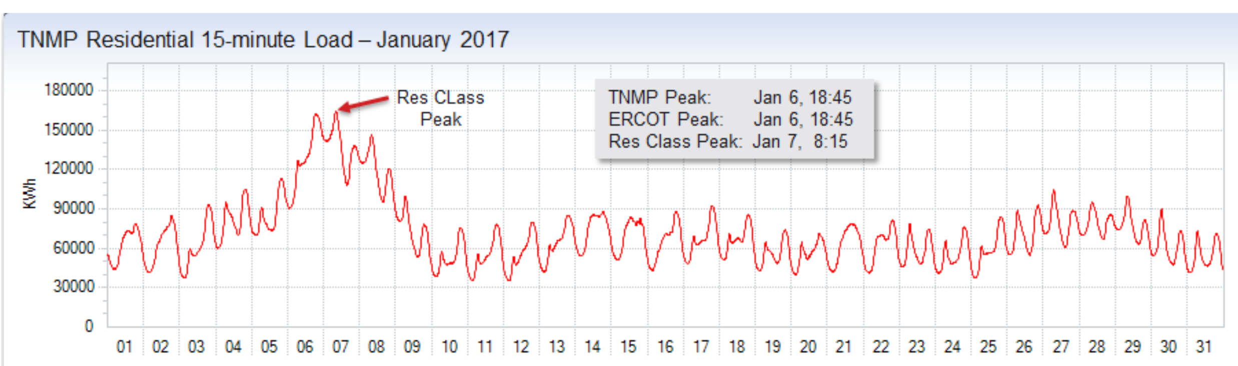
Class	Multiplier
Residential	1.00079
Secondary LT 5	1.00342
Secondary GT 5	1.00096
Primary	1.00070

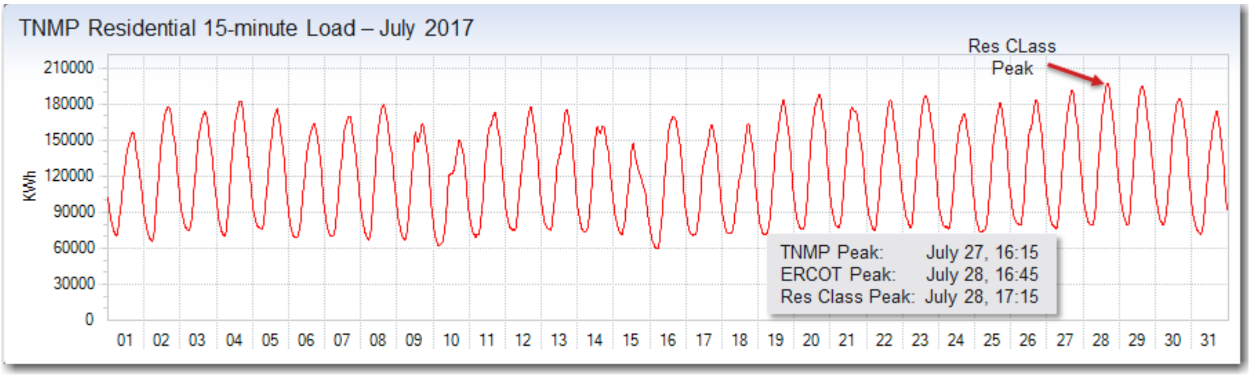
Q. PLEASE EXPLAIN HOW THE AMS DATA WERE USED IN THE WEATHER ADJUSTMENT MODELS.

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. 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.
>
> Coincident loads. On 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 were used for 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 January. 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 the month of July. In these panels, the times identify the beginning of the 15-minute interval, so 16:45 is for the interval for 16:45 to 17:00. These data support estimation of diversity factors and load factors as well as weather adjustment models for energy and peak loads.





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. Settlement data from ERCOT were used to identify the time of the daily peak interval for the sum of TNMP customer loads on 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 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. These map to two engineering formulas, one for Urban areas and one for Rural areas. For both formulas, ERCOT calculates distribution loss factors for each 15-minute interval based on the ERCOT load in that interval. The West and Central regions are both mapped to the Rural formula, so the Rural values were used for all classes except Transmission in these areas. The Gulf and North regions contain a mix of urban and rural areas. For these regions the Urban and Rural loss factors were combined with weights for each class based on the Urban/Rural sales mix for that class in each region. The result is a 15-minute loss factor data series for each class in each region.

The DLF were applied to all classes except Transmission. The 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)

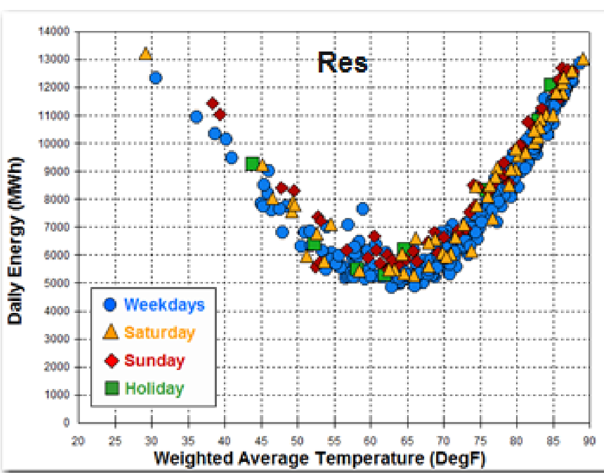
For the transmission class, the form is the same but the term with DLF is excluded.

