<u>BEFORE THE NEW MEXICO PUBLIC REGULATION COMMISSION</u>

IN THE MATTER OF THE APPLICATION OF PUBLIC SERVICE COMPANY OF NEW MEXICO FOR REVISION OF ITS RETAIL ELECTRIC RATES PURSUANT TO ADVICE NOTICE NO. 595	)	**Case No. 22-00270-UT**
PUBLIC SERVICE COMPANY OF NEW MEXICO,	)	
Applicant	)	

DIRECT TESTIMONY

OF

DR. J. STUART MCMENAMIN

December 5, 2022

NMPRC CASE NO. 22-00270-UT
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WITNESS FOR
PUBLIC SERVICE COMPANY OF NEW MEXICO

DIRECT TESTIMONY
OF DR. J. STUART MCMENAMIN
NMPRC CASE NO. 22-00270-UT

I. INTRODUCTION AND PURPOSE

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

A. My name is John Stuart McMenamin. I am Director of Forecasting at Itron Inc. ("Itron"), 10870 Rancho Bernardo Road, San Diego, CA 92127.

Q. ON WHOSE BEHALF ARE YOU TESTIFYING?

A. I am testifying on behalf of Public Service Company of New Mexico ("PNM").

Q. WHAT IS THE PURPOSE OF YOUR TESTIMONY?

A. The purpose of my testimony is to describe the data and modeling methods that are used to develop some of the Base Period estimates and Test Period projections that support rate case calculations. In particular, my testimony provides key data used to allocate costs among the customer classes and to develop rates, by providing PNM with the Test Period projections related to customer growth, energy sales, class peaks and class loads. The testimony covers two 12-month time periods, the rate case Base Period and the rate case Test Period.

The Base Period is the 12-month period from July 2021 to June 2022. For this period, historical sales and hourly load data are analyzed and modeled to develop the following:

- Weather adjustments for customer class sales in the Base Period
- Estimates of customer class peaks and loads at the time of the system peak.

The Base Period results provide the starting point for development of projections in the Test Period. The Test Period is the 12-month period from January 2024 through December 2024, which is exactly 2.5 years after the Base Period. Test Period projections are developed for the following:

- Number of customers by customer class and rate schedule
- Billed sales by customer class and rate schedule
- Billing determinants by rate schedule
- Estimates of customer class peaks and class loads at the time of system peak

Test Period estimates of customer class peaks and class loads at the time of system peak are used by PNM in cost allocation calculations that drive revenue requirements by class. Test Period projections of monthly billing determinants are used by PNM to calculate the revenue that can be expected from the proposed rates. PNM Figure SC-1 in the Direct Testimony of PNM witness Chan shows how PNM uses the forecasting data that I support in the cost allocation and rate design process.

My testimony provides an overview of the main analysis and modeling methods that are used to develop the Base Period and Test Period results. It also provides tables and charts that present the high-level results. Additionally, I sponsor 530 Schedule P-6.

II. BACKGROUND AND QUALIFICATIONS

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, which was received 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 during this period. More recently, my work has focused on methods that combine econometric and end-use concepts. For the last 20 years, I have been employed by Itron, and I am currently Director of the Forecasting Solutions group at Itron. Additional details are available in my resume, which is attached to this testimony as PNM Exhibit SM-1.

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

A. For the last 20 years, I have been employed by Itron as Director of the Forecasting Solutions group. During this period, I have managed the development of 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 approximately 200 utilities to forecast customer growth, sales, revenues, and hourly loads. In addition to product design and algorithm development, I manage 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 more granular data from advanced metering systems.

III. CUSTOMER CLASSES AND RATE SCHEDULES

Q. PLEASE DEFINE THE TERM CUSTOMER CLASS AS IT IS USED IN YOUR TESTIMONY.

A. Customer classes are customer groupings based on the type of customer, customer size, and the voltage level at which energy is delivered. PNM Table SM-1 provides a list of the customer classes and their definitions. It also provides Base Period data for the number of customers, sales in GWh, sales per customer ("SPC") in MWh, and the percentage of total sales for each class. The customer and sales data are measured historical data from the customer billing system for the months in the Base Period. Sales are measured in kilowatt hours (KWh) at the customer premise by electric meters. In my testimony, sales per customer values are reported in megawatt hours (MWh = 1,000 KWh) and sales levels are reported in gigawatt hours (GWh = 1,000 MWh).

PNM Table SM-1: Base Period Customer Class Data

Class Definition	Customer Class	Average Customers	Annual Sales (GWh)	Sales Per Customer (MWh)	Percent of Sales (%)
Residential	Res	482,222	3,348.9	6.9	41.8%
Small Power	SP	54,412	927.3	17.0	11.6%
General Power	GP	4,137	1,863.2	450.4	23.3%
Large Power	LP	169	1,082.2	6,409.7	13.5%
Large Service	LS	5	534.7	106,931.5	6.7%
Irrigation	Irr	310	20.6	66.4	0.3%
Water and Wastewater	Water	152	177.4	1,169.1	2.2%
Private Area Lighting	PAL		13.8		0.2%
Streetlights	SL	153	34.6	226.1	0.4%
Total All Classes		**541,560**	**8,002.6**	**14.78**	**100.0%**

Q. PLEASE DEFINE THE TERMS RATE SCHEDULE AND BILLING DETERMINANTS AS THEY ARE USED IN YOUR TESTIMONY.

A. Rate schedules divide customer classes into more specific groupings. Rate schedules define the specific prices (called rates) that are applied to measured quantities on a customer bill (called billing determinants). PNM Table SM-2 provides a list of the rate schedules for which billing determinant predictions are made. Test Period values for billing determinants are provided in the Rate Design Model, which is attached to the testimony of PNM witness Pitts as PNM Exhibit

HMP-2. In addition to the billing determinants shown in the table, all rate schedules include a monthly customer charge.

PNM Table SM-2: Rate Schedules

Class Definition	Customer Class	Rate Schedule	Description	Energy Charges	On-Peak Demand	Reactive KVA
Residential	Res	1A	Energy by Usage Block	By Block		
		1B	Time of Use	TOU		
Small Power	SP	2A	Energy	Energy		
		2B	Time of Use	TOU		
General Power	GP	3B_S	Secondary	TOU	Yes	Yes
		3B_P	Primary	TOU	Yes	Yes
		3C_S	Secondary, Low Load Factor	TOU	Yes	Yes
		3C_P	Primary, Low Load Factor	TOU	Yes	Yes
Municipal General Power	GP	3D_S	Secondary	TOU	Yes	Yes
		3D_P	Primary	TOU	Yes	Yes
		3E_S	Secondary, Low Load Factor	TOU	Yes	Yes
		3E_P	Primary, Low Load Factor	TOU	Yes	Yes
Large Power	LP	4B	Utility Owned Transmission	TOU	Yes	Yes
		4B COT	Customer Owned Transmission	TOU	Yes	Yes
Large Power (>3 MW)		35B		TOU	Yes	
Large Service (>8MW)	LS	5B		TOU	Yes	Yes
Large Service UNM		15B		TOU	Yes	
Large Service (>30 MW)		30B		TOU	Yes	Yes
Large Service Stn Pwr		33B		TOU	Yes	Yes
Water and Wastewater	Water	11B		TOU		
Irrigation	Irr	10A	Energy	Energy		
		10B	Time of Use	TOU		

As shown in the table, all schedules have an energy charge that applies to monthly net energy deliveries (also called monthly sales in my testimony). These charges have three forms: energy, energy by usage block, and energy by time-of-use ("TOU") period. There are two TOU periods, named on-peak (for usage during the day on weekdays) and off-peak (for usage at night and on weekend days). For most of the larger customer classes, there is also a demand charge, which is measured in kilowatts (KW) representing the highest level of demand in the on-peak period.

Most of the large classes also have an additional charge, labeled Reactive KVA (Kilovolt Amps), for customers who have a power factor below a specified level. For the Residential ("Res") customer class there are two rate schedules (1A and 1B). Rate Schedule No. 1A applies to most of the residential customers and includes a different price for each of three usage blocks (less than 450 kWh, 450 to 900 KWh, and over 900 KWh). The Residential class also has a small fraction (about .02%) of customers on a TOU rate. The Small Power ("SP") customer class has a similar pair of Rate Schedules 2A and 2B, but there are no usage blocks in the 2A rate. Similarly, the Irrigation class has two rates, 10A that is a simple energy charge and 10B that is energy by TOU.

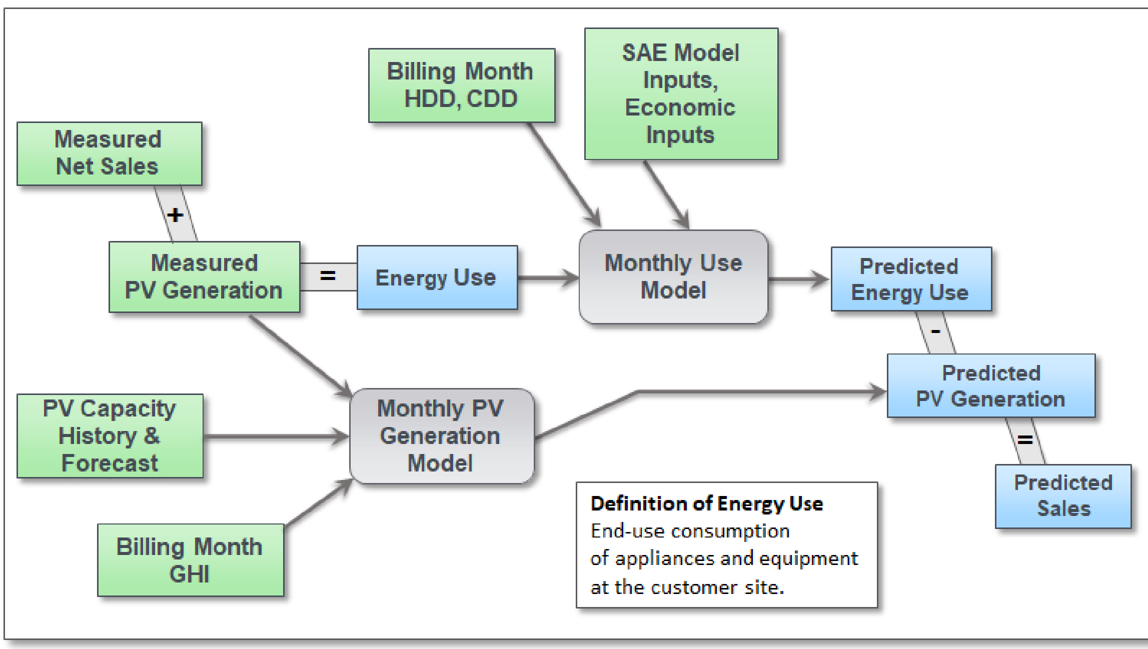
There is an additional Special Service rate schedule (36B) that is for customers who use renewable energy resources to offset some of their electricity requirements. This rate schedule is not covered by my testimony. For information about this rate schedule, see the testimony of PNM witness Chan.

