Volume 2B

Direct Testimony and Supporting Schedules:

Tammy K. Mortenson

11 PU-23-342 Filed 11/02/2023 Pages: 63
Prefiled Direct Testimony and Schedules of Tammy K. Mortenson - Volume 2B - Redacted
Otter Tail Power Company

Before the North Dakota Public Service Commission
State of North Dakota

In the Matter of the Application of Otter Tail Power Company
For Authority to Increase Rates for Electric Utility
Service in North Dakota

Case No. PU-23-

Exhibit_

SALES FORECAST

Direct Testimony and Schedules of

TAMMY K. MORTENSON

PUBLIC DOCUMENT –

NOT PUBLIC (OR PRIVILEGED) DATA HAS BEEN EXCISED

November 2, 2023

TABLE OF CONTENTS

ATTACHED SCHEDULES

I. INTRODUCTION AND QUALIFICATIONS

Q. PLEASE STATE YOUR NAME AND CURRENT EMPLOYER.

A. My name is Tammy K. Mortenson. I am employed by Otter Tail Power Company (OTP).

Q. PLEASE SUMMARIZE YOUR CURRENT RESPONSIBILITIES.

A. I am the Senior Data Analyst in the Business Planning Department. I am responsible for creating the Sales and Demand forecasts for OTP.

Q. HAVE YOU INCLUDED AN ATTACHMENT OF YOUR QUALIFICATIONS AND EXPERIENCE?

A. Yes. A summary of my qualifications and experience is included as Exhibit___(TKM-1), Schedule 1.

II. PURPOSE AND OVERVIEW OF DIRECT TESTIMONY

Q. WHAT IS THE PURPOSE OF YOUR DIRECT TESTIMONY?

A. The purpose of my Direct Testimony is to discuss OTP's energy forecasting process and present the results of OTP's sales forecast, which forms the basis of the 2024 Test Year sales and revenues in this proceeding.

Q. PLEASE PROVIDE A BRIEF OVERVIEW OF YOUR DIRECT TESTIMONY.

A. OTP forecasts approximately 2,560 gigawatt hours (GWh) of North Dakota retail sales in the 2024 Test Year. OTP's sales forecast includes refinements on the process used in OTP's last North Dakota rate case (Case No. PU-17-398). OTP's 2024 Test Year sales are reasonable and form an appropriate basis for establishing rates in this case.

Q. HOW IS YOUR DIRECT TESTIMONY ORGANIZED?

A. In Section III, I discuss the sales forecast methodology. In Section IV, I discuss the test year sales forecast class-by-class.

III. SALES FORECAST METHODOLOGY

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

A. In this section, I will discuss the methods OTP uses to forecast sales. Additional details regarding our sales forecast methodology, including procedures used to develop the sales forecasts, are provided in Exhibit___(TKM-1), Schedule 2.

Q. WHAT METHODS DOES OTP USE TO FORECAST SALES?

A. OTP prepares sales forecasts for eight separate customer groupings, or sales forecast classes, though only seven are part of the calculation of retail rates.[1] As shown in the table below, OTP uses a mixture of statistical models and manual forecasts to develop its sales forecast.

Table 1
OTP Sales Forecast Classes

Sales Forecast Class	Forecast Methodology
Residential	Statistical – UPM and Meters
Farm	Statistical – UPM and Meters
Small Commercial	Statistical – UPM and Meters
Large Commercial	Statistical – Total Sales / Manual
Pipeline / Industrial	Manual
Other Public Authority	Statistical – UPM and Meters
Area / Street Lighting	Manual

Q. HAS OTP REFINED ITS STATISTICAL-BASED FORECAST METHODOLOGIES SINCE ITS LAST NORTH DAKOTA RATE CASE?

A. Yes. In 2020, OTP worked with Dr. Daniel G. Hansen of Christensen Associates Energy Consulting, LLC to refine the statistical models used in its sales forecast process. Since that time, the refined sales statistical models have supported all of OTP's regulatory and financial filings.

Q. WHAT IS THE PRIMARY REFINEMENT TO THE STATISTICAL FORECAST MODELS?

A. OTP replaced customer-level forecasting with meter-level forecasting, transitioning to a use-per-meter (UPM) model for most statistically forecasted classes. Large Commercial sales are developed using a total sales model (rather than separate UPM and number of meters models) because of the effects of a

[1] Unclassified sales, which pertain to OTP's own use of electricity, are not part of the calculation of retail rates.

reclassification of some higher-use Small Commercial customers into the Large Commercial class that occurred during the analysis period.

Q. WHY DOES THE LARGE COMMERCIAL CLASS FORECAST USE A TOTAL SALES MODEL?

A. There are two reasons. First, there are four Large Commercial customers that are manually forecasted outside of the statistical model. Using a total sales approach makes it easier to incorporate the sales of these manually forecasted customers. Second, some higher-use Small Commercial customers moved into the Large Commercial class during the historical period, which distorted the resulting UPM. Because of the resulting change in the average meter usage during the analysis period, a more straightforward approach was to model total usage.

Q. HOW WERE THE SALES FORECASTS CREATED FOR THE UPM-BASED CUSTOMER CLASSES?

A. The kilowatt hour (kWh) sales forecast is created from separate forecasts of UPM and the number of meters served per customer class. Specifically, for each forecast month, the sales forecast equals the product of the UPM forecast and the meter forecast.

Q. WHY SEPARATE THE SALES FORECAST INTO THE UPM AND METER COMPONENTS?

A. Dividing the sales forecast into the UPM and meter components improves OTP's ability to distinguish between the effect of drivers on meter-level usage versus the number of meters served. For example, one would expect variations in weather conditions to explain some of the variation in average per-meter usage levels (e.g., the average customer uses more when summer weather is hotter, all else equal), but weather variations should not be a significant driver of the number of meters served. By separating the sales forecast into UPM and meter models, OTP is better able to isolate the effect of weather on UPM. A similar effect and rationale for dividing the sales forecast into the UPM and meter components applies to other explanatory variables. A customer-meter may use more electricity as economic conditions improve and/or more customers (and hence meters) may be attracted to the service territory by improved economic conditions. These potential effects can be separately estimated using these methods.

Q. WHAT TIME PERIOD IS INCLUDED IN THE STATISTICAL MODELS?

A. Each model is estimated using 20 years of monthly historical data beginning January 2003 and ending December 2022. The forecast is developed using 20-year normal weather conditions and forecast economic and demographic conditions for 2024 provided by Woods & Poole Economics, Inc. (W&P).

A. Residential

Q. PLEASE DESCRIBE THE STATISTICAL MODELS USED IN OTP'S RESIDENTIAL SALES FORECAST.

A. The Residential sales forecast is the product of two models: a UPM model and a meter model.

1. Residential UPM Model

Q. PLEASE DESCRIBE THE RESIDENTIAL UPM MODEL.

A. The Residential UPM model includes the following variables:

1. The number of cooling degree days based on a 65-degree threshold (CDD65);
2. The number of heating degree days, based on a 55-degree threshold (HDD55);
3. The number of days in the billing month;
4. A linear time trend;
5. An indicator variable for January 2011 and beyond and an interaction of this variable with the linear time trend; and
6. Monthly indicator variables.

The dependent variable is UPM which is calculated by dividing Residential sales by the number of Residential meters. The model includes a correction for first-order serial correlation, which corrects for autocorrelation of a predicted value in the current period being a function of the immediate prior period error if it exists, which may occur in time series data. The UPM model leads to estimates of coefficients related to the variables.

Q. HOW IS CDD65 CALCULATED?

A. Cooling degree days (CDD65) are calculated by taking the average temperature for a particular weather station on a particular date and subtracting 65 degrees. If the difference is negative, the value is set to zero. This calculation is expressed in the following formula in which "s" stands for a given weather station and "t" represents the date:

$$CDD65_{s,t} = MAX\{(MaxTemp_{s,t} + MinTemp_{s,t}) / 2 - 65, 0\}$$

Once CDD65 is calculated, the values for the weather stations are combined using weights to reflect the Company's service territory.

Q. HOW IS CDD65 INTERPRETED?

A. CDD65 is intended to reflect the demand for cooling (i.e., air conditioner use). The model assumes that there is no cooling load below the daily average temperature of 65°F and that cooling load increases as temperatures increase above 65°F.

Q. HOW IS HDD55 CALCULATED?

A. Heating degree dates (HDD55) are calculated by subtracting the average temperature from 55 degrees. If the difference is negative, then HDD55 is set to zero. This calculation is expressed in the following formula:

$$HDD55_{s,t} = MAX\{55 - (MaxTemp_{s,t} + MinTemp_{s,t}) / 2, 0\}$$

The HDD55 values for the weather stations are then combined using weights to reflect the Company's service territory.

Q. HOW IS HDD55 INTERPRETED?

A. HDD55 reflects the demand for heating. The model assumes that there is no heating load when the daily average temperature is above 55°F and that heating load increases as temperatures fall below 55°F.

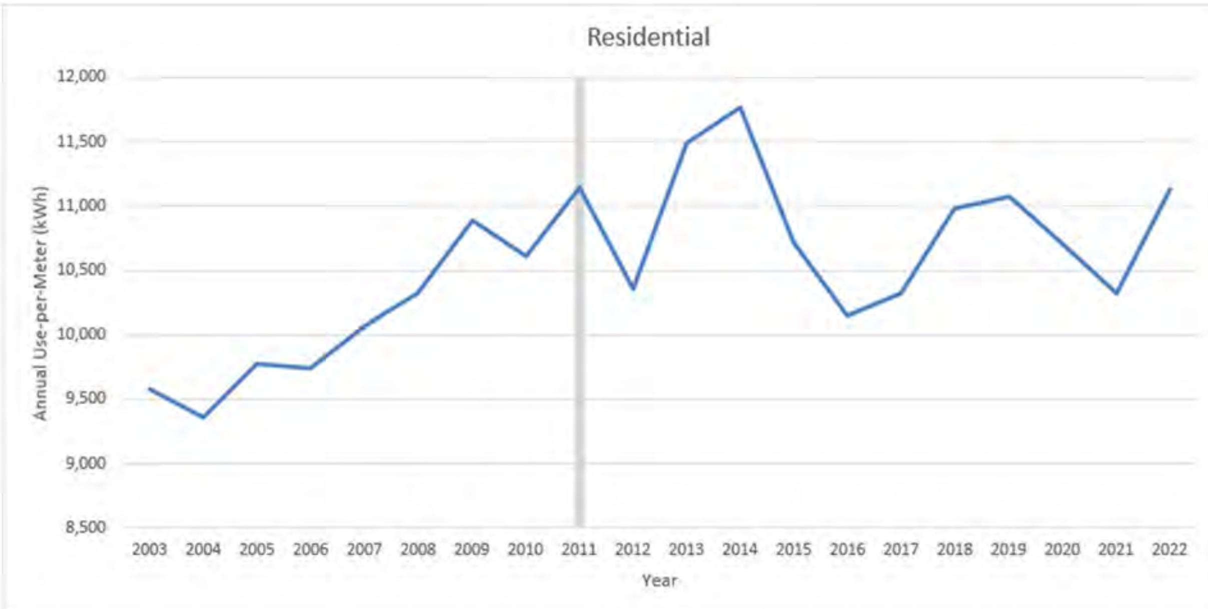
Q. WHAT IS THE PURPOSE OF THE LINEAR TIME TREND VARIABLE?