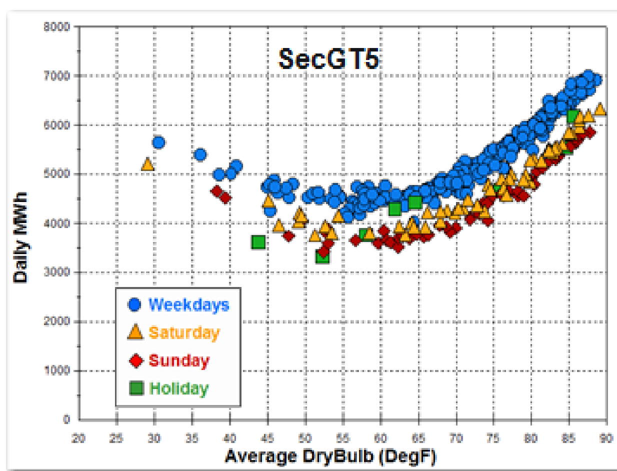
The 15-minute data for Load@Source and the 15 minute data for Load@Meter were then used to compute daily and monthly loss factor multipliers for daily and monthly energy, daily and monthly class peaks, and daily and monthly coincident peaks.

IV. <u>WEATHER ADJUSTMENT MODELS FOR ENERGY</u>

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 80% 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 2017. 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 relatively weak 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. 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.

(1) Variable	(2) Estimated Coefficient	(3) Standard Error	(4) Slope (MWh/Degree)	(5) Spline Weight
CD65	93.9	28.52	93.9	0.217
CD70	190.3	49.10	284.2	0.440
CD75	71.6	42.81	355.8	0.166
CD80	76.6	32.95	432.4	0.177

The estimated coefficients in column (2) are the slopes for each successive cooling degree variable. The unit of measurement for these slopes is daily MWh per degree. The first variable CD65 adds about 94 MWh per degree. Moving above 70 degrees, this jumps up by an additional 190 MWh per degree (for a total slope of 284). Moving above 75 degrees, we gain an additional 72 MWh per degree (for a total slope of 356). Finally, moving past 80 degrees, we gain an additional 77 MWh per degree (for a total slope of 432). The spline weights are computed from these values by taking each estimated coefficient and dividing by the total slope for the highest power degrees (432 in this case). So the initial degrees above 65 have a weight of .217 (computed as 93.9/432.4), indicating that these degrees have about 22% of the power of the highest power degrees. With these numbers, the CD spline variable is computed as:

CDSpline = .217 * CD65 + .440 * CD70 + .166 * CD75 + .177 * CD80

The comparable heating degree spline variable is:

HDSpline = .041 * HD65 + .377 * HD60 + .582 * HD50

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 daily weather variations. As I will show below, they are also used to compute weather adjustments for the test year data.

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

A. 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 larger TNMP classes (Secondary IDR, Primary, Primary IDR) there was no detectable heating activity. For Transmission customers, 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 a full list of Model Variables.

	Heating Degree Weights					Cooling Degree Weights					
Class	HDD65	HDD60	HDD55	HDD50	HDD45	CDD55	CDD60	CDD65	CDD70	CDD75	CDD80
Residential	0.041	0.377		0.582				0.217	0.440	0.166	0.177
Secondary LT 5			1.000					0.155		0.845	
Secondary GT 5				1.000			0.233		0.375	0.162	0.230
Secondary IDR						0.259		0.452		0.289	
Primary								1.000			
Primary IDR								0.248		0.752	