IV. MONTHLY CUSTOMER CLASS SALES MODELING FRAMEWORK

Q. CAN YOU PROVIDE A SUMMARY OF THE APPROACH THAT IS USED TO MODEL MONTHLY CUSTOMER CLASS SALES?

A. At a high level, statistical models that are based on measured sales data, measured weather data, and measured solar generation data are used to develop monthly customer class models. Once estimated, the models are used to simulate weather adjustments in the Base Period, to project sales in the Test Period, and to simulate calendar month sales in the Base Period and the Test Period. The calendar month sales numbers are inputs to the following steps used to project hourly system loads and system peaks. Because the models are different than models used in prior rate cases, I will provide some details on the approach. PNM Figure SM-1 provides an overview of the monthly sales modeling framework.

PNM Figure SM-1: Monthly Sales Forecasting Framework



Q. WHAT IS THE FIRST MODELING MODIFICATION THAT DIFFERS FROM THE LAST RATE CASE?

A. The first change in the modeling approach from prior filings is driven by the significant impact that behind-the-meter distributed energy resources ("DERs"), specifically solar photovoltaic systems ("PV"), have had on electricity sales. When a KWh of electricity is generated by the customer, that energy is either consumed on-site or is sent back through the distribution system and delivered to a nearby neighbor. Either way, the generated electricity reduces net sales to the customer (net sales is energy delivered to the customer minus energy received from the customer). This reduction masks the actual end-use consumption of power by appliances and equipment at the customer site.

I have been working with PNM since 2019 to develop methods and data required to explicitly account for the impacts of PV generation. The resulting framework is shown on the left-hand side of PNM Figure SM-1. PNM requires each solar customer to have a production meter that measures solar generation. The generation data are collected on the same cycles as data from the monthly billing meters. As a result, there is no need to estimate PV generation, in that it is directly measured. The measured generation can be added to measured net deliveries (sales) to calculate energy use. As highlighted in PNM Figure SM-1, the resulting value for energy use represents the end-use energy consumption of appliances and equipment at the customer site, and it is energy use that is modeled in the monthly use models.

Although measured PV generation data is available for the Base Period, it is necessary to develop PV generation predictions for the Test Period. This is represented in the lower left-hand portion of PNM Figure SM-1, which shows the inputs to the monthly PV generation model. This is a regression model that explains variations in measured monthly generation. The main explanatory factor is GHI, which stands for Global Horizontal Irradiation. GHI values are included in the historical hourly weather data, which is acquired from AccuWeather, a widely recognized vendor of quality weather data. Hourly GHI data for four PNM weather stations (Albuquerque, Alamogordo, Deming, and Santa Fe) are weighted together and then summed to the daily level. For each month, these daily GHI values are then summed across the days in each billing cycle. This process aligns the GHI values that occurred during the monthly billing cycles with the PV generation that occurred over these cycles. The estimated model is then used to project monthly, daily, and hourly PV generation for the Test Period, based on growth in installed PV capacity and a normal pattern for GHI values.

In summary, the models used in this rate case are models of monthly use, usually in the form of use per customer ("UPC") or use per customer per day ("UPCD"). As shown in PNM Figure SM-1, after monthly use is projected, the PV generation is subtracted, providing the estimate for monthly sales. For the classes that have no on-site PV, the numbers for monthly use and sales will be the same. For the classes that do have on-site PV, monthly use will be a larger number than monthly sales. The difference is most significant for the residential customer class, where use is projected to be 13% larger than sales in the Test Period.

Q. CAN YOU DESCRIBE THE SECOND MODELING DIFFERENCE BETWEEN PNM'S LAST RATE CASE AND THIS RATE CASE?

A. The second difference from prior filings is the form of the monthly model. For the current rate case, PNM is using Statistically Adjusted End-Use ("SAE") models for the Residential and commercial customer classes.[1] This method was developed by the Itron forecasting team to utilize end-use inputs in an econometric framework. The approach is widely used by utilities and system operators in North America. The essence of the approach is to develop saturation and efficiency assumptions for a list of appliance and equipment types and combine these assumptions into three index variables for Heating, Cooling, and Other. The Heating index is interacted with monthly weather variables for cold weather (Heating Degree Days or HDD). The Cooling index is interacted with monthly weather variables for warm weather (Cooling Degree Days or CDD). The model also includes seasonal variables, time-trend variables, and variables that represent several phases of the Covid pandemic.

The end-use inputs for the SAE model are based on data released as part of the Annual Energy Outlook, which is published each year by the Energy Information Administration ("EIA") within the U.S. Department of Energy. These data are provided by region, and for PNM the Mountain Region data are used as a starting point. For PNM, evaporative cooling is added to the list of cooling technologies. For all end uses, market data from the most recent PNM Demand Side Management

[1] For purposes of this testimony, the commercial customer class includes Small Power (Rate Schedules 2A/2B), General Power (Rate Schedules 3B, 3C, 3D, 3E) and Large Power (Rate Schedule 4B).

("DSM") Potential Study are used to adjust saturation levels and energy intensity levels to represent the end-use mix and conditions in the PNM service territory. Finally, energy use estimates for electric vehicle ("EV") adoption in the PNM territory are added to the group of end uses that are not weather sensitive.

The SAE modeling approach is specifically designed for models of energy use. The SAE inputs combine to provide an estimate of the energy use of appliances and equipment. Therefore, energy use (not sales) is the appropriate variable for the models to explain.

Q. PLEASE DESCRIBE OTHER FEATURES OF THE MONTHLY SALES MODELS.

A. The methods used to model energy use vary across classes and are summarized in PNM Table SM-3. As shown in the table, models for Residential, Small Power, General Power Rate Schedules 3B, 3C, 3D and 3E ("GP"), and Large Power Rate Schedule 4B ("LP4") are configured to predict monthly use per customer per billing day ("UPCD"). These models use the SAE approach described earlier, and therefore, include detailed end-use inputs as well as monthly weather variables. Forecasts from these models are then multiplied by the forecasted number of customers and the number of billing days in the month to generate a billed sales forecast.

PNM Table SM-3: Summary of Modeling Methods

Class Definition	Customer Class	Rate Schedule	Use or Sales Per Day	Use Per Cust Day (UPCD)	SAE	Solar	Usage Model	Customer Model	Sales Adjust
Residential	Res	1		Yes	Yes	Yes	Regression	Smoothing	
Small Power	SP	2		Yes	Yes	Yes	Regression	Smoothing	
General Power	GP	3		Yes	Yes	Yes	Regression	Regression	
Large Power	LP	4		Yes	Yes	Yes	Regression	Smoothing	Yes
Large Power (>3MW)	LP	35	SPD				Regression		
Large Service (>8MW)	LS	5	SPD				Regression		Yes
Large Service UNM	LS	15	UPD			Yes	Regression		
Large Service (>30MW)	LS	30	SPD				Smoothing		Yes
Large Service Stn Pwr	LS	33	SPD				Regression		
Irrigation	Irr	10	UPD			Yes	Regression		
Water and Wastewater	Water	11	UPD			Yes	Regression		
Private Area Lighting	PAL	6					Lamps		
Streetlights	SL	20					Lamps		

For the large customer classes/rate schedules (LP35, LS5, LS15, LS30 and LS33),[2] either regression or exponential smoothing models are used to predict sales per day ("SPD") or use per day ("UPD"), depending on the presence of solar PV. The regression models include monthly constant terms to account for seasonality and shift variables for the impact of Covid Phases.[3] The smoothing model used for LS30 is set to detect the level of the data and the seasonal pattern. There are no time trend or other growth variables in these models.

Regression models are also used for the Irrigation customer class and the Water and Wastewater customer class. These models have monthly constants to account for seasonal patterns and time trend variables to capture growth trends in energy use.

[2] Rate Schedule 35B is referred to as "LP35"; Rate Schedule 5B is referred to as "LS5"; Rate Schedule 15B is referred to as "LS15"; Rate Schedule 30B is referred to as "LS30"; and Rate Schedule 33B is referred to as "LS33".
[3] "Covid Phase" variables are defined in PNM Exhibit SM-2.

Finally, the predictions developed for the lighting classes (PAL and SL)[4] are based on detailed fixture projections with specific assumptions about the number of lighting fixtures and type of lamp in each fixture. Energy forecasts for the lighting classes are provided by PNM and reflect specific assumptions about changes in lamp types toward more efficient LED lamp options.

Manual adjustments are made for planned expansions (for LS30) and expected new customer additions related to economic development activity (for LP4). The combination of these adjustments adds 387 GWh to annual sales, which is a 4.8% increase over the model-based projection of total annual sales.

Q. ARE THE MONTHLY USE AND SALES MODELING TECHNIQUES USED BY PNM FOR ANYTHING OTHER THAN THE RATE CASE?

A. Yes, they are. These modeling techniques also generate the customer and monthly sales forecast for the Annual Operating Plan ("AOP") and the long-term forecasts for the Integrated Resource Plan ("IRP"). For the IRP, the model forecasts extend through 2042, and the SAE framework is used to drive alternative economic growth and electrification scenarios.