A. The linear time trend variable is intended to identify and account for any trend in Residential UPM, controlling for the other included variables (e.g., CDD and HDD). A time trend is appropriate when UPM is trending over time, but other available variables do not do a good job of explaining the trend.

Q. WHY DID OTP INCLUDE AN INDICATOR VARIABLE FOR JANUARY 2011 ONWARD?

A. Historical data shows that UPM was trending at a different rate prior to, as compared to after, 2011. As shown in the figure below, UPM generally increased prior to 2011 at an average annual rate of 2 percent. After 2011, UPM became more variable, so by including this variable and the associated trend we were able to more appropriately forecast future per-meter usage using a more current trend. This change in per-meter usage is likely related to energy efficiency seen in household appliances, electronics and lighting. The 2024 Test Year Residential UPM is 1.7 percent less than the actual 2022 weather normalized UPM.

Figure 1: Annual Residential Use-per-Meter, 2003 through 2022



Q. WHAT IS THE PURPOSE OF THE MONTHLY INDICATOR?

A. The monthly indicator variables reflect seasonal patterns in electricity usage that are not captured by the other variables. For example, lighting demand may vary seasonally due to changes in the number of daylight hours, which would not be well reflected by other included variables, such as CDDs and HDDs.

Q. ARE THE MONTHLY INDICATOR VARIABLES RELEVANT EXPLANATORY FACTORS?

A. Yes. The coefficients on the monthly indicator variables are jointly statistically significant, meaning they are relevant explanatory factors for this class. Together they provide for a similar annual coefficient but provide seasonal insight.

2. Residential Meter Model

Q. PLEASE DESCRIBE THE RESIDENTIAL METER MODEL.

A. The residential meter model is used to determine the number of Residential meters served during the billing month. The model uses the following variables:

1. A linear time trend; and
2. Monthly indicator variables.

Q. WHAT IS THE PURPOSE OF THE LINEAR TIME TREND VARIABLE?

A. The linear time trend variable is intended to identify and account for any trend in the number of Residential meters the Company is expected to serve. The model includes a correction for first-order serial correlation.

Q. DOES THE MODEL PRODUCE REASONABLE ESTIMATES?

A. Yes, the coefficient on the linear time trend variable is positive and statistically significant, indicating a pattern of growth of the number of Residential meters. The monthly indicator variables help account for the slight increase we see during warmer months where seasonal homes are reconnected for a period of time.

B. Farm

Q. PLEASE DESCRIBE OTP'S FARM FORECAST.

A. Two statistical models are estimated for OTP's Farm customers: a UPM model and a meter model.

1. Farm UPM Model

Q. PLEASE DESCRIBE THE FARM UPM MODEL.

A. The Farm UPM model includes the following variables:

1. HDD55;
2. The number of days in the billing month;
3. A linear time trend;
4. An indicator variable for May 2020; and
5. Monthly indicator variables.

The dependent variable in the UPM model is use-per-meter (sales divided by the number of meters) in each billing month. Note that we did not find a statistically significant relationship between UPM and cooling degree days for this class. The UPM model includes a correction for first-order serial correlation. The UPM model leads to estimates of coefficients related to the variables.

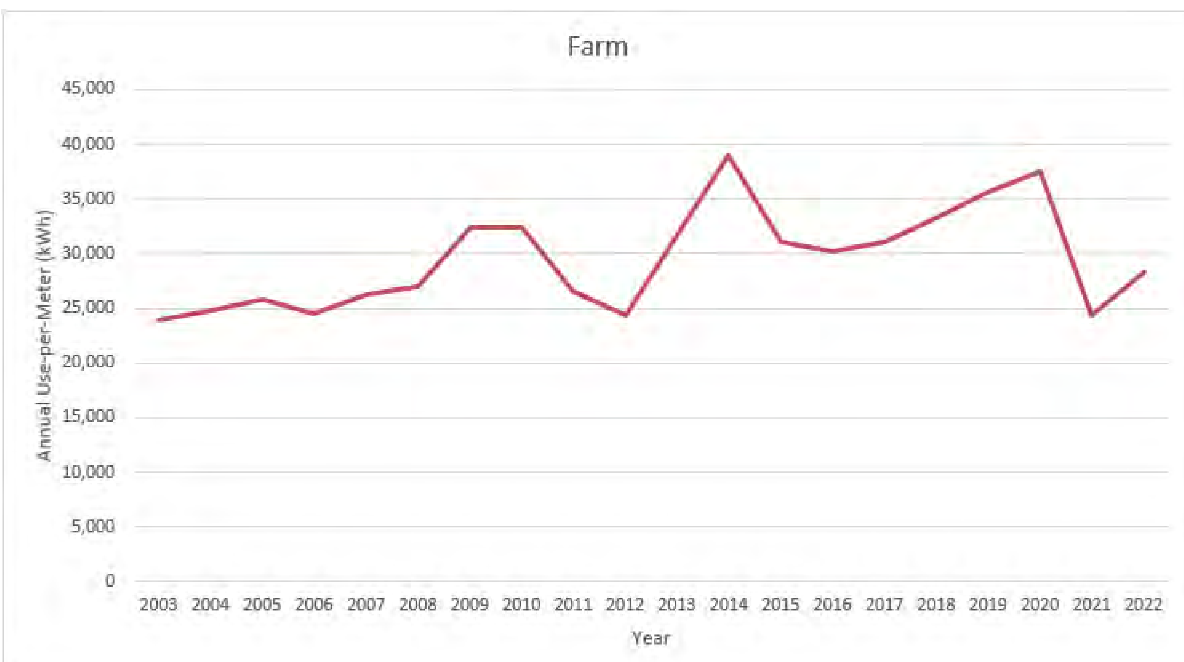
Q. ARE THE ESTIMATED COEFFICIENTS FROM THE FARM UPM MODEL REASONABLE?

A. Yes. The estimates can be summarized as follows:

- Farm UPM is positively related to HDDs (i.e., UPM increases when winter weather is colder);
- UPM increases with the number of billing days;

- Figure 2, below, shows the variability in the Farm class load, which consists primarily of grain drying. With 2013 being a well above average wet year, it created a significant amount of grain drying during the fall and winter months, causing a high UPM during 2013-2014. OTP also saw an average increase of 3 percent in meters annually between 2011-2014, which was likely another contributing factor to the increased UPM during that timeframe. Over the 20-year historical period, the Farm UPM had a 2 percent annual average growing trend prior to 2020, then the pandemic likely impacted sales in 2020. Beginning in 2021, Farm UPM is showing recovery, which is forecast to continue at a rate of approximately 1 percent annually, all else equal;
- Historical data by month shows that UPM in May 2020 was uncharacteristically high. By including an indicator variable for May 2020, the model will prevent that outlier from biasing the estimates of the other variables; and
- Seasonal patterns are relevant explanatory factors (i.e., the coefficients on the monthly indicator variables are jointly statistically significant).

Figure 2: Annual Farm Use-per-Meter, 2003 through 2022



2. Farm Meter Model

Q. PLEASE DESCRIBE THE FARM METER MODEL.

A. The dependent variable in the Farm meter model is the number of Farm meters served during the billing month. The model includes the following explanatory variables:

1. Farm Employment;[2] and
2. Monthly indicator variables.

Farm Employment is intended to reflect the economic and demographic factors that affect the number of farm meters the Company is expected to serve. The model includes a correction for first-order serial correlation.

Q. DOES THE METER MODEL PRODUCE REASONABLE ESTIMATES?

A. Yes, the interaction between farm employment and historical data reflects a positive relationship between economic conditions and meters served for the analysis period and extending into the forecast period. Although OTP historically saw growth in the farming class, economic predictors indicate there likely will be a decline in this sector, and our forecast reflects this. In addition, the monthly indicator variables are jointly statistically significant, reflecting a seasonal pattern in meters served.

C. Small Commercial

Q. PLEASE DESCRIBE OTP'S SMALL COMMERCIAL FORECAST.

A. The Small Commercial sales forecast is the product of two models: a UPM model and a meter model.

1. Small Commercial UPM Model

Q. PLEASE DESCRIBE THE SMALL COMMERCIAL UPM MODEL.

A. The Small Commercial UPM model includes the following variables:

1. CDD65;
2. HDD55;
3. The number of days in the billing month;
4. A linear time trend; and
5. Monthly indicator variables.