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

A. 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 holidays from New Year's day through Christmas.

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 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 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	5218.79	93.19	56.004		Constant term
Month	Jan	-147.37	97.58	-1.510	Binary	Binary = 1 in January
Month	Feb	-284.56	112.12	-2.538	Binary	Binary = 1 in February
Month	Mar	-187.24	117.52	-1.593	Binary	Binary = 1 in March
Month	Apr	-26.62	112.15	-0.237	Binary	Binary = 1 in April
Month	May	105.65	116.93	0.904	Binary	Binary = 1 in May
Month	Jun	69.49	139.60	0.498	Binary	Binary = 1 in June
Month	Jul	-50.44	160.62	-0.314	Binary	Binary = 1 in July
Month	Aug	-132.04	150.10	-0.880	Binary	Binary = 1 in August
Month	Sep	-38.56	133.56	-0.289	Binary	Binary = 1 in September
Month	Oct	-90.13	114.57	-0.787	Binary	Binary = 1 in October
Month	Nov	-251.98	110.10	-2.289	Binary	Binary = 1 in November
Day	Monday	90.48	48.23	1.876	Binary	Binary = 1 on Monday
Day	Tuesday	-33.06	40.20	-0.822	Binary	Binary = 1 on Tuesday
Day	Thursday	-78.63	40.12	-1.960	Binary	Binary = 1 on Thursday
Day	Friday	-114.13	47.13	-2.421	Binary	Binary = 1 on Friday
Day	Saturday	388.28	61.11	6.354	Binary	Binary = 1 on Saturday
Day	Sunday	630.23	59.46	10.599	Binary	Binary = 1 on Sunday
Holiday	MLK	-117.22	239.46	-0.490	Binary	Binary = 1 on M L King Day
Holiday	PresDay	182.47	236.43	0.772	Binary	Binary = 1 on Presidents Day
Holiday	GoodFri	346.61	224.29	1.545	Binary	Binary = 1 on Good Friday
Holiday	MemDay	433.38	238.84	1.815	Binary	Binary = 1 on Memorial Day
Holiday	July4th	861.00	244.65	3.519	Binary	Binary = 1 on Independence Day
Holiday	LaborDay	640.23	241.61	2.650	Binary	Binary = 1 on Labor Day
Holiday	Thanks	568.70	242.21	2.348	Binary	Binary = 1 on Thanksgiving Day
Holiday	FriAThanks	111.71	252.90	0.442	Binary	Binary = 1 on Friday after Thanksgiving
Holiday	XMasWkB4	895.76	286.72	3.124	Binary	Binary = 1 on week before XMas
Holiday	XMasEve	1125.77	768.08	1.466	Binary	Binary = 1 on XMas Eve
Holiday	XMasDay	1028.87	265.67	3.873	Binary	Binary = 1 on XMas Day
Holiday	XMasWk	350.24	229.93	1.523	Binary	Binary = 1 during week after XMas
Holiday	NYEve	3301.85	680.44	4.853	Binary	Binary = 1 on New Years Eve
Heating	HDSpline	266.11	8.40	31.677	DegF	Heating Degree Spline
Heating	LagHD	93.58	9.64	9.703	DegF	Two day lagged Heating Degrees (80/20 weights)
Heating	WkEndHD	-44.76	10.13	-4.419	DegF	Heating Degree Spline on Weekend Days
Heating	SpringHD	-157.25	44.26	-3.553	DegF	Heating Degree Spline on Spring Days
Heating	FallHD	-201.55	46.92	-4.296	DegF	Heating Degree Spline on Fall Days
Cooling	CDSpline	409.38	9.33	43.864	DegF	Cooling Degree Spline
Cooling	LagCD	46.20	8.98	5.145	DegF	Two day lagged Cooling Degrees (80/20 weights)
Cooling	WkEndCD	-14.14	5.76	-2.455	DegF	Cooling Degree Spline on Weekend Days
Cooling	SpringCD	-63.62	30.57	-2.082	DegF	Cooling Degree Spline on Spring Days
Cooling	FallCD	-47.51	22.72	-2.091	DegF	Cooling Degree Spline on Fall Days
AR1	AR(1)	0.344	0.055	6.294		

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 of per full powered cooling degree. For the residential model, all weather coefficients are well defined and statistically significant, as indicated by relatively small standard errors and large T statistics.

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 about 94 MWh per degree, which is about 35% of the same day parameter (266 MWh per degree). For cooling, the lag effect is about 46 MWh per degree, which is about 11% of the same day effect (409 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. For residential heating, the HDSpline slope is estimated to be about 45 MWh per degree smaller on weekend days than it is on weekdays. For residential cooling, the CDSpline slope is estimated to be about 14 MWh per degree smaller on weekend days than it is on weekdays.

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 coefficients suggest a much weaker response for residential heating on both sides of the winter months. The Fall response is estimated to be 202 MWh per degree (or 76%) weaker than the Winter response. The Spring response is estimated to be 157 MWh per degree (or 59%) weaker than the 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 coefficients suggest a slightly reduced response for residential cooling on both sides of the Summer months. The Spring response is estimated to be 64 MWh per degree (or 16%) weaker than the Summer response. The Fall response is estimated to be 48 MWh per degree (or 12%) weaker than the Summer response.

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

When actual weather is milder than normal weather, the predicted value with normal weather is higher and the weather adjustment will be positive. For example, on the heating side, the winter months were warmer than normal. As a result, the heating energy adjustments are positive in these months, especially for the smaller customers with significant heating loads.

When actual weather is more extreme than normal, the predicted values with normal weather will be lower and the weather adjustment will be negative. On the cooling side, in 2017, this is the case for most of the summer months. As a result, the cooling energy adjustments are negative in these months for all customers.

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.