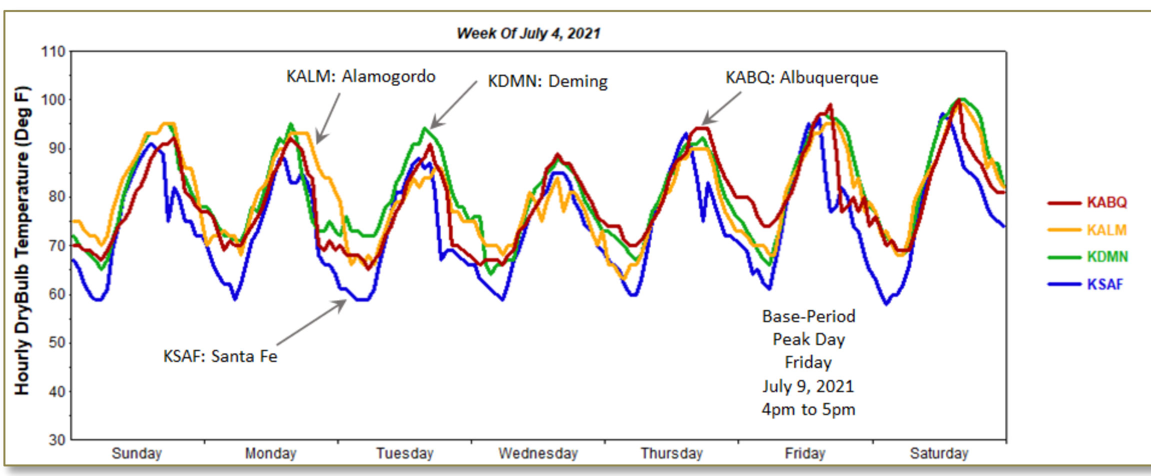
[4] Rate Schedule 6 is referred to as "PAL"; Rate Schedule 20 is referred to as "SL".

V. BASE-PERIOD WEATHER ADJUSTMENTS

Q. PLEASE SUMMARIZE THE WEATHER DATA THAT ARE USED TO CALCULATE BASE PERIOD WEATHER ADJUSTMENTS.

A. Hourly weather data were acquired from AccuWeather for the years from 1999 through June 2022. As explained in PNM 530 Schedule P-6, data for four weather stations are used: Albuquerque (KABQ), Alamogordo (KALM), Deming (KDMN), and Santa Fe (KSAF). For each station, two of the hourly data series are used in the analysis: hourly drybulb temperature ("DBT") in degrees Fahrenheit and GHI measured in watts per square meter. The hourly data for temperature are shown in PNM Figure SM-2 for the summer peak week in the Base Period.

PNM Figure SM-2: Hourly Temperature Data for Base-Period Peak Week



Temperature data are processed in several steps. First, for each weather station, daily average temperature is computed by averaging the 24 hourly values for that day. These hourly values are used to compute Cooling Degrees ("CD") and Heating Degrees ("HD") for each day.

Cooling Degrees are the number of degrees above a base temperature level. For example, CD base 70 ("CD70") is the number of degrees above 70. If the average temperature is 63, which is below 70, this variable has a value of zero. If the average temperature is 82, which is 12 degrees above 70, then this variable has a value of 12. The warmer it is, the bigger this value will be.

Similarly, Heating Degrees are the number of degrees below a base temperature. For example, HD base 60 ("HD60") is the number of degrees below 60. If the average temperature is 45, which is 15 degrees below 60, then this variable has a value of 15. The colder it is, the bigger this value will be.

When daily values for HDs and CDs are added across the days in a month or the days in a billing cycle, the sums are called Heating Degree Days ("HDD") and Cooling Degree Days ("CDD"). In my testimony, HD and CD refer to temperatures on a day. HDD and CDD refer to temperatures during a billing month or a calendar month.

For technical reasons, PNM's standard practice is to compute daily HD and CD values with multiple base values. CDs with base temperatures of 55, 60, 65, 70, and 75 are computed for each station on each day. HDs with base temperatures of 60, 55, 50, 45, and 40 are computed for each station on each day.

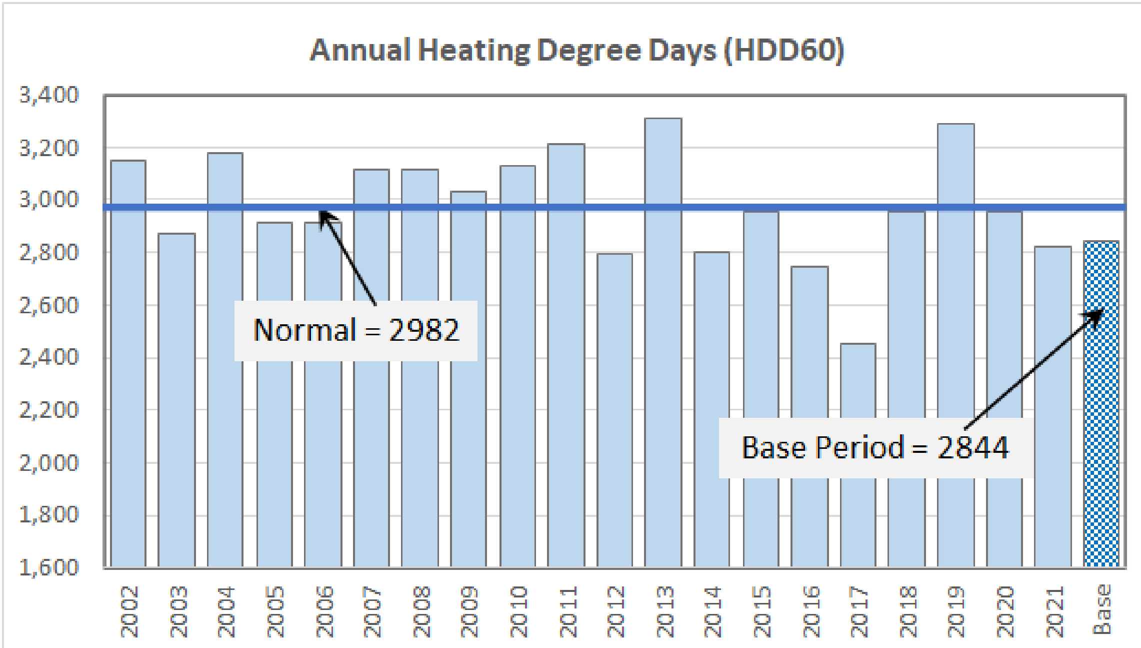
Next, the daily CD values are combined across stations using shares of summer month energy as weights. The daily HD values are combined across stations using shares of winter month energy as weights. Additional detail is provided in PNM 530 Schedule P-6.

The daily HD and CD values for each base temperature are summed across the days in each billing cycles and then combined across cycles to give a billing month HDD value for each heating base temperature and a billing month CDD value for each cooling base temperature. These billing month sums capture the weather that occurred on the days that are included in billed sales in each billing month.

Appropriate alignment of the weather data with the sales/use data is extremely important for model estimation, and the steps above ensure that this is an "apples-to-apples" relationship.

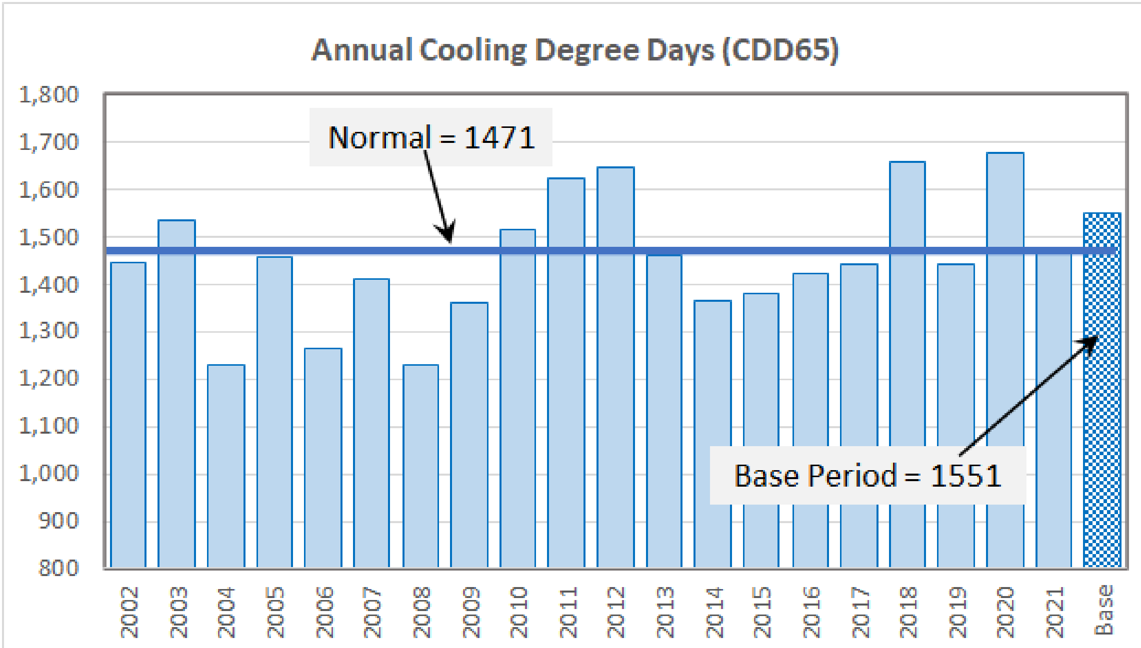
PNM Figure SM-3 shows the annual sum of monthly HDD values computed from a base temperature of 60 degrees for the 20-year period from 2002 through 2021. The line labeled "Normal" shows the 20-year average as 2,982 degree days for a 365-day calendar year. The Base Period value is approximately 5% lower, indicating a milder than normal winter. This will cause lower than normal sales related to heating, especially in the residential and small commercial classes, which have the highest sensitivity to cold weather.

PNM Figure SM-3: Annual Heating Degree Days (Degrees Below 60)



PNM Figure SM-4 shows the annual sum of monthly CDD values computed from a base temperature of 65 degrees for the 20-year period from 2002 through 2021. The line labeled "Normal" shows the 20-year average as 1471 degrees for a 365-day calendar year. The Base Period value is approximately 5% higher, which will increase Base-Period sales related to cooling for the weather sensitive classes.

PNM Figure SM-4: Annual Cooling Degree Days (Degrees Above 65)



Q. HOW DO YOU CALCULATE THE BASE PERIOD WEATHER ADJUSTMENTS?

A. The models of monthly use are estimated with actual billing month HDD and CDD values. As described earlier, the most recent 20 years of daily data are used to construct normal monthly HDD and CDD values for each billing month, based on the days that are included in the cycles for that month.