---

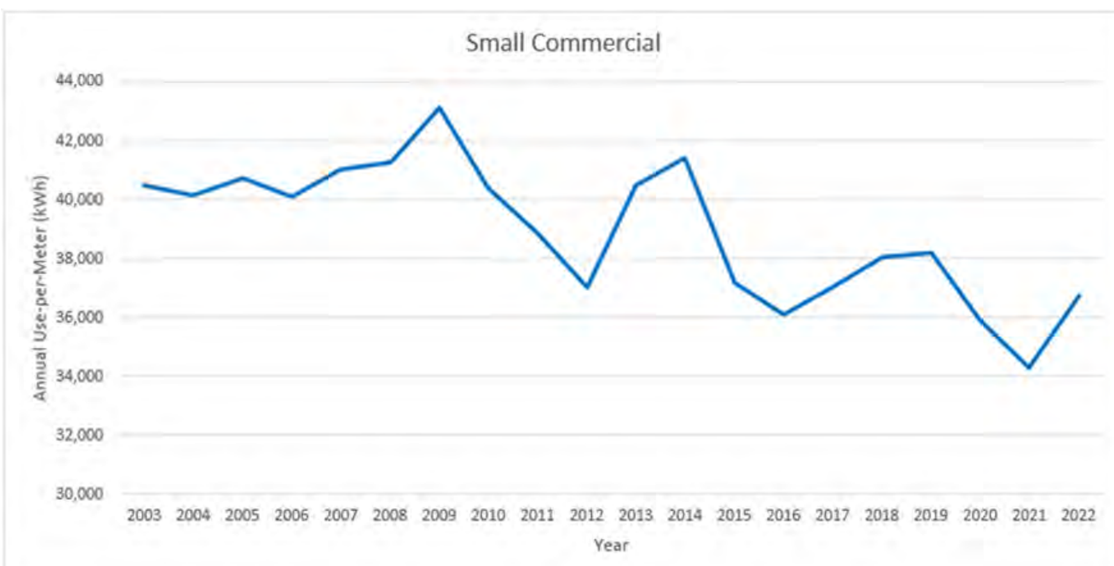
[2] Included as 12-month moving averages using the six prior months, the current month, and five following months.

The dependent variable is use-per-meter, which is sales divided by the number of meters, in each billing month. The model includes a correction for first-order serial correlation. The UPM model leads to estimates of coefficients related to the variables.

Q. WHAT IS THE PURPOSE OF THE LINEAR TIME TREND VARIABLE IN THE SMALL COMMERCIAL UPM MODEL?

A. A time trend is appropriate when UPM is trending over time, and other available variables do not do a good job of explaining the trend, which was accurate for the Small Commercial UPM. There has been some variability over the 20-year history, but Small Commercial UPM has had an overall decline of 9 percent from 2003 to 2022. During 2009 to 2012, there was a reclassification of meters from this class to the Large Commercial class resulting in a 5.0 percent average annual reduction of sales, while still seeing an average growth of 0.5 percent annually during this same time. The impact of the reclassification of meters was minimal to this class due to there being far more meters in this class. The addition of customers with higher sales accounted for the increase in UPM in 2013-2014 as seen in Figure 3. The scale has been condensed (i.e., starting at 30,000 kWh rather than zero) to make it easier to view trends in UPM.

Figure 3: Annual Small Commercial Use-per-Meter, 2003 through 2022



Q. ARE THE ESTIMATED COEFFICIENTS FROM THE SMALL COMMERCIAL UPM MODEL REASONABLE?

A. Yes. The estimates can be summarized as follows:

- Small Commercial UPM is positively related to both CDDs and HDDs (i.e., UPM increases when summer weather is hotter and winter weather is colder);
- UPM is more sensitive to CDDs than HDDs, which reflects a larger effect of temperatures on cooling-related load than heating-related load;
- UPM increases with the number of billing days;
- UPM has a declining trend of 27 kWh per meter per year, all else equal; and
- Seasonal patterns are relevant explanatory factors (i.e., the coefficients on the monthly indicator variables are jointly statistically significant).

2. Small Commercial Meter Model

Q. PLEASE DESCRIBE THE SMALL COMMERCIAL METER MODEL.

A. The dependent variable in the Small Commercial meter model is the number of Small Commercial meters served during the billing month. The model includes the following explanatory variables:

1. A linear time trend;
2. An indicator variable for 2007 and beyond; and
3. Monthly indicator variables.

The linear time trend reflects the increasing trend in meters served over time. Starting January 2007, the average growth in Small Commercial meters was less than in the prior years. The indicator variable for 2007 and beyond was found statistically significant in accurately predicting growth beginning in 2007. The model includes a correction for first-order serial correlation.

Q. DOES THE METER MODEL PRODUCE REASONABLE ESTIMATES?

A. Yes. The years prior to 2007 had an average annual growth rate of 0.9 percent, whereas the average growth rate for 2007 and beyond was 0.6 percent. Using the time trend variable and the 2007 and beyond variable together, the model predicts a reasonable increase of 878 meters served per year versus 937 meters without the time trend variable. When multiplying the growing meter counts with the declining use-per-meter, the forecasted energy sales were reasonable. The 2024 Test Year sales for this class are 0.2 percent lower than actual 2022 weather normalized sales.

D. Large Commercial and Pipeline

Q. PLEASE DESCRIBE OTP'S LARGE COMMERCIAL FORECAST.

A. As described earlier, a single statistical model is developed for OTP's Large Commercial customers representing total monthly sales. In addition to the model, OTP has several customers, including pipeline customers, that currently will not "fit" into the modeling process and are manually forecast.

1. Statistical Forecast

Q. PLEASE DESCRIBE THE LARGE COMMERCIAL SALES MODEL.

A. The Large Commercial sales model uses the following variables to determine total class sales in each billing month:

1. HDD55;
2. The number of days in the billing month;
3. Gross Regional Product (GRP) in conjunction with the years 2009 through 2010;
4. An indicator variable for January 2009 through December 2010;
5. An indicator variable for January 2011 and beyond;
6. Indicator variables for February 2019 and May 2019; and
7. Monthly indicator variables.

The model leads to estimates of coefficients related to the variables. The model includes a correction for first-order serial correlation.

Q. WHAT IS THE PURPOSE OF THE GRP VARIABLE?

A. GRP is a measure of the value of goods and services produced in a region. It is similar to gross domestic product (GDP), but whereas GDP measures economic activity at a national level, GRP measures it at a local level. It is intended to reflect the effect of economic conditions on class usage.

Q. WHAT IS THE PURPOSE OF INCLUDING THE GRP INDICATOR VARIABLE FOR THE YEARS 2009 THROUGH 2010?

A. There were two events that contributed to a change in Large Commercial sales from 2009 to 2011: (1) reclassification of some Small Commercial customers into the Large Commercial class; and (2) one very large customer coming online in

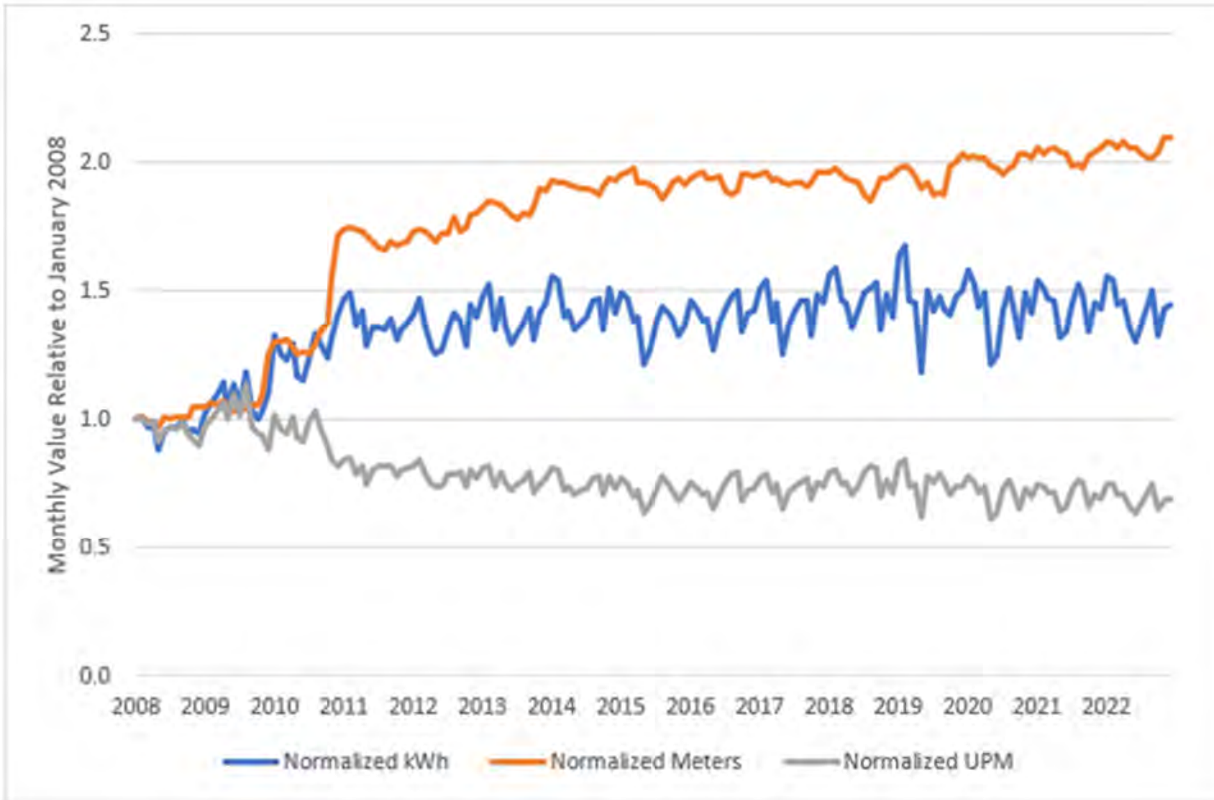
2009. The GRP indicator variable is used in the model to adjust for the changes in general economic conditions occurring at this same time.

Q. PLEASE DISCUSS THE RECLASSIFICATION OF SMALL COMMERCIAL CUSTOMERS INTO THE LARGE COMMERCIAL CLASS.

A. As mentioned earlier, from 2009 to 2011, there was a reclassification of some higher-use Small Commercial customers into the Large Commercial class. This reclassification contributed to the 7 percent increase in meters for 2009 (over 2008 levels), with an associated 4 percent growth in sales. 2010 saw a 26 percent increase in meters over the prior year, with an annual sales growth of 10 percent from the reclassification. Figure 4, below, shows the monthly total sales, number of meters, and UPM for the Large Commercial class normalized to their January 2008 value.[3] By normalizing to January 2008, we can more easily see how each series evolves over the analysis period on a single graph. There is an increase in the number of meters and a corresponding decrease in UPM from 2009 to 2011 due to the smaller commercial customers entering this class. At the same time, sales had a modest growth.

[3] Specifically, each graphed data point is equal to that month's value divided by the value in January 2008.