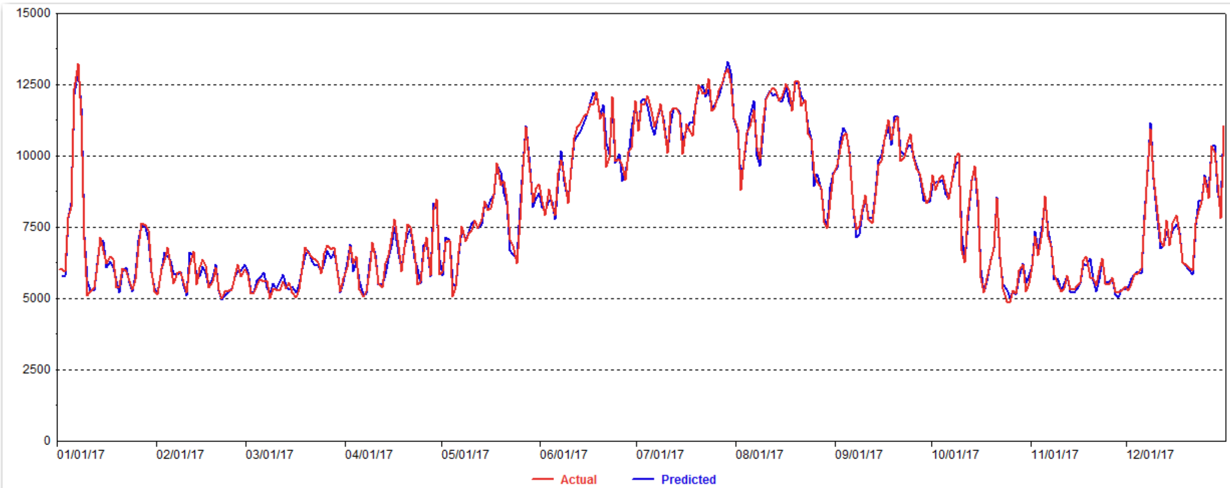
		Static Model (No AR1)			Model with AR1		
Type	Variable	Coefficient	StdErr	T-Stat	Coefficient	StdErr	T-Stat
Heating	HDSpline	267.96	7.96	33.683	266.11	8.40	31.677
Heating	LagHD	89.25	9.09	9.820	93.58	9.64	9.703
Heating	WkEndHD	-42.35	11.12	-3.809	-44.76	10.13	-4.419
Heating	SpringHD	-151.01	44.62	-3.384	-157.25	44.26	-3.553
Heating	FallHD	-215.37	43.29	-4.975	-201.55	46.92	-4.296
Cooling	CDSpline	404.53	9.10	44.463	409.38	9.33	43.864
Cooling	LagCD	50.34	8.82	5.709	46.20	8.98	5.145
Cooling	WkEndCD	-15.65	5.85	-2.675	-14.14	5.76	-2.455
Cooling	SpringCD	-32.55	28.89	-1.127	-63.62	30.57	-2.082
Cooling	FallCD	-52.54	18.956	-2.772	-47.51	22.72	-2.091

The coefficient pattern from the two specifications is consistent, and all coefficient estimates are well within two standard errors between the two specifications. For example, the CDSpline coefficient is 405 MWh per degree in the static model and 409 MWh per degree in the model with the AR1 term. The standard error in both models is about nine, so the two slopes are basically the same in a practical sense and in a statistical sense. Both parameters are strongly statistically significant (t-statistics of > 40) and the difference between them is not statistically significant. This is the signature of a strong 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.

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 values. 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	365.00	364.00
R-Squared	0.990	0.991
Adjusted R-Squared	0.989	0.990
AIC	11.12	11.02
BIC	11.56	11.48
F-Statistic	798.24	862.74
Prob (F-Statistic)	0.000	0.000
Std. Error of Regression	245.62	233.32
Mean Abs. Dev. (MAD)	181.38	172.98
Mean Abs. % Err. (MAPE)	2.40%	2.29%
Durbin-Watson Statistic	1.393	2.022

The quality of the model fit is excellent with mean absolute percent error (MAPE) values of 2.40% for the static model and 2.29% 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 1.39 indicates moderate positive autocorrelation. With the AR1 correction there is no indication of first order autocorrelation (as indicated by the Durbin-Watson statistic of 2.02).

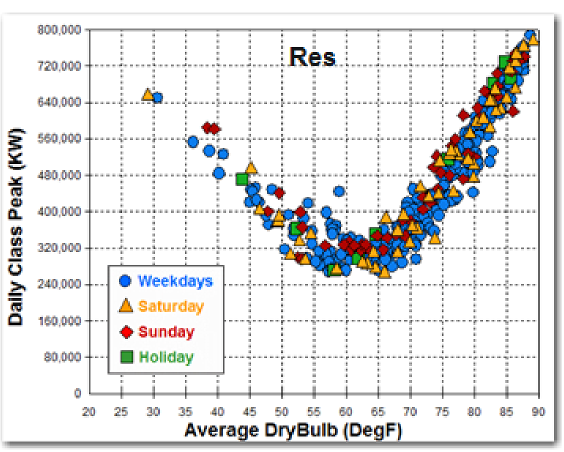
The following table provides the daily energy model summary statistics for all of the weather sensitive classes. As this shows, the model fit for all classes is strong, with MAPE values in the 1.3% to 2.4% range.