As part of estimation, the sales modeling process provides monthly predicted values using the actual HDD and CDD values. The estimated models are also used to generate a second set of predicted values using the normal HDD and CDD values. The difference between the two sets of predicted values is the weather adjustment.

Q. PLEASE SUMMARIZE THE MONTHLY WEATHER ADJUSTMENTS FOR THE BASE PERIOD.

A. As described earlier, the winter months in the Base Period were warmer than normal (actual HDD was 5% lower than normal HDD). As expected, the predicted values with normal weather indicate that sales would have been higher had the weather been normal. This leads to an upward (positive) weather adjustment for winter months.

The summer months in the Base Period were also warmer than normal (actual CDD was 5% higher than normal CDD). As expected, actual sales with warmer summer weather are higher than they would have been under normal conditions. This leads to a downward (negative) weather adjustment for the summer months.

When summer and winter months are combined, the downward sales adjustment in summer is stronger than the upward sales adjustment in winter, and the overall weather adjustment is negative. As shown in PNM Table SM-4, the overall negative adjustment is small at 16 GWh, which is 0.2% of total sales. The largest negative adjustment in percentage terms is for the GP class, which is more sensitive to warm weather than to cold weather. The smallest negative adjustment in percentage terms is for the Residential class, which is more heavily influenced by cold weather than the commercial classes.

PNM Table SM-4: Summary of Base Period Weather Adjustments

Class Definition	Customer Class	Rate Schedules	Base Period Sales (GWh)	Weather Adjust (GWh)	Adjust Percent (%)	Adjusted Sales (GWh)	Percent of Adjusted Sales (%)
Residential	Res	1	3,348.9	-3.23	-0.10%	3,345.7	41.89%
Small Power	SP	2	927.3	-2.70	-0.29%	924.6	11.58%
General Power	GP	3	1,863.2	-6.12	-0.33%	1,857.1	23.25%
Large Power	LP	4,35	1,082.2	-3.50	-0.32%	1,078.7	13.51%
Large Service	LS	5,15,30,33	534.7	-0.59	-0.11%	534.1	6.69%
Irrigation	Irr	10	20.6	0.00	0.00%	20.6	0.26%
Water & Wastewater	Water	11	177.4	0.00	0.00%	177.4	2.22%
Private Area Lighting	PAL	6	13.8	0.00	0.00%	13.8	0.17%
Streetlights	SL	20	34.6	0.00	0.00%	34.6	0.43%
Total			8,002.6	-16.16	-0.20%	7,986.4	100.00%

VI. CUSTOMER GROWTH FORECASTS

Q. CAN YOU SUMMARIZE THE PROCESS USED TO GENERATE CUSTOMER GROWTH FORECASTS?

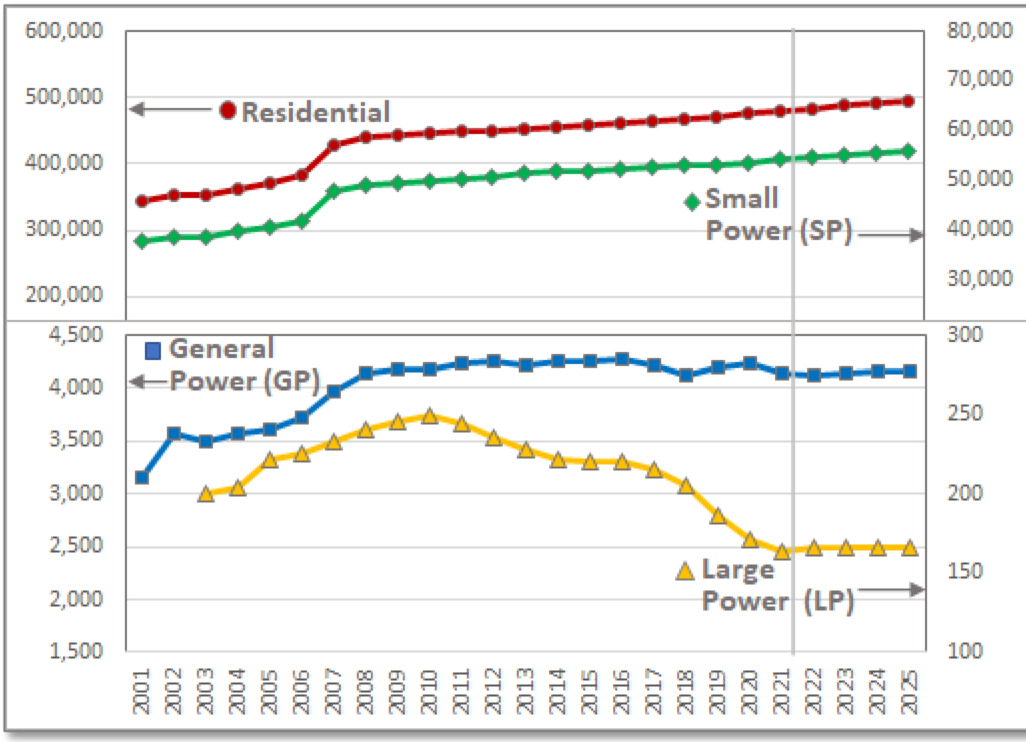
A. Starting with the Residential and SP classes, exponential smoothing models with a linear trend are used to extend recent customer growth trends out through the end of the Test Period. For the GP class, a regression model is used with residential customers and non-manufacturing employment as the explanatory variables.

Typically, I would use models that are driven by economic forecasts for the Residential and small commercial (SP) classes. However, the relationship between economic growth and customer growth was disrupted during the Covid pandemic. Despite the strong economic impacts of the pandemic, especially on employment, customer growth for PNM continued at a relatively smooth pace. Therefore, exponential smoothing models are used to identify the trend for customer gains and to extend that trend through the Test Period for these classes.

For the Large Service classes (Rate Schedules 5B, 15B, 30B and 33B) and Rate Schedule 35B, the number of customers is held constant in the forecast, following adjustments for the closing of the San Juan Generating Station (an LS5 customer) in September of 2022. One customer is added to the LP4 Rate Schedule for the planned addition of a new customer in January of 2023.

The customer forecast is best summarized with a graph of the historical and forecast data, which is provided in PNM Figure SM-5. This figure shows the stable historical growth patterns and the extension of these patterns into the Test Period. The growth rate for the Residential class averages 0.8% per year, and the growth rate for the SP class averages 0.7% per year.

PNM Figure SM-5: PNM Customers: History and Forecasts



VII. TEST PERIOD SALES FORECASTS

Q. PLEASE SUMMARIZE THE OVERALL CHANGE IN CUSTOMER CLASS SALES FROM THE BASE PERIOD TO THE TEST PERIOD.

A. The sales data and forecasts are summarized in PNM Table SM-5. The table shows Base Period sales, projected Test Period sales, the change in sales and the percent change in sales.

PNM Table SM-5: Change in Sales from the Base Period to the Test Period

Class Definition	Customer Class	Rate Schedules	Base Period Sales (GWh)	Test Period Sales (GWh)	Change in Sales (GWh)	Percent Change in Sales (%)
Residential	Res	1	3,348.9	3,251.9	-97.0	-2.9%
Small Power	SP	2	927.3	928.4	1.2	0.1%
General Power	GP	3	1,863.2	1,810.5	-52.7	-2.8%
Large Power	LP	4,35	1,082.2	1,145.1	62.9	5.8%
Large Service	LS	5,15,30,33	534.7	793.1	258.5	48.3%
Irrigation	Irr	10	20.6	24.1	3.5	16.9%
Water and Wastewater	Water	11	177.4	181.9	4.5	2.5%
Private Area Lighting	PAL	6	13.8	13.3	-0.5	-3.5%
Streetlights	SL	20	34.6	33.1	-1.5	-4.2%
Total All Classes			**8,002.6**	**8,181.5**	**178.9**	**2.2%**

For the Residential class, sales are projected to decline, despite positive customer growth. The two main factors driving Residential sales downward are the ongoing adoption of solar PV systems and energy efficiency improvements.

The commercial classes are not as heavily influenced by PV adoption. Sales increase slightly for the SP class as customer growth and the rebound from Covid slightly outweigh sales reductions from efficiency gains. For the GP class, sales reductions from efficiency gains are the main driver, although incremental adoption of solar PV is responsible for 0.5% of the 2.8% decline.

The Large Power (Rate Schedules 4B and 35B) ("LP") sales increase is driven by manual adjustments to the forecast to represent addition of a new economic development customer in January 2023. Similarly, sales growth in the LS class is driven by manual adjustments to the forecast to represent the expected expansion of operations in the LS30 rate schedule. This expansion started in July 2022, right after the end of the Base Period.

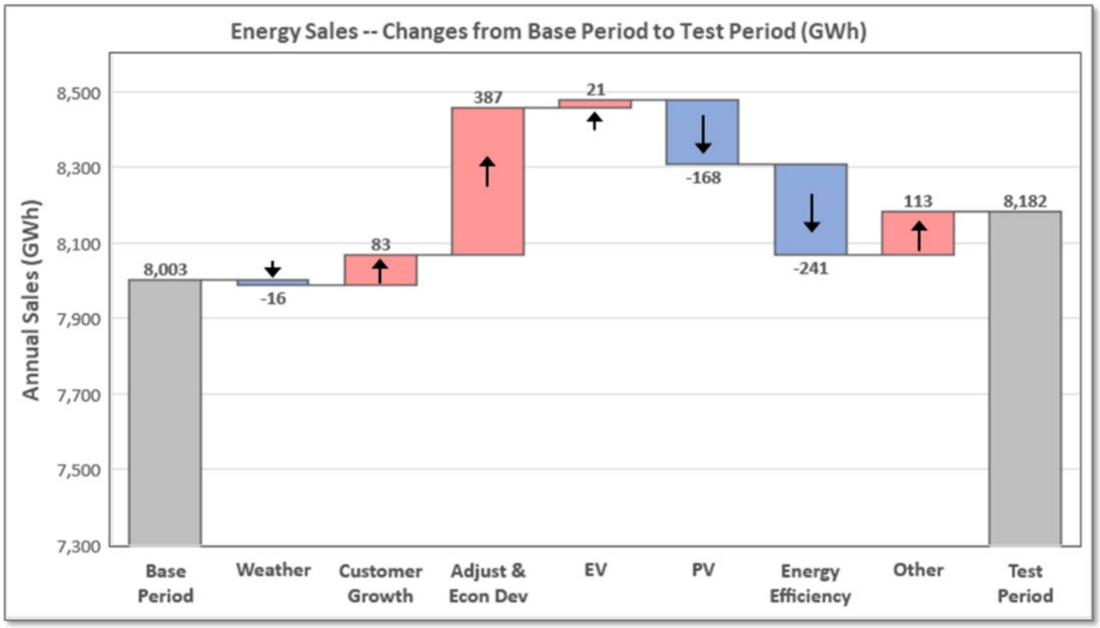
Growth in the Irrigation class reflects an assumed return to normal levels relative to the low sales levels in the Base Period. Sales growth for the Water and Wastewater class reflect continued population growth.