Figure 4: Large Commercial Sales, Number of Meters and Use Per Meter, Normalized to the January 2008 Level



Q. WHAT IS THE PURPOSE OF THE INDICATOR VARIABLE FOR JANUARY 2011 AND BEYOND?

A. With the significant change in sales, the January 2011 and beyond indicator variable allowed the model to more accurately forecast future sales based on the higher mean established after 2010.

Q. WHAT IS THE PURPOSE OF THE FEBRUARY 2019 AND MAY 2019 INDICATOR VARIABLES?

A. These variables control for anomalies in the historical billing information.

Q. ARE THE ESTIMATED COEFFICIENTS FROM THE LARGE COMMERCIAL SALES MODEL REASONABLE?

A. Yes. The estimates can be summarized as follows:

- Large Commercial usage is positively related to HDDs (i.e., usage increases when winter weather is colder);

- Usage increases with the number of billing days;
- The combined coefficients during January 2009 to December 2010, including the influence of GRP, produces the resulting sales during that timeframe;
- Large Commercial usage is higher following January 2011, all else equal;
- Indicator variables for February 2019 and May 2019 negate these outliers from affecting the overall coefficients of the other included variables; and
- Seasonal patterns are relevant explanatory factors (i.e., the coefficients on the indicator variables are jointly statistically significant).

2. Manual Forecasts

Q. WHAT CUSTOMERS ARE MANUALLY FORECASTED?

A. OTP has four Large Commercial class customers in North Dakota that are currently forecast manually, for various reasons, and added to the Large Commercial class model total. **[PROTECTED DATA BEGINS…**

….

PROTECTED DATA ENDS]

Q. CAN THESE CUSTOMERS' SALES BE ACCURATELY FORECAST WITH A STATISTICAL MODEL?

A. No. While we prefer to use statistical models to forecast sales for all customers, there are situations where models are not able to accurately capture the nuances of particular situations. This is particularly true for very large customers, as situations affecting their usage do not apply to the broader customer population.

Q. WHY ARE LARGE COMMERCIAL SALES DIFFICULT TO FORECAST USING ONLY STATISTICAL MODELS?

A. Due to the nature of their business, the energy needs of customers in this class can vary greatly, so when a new customer is introduced or an existing customer leaves, it has the potential to significantly impact the entire class. The large changes in load can be very difficult for a statistical model to predict. This class also has fewer meters providing input, so regular, predictable patterns may not emerge.

Q. CAN YOU PROVIDE AN EXAMPLE OF THE EXTREME VARIABILITY OF LARGE COMMERCIAL SALES?

A. Yes. OTP had a single customer that represented nearly 10 percent or more of the total Large Commercial sales up until 2016 and by 2019 only represented 0.2 percent of the total sales. A load drop of this magnitude in this class would negatively influence the accuracy of a statistical model.

Q. ARE THERE OTHER UNIQUE CHARACTERISTICS THAT COMPLICATE FORECASTING LARGE COMMERCIAL SALES?

A. Yes. The entry of a large load in 2022 has had a significant impact on sales in this class. Also, behind-the-meter generation is emerging and may result in reduced sales in the future.

Q. WHY ARE PIPELINE SALES MANUALLY FORECAST RATHER THAN STATISTICALLY MODELED?

A. Pipeline sales are significantly impacted by world and national economic trends and federal and state energy and environmental policy. Further, the petroleum industry is in a state of constant flux. As shown in Figure 11, below, Pipeline sales can be quite variable **[PROTECTED DATA BEGINS ...**

... PROTECTED DATA ENDS]. This load is not a good candidate for a statistical model.

Q. HOW ARE THE MANUAL FORECASTS DEVELOPED?

A. Manual forecasts are developed by OTP employees that work directly with the manually forecast Large Commercial and Pipeline customers. These forecasts incorporate information provided by the customers, historic information (as applicable), comparisons of how the customers' projections have compared to actual results, and sales trends.

E. Other Public Authority

Q. PLEASE DESCRIBE OTP'S OTHER PUBLIC AUTHORITY FORECAST.

A. Two statistical models are estimated for OTP's Other Public Authority (OPA) customers: a UPM model and a meter model. OPA loads include municipal pumping and fire sirens.

1. OPA UPM Model

Q. PLEASE DESCRIBE THE OPA UPM MODEL.

A. The OPA UPM model includes the following variables:

1. HDD55;
2. The number of billing days; and
3. Monthly indicator variables.

The dependent variable in the UPM model is use-per-meter (sales divided by the number of meters) in each billing month. Note that we did not find a statistically significant relationship between UPM and cooling degree days for this class. The UPM model includes a correction for first-order serial correlation. The UPM model leads to estimates of coefficients related to the variables.

Q. ARE THE ESTIMATED COEFFICIENTS FROM THE OPA UPM MODEL REASONABLE?

A. Yes. The estimates can be summarized as follows:

- OPA UPM is positively related to HDDs (i.e., UPM increases when winter weather is colder);
- UPM increases with the number of billing days;
- UPM has remained mostly steady from 2003 to 2022, with only a 2.5 percent decrease (880 kWh) between the beginning and end of the 20-year period; and
- Seasonal patterns are relevant explanatory factors (i.e., the coefficients on the indicator variables are jointly statistically significant).

2. OPA Meter Model

Q. PLEASE DESCRIBE THE OPA METER MODEL.

A. The dependent variable in the OPA meter model is the number of OPA meters served during the billing month. The model includes the following explanatory variables:

1. A linear time trend;
2. Indicator variables for April 2019 and May 2021; and
3. Monthly indicator variables.

The model includes a correction for first-order serial correlation.

Q. DOES THE MODEL PRODUCE REASONABLE ESTIMATES?

A. Yes. The estimates can be summarized as follows:

- The model trend reflects modest growth in meters (approximately 1 per year);
- When viewing historical data by month, both April 2019 and May 2021 show a large increase in meter counts over their previous month followed by a similar average to all other months. This may occur if a certain set of customers are billed both at the beginning of a month and again at the end, so they receive two bills in one month. By including specific indicator variables for those months, the model will evaluate each time uniquely and estimate an appropriate coefficient to be used in the forecast of meters; and
- The monthly indicator variables are jointly statistically significant, reflecting a seasonal pattern in meters served.

F. Street Lighting and Area Lighting

Q. HOW WERE STREET AND AREA LIGHTING SALES FORECAST?

A. We developed an Excel-based template that forecasts Street Lighting and Area Lighting using two fundamental elements: sales during a recent 12-month period, and assumptions about the light-emitting diode (LED) fixture installation rate and the kWh savings realized when LED fixtures replace existing fixtures.

Q. WHY DID YOU USE THIS APPROACH RATHER THAN A STATISTICAL MODELING METHOD?

A. The largest expected change to Street Lighting and Area Lighting sales in coming years is expected to be due to replacing existing fixtures with LED fixtures. OTP believes LEDs reduce a fixture's electricity usage by 75 percent. Rather than attempt to estimate the change in sales from increased LED installations, which is currently in process, we use a simulation approach that adjusts historical lighting sales for the expected change in LED installations in each month.

Q. WHAT ASSUMPTIONS DOES YOUR STREET LIGHTING FORECAST USE?

A. We assume that LED installations occur from May through September of each year until LEDs comprise 69 percent of installations. In each month installations occur, the LED share increases by 3.3 percent. Finally, as described earlier, a fixture's usage is assumed to decline by 75 percent after LEDs are installed.

Q. DID YOU USE THE SAME GENERAL APPROACH TO FORECAST AREA LIGHTING SALES?

A. Yes. We forecast Area Lighting sales accounting for a LED installation schedule similar to the Street Lighting forecast, with a slightly slower installation rate and lower saturation level. The process for allocating Area Lighting sales to the relevant customer classes is described in Exhibit___(TKM-1), Schedule 2 under Class Forecasts of kWh.

IV. TEST YEAR SALES FORECAST

A. Overview

Q. WHAT IS OTP'S OVERALL FORECASTED 2024 TEST YEAR SALES?

A. OTP forecasts approximately 2,560 GWh of North Dakota retail sales in the 2024 Test Year. Table 2, below, identifies the 2024 Test Year sales by sales forecast class.

Table 2
Summary of 2024 Test Year Sales Forecast

Customer Class	kWh Sales
Residential	591,642,942
Farm	41,513,920
Small Commercial	467,433,150
Large Commercial and Pipeline[4]	1,433,405,558
Street Lighting	7,202,486
OPA	18,713,442
Total Sales	**2,559,911,498**

[4] Large Commercial and Pipeline sales are aggregated in order to protect the sales figures for the Pipeline class, which includes only one customer.

Q. WHAT ARE THE PRIMARY FACTORS CONTRIBUTING TO THE 2024 TEST YEAR SALES FIGURES?

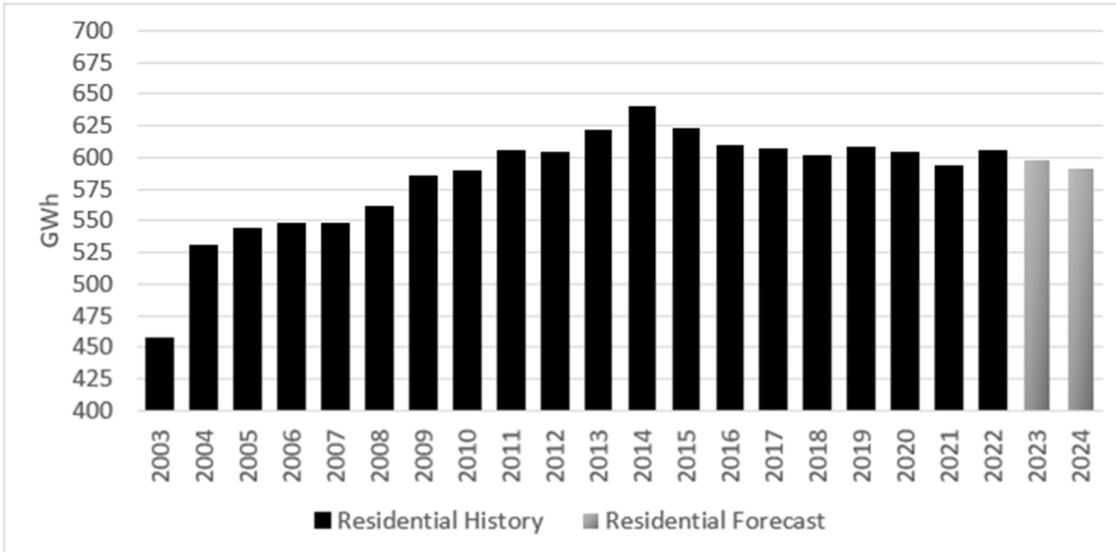
A. OTP's service area in Minnesota, North Dakota, and South Dakota is made up of rural areas and small towns. For example, only three towns we serve have populations of more than 10,000, with only one being located in North Dakota (Jamestown). We do not anticipate significant economic or demographic growth for 2024, which is confirmed by the W&P data that informs our sales forecasts. The moderate growth in the W&P data translates to very moderate growth in sales. Weather is also a significant input into the 2024 sales forecast. Twenty years of historical weather was used to create the 2024 sales forecast. Weather is an input into most of the UPM models.