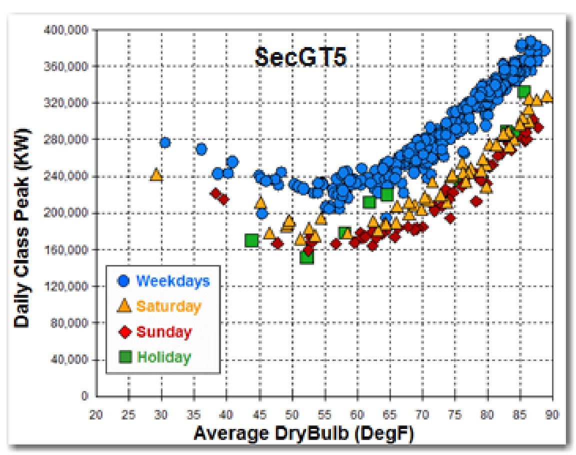
Daily Energy Model Statistics	Residential	Secondary Less Than 5	Secondary Greater Than 5	Secondary IDR	Primary	Primary IDR
Adjusted Observations	364.00	364.00	364.00	364.00	364.00	364.00
R-Squared	0.991	0.899	0.991	0.968	0.968	0.851
Adjusted R-Squared	0.990	0.887	0.990	0.965	0.965	0.836
AIC	11.015	2.326	9.008	7.128	6.603	6.71
BIC	11.476	2.754	9.414	7.503	6.957	7.07
F-Statistic	862.738	73.755	962.698	296.586	310.192	56.93
Prob (F-Statistic)	0.000	0.000	0.000	0.000	0.000	0.000
Std. Error of Regression	233.32	3.040	86.02	33.74	26.01	27.34
Mean Abs. Dev. (MAD)	172.98	1.980	63.66	23.80	18.44	20.30
Mean Abs. % Err. (MAPE)	2.29%	1.90%	1.27%	2.44%	2.20%	1.54%
Durbin-Watson Statistic	2.022	1.669	1.961	1.909	1.903	1.967

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

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

A. The daily class peak models are similar to the daily energy models, except daily class peak load is the variable that is explained. As examples, the following figures show scatter plots of daily class peak vs daily average temperature for the residential (Res) and Secondary Greater Than 5 KW (SecGT5) classes.





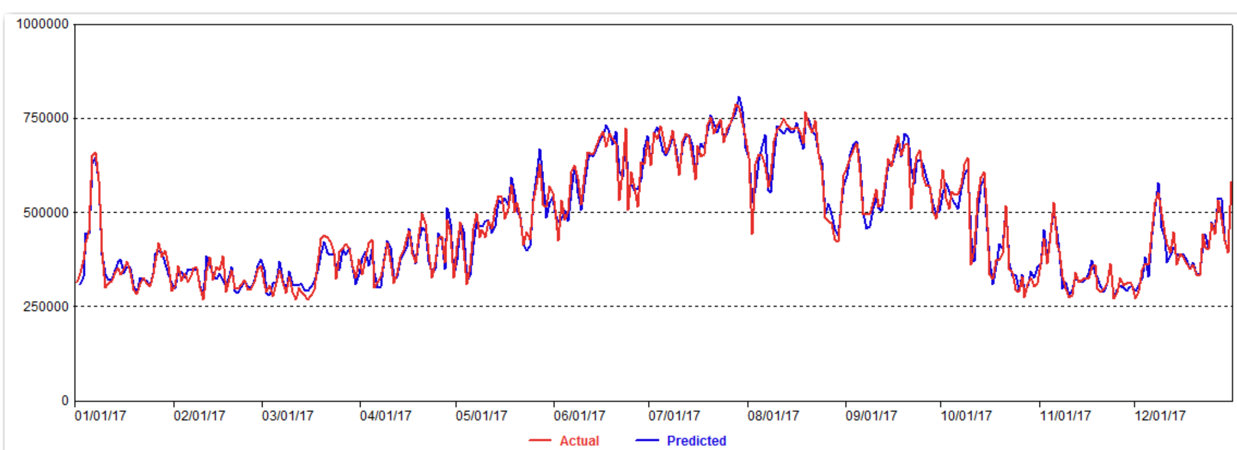
These graphs show weather response patterns for daily class peaks that are similar to the daily energy patterns. However there are some differences, and as a result, we estimated a different set of HD and CD weights for the class peak and coincident peak models. These weights are shown in the following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

Class	Heating Degree Weights					Cooling Degree Weights					
	HDD65	HDD60	HDD55	HDD50	HDD45	CDD55	CDD60	CDD65	CDD70	CDD75	CDD80
Residential		0.096	0.760		0.144			0.364		0.288	0.348
Secondary LT 5		1.000						0.606		0.394	
Secondary GT 5			1.000				0.436		0.174		0.390
Secondary IDR						0.437		0.279		0.285	
Primary								1.000			
Primary IDR						0.128			0.382		0.490

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 of 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 for the energy models. The mean absolute percent errors for these models range from 1.9% (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 using load at the time of the daily TNMP peak and the other using load at the time of the daily ERCOT peak. The models are very similar to the daily class peak models in terms of weather parameters and model fit statistics. The full set of model results with and with 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?