The lighting categories (PAL and SL) show sales declines driven by the continuing trend toward more efficient lighting technologies.

Q. PLEASE PROVIDE A SUMMARY OF THE FACTORS THAT ARE DRIVING THE CHANGE IN TOTAL ELECTRICITY SALES.

A. PNM Figure SM-6 shows a "waterfall chart" that breaks down the components of change between Base Period sales and Test Period sales. Each step quantifies the impact of a category of inputs to the modeling process, and the series of steps provide a bridge across the 2.5-year prediction interval.

PNM Figure SM-6: Components of Change – Base Period to Test Period



Starting with recorded sales of 8,003 GWh, the first element of change is from weather. This was discussed earlier in my testimony and represents the combined impact of weaker than normal winter weather and stronger than normal summer weather. The result is a small downward adjustment (16 GWh or 0.2%), representing the conclusion that Base Period sales would have been smaller under normal weather conditions.

The second major component is customer growth, which comes mainly from the Residential and SP classes. Because of these two classes, the total number of customers is expected to increase by approximately 1.9% between the Base Period and the Test Period. Holding sales per customer constant, this customer growth would add 83 GWh to Test-Period sales, which is 1.04% of Base-Period sales.

The next component, labeled Economic Development and Adjustments, is also part of economic growth, and represents the net effect of manual adjustments to the forecast. These adjustments reflect the expected sales impact from the addition of a new customer in the LP4 class in January of 2023 and the planned expanssion of operations for LS30 beginning in July 2022. The total sales impact of these additions is 387 GWh, which is 4.8% of Base Period sales.

The next step upward accounts for sales changes related to incremental adoption of EVs. It is estimated that approximately 5,200 additional EVs will be added in the PNM service territory between the Base Period and the Test Period. The energy use from the incremental adoption of EVs is estimated to be 21 GWh, which is 0.26% of Base Period sales.

The next step is downward and represents lost energy sales due to incremental adoption of behind-the-meter solar (PV). There was 203 MW of solar generation capacity in the PNM service territory on average in the Base Period, and this is expected to increase to an average of approximately 303 MW in the Test Period. The incremental PV capacity is estimated to reduce Test Period sales by approximately 168 GWh, which is approximately 2.1% of Base Period sales.

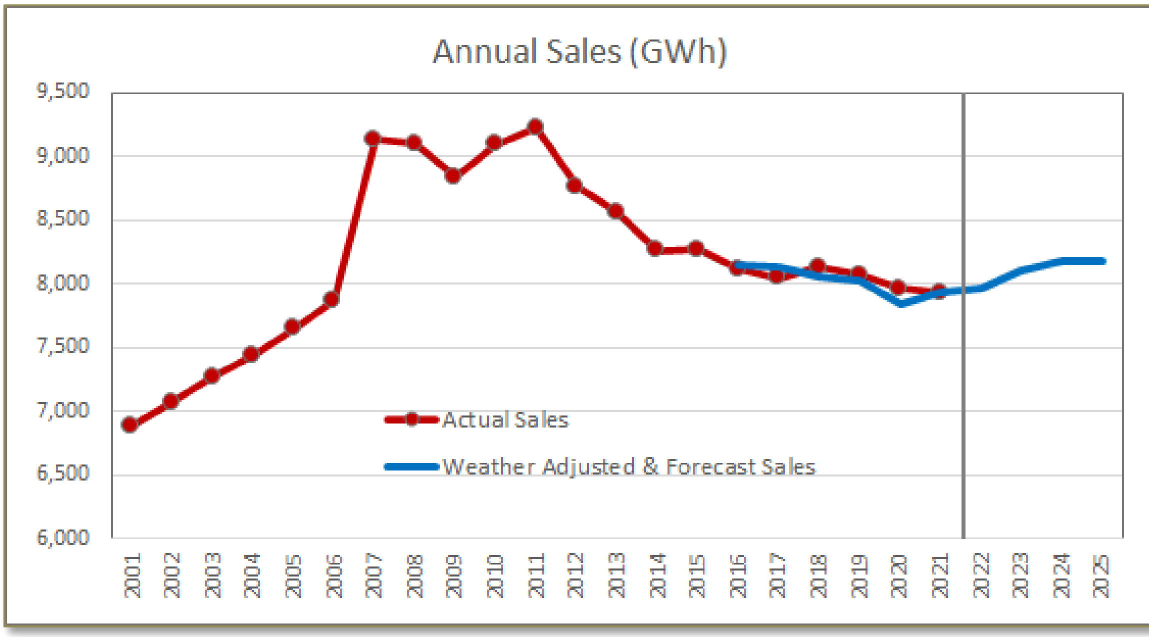
The next step is also downward and represents lost energy sales due to improvements in the energy efficiency of appliances, equipment and buildings.

The efficiency gains come from a wide range of end uses, including heating, cooling, water heating, cooking, refrigeration, appliances, and lighting. As discussed above, efficiency changes are based on regional efficiency forecasts from the EIA, which include impacts from utility efficiency programs. These changes are expected to reduce Test Period sales by approximately 241 GWh, which is 3.0% of Base Period sales.

The last step, labeled "Other," captures the net effect of remaining changes, including changes in equipment and appliance saturation levels, miscellaneous end-use load growth, statistically estimated time trends, and changes in economic and demographic variables on Residential sales. The net impact of these factors is estimated to add 113 GWh to Test Period sales, an increase of approximately 1.4% of Base Period sales.

The resulting forecast for Test Period sales is 8,182 GWh, which is approximately 2.2% higher than Base Period sales. To put this in perspective, PNM Figure SM-7 shows the history and forecast for annual sales from 2010 through 2025. This figure shows actual annual sales values in red through 2021. The blue line shows weather-adjusted sales for 2015 through 2021 and projected sales with normal weather through 2025. The weather-adjusted line shows the impact of Covid in 2020 and the subsequent recovery in 2021 and 2022.

PNM Figure SM-7: PNM Annual Sales in GWh – History and Forecast



VIII. FRAMEWORK FOR HOURLY LOAD PROJECTIONS

Q. CAN YOU EXPLAIN THE TERMS NONCOINCIDENT CLASS PEAK (NCP) AND COINCIDENT PEAK (CP)?

A. The Noncoincident Class Peak ("NCP") for a class is the combined load of customers in the class on the day and hour when the combined load is at its highest level. Class peaks typically do not occur in the day and hour that the PNM system reaches its highest value, thus the use of the word "noncoincident." The PNM system peak tends to occur in the late afternoon on a hot summer weekday. In contrast, Residential class peaks often occur on a weekend day with hot weather. Nonresidential class peaks occur on a hot weekday in the early afternoon. Industrial class peaks occur in an hour when production is high. Lighting class peaks occur at night.

Coincident Peak ("CP") for a class is the class load at the time of the system peak. The CP value will be smaller than the NCP value in most cases, unless the class peak happens to occur on the same day and hour as the system peak.

Q. ARE NCP AND CP VALUES MEASURED OR ESTIMATED?

A. Hourly measurements are available for individual customers in the Large Power or Large Service classes (LP35, LS5, LS15, LS30, and LS33). Large Power (LP4) and Water (11) also have many customers with hourly meters, but some meters for these groups are monthly billing meters that provide no hourly measurements. For the Residential and smaller commercial classes (Res, SP, GP), the majority of meters are monthly billing meters. For these classes, PNM has installed hourly meters for a statistical sample of customers, called a Load Research sample. The PNM Load Research staff performs statistical expansion calculations to estimate the hourly class loads for these classes based on the measured hourly loads of the sampled customers.

The NCP and CP estimates developed for my testimony use both the measured data for the classes with hourly meters and the load research estimates for the sampled classes.

Q. HOW ARE THE HOURLY DATA USED IN THE MODELING PROCESS?

A. The historical hourly load data for large customers and the hourly load research estimates are used for two purposes. First, these data are used to construct weighted weather response variables that are used in the sales modeling process. Second, the hourly load data are used to estimate hourly class profile models. These models relate class load in each hour to daily weather conditions and calendar conditions. Once estimated with historical data, these models are used to project hourly customer load for all classes without the influence of incremental EV or PV penetration.

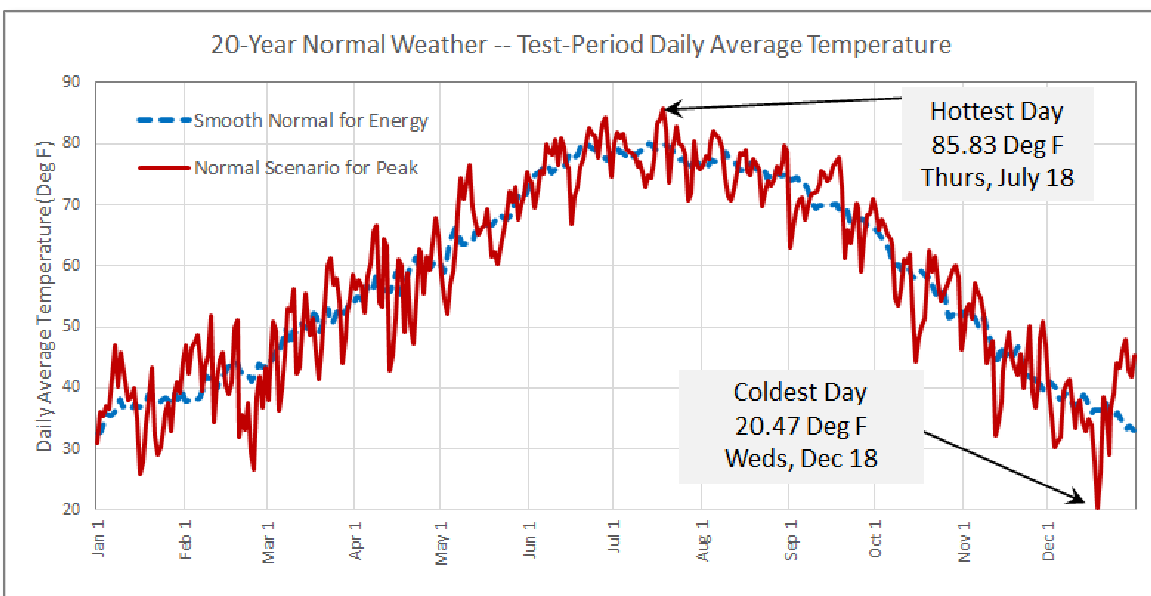
Q. HOW ARE NORMAL WEATHER DATA CONSTRUCTED FOR THE HOURLY LOAD PROJECTIONS?