B. Residential

Q. WHAT ARE THE 2024 TEST YEAR FORECASTED RESIDENTIAL SALES?

A. Residential sales are forecasted to be 592 GWh. This is a decrease from 2022 weather normalized Residential sales and forecasted 2023 weather normalized Residential sales, as shown in Figure 5 below. The decline in 2024 Test Year Residential sales is consistent with the recent trend in sales for this class.

Figure 5
Weather Normalized North Dakota Residential Sales

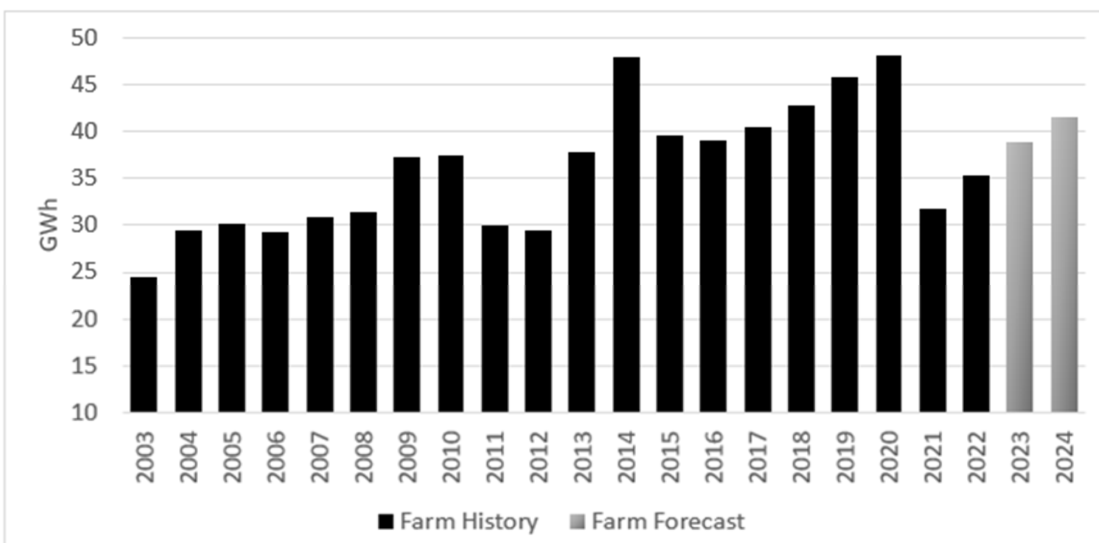


C. Farm

Q. WHAT ARE 2024 TEST YEAR FORECASTED FARM SALES?

A. Farm sales are forecasted to be 42 GWh. This is an increase over 2022 weather normalized Farm sales, as shown in Figure 6 below. It is consistent with the recent upward trend in Farm sales.

Figure 6
Weather Normalized North Dakota Farm Sales

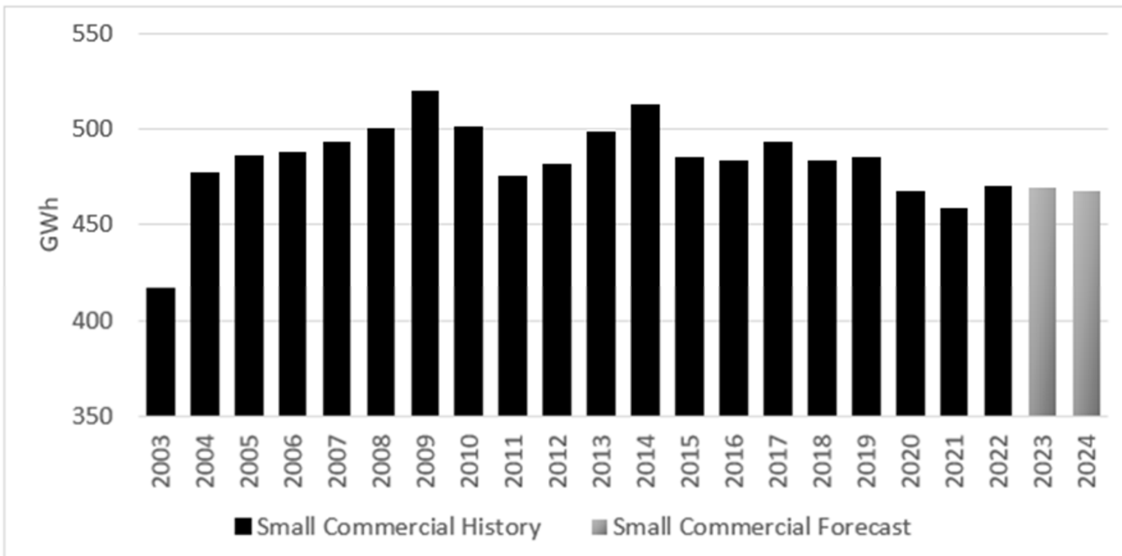


D. Small Commercial

Q. WHAT ARE 2024 TEST YEAR FORECASTED SMALL COMMERCIAL SALES?

A. Small Commercial sales are forecasted to be 467 GWh. This is a slight decrease from 2022 weather normalized Small Commercial sales, and similar to the 2023 forecasted Small Commercial sales. The 2024 Small Commercial forecast trend is consistent with the historical trend for this class, as shown in the figure below.

Figure 7
Weather Normalized North Dakota Small Commercial Sales



E. Large Commercial

Q. WHAT ARE 2024 TEST YEAR FORECASTED LARGE COMMERCIAL SALES?

A. Large Commercial sales are forecasted to be **[PROTECTED DATA BEGINS … … PROTECTED DATA ENDS]**. Large Commercial sales are a combination of statistically modeled sales and manually forecasted sales. Large Commercial sales for the 2024 Test Year, excluding manually forecasted loads (shown in the solid gray bars), are slightly lower than both the 2022 weather normalized Large Commercial sales and the 2023 forecast sales. **[PROTECTED DATA BEGINS …**

… PROTECTED DATA ENDS]. The total 2024 Large Commercial sales are forecasted to be higher than expected 2023 Large Commercial sales, as shown in Figure 8 below.

Figure 8
Weather Normalized North Dakota Large Commercial Sales

[PROTECTED DATA BEGINS…

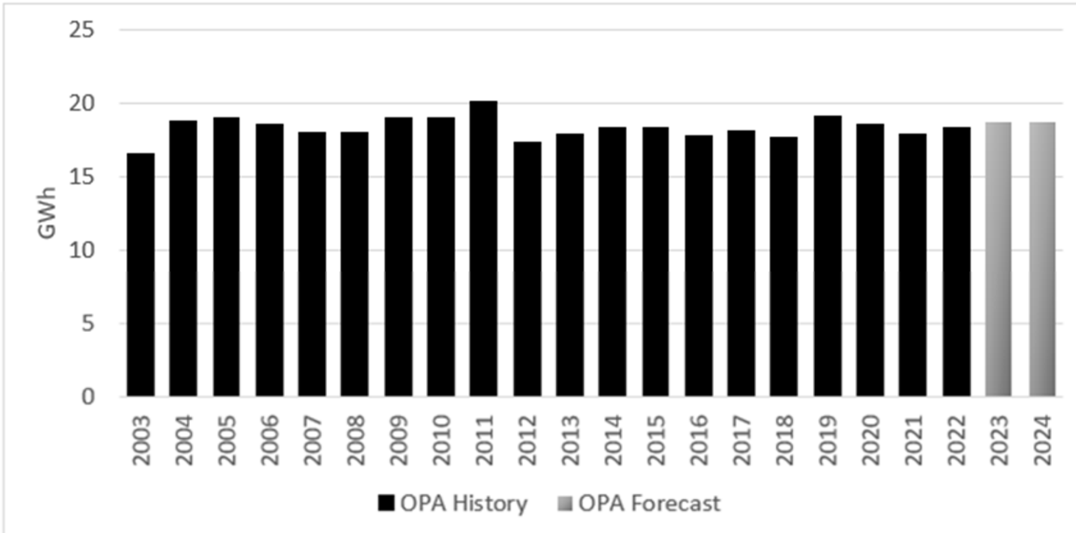
… PROTECTED DATA ENDS]

F. OPA

Q. WHAT ARE 2024 TEST YEAR FORECASTED OPA SALES?

A. OPA sales are forecasted to be 19 GWh. OPA 2024 Test Year sales are slightly higher than 2022 weather normalized OPA sales and match the expected 2023 OPA sales, as shown in the figure below.