A. 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 averaged about 327 MW in 2017, whereas the average monthly customer demand values were about 77% larger at 578 MW. Similarly billing demands are larger than actual demand reflecting the 12 month “ratchet.” In 2017, monthly billing demands averaged about 13% higher than monthly actual demands for the SecGT5 class.

To model customer demands, the monthly AMS data values were used in regressions that explain customer demand as a function of average daily energy use in the month and monthly class peak. For the smaller classes (Res, SecLT5, and SecGT5), it was also necessary to include a heating degree variable to account for the impact of cold weather on heating loads for customers with electric heating. These customers are likely to have their maximum demands on a cold day. The weather variable that was used is the maximum of the HD60 daily values in each month.

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 with demand charges (SecGT5, SecIDR, Primary, and PrimaryIDR). Although the models are very simple, the models are strong with mean absolute percent errors of less than 1.5% for all classes except SecIDR which came in at 3.3%.

To calculate weather adjustments for actual demand, the estimated models were used to simulate predicted loads with weather adjusted average daily energy, weather adjusted class peaks, and the normal maximum HD60 values representing the typical coldest day in each month. In this way, the estimated weather adjustments for monthly energy and monthly class peaks flow through to the weather adjustments for actual demand.

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

A. The billing demand models use simple regressions that explain billing demand as a function of actual demand. These models are estimated with monthly billing data from the last two to three years. Models are only estimated for the weather sensitive classes that have demand charges (SecGT5, SecIDR, Primary, and PrimaryIDR).

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. Although the models are very simple, they are strong with mean absolute percent errors ranging from .6% for SecGT5 to 2.1% for PrimaryIDR.

To estimate weather adjustments for billing demand, the models are simulated twice using the AMS demand data. First, model predicted values are calculated using the actual monthly class demand values. Second, the model predicted values are calculated using the weather adjusted class demand values. The difference between the two sets of simulated monthly values is the weather adjustment for billing demand. In this way, weather adjustments for the monthly actual class demands flow through to the monthly billing demand values.

VI. NORMAL WEATHER CALCULATIONS

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 daily weather. In order to represent normal weather for both energy and peak calculations a "rank and average" approach was used. This was done with daily weather data for the 20-year period between 1997 and 2016. In prior decades, the common practice was to use a 30-year period for defining normal weather. Our most recent industry survey in 2017 indicates that a 20-year period is now the prevalent practice.

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

Compute daily average temperature for each historical day as the average of the hourly values for that day.

Compute daily heating degree (HD) and cooling degree (CD) values for each temperature base using the daily average temperature value for each historical day.

Rank the daily data for each month by sorting the data from hottest to coldest based on daily average temperature.

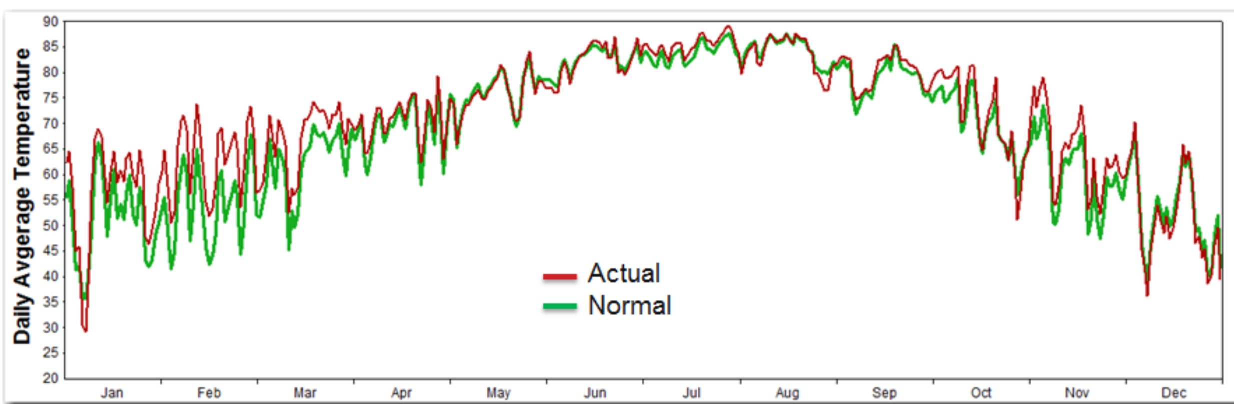
For each month, average the ranked data across the 20-year historical period. This gives an average hottest day, an average second hottest data, and so on through to an average coldest day for each month.