A. The 20-year historical weather period that is used to construct normal weather values for the monthly sales projections is also used to define normal weather for the hourly model projections. Although the data are the same, the processing steps are different for these two uses. For the sales models, we used an "average-by-date" method. This process creates a relatively smooth normal pattern, like you would see in the newspaper as the normal average temperature for this time of year. This approach is appropriate for monthly weather adjustment calculations and for forecasting monthly energy sales, but it will not work for projecting daily and hourly load patterns because it does not represent typical extremes for hot days and cold days in each month.

For hourly projections, a "rank-and-average" approach is used. This approach sorts the historical daily data for each month from hottest to coldest. Then the hottest temperatures for each month are averaged across the years, giving a typical hottest temperature value for that month. Then the second hottest days are averaged. And this proceeds through to the coldest days. The resulting range of temperature values for a month is then assigned to calendar days based on an actual weather pattern. If the calculations are done correctly, the HDD and CDD values at the monthly and annual level are the same for these two methods.

PNM Figure SM-8 provides a comparison of the daily average temperature values used for the monthly sales projections (labeled "Smooth Normal for Energy") and for the hourly load projections (labeled "Normal Scenario for Peak").

PNM Figure SM-8. Normal Weather Scenario for Hourly Loads and Peaks



Q. PLEASE SUMMARIZE THE STEPS IN THE HOURLY LOAD SHAPE MODELING PROCESS.

A. Regression models are estimates that explain hourly UPC as a function of daily temperature, day type, season, holiday schedules, and Covid Phase variables. For each class, a separate equation is estimated for each hour. These estimated models are then used to project hourly UPC in the Test Period using the normal daily weather scenario for the Test Period, as displayed in PNM Figure SM-8.

The UPC projections are then reduced to remove the influence of PV installed through 2022. The resulting profile represents what the SPC load shape would look like if no additional solar is added beyond 2022 levels and with EV penetration held at the 2022 level.

Q. HOW ARE THE HOURLY SPC PROJECTIONS CONVERTED TO CLASS HOURLY LOAD PROJECTIONS?

A. The projected SPC class profiles provide a load shape for each class without incremental EV or PV adoption. For each class, these shapes are combined with projections of calendar-month sales that are also projected without incremental PV or EV adoption. The calendar-month sales estimates are similar to the billing-month sales estimates that are discussed earlier in my testimony, but they are adjusted to represent the number of days in the calendar month and weather conditions in the calendar month. The result is a projection of hourly class loads at the meter without incremental EV or PV adoption.

These hourly load projections are then increased for incremental EV adoption, reflecting the projected number of new vehicles and hourly charging shapes, and for incremental PV adoption, reflecting incremental PV capacity additions and the hourly generation shape. For each class, the result is a projection of hourly load (sales) at the customer meter for each hour in the Test Period.

IX. CLASS NCP, SYSTEM LOAD, AND CLASS CP PROJECTIONS

Q. HOW ARE THE CLASS NCP PROJECTIONS COMPUTED?

A. This calculation is simple. The hourly class load projections are used to compute the largest hourly value in each month of the Test Period (the monthly NCP). The largest of the monthly NCP values is the annual NCP value. These results are all at the customer meter without any adjustment for transmission and distribution losses. The results are shown in PNM Table SM-6.

PNM Table SM-6: Noncoincident Class Peak (NCP) Projections

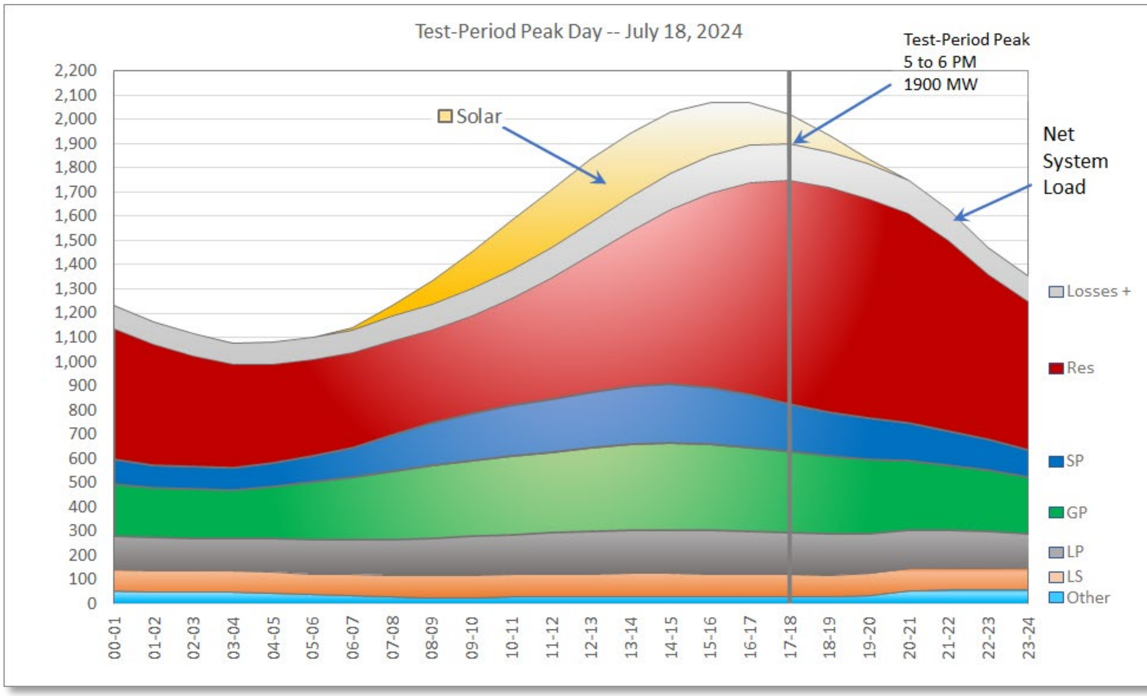
	Base Period (2021/2022)		Test Period (2024)	
Class Definition	NCP at Meter	Date/Time (HB)	NCP at Meter	Date/Time (HB)
Residential	820.92	Sat 8/7/2021 16	830.79	Mon 8/5/2024 17
Small Power	217.55	Wed 8/25/2021 14	232.55	Thu 7/18/2024 14
General Power	346.96	Thu 9/9/2021 13	343.68	Mon 8/5/2024 14
Large Power	170.82	Tue 9/7/2021 14	164.46	Thu 6/27/2024 13
Large Service	78.30	Sun 7/11/2021 13	120.47	Sat 6/29/2024 14
Irrigation	5.07	Sat 6/25/2022 10	5.22	Sat 7/20/2024 09
Water&Wastewater	42.57	Sun 7/11/2021 13	38.73	Wed 9/18/2024 21
Private Area Lighting	3.45		3.43	
Streetlights	6.47		6.28	

Q. HOW ARE THE CLASS LOAD PROJECTIONS USED TO PROJECT SYSTEM LOADS?

A. The hourly load projections for each customer class are based on measurements at the customer meter (billing data, solar generation data, and load research data). For a given load at the meter, generation requirements will be a larger number because of energy losses in the transmission system, at the substation, and in the distribution system. The first step is to adjust load projections at the meter upward to account for the transmission and distribution system losses. This adjustment uses energy loss rates that range from 3.4% for energy deliveries at transmission voltage levels to 8.5% for energy deliveries at secondary voltage levels.

The class hourly loads including energy losses are added up, providing a bottom-up estimate of the hourly system load. For historical years, these hourly sums are then compared to the measured system loads, and a set of calibration factors is computed by month and hour. These calibration factors tend to be largest in the summer months, when losses are higher than average, and lowest in the winter months, when losses are lower. Projected hourly loads at the generation source include both the losses and the calibration adjustments. The results of this process are shown in PNM Figure SM-9, which shows the hourly loads for the projected peak day in the Test Period (July 18, 2024). The projected system peak is 1,900 MW. The projected customer usage peak occurs in the previous hour and is approximately 2,070 MW including losses.

PNM Figure SM-9: Hourly Loads on Test-Period Peak Day



Q. HOW ARE THE CLASS CP RESULTS COMPUTED?

A. Based on the system hourly load projections, the projected date and time of the system peak is known. For the Test Period, this is July 18, 2024 at the hour beginning 17 (5 pm) and ending 18 (6 pm). Given the date/time for the system peak, the projected class loads at the meter or at the generation source can be identified from the bottom-up class load projections at that time.

PNM Table SM-7 provides the estimated CP values at the generation source (including losses) for the Test Period. Base Period values are also provided for comparison purposes. One important source of change is that the Base Period actual peak is at hour beginning 16 (4 to 5 pm). The projected Test Period system peak occurs in hour beginning 17 (5 to 6 pm). This one-hour shift is driven in part by the increase in PV solar generation. Residential loads are increasing at this time of day, and business loads are decreasing, which helps explains the increase in the Residential CP values and the decrease in CP values for the SP and GP classes. The increases for Large Power and Large Service are driven by the manual adjustments to the forecast for LP4 and LS30.