Figure 9
Weather Normalized North Dakota OPA Sales

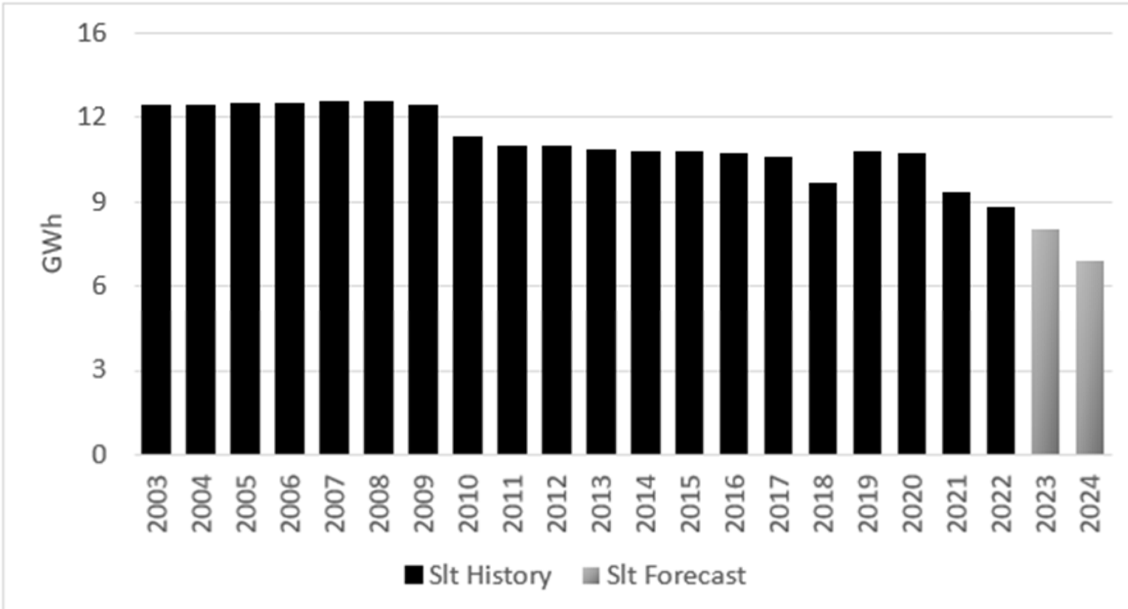


G. Street Lighting

Q. WHAT ARE 2024 TEST YEAR FORECASTED STREET LIGHTING SALES?

A. Street Lighting sales are forecasted to be 7 GWh. This is a decrease from 2022 weather normalized Street Lighting sales and expected 2023 Street Lighting sales, as shown in the figure below. The decline is due to the continued penetration of LED lights.

Figure 10
Weather Normalized North Dakota Street Lighting Sales



H. Pipeline

Q. WHAT ARE 2024 TEST YEAR FORECASTED PIPELINE SALES?

A. Pipeline sales are forecasted to be **[PROTECTED DATA BEGINS ...**
... PROTECTED DATA ENDS] This is **[PROTECTED DATA BEGINS ...**
...
PROTECTED DATA ENDS], as shown in the figure below. The sales forecast for this class represents a single customer. Economic factors are the drivers for the increase.

Figure 11
North Dakota Pipeline Sales[5]

[PROTECTED DATA BEGINS …

… PROTECTED DATA ENDS]

Q. DOES THIS CONCLUDE YOUR DIRECT TESTIMONY?

A. Yes, it does.

[5] Pipeline sales are not weather normalized, as weather does not affect sales to this class.

TAMMY KAY MORTENSON
Fergus Falls, MN 56537
218-205-5616

Qualifications Summary

Nearly 30 years within the electric utility industry. Have served as both a coordinator and team member for many projects defining, documenting, and communicating processes to see projects to completion. Possesses a strong technical background from start in Otter Tail Power Company's Information Technology Department with further development within the Regulatory and System Operations departments

Education St. Cloud State University (St. Cloud, MN): 1992 – 1994
Bachelor of Science Degree in Business Computer Information Systems

Fergus Falls Community College (Fergus Falls, MN): 1990-1992
Associate of Arts Degree

Employment History

Otter Tail Power Company (Fergus Falls, MN) –

<u>Senior Data Analyst</u> October 2022 to present
Development of Sales Forecasts and Demand Forecasts using the SAS, ITron MetrixND and Excel applications; assist with accuracy of customer usage data used as the basis for many different analysis applications

<u>Load and Settlements Analyst</u> January 2022 to October 2022
Responsible for the monitoring and correcting of data collected to determine the company's portion of generation and load served within their Reliability Coordination regions to support settlement processes; monitor the accuracy of results from forecasting tools and adjust as necessary

<u>Senior Load Management Specialist</u> March 2018 to January 2022
<u>Load Management Specialist</u> June 2008 to September 2015
Administration of the Comverge Load Management application and supporting applications; member of the Load Management Steering Team assisting with decision-making for seasonal control strategies, develop and implement control sequences within the LMS application and provide post analysis of control events; primary support of the department's SAS applications; development and support of internal C# applications; prior implementation and administration of the eDNA data historian capturing data for several real time systems

<u>Pricing and Tariff Administrator Analyst</u> June 2016 to March 2018
Responsible for maintaining the accuracy of the company's tariff sheets as filed with each state regulatory department; monitor the accuracy of customer billing; assist with regulatory filings as required; customer data analysis to assist with pricing design

<u>Load Researcher</u> September 2015 to June 2016
Analysis of customer usage data using the SAS application, Microsoft Excel and other applicable tools; financial calculations assisting the Accounting department with monthly closing tasks; assist with rate design and customer data analysis requests

<u>Systems Specialist</u> July 1999 to June 2008
Responsible for the procurement of servers and resolution of hardware issues; support of an EMC Storage Area Network; management of a VMWare virtualized environment; administration of many server applications, such as Microsoft operating systems including Active Directory, Microsoft Exchange Server and related products, Microsoft SQL Server, CaseWorks built on the Microsoft SharePoint environment, Documentum document management system, and more

<u>Information Center Specialist</u> Nov 1993 to Aug 1994/January 1995 to July 1999
Employed twice as an intern prior to being hired full-time within the Information Center as a member of a support call team; taught and assisted clients with the Microsoft Office software applications and performed troubleshooting on a variety of PC hardware and software problems

Skills

* Strong interpersonal skills
* Task oriented with a strong attention to detail
* Analytical and troubleshooting skills to resolve issues/tasks as quickly as possible
* Data analysis and interpretation skills for decision making purposes
* Well versed in Microsoft Office products, as well as a growing knowledgebase of SAS/SAS Enterprise Guide Analytics software, Structured Query Language (SQL) and C# programming, and ITron's MetrixND modeling application

Before the North Dakota Public Service Commission
State of North Dakota

In the Matter of the Application of Otter Tail Power Company
For Authority to Increase Rates for Electric Utility
Service in North Dakota

Case No. PU-23-

Exhibit___

OTTER TAIL POWER COMPANY SALES AND REVENUE FORECAST METHODOLOGY

November 2, 2023

TABLE OF CONTENTS

INTRODUCTION AND BACKGROUND

This filing explains OTP's process for forecasting energy sales and revenues for in its 2024 Test Year North Dakota electric rate case. Section A of this filing provides an overview of the process OTP uses to develop its sales forecast. This overview includes the methodologies employed to develop the forecasts for various rates within each class of customers. Section B provides an overview of the processes OTP uses to develop various pricing and billing determinants for its revenue forecast. This section also provides an overview of a workbook model that combines the sales forecast (section A) and the pricing and billing determinant information (section B). The workbook generates the 2024 Test Year revenue forecast. The final Section C discusses our transition from a customer based model to a meter based model.

A. SALES FORECAST

1. OVERVIEW

OTP forecasts sales for eight separate sales forecast classes, of which seven are used in the calculation of North Dakota retail rates.[1] OTP uses a sales forecast model to develop test year sales for the following North Dakota sales classes: Residential (Res); Farm (Far); Small Commercial (Scom); and Other Public Authority (OPA). Test year sales for the Pipeline (Pipe), Area Lighting (Alt) (resulting sales are added to the other relevant classes noted), and Street Lighting (Slt) classes are prepared manually, as discussed below. Test year sales for Large Commercial (Lcom) is prepared using both a statistical model and manual forecasting.

The sales forecast models use economic, weather, and usage data through December 2022.

Numerous workbooks provide all the regression models, results, and data used to create the test year forecast.

OTP used the forecasting software MetrixND (developed by Itron - https://www.itron.com) to prepare the 2024 Test Year sales forecast. Econometric models were developed by state and by sales forecast class. For the Residential, Farm, Small Commercial, and OPA classes, OTP uses MetrixND, to create sales forecasts for each class by first developing a model to forecast use-per-meter (UPM), and second, developing a model to forecast the number of meters. Total sales for these classes are equal to the forecasted UPM multiplied by the forecasted number of meters. The UPM and meter

[1] Unclassified sales, which pertains to OTP's own use of electricity, are not part of the calculation of retail rates.

models are developed for each state/class/year/month using historical sales, meter counts, economic data, weather data, and indicator variables.

Area and Street Light sales are manually forecast in Excel using a combination of factors that include: existing sales, rate of LED installations, reduction of sales due to LEDs, and maximum saturation of LED fixtures. The area light forecast is proportioned to the associated classes, and then added to the forecast of each class.

OTP does not model Pipeline customers. Pipeline pumping is a load that is very difficult to forecast using econometric models. This load is significantly impacted by world and national economic trends and federal and state energy and environmental policy.

For the Large Commercial class, OTP uses a statistical kWh model for most customers, supplemented by manual forecast of four Large Commercial customers in North Dakota.[2] These four customers are forecast based on input directly from the customers. One of the manually forecasted customers will begin receiving electric service in 2024. Another Large Commercial customer has load that is very significant and accounts for about **[PROTECTED DATA BEGINS ... ... PROTECTED DATA ENDS]** percent of OTP's North Dakota retail sales. This is a load that was added in 2022, so little history exists at this time on which to build a forecast. The third manually forecasted customer had a significant reduction in their sales in 2018, which has had a large impact on the Large Commercial class, so to accurately reflect this change, their forecast at the lower levels is excluded from the Large Commercial class kWh model and is included manually. OTP also has an existing customer that will have a significant load reduction in 2024 due to infrastructure changes; that reduction has been included manually.

OTP has worked very closely with the Pipeline and Large Commercial customers to acquire their updated projections on demand (kW) and energy (kWh).

Class sales are added together at the state level to yield the state sales. State sales are added together to produce total system sales. Table 1 provides North Dakota 2024 Test Year sales by sales forecast class.[3]

---

[2] There is also one Large Commercial customer located in South Dakota that is manually forecast.
[3] With 2024 being a leap year, all modeled forecast sales in the month of February were adjusted for 28/29 days.