Assign the rank-and-average results to days in 2017 based on the weather order that actually occurred in 2017. For example, the coldest day in January 2017 will be assigned the value for the typical coldest day in January. Similarly, the hottest day in July 2017 will be assigned the value for the typical hottest day in July.

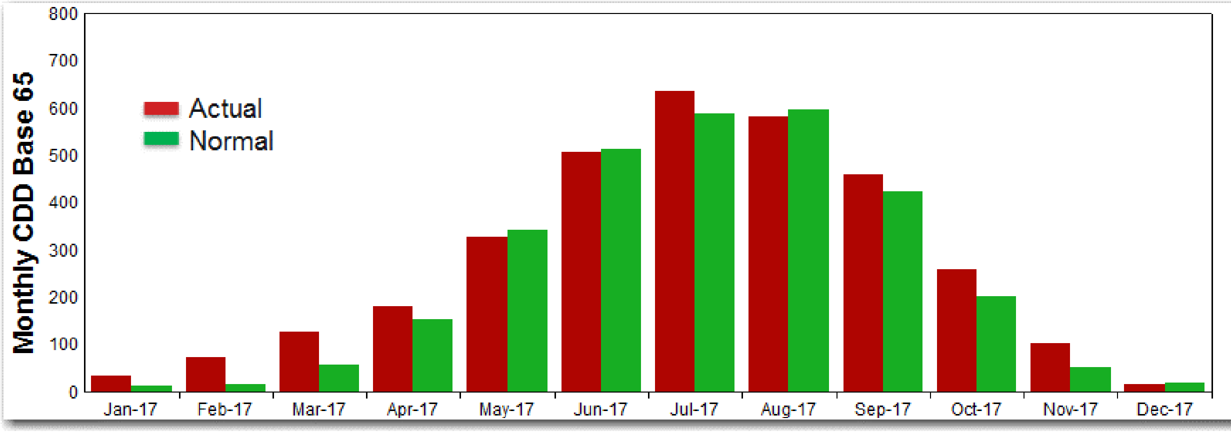
This process was applied separately to the weather stations for each of the four TNMP regions. The resulting HD and CD values were then averaged across stations using annual energy weights.

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. The daily chart is followed by charts showing monthly cooling and heating degree days with a base temperature of 65. These charts show that the early part of the year was warmer than normal for most days, excluding 3 days in early January, which were about 5 degrees colder than normal. On average the summer was slightly warmer than normal, with the exception of a few days in late August. The Fall months came in steadily warmer than normal until December, which was slightly colder than normal. More details on weather data are presented in Schedule II-H.5.1 and II-H.5.2.

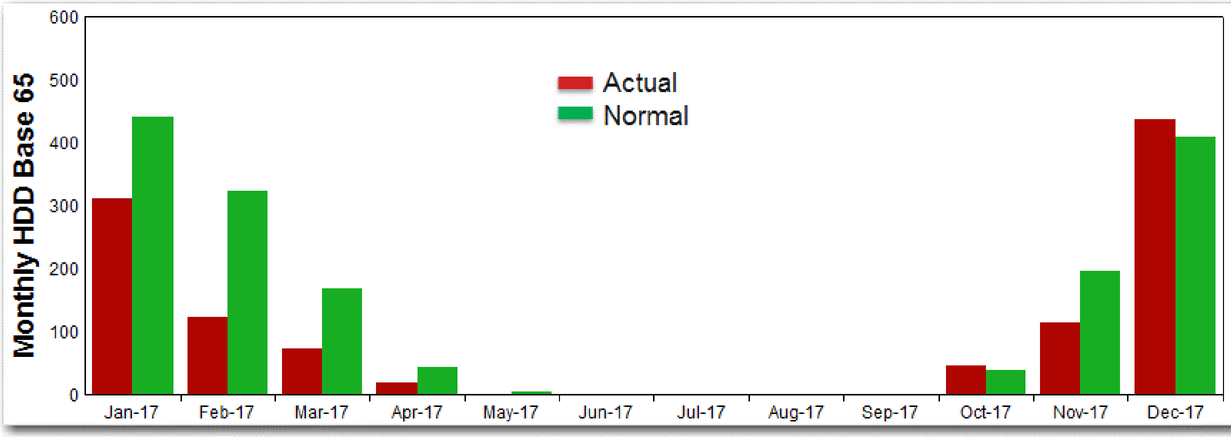
Actual and Normal Daily Average Temperature



2017 Actual and Normal Monthly CDD Base 65


Monthly CDD Base 65
Actual
Normal
0
100
200
300
400
500
600
700
800
Jan-17
Feb-17
Mar-17
Apr-17
May-17
Jun-17
Jul-17
Aug-17
Sep-17
Oct-17
Nov-17
Dec-17

2017 Actual and Normal Monthly HDD Base 65



VII. <u>SCHEDULES FOR TEST-YEAR LOAD DATA</u>

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 from monthly billing data. Comparable values computed on a calendar month basis using the 15-minute AMS data for each customer are shown in the working papers that are filed with this testimony. 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. A small scaling adjustment is applied for some classes to reflect customers who do not have AMS meters.