PNM Table SM-7: Test Period CP Values at the Generation Source

	Load at Source at PNM Peak (CP)			
Class Definition	Base Period	Base Period %	Test Period	Test Period %
Residential	949.55	51.22%	996.06	52.43%
Small Power	216.28	11.67%	209.29	11.02%
General Power	379.92	20.49%	361.58	19.03%
Large Power	183.65	9.91%	185.78	9.78%
Large Service	68.48	3.69%	117.67	6.19%
Irrigation	5.05	0.27%	5.59	0.29%
Water&Wastewater	50.58	2.73%	23.44	1.23%
Private Area Lighting	0.20	0.01%	0.11	0.01%
Streetlights	0.11	0.01%	0.20	0.01%
Total	1,853.81		1,899.72	

X. BILLING DETERMINANT MODELING FRAMEWORK AND TEST PERIOD PROJECTIONS

Q. CAN YOU DESCRIBE THE METHODS USED TO DISAGGREGATE THE CUSTOMER CLASS FORECASTS TO THE RATE SCHEDULES WITHIN EACH CLASS?

A. Yes. The disaggregation methods vary by class. For example, for the Residential class, Rate Schedule 1A, which has usage blocks, contains more than 99.9% of the customers. For this class, customers and sales for the smaller Rate Schedule 1B are modeled directly and these values are subtracted from the class totals to derive forecasts for the larger Rate Schedule 1A. A similar approach is taken for the SP class (to split the totals between the smaller Rate Schedule 2B and the larger Rate Schedule 2A) and for Irrigation (to split the totals between the smaller Rate Schedule 10A and the larger Rate Schedule 10B).

For the GP customer class, there are four rate schedules, and for billing determinant purposes, a further distinction is required based on voltage level. The class level projections are computed as the sum of projections for the following two groupings:

- Regular load factor: Commercial (3B) and Municipal (3D)
- Low load factor: Commercial (3C) and Municipal (3E)

The initial sales and customer models are estimated for these two groups, and subsequent regression models are used to further split the projections between the Commercial and Municipal categories. A final set of regression models is used to split the results for the four rate schedules (3B, 3C, 3D, and 3E) between customers that receive energy at primary voltages versus customers who receive energy at secondary voltages.

Finally, for the large commercial classes (LP and LS), customer and sales models are estimated for the individual rate schedules and the predictions are summed across the schedules to produce the class forecast.

The results for customers and sales are shown in PNM Table SM-8. The Base Period customer value is the average of the actual monthly customer values for months in the Base Period. The Test Period customer value is the average of forecasted monthly customers in the 12 months in the Test Period. Annual sales values are the sum of actual monthly billed sales for the Base Period and the sum of forecasted monthly billed sales in the Test Period.

PNM Table SM-8 also shows the percent change in customers and sales in each of the classes. As shown in the waterfall chart in PNM Figure SM-6, the forces driving changes in sales are complicated, and include Base Period weather impacts, customer growth, the adoption of PV and EV, improvements in energy efficiency, and other factors, such as changes in appliance and equipment saturation levels. The largest percentage sales changes occur for Rate Schedule 5B (which has a large decline reflecting the closing of the San Juan Generating Station in late 2022), Rate Schedule LP4B (which includes a manual adjustment for an expected customer addition), and Rate Schedule LS30 (which has a manual adjustment for expected business expansion).

PNM Table SM-8: Sales and Customers by Rate Schedule

Class Definition	Customer Class	Rate Schedule	Description	Base-Period Customers	Test-Period Customers	Percent Difference (%)	Base-Period Sales (GWh)	Test-Period Sales (GWh)	Percent Difference (%)
Residential	Res	1A	Energy Blocks	482,103	491,775	2.0%	3,345.6	3,248.4	-2.9%
		1B	Time of Use	120	121	1.0%	3.4	3.5	4.9%
Small Power	SP	2A	Energy	53,513	54,447	1.7%	912.8	913.3	0.1%
		2B	Time of Use	899	896	-0.3%	14.5	15.1	4.6%
General Power	GP	3B Sec	Secondary	2,985	3,029	1.5%	1,423.1	1,392.4	-2.2%
		3B Pri	Primary	93	93	0.4%	111.0	109.2	-1.6%
		3C Sec	Secondary, LLF	769	738	-4.1%	181.7	165.8	-8.7%
		3C Pri	Primary, LLF	12	13	8.2%	12.0	11.5	-4.9%
Municipal General Power	GP	3D Sec	Secondary	188	190	1.5%	110.2	107.9	-2.1%
		3D Pri	Primary	15	15	0.4%	10.0	9.9	-1.4%
		3E Sec	Secondary, LLF	75	72	-4.1%	15.0	13.7	-8.6%
		3E Pri	Primary, LLF	1	1	0.0%	0.1	0.1	0.0%
Large Power	LP	4B	Utility Owned	56	57	1.9%	248.4	311.3	25.3%
		4B COT	Customer Owned	109	108	-0.8%	652.1	648.8	-0.5%
Large Power (>3MW)		35B	Industrial	4	4	0.0%	181.7	185.0	1.8%
Large Service (>8MW)	LS	5B	Mining	2	3	50.0%	60.1	28.9	-51.9%
Large Service UNM		15B	UNM	1	1	0.0%	53.2	48.5	-8.7%
Large Service (>30MW)		30B	Industrial	1	1	0.0%	418.1	712.4	70.4%
Large Service Stn Pwr		33B	Station Power	2	2	0.0%	3.1	3.3	6.9%
Water and Wastewater	Water	11B	Time of Use	155	155	0.0%	177.4	181.9	2.5%
Irrigation	Irr	10A	Energy	106	106	0.0%	3.1	4.2	38.5%
		10B	TOU	208	208	0.1%	17.6	19.9	13.2%

Q. PLEASE DESCRIBE THE USAGE BLOCK MODELING FRAMEWORK AND TEST PERIOD RESULTS.

A. The only rate schedule with usage blocks is the residential Rate Schedule 1A. This rate schedule has three monthly usage blocks. The first block has the lowest price for usage less than 450 KWh. The second block has a higher price for usage from 450 KWh up to and including 900 KWh. The third block has the highest price for usage over 900 KWh.

Analysis of the data shows a strong and stable relationship between block sales and total monthly sales. For each of the three blocks, a regression models is used with monthly constants, monthly sales, monthly sales squared, and Covid Phase variables as the explanatory factors. The squared terms are included because the block-to-sales relationship is not a straight line, and the squared term explains this nonlinearity. The resulting block-level predictions are converted to percent shares, and these shares are used to allocate total monthly sales to the three usage blocks.

The actual block sales data for the Base Period and forecasts for the Test Period are summarized in PNM Table SM-9. Block sales values are presented in GWh and are also shown as a percent of total sales in each period. As shown, sales are expected to decline in Block 3, reflecting, in part, continued high adoption of PV systems by larger Residential energy users.

PNM Table SM-9: Base Period and Test Period Sales by Usage Block

Class Definition	Customer Class	Rate Schedule	Description	Base Period	Test Period	Percent Difference
Residential	Res	1A	Sales (GWh)	3,346	3,248	-2.9%
			Block 1 Sales (GWh)	1,959	1,966	0.4%
			Block 2 Sales (GWh)	839	855	1.9%
			Block 3 Sales (GWh)	548	427	-22.0%
			Block 1 Percent (%)	58.5%	60.5%	2.0%
			Block 2 Percent (%)	25.1%	26.3%	1.2%
			Block 3 Percent (%)	16.4%	13.2%	-3.2%

Q. PLEASE DESCRIBE THE TIME-OF-USE SALES MODELING FRAMEWORK AND THE TEST PERIOD RESULTS.

A. Current PNM rate schedules define two TOU periods, the on-peak period (8 am to 8 pm on weekdays) and the off-peak period (all other hours). For the Test Period, monthly class sales are allocated to the TOU periods using a simple ratio approach. For each TOU rate schedule, the historical data are used to compute a monthly on-peak fraction (on-peak sales divided by total sales). Regression models are used to model this fraction based on monthly constants and Covid Phase variables. Models are estimated using monthly data through June of 2022. The projected on-peak fractions for months in the Test Period are used to allocate total monthly sales to monthly on-peak sales and monthly off-peak sales.

Base Period values and Test Period forecasts are summarized in PNM Table SM-10. Off-peak fractions are not shown, but they can be computed as one minus the on-peak fraction. As the figure shows, the on-peak fractions of sales in the Test Period are very close to the on-peak fractions in the Base Period in all cases.

PNM Table SM-10: On-Peak Fractions of Monthly Sales

Class Definition	Customer Class	Rate Schedule	Sales (GWh)		% On Peak		
			Base Peaiod	Test Period	Base Peaiod	Test Period	Diff
Residential	Res	1B	3.4	3.5	34.9%	35.1%	0.2%
Small Power	SP	2B	14.5	15.1	36.8%	37.2%	0.4%
General Power	GP	3B_Sec	1,423.1	1,392.4	41.4%	41.3%	-0.1%
		3B_Pri	111.0	109.2	40.1%	40.2%	0.1%
		3C_Sec	181.7	165.8	50.2%	50.1%	-0.1%
		3C_Pri	12.0	11.5	57.2%	59.3%	2.1%
Municipal General Power	GP	3B_Sec	110.2	107.9	36.8%	36.7%	-0.1%
		3B_Pri	10.0	9.9	30.6%	30.7%	0.0%
		3C_Sec	15.0	13.7	29.2%	29.1%	0.0%
		3C_Pri	0.1	0.1	32.4%	32.4%	0.0%
Large Power	LP	4B	248.4	311.3	39.8%	39.7%	-0.1%
		4B COT	652.1	648.8	38.1%	38.1%	-0.1%
Large Power (>3MW)		35B	181.7	185.0	35.2%	35.2%	0.0%
Large Service (>8MW)	LS	5B	60.1	28.9	39.1%	38.5%	-0.7%
Large Service UNM		15B	53.2	48.5	38.4%	38.5%	0.1%
Large Service (>30MW)		30B	418.1	712.4	35.9%	35.9%	-0.1%
Large Service Stn Pwr		33B	3.1	3.3	34.5%	34.4%	-0.1%
Water and Wastewater	Water	11B	166.8	166.3	20.5%	20.2%	-0.3%
Irrigation	Irr	10B	17.6	19.9	35.8%	36.3%	0.6%

Q. PLEASE DESCRIBE THE BILLING DEMAND MODELING FRAMEWORK AND THE TEST PERIOD RESULTS.

A. Most of the nonresidential rate schedules include a demand charge. The billing demand for a customer in a month is computed from the maximum hourly demand in the on-peak period. Monthly demand for a class is the sum of these customer billing demand values. To model billing demand, the ratio of monthly demand to average load is computed, where average load is billing month sales divided by the number of hours in the billing month. The definition is:

Demand Ratio = (Billing Demand)/(Average Hourly Sales)

Using measured billing data, a demand ratio is computed for each class in each historical billing month. At the class level, this demand ratio is almost always greater than 1.0, indicating that maximum hourly demand in the on-peak period is greater than the average hourly load. For example, the monthly demand ratios for the GP Rate Schedule 3B average to 1.78 in the Base Period. The monthly demand ratios for the low-load factor category (GP Rate Schedule 3C) average to 3.57 in the Base Period.