Table 1
Summary of 2024 Test Year Sales Forecast
(kWh)

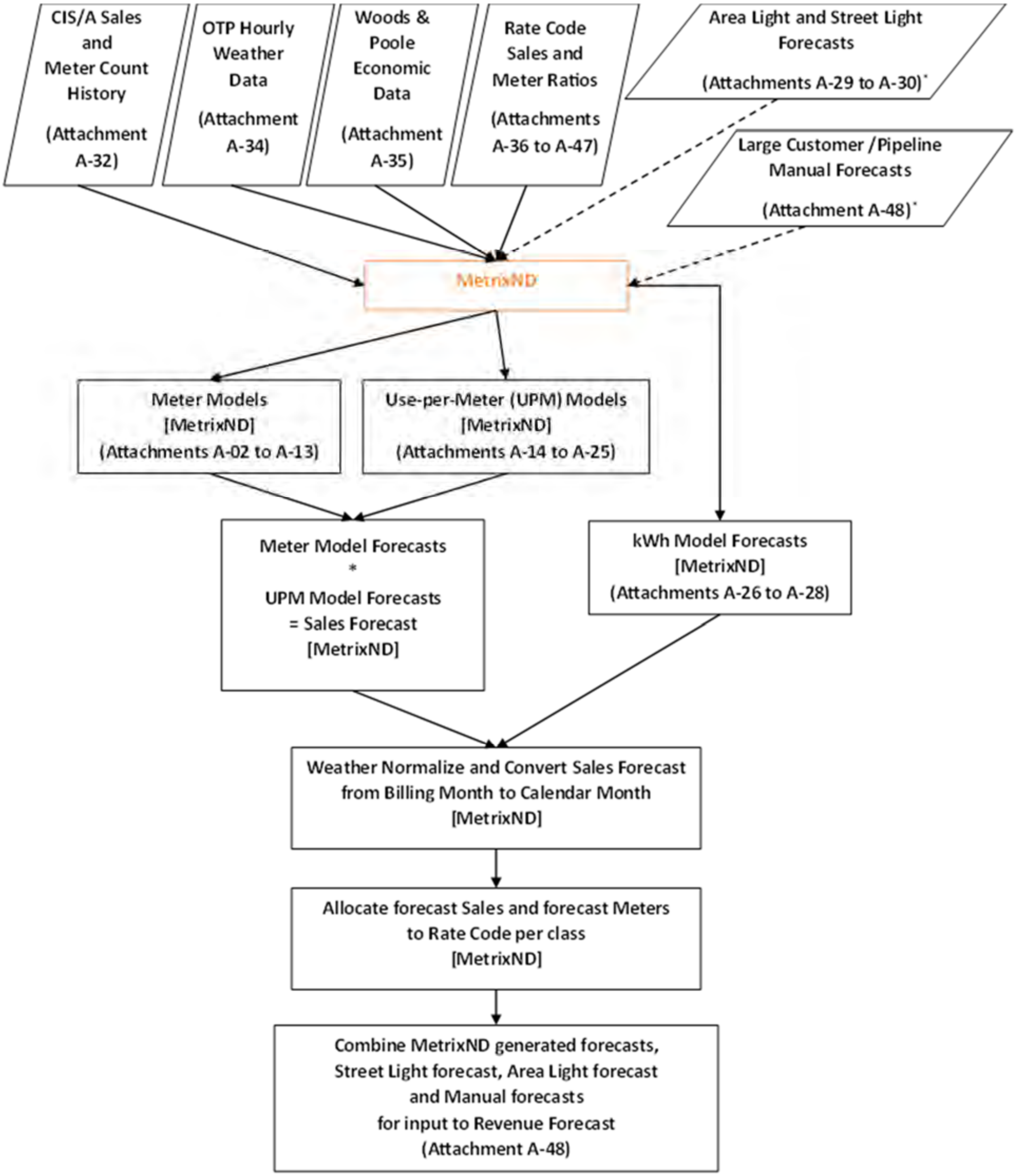
Customer Class			
Residential		591,642,942	
Farm		41,513,920	
Small Commercial		467,433,150	
Large Commercial[4]	**[PROTECTED DATA BEGINS…**		
Pipeline			**…PROTECTED DATA ENDS]**
OPA		18,713,442	
Area / Street Lighting		7,202,486	
Total Sales		**2,559,911,498**	

2. SALES MODEL DESCRIPTION

The following flowchart is the process OTP follows to create its sales forecast.

[4] Large Commercial and Pipeline sales are marked Protected Data in order to protect the sales figures for the small number of manually forecast Large Commercial and Pipeline customers.

Figure 1
Sales Forecast Flow Chart



* Forecasts are created outside of MetrixND, but are read into MetrixND to be added into the appropriate classes and/or be included in final results

a) Class Forecasts Using UPM

i. Meter Model

The meter models, designed in MetrixND, forecast monthly meter counts, by state and by class, based on twenty years of historical meter counts, economic indicators, and various indicator variables. All economic data is based on Woods and Poole Economic, Inc. 2022 databases.

The table in *Attachment A-01 Independent Variables.xlsx* shows the variables that are included in each model.

The following attachments contain all meter model and statistical information:

- *Attachment A-02 MN ResMtr.xlsx*
- *Attachment A-03 MN FarmMtr.xlsx*
- *Attachment A-04 MN SComMtr.xlsx*
- *Attachment A-05 MN OPAMtr.xlsx*
- *Attachment A-06 ND ResMtr.xlsx*
- *Attachment A-07 ND FarmMtr.xlsx*
- *Attachment A-08 ND SComMtr.xlsx*
- *Attachment A-09 ND OPAMtr.xlsx*
- *Attachment A-10 SD ResMtr.xlsx*
- *Attachment A-11 SD FarmMtr.xlsx*
- *Attachment A-12 SD SComMtr.xlsx*
- *Attachment A-13 SD OPAMtr.xlsx*

ii. UPM Model

The UPM models, also designed in MetrixND, forecast estimated monthly UPM as a function of twenty years of historical usage, weather conditions, indicator variables, and economic variables. Weather conditions are represented using monthly Heating Degree Days and Cooling Degree Days (definitions to follow), with a base of 65 degrees for cooling and 55 degrees for heating. In some cases, indicator variables are included in the equation to account for events in the historical period.

The table in *Attachment A-01 Independent Variables.xlsx* shows the variables that are included in each model.

The following attachments contain all UPM model and statistical information:

- *Attachment A-14 MN ResUPM.xlsx*
- *Attachment A-15 MN FarmUPM.xlsx*
- *Attachment A-16 MN SComUPM.xlsx*
- *Attachment A-17 MN OPAUPM.xlsx*
- *Attachment A-18 ND ResUPM.xlsx*
- *Attachment A-19 ND FarmUPM.xlsx*
- *Attachment A-20 ND SComUPM.xlsx*
- *Attachment A-21 ND OPAUPM.xlsx*
- *Attachment A-22 SD ResUPM.xlsx*

- *Attachment A-23 SD FarmUPM.xlsx*
- *Attachment A-24 SD SComUPM.xlsx*
- *Attachment A-25 SD OPAUPM.xlsx*

b) Class Forecasts of kWh

i. Large Commercial kWh Model

OTP modeled Large Commercial sales directly, rather than by developing a forecasted UPM and forecasted meter counts. The forecast sales are a function of twenty years of historical usage, weather conditions, indicator variables and economic variables. OTP utilized direct forecasting rather than a UPM approach because of a reclassification of commercial meters in the middle of the historical data. With so few meters in the Large Commercial class, reclassification to add additional meters distorted UPM data.

The table in *Attachment A-01 Independent Variables.xlsx* shows the variables that are included in the Large Commercial model.

The following attachments contain all Large Commercial kWh model and statistical information:

- *Attachment A-26 MN LComKWH.xlsx*
- *Attachment A-27 ND LComKWH.xlsx*
- *Attachment A-28 SD LComKWH.xlsx*

ii. Street Lighting Model

OTP forecasted Street Lighting sales directly to account for OTP's plans for installing LED fixtures in the near future. This will have a significant effect on the sales to this class. Historical data does not yet provide a long record upon which to base a statistical model of that effect. Therefore, OTP used a recent 12-month period that identified a share of fixtures that were LED to serve as a base year in a simulation of Street Lighting sales. The simulation assumes the following: (1) LED adoption reduces a fixture's usage by 75 percent; (2) LED installations occur from May through September each year; (3) the maximum LED share is 69 percent of fixtures; and (5) the share of LED fixtures will increase by 3.3 percent per month (during months when installations are happening). OTP forecasted the monthly LED shares using those assumptions. The forecast sales in each month is then simulated by adjusting the base year sales to account for the difference between the forecast and base-year LED shares.

The following attachment contains the Street Lighting forecast model:

- *Attachment A-29 Street Light Forecast.xlsx*

iii. Area Lighting Model

OTP provides lighting service under a variety of tariffs. This service can be street lighting, sales of which are accounted for in the Street Lighting class as mentioned above, or area lighting, which is included within the relevant customer class. For example, a Small Commercial business customer could take traditional service under Sections 10.01, 10.02 or 10.03 for the bulk of its electricity usage and have a parking lot light served under Section 11.07. All sales to that Small Commercial customer would be part of the Small Commercial class.

The Area Lighting forecast applies the expected growth rate of LED bulbs to historical data to calculate forecast values. This results in lower forecasted area lighting sales in 2024, with the shape of future sales being similar to what it was in the past, at a much lower level.

The method used to calculate an overall Area Light forecast is identical to what was used to calculate the Street Light forecast, with a slightly lower saturation level of 55% and at a lesser monthly installation rate of 2.3%.