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 coincident load at the Meter.

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 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 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. Comparable data for calendar month energy computed from AMS data are provided in the working papers filed with this testimony. Despite significant differences in timing (billing data is for staggered cycles, AMS data is for calendar months), the data are in very close agreement on an annual basis.

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. For each class, 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 value in a 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 interacting with weekend variables and seasonal variables that allow the weather response to be different on different types of days.

Daily weather models are estimated with actual daily weather in 2017. 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 is the weather adjustment. 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 added across days to get the monthly weather adjustment. The monthly weather adjustment is added to the monthly sales value, and the result is further adjusted for customer growth and hurricane effects giving the adjusted class sales at the Meter.

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. These models are discussed earlier in the testimony. Variables in the monthly models include average daily energy in the month, monthly class peak, and for some classes, the maximum HD60 value in the month.

Predicted values for these models are simulated with adjusted average daily energy, adjusted monthly class peak, and normal maximum HD60 values. The difference between predicted values with the normal values and predicted values with the actual values is the weather adjustment at the Meter. The weather adjustment is added to the actual customer maximum demand value, and this result is further adjusted for customer growth, 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 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 in 2017. 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, and the result is further adjusted for customer growth, 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.

A. 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 interacting with weekend variables and seasonal variables that allow the weather response to be different on different type of days.

Daily coincident load models are estimated with actual daily weather data for days in 2017. The estimated models are used to recalculate what daily coincident class loads would have been with normal weather on each day. On the TNMP peak day in each month, the difference between 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, and the result is further adjusted for customer growth, 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 also interacting with weekend variables and seasonal variables that allow the weather response to be different on different type of days.

Daily coincident load models are estimated with actual daily weather data for days in 2017. 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, and the result is further adjusted for customer growth, 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 II-H-1.2, which shows adjustments for weather, hurricane effects, and customer growth.

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 shown on Schedule II-H-1.2, but starting with the AMS data for calendar month energy rather than billed energy.

IX. ADJUSTED ACTUAL CUSTOMER DEMAND AND BILLING DEMAND

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENT FOR MONTHLY BILLED KW PROVIDED IN SCHEDULE WP II-H-4-1-6.

A. Models of monthly actual demand (the sum of individual customer maximum demands in a month) are discussed earlier in the testimony. These models are based on AMS data for each class, and they explain monthly actual demand as a function of daily average energy in each month, monthly class peaks, and for SGT5 and below, the maximum HD60 value in each month. The predicted values for these models are recomputed using weather adjusted energy, weather adjusted class peaks, and normal maximum HD60 values. The difference between predicted values with adjusted normal inputs and predicted values with actual inputs is the weather adjustment. The weather adjustment for each month is added to the actual demand value for the month, and the result is further adjusted for customer growth, giving the adjusted class demand value.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENT FOR MONTHLY BILLED KW PROVIDED IN SCHEDULE WP II-H-4-1-6.

A. Monthly billing demand for a customer is the actual customer demand in the current month, but not less than 80% of the maximum demand value from the prior 12 months. Models of billing demand are estimated using historical monthly billing data. In the models, billing demand is the dependent variable that is being explained and actual demand is the explanatory variable on the right-hand side of the equation. The models are used to calculate predicted billing demand using the actual monthly demand from AMS data and again using the weather adjusted monthly demand. The difference between the predicted value with weather adjusted demand and the predicted value with actual demand is the weather adjustment. The weather adjustment for each month is added to the billing demand value for the month, and the result is further adjusted for customer growth, giving the adjusted billing demand value.

X. CONCLUSIONS

Q. PLEASE SUMMARIZE YOUR TESTIMONY AND RECOMMENDATIONS.

A. AMS data provide the opportunity to understand weather adjustments at a deeper level than was possible with monthly billing data. 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. Also, 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 adjustment results that are accurate and that are based on powerful statistical relationships. These results provide a strong foundation for revenue requirement calculations based on 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."

5/10/2018
Witness

* * * * *

SWORN TO AND SUBSCRIBED before me, Notary Public, on this 10 day of May 2018, to certify which witness my hand and seal of office.

KI HOON CHOI
COMMISSION NO. 2132620
NOTARY PUBLIC - CALIFORNIA
SAN DIEGO COUNTY
COMMISSION EXPIRES DEC 1, 2019
CLS1

SEAL:

NOTARY PUBLIC in and for the
State of California

Printed Name: Ki Hoon Choi

My Commission expires: Dec. 1. 2019

Notary ID# 2132620