For the GP class, demand ratios are modeled for four rate schedules (3B, 3C, 3D, and 3E) and two voltage levels (secondary and primary). For LP4, demand ratios are modeled separately for customers with utility-owned transformers (4B) and customer-owned transformers (4B COT). Demand ratios for the large rate schedules (LP35, LS5, LS15, LS30 and LS33) are modeled and projected for each rate schedule.

The demand ratio models are regression models with 12-monthly binary variables, a binary shift variable in 2019 to tune the ratios to more recent data, and a set of Covid Phase variables as the explanatory factors. Models are estimated using monthly data through June 2022. Base Period values and Test Period forecasts are summarized in PNM Table SM-11. For the most part, the forecasted Test Period demand ratios are close to the Base Period demand ratios, and the differences in demand levels flow directly from changes in sales volumes.

PNM Table SM-11: Base Period and Test Period Demand Projections

Class Definition	Customer Class	Rate Schedule	Base Period		Test Period	
			Demand (MW)	Demand Ratio	Demand (MW)	Demand Ratio
General Power	GP	3B_Sec	287.6	1.779	281.7	1.777
		3B_Pri	22.4	1.776	22.1	1.777
		3C_Sec	73.6	3.567	63.2	3.348
		3C_Pri	6.5	4.757	6.8	5.186
General Power	GP	3D_Sec	22.6	1.808	22.2	1.807
		3D_Pri	2.9	2.566	2.9	2.562
		3E_Sec	12.9	7.552	7.3	4.694
		3E_Pri	0.1	5.686	0.1	5.662
Large Power	LP	4B	41.9	1.484	41.9	1.496
		4B COT	114.6	1.547	113.8	1.541
Large Power (>3MW)		35B	25.5	1.239	26.6	1.261
Large Service (>8MW)	LS	5B	16.6	2.451	8.2	2.501
Large Service UNM		15B	16.6	2.751	16.9	3.074
Large Service (>30MW)		30B	49.7	1.043	94.1	1.160
Large Service Stn Pwr		33B	2.1	5.797	2.0	5.317

Q. PLEASE DESCRIBE REACTIVE KVA MODELING FRAMEWORK AND TEST-PERIOD RESULTS.

A. Reactive Kilovolt Amperes ("RKVA") are related to power factor adjustments. To model RKVA values, the ratio of monthly RKVA to monthly kW demand is used. The definition is:

RKVA Ratio = RKVA/Billing Demand

This ratio is usually small. Except for Rate Schedule 33B, the ratio averages between 0.03 and 0.15 in the Base Period for the schedules that have this billing component.

The RKVA ratio models are simple regression models. Explanatory variables include monthly constants, monthly average load, a set of Covid Phase variables, and in some cases, constant shifts. Base Period values and Test Period forecasts are summarized in RMVA (thousand RKVA) in PNM Table SM-12.

PNM Table SM-12: Base Period and Test Period Average MVAR

Class Definition	Customer Class	Rate Schedule	Base Period		Test Period	
			Average RMVA	RKVA Ratio	Average RMVA	RKVA Ratio
General Power	GP	3B_Sec	7.81	0.0271	7.97	0.0283
		3B_Pri	2.51	0.1122	2.48	0.1124
		3C_Sec	3.67	0.0499	3.45	0.0545
		3C_Pri	0.67	0.1029	0.68	0.1012
General Power	GP	3D_Sec	0.91	0.0402	0.94	0.0425
		3D_Pri	0.35	0.1209	0.35	0.1208
		3E_Sec	0.22	0.0174	0.22	0.0304
		3E_Pri	0.00	-	0.00	-
Large Power	LP	4B	2.66	0.0636	3.30	0.0789
		4B COT	12.77	0.1114	12.73	0.1118
Large Power (>3MW)		35B	na		na	
Large Service (>8MW)	LS	5B	2.50	0.1502	1.18	0.1435
Large Service UNM		15B	na		na	
Large Service (>30MW)		30B	2.16	0.0435	4.22	0.0449
Large Service Stn Pwr		33B	21.07	10.1853	19.94	9.8283

XI. CONCLUSION

Q. DOES THIS CONCLUDE YOUR TESTIMONY?

A. Yes it does. The methods used to compute weather adjustments in the Base Period reflect best practices in the industry. The methods used to project 2.5 years forward to the Test Period are complicated by the increasingly significant impact of behind-the-meter solar generation and the continuation of strong energy efficiency gains. The methods used to project PNM Test-Period sales and billing determinants account for these factors and provide a sound basis for cost allocation and rate design supported by PNM witnesses Chan, Casas and Pitts.

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Statement of Qualifications

PNM Exhibit SM-1

Is contained in the following 5 pages.

PNM Exhibit SM-1: Resume

Dr. J. Stuart McMenamin

Education

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

Employment History

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

Research Experience

Dr. McMenamin is a nationally recognized expert in the field of energy forecasting. Over the last 40 years, he has specialized in the following areas: end-use modeling, energy technology data development, end-use load shape modeling, system load forecasting, price forecasting, retail load forecasting, financial forecasting, load research data analysis, and smart grid data analytics. In addition to his work in the energy area, Dr. McMenamin has completed numerous studies in the areas of telecommunications markets, regional economic modeling, and statistical analysis of employment practices.

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

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

Over the last 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

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

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

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

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

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

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

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

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

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

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

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

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.

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

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

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

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. In *Pricing in Competitive Electricity Markets*, Kluwer Academic Publishers, A. Faruqui and K. Eakin, eds, April, 2000.

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

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

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.

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.

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

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

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

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

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

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

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

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

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

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

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

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Alphabetical Listing of Acronyms Used in This Testimony

PNM Exhibit SM-2

Is contained in the following 2 pages.

PNM Exhibit SM-2: Acronym Definition Table

Acronym	Definition
Base Period	July 2021 through June 2022
CD	Cooling Degree -- degrees above a base temperature on a day
CDD	Cooling Degree Days -- sum of cooling degrees across multiple days
CP	Coincident peak -- customer or class load at the time of the system peak
DBT	Drybulb temperature
EIA	U.S. Department of Energy, Energy Information Administration
EV	Electric vehicle
GHI	Global horizontal irradiation measured in Watts per square meter
HD	Heating Degree (degrees below a base temperature on a day)
HDD	Heating Degree Days -- sum of heating degrees across multiple days
Load Factor	Average hourly energy divided by peak load
LED	Light Emitting Diode
NCP	Non-coincident peak -- the largest load for a customer or customer class
Peak Ratio	Peak load divided by average hourly energy (the inverse of load factor)
PV	Photo voltaic -- usually applied to mean behind-the-meter solar
SAE	Statistically Adjusted End-Use Model
Sales	Net delivered energy (delivered to customer - received from customer)
SPCD	Sales per customer per day
SPD	Sales per day
Test Period	January 2024 through December 2024
TOU	Time of Use
UPCD	Energy use per customer per day
UPD	Energy use per day
Use	Electricity consumed by end-use equipment at a customer site

PNM Exhibit SM-2 (continued): Modeling Definitions

Term	Definition
Binary Variable	A variable that has a value of 0 or 1 depending on conditions. For example, a monthly binary variable for January will have a value of 1.0 if the observation is for January and a value of 0.0 for all other months.
Constant Term	In a linear model (Y = a + bX) the model coeficient (a) is called the model intercept or the constant term. The value of this constant term does not vary over time.
Covid Phase Variables	A set of binary variables introduced to account for shifts in behavior related to the Covid pandemic. The first shift is introduced for April and May of 2020. The second shift is for June through November of 2020. The third shift is for December of 2020 through March of 2021. The fourth shift is for April 2021 and beyond.
Explanatory Factor	In a linear model (Y = a + b X), the variable X is an explanatory factor. Explanatory factors are numerical variables that have a value that changes over time. In a regression model, each explanatory factor has an associated coefficient that is estimated and that determines the contribution of that explanatory factor to projected values.
Exponential Smoothing Model	Exponential smoothing models are time-series models that can be used to project the level, trend, and seasonal pattern of a variable. Projected values depend only on the history of the variable being explained, and there are no other explanatory factors.
Monthly Constant	If a model includes binary variables for individual months, the estimated coefficients for these monthly binary variables are added to the overall model constant for observations in those months. Monthly constants based on monthly binary variables are included in models to account for seasonal patterns in the data.
Regression Model	Regression models are linear models of the form Y = a + bX. Y is the variable to be explained. The first coefficient (a) is the intercept or constant term. The second coefficient (b) is the slope or multiplier on the explanatory factor (X). A multivariate regression model has more than one explanatory factor. The model is estimated by finding the coefficient values that minimize the sum of squared model errors.

GCG#530075

BEFORE THE NEW MEXICO PUBLIC REGULATION COMMISSION

IN THE MATTER OF THE APPLICATION OF PUBLIC SERVICE COMPANY OF NEW MEXICO FOR REVISION OF ITS RETAIL ELECTRIC RATES PURSUANT TO ADVICE NOTICE NO. 595	)))))	**Case No. 22-00270-UT**
PUBLIC SERVICE COMPANY OF NEW MEXICO,	)))	
Applicant	))	

SELF AFFIRMATION

DR. J. STUART MCMENAMIN, Director of Forecasting, Itron, Inc., upon penalty of perjury under the laws of the State of New Mexico, affirm and state: I have read the foregoing **Direct Testimony of Dr. J. Stuart McMenamin** and it is true and accurate based on my own personal knowledge and belief.

Dated this 5th day of December, 2022.

/s/ J. Stuart McMenamin
DR. J. STUART MCMENAMIN

GCG # 530015