The following attachment contains the model calculations for the Area Lighting forecast model:

- *Attachment A-30 Area Light Forecast.xlsx*

To assign the area light sales to the appropriate class, a ratio was developed using the last 24 months of area light sales. *Attachment A-31 kwh Area.xlsx* contains the data that was used to develop the ratios for each class. All calculations are done within the spreadsheet. This data is read into MetrixND and class area light sales are calculated and added to the appropriate class. *Attachment A-31 kwh Area.xlsx* contains the following data:

MNALL	MN - All area light sales summed across classes by year/month
MN_Ratios	MN - Area light monthly ratios by class
MN_Ratios_2_Yrs	MN - Two-year average ratio by class/month
NDALL	ND - All area light sales summed across classes
ND_Ratios	ND - Area light monthly ratios by class
ND_Ratios_2_Yrs	ND – Two-year average ratio by class/month
SDALL	SD - All area light sales summed across classes
SD_Ratios	SD - Area light monthly ratios by class
SD_Ratios_2_Yrs	SD – Two-year average ratio by class/month
kwh	Twenty years of area light sales for all classes in all states
MNRES	Twenty years of area light sales in the MN Residential Class
MNFARM	Twenty years of area light sales in the MN Farm Class
MNSCOM	Twenty years of area light sales in the MN Small Commercial Class
MNLCOM	Twenty years of area light sales in the MN Large Commercial Class
MNOPA	Twenty years of area light sales in the MN OPA Class
MN UNCL	Twenty years of area light sales in the MN Unclassified Class
NDRES	Twenty years of area light sales in the ND Residential Class
NDFARM	Twenty years of area light sales in the ND Farm Class
NDSCOM	Twenty years of area light sales in the ND Small Commercial Class
NDLCOM	Twenty years of area light sales in the ND Large Commercial Class
NDOPA	Twenty years of area light sales in the ND OPA Class
ND UNCL	Twenty years of area light sales in the ND Unclassified Class
SDRES	Twenty years of area light sales in the SD Residential Class
SDFARM	Twenty years of area light sales in the SD Farm Class
SDSCOM	Twenty years of area light sales in the SD Small Commercial Class
SDLCOM	Twenty years of area light sales in the SD Large Commercial Class
SDOPA	Twenty years of area light sales in the SD OPA Class
SD UNCL	Twenty years of area light sales in the SD Unclassified Class

3. MODEL INPUTS

a) Sales and Meter Count Historical Data

Data: *Attachment A-32 Sales and Meter Count History.xlsx*

Adjustments Made:

Monthly kWh data was checked for errors and corrected or adjusted due to meters not being billed, being billed twice in one month, etc. As further described below, any bill adjustments are applied to the month in which the billing error occurred. In most cases the corrections are found and downloaded during the next monthly update.

Detailed Information:

Historical kWh data and a meter count are read from statistical analysis software (SAS) Customer Information System / Analysis (CIS/A) datasets. The SAS datasets are created from extracts of OTP's Customer Information System (CIS) billing data, which are downloaded the first day of each month for the prior month. These datasets are also updated monthly for billing adjustments to appropriately reflect actual usage and billing details in the month of the original bill. Any changes made in OTP's CIS are also made in the CIS/A download, and the adjustments are made to the month the error occurred (as opposed to the month the adjustment was made). For example, if a meter has a bill adjustment made to their July bill, but the need for the adjustment was not determined or made in the CIS until December, the adjustment in the CIS/A dataset would adjust the July bill, not the December bill.

From the CIS/A dataset, the data is written into a totalized SAS dataset called cisa_allyrs. This dataset is an input in both the sales forecast and the revenue forecast. Each record in the dataset is assigned to one of five[5] classes used in the forecast. All kWh and meter counts for all classes used in the sales forecast are downloaded to the workbook referenced in this section (*Attachment A-32 Sales and Meter Count History.xlsx*). The data is divided into one of the following worksheets (tabs), one for each state and class:

- MNRes
- NDRes
- SDRes
- MNFarm
- NDFarm
- SDFarm
- MNSCom
- NDSCom
- SDSCom
- MNLCom
- NDLCom
- SDLCom
- MNOPA
- NDOPA
- SDOPA

[5] With Street Lighting manually forecast, they are handled separately from this process; Unclassified is also identified, but is not used in the sales forecast.

The variable UPM is created by dividing the monthly kWh by the monthly number of meters, for classes in which it is used.

b) OTP's Weather Data

Data: *Attachment A-33 Hourly Weather Data by Division.xlsx*

Adjustments Made:

OTP reviews hourly monitoring station temperatures each month after downloading the data. Any missing temperatures or temperatures that are clearly incorrect are corrected based on temperatures from other nearby monitoring points or by judgment when necessary.

Detailed Information:

OTP used twenty years of historical weather in its 2024 sales forecast (2003-2022). This weather was collected from 14 monitoring stations throughout Minnesota, North Dakota and South Dakota. OTP's service territory consists of 14 geographic divisions. There is one weather station in each of OTP's 14 divisions, so that the weather across OTP's entire service territory is well represented.

Attachment A-33 Hourly Weather Data by Division.xlsx contains the weather downloaded for these 14 weather stations. There is one worksheet for each weather station. The data in this spreadsheet is input into *Attachment A-34 HDD CDD By Division.xlsx* to calculate average dry bulb, Heating Degree Days (HDD), and Cooling Degree Days (CDD), for both calendar and billing month. The worksheets are as follows:

Table 2

Hourly Dry Bulb Values	
Worksheets	**Description**
FergusFallsHourlyDB	Hourly Dry Bulb/HDD/CDD for Fergus Falls Division
DevilsLakeHourlyDB	Hourly Dry Bulb/HDD/CDD for Devils Lake Division
JamestownHourlyDB	Hourly Dry Bulb/HDD/CDD for Jamestown Division
MorrisHourlyDB	Hourly Dry Bulb/HDD/CDD for Morris Division
OakesHourlyDB	Hourly Dry Bulb/HDD/CDD for Oakes Division
WahpetonHourlyDB	Hourly Dry Bulb/HDD/CDD for Wahpeton Division
LangdonHourlyDB	Hourly Dry Bulb/HDD/CDD for Langdon Division
RugbyHourlyDB	Hourly Dry Bulb/HDD/CDD for Rugby Division
CanbyHourlyDB	Hourly Dry Bulb/HDD/CDD for Canby Division
BemidjiHourlyDB	Hourly Dry Bulb/HDD/CDD for Bemidji Division
CrookstonHourlyDB	Hourly Dry Bulb/HDD/CDD for Crookston Division
HallockHourlyDB	Hourly Dry Bulb/HDD/CDD for Hallock Division
GarrisonHourlyDB	Hourly Dry Bulb/HDD/CDD for Garrison Division
MilbankHourlyDB	Hourly Dry Bulb/HDD/CDD for Milbank Division

Data: *Attachment A-34 HDD CDD By Division.xlsx*

Adjustments Made:

None.

Detailed Information:

This is built from the information in Attachment A-33. The UPM forecast uses HDD and CDD as inputs – values calculated from dry bulb temperatures in the weather data referenced above. The following is a definition of Heating and Cooling Degree Days from The National Oceanic and Atmospheric Administration (NOAA) (www.noaa.gov):

> Degree days are the difference between the daily temperature mean and 65°F. If the temperature mean is above 65°F, we subtract 65 from the mean and the result is Cooling Degree Days. If the temperature mean is below 65°F, we subtract the mean from 65 and the result is Heating Degree Days.

For each weather station, an average dry bulb temperature is calculated for each day. After determining that 55 degrees is a better fit to OTP's data for a baseline, the HDD are calculated by subtracting the average daily temperature from 55 degrees (the base). For example, if the average temperature for the day is 30 degrees, the HDD for that day is 25 (55-30). CDD are calculated by subtracting 65 (the base) from the average daily temperature. For example, if the average daily temperature is 70 degrees, the CDD for that day is 5 (70-65).

Table 3 lists each worksheet in *Attachment A-34 HDD CDD By Division.xlsx,* and its description/purpose. A brief overview of the HDD and CDD calculation follows.

Table 3

HDD CDD By Division	
Worksheets	**Description**
MNDailyAvgDB	MN Daily Average HDD and CDD, weighted by station
NDDailyAvgDB	ND Daily Average HDD and CDD, weighted by station
SDDailyAvgDB	SD Daily Average HDD and CDD, weighted by station
MNMeterSchedule	MN - Calculates Average HDD and CDD by individual billing cycle
NDMeterSchedule	ND - Calculates Average HDD and CDD by individual billing cycle
SDMeterSchedule	SD - Calculates Average HDD and CDD by individual billing cycle
MNMonthlyBilling	MN - Combines individual cycles into billing month HDD and CDD
NDMonthlyBilling	ND - Combines individual cycles into billing month HDD and CDD
SDMonthlyBilling	SD - Combines individual cycles into billing month HDD and CDD
MNBillingNormal20	MN - Combines 20 years of billing month HDD & CDD to create Normal HDD & CDD
NDBillingNormal20	ND - Combines 20 years of billing month HDD & CDD to create Normal HDD & CDD
SDBillingNormal20	SD - Combines 20 years of billing month HDD & CDD to create Normal HDD & CDD
MNMonthlyCalendar	MN - Combines calendar month HDD and CDD
NDMonthlyCalendar	ND - Combines calendar month HDD and CDD
SDMonthlyCalendar	SD - Combines calendar month HDD and CDD
MNCalendarNormal20	MN - Combines 20 years of calendar month HDD & CDD to create normal HDD & CDD
NDCalendarNormal20	ND - Combines 20 years of calendar month HDD & CDD to create normal HDD & CDD
SDCalendarNormal20	SD - Combines 20 years of calendar month HDD & CDD to create normal HDD & CDD

To determine the HDD and CDD for North Dakota, the weather stations in North Dakota are weighted by sales and summed.

ND Daily Heating Degree Days=
[(Station 2 Sales/Total ND Sales)*Station 2 HDD]+
[(Station 3 Sales/Total ND Sales)*Station 3 HDD]+
[(Station 5 Sales/Total ND Sales)*Station 5 HDD]+
[(Station 6 Sales/Total ND Sales)*Station 6 HDD]+
[(Station 7 Sales/Total ND Sales)*Station 7 HDD]+
[(Station 8 Sales/Total ND Sales)*Station 8 HDD]+
[(Station 11 Sales/Total ND Sales)*Station 11 HDD]+
[(Station 13 Sales/Total ND Sales)*Station 13 HDD]

ND Daily Cooling Degree Days=
[(Station 2 Sales/Total ND Sales)*Station 2 CDD]+
[(Station 3 Sales/Total ND Sales)*Station 3 CDD]+
[(Station 5 Sales/Total ND Sales)*Station 5 CDD]
[(Station 6 Sales/Total ND Sales)*Station 6 CDD]+
[(Station 7 Sales/Total ND Sales)*Station 7 CDD]+
[(Station 8 Sales/Total ND Sales)*Station 8 CDD]+

[(Station 11 Sales/Total ND Sales)*Station 11 CDD]+
[(Station 13 Sales/Total ND Sales)*Station 13 CDD]

This process is repeated for Minnesota and South Dakota.

OTP creates HDD and CDD based on billing month weather and calendar month weather. The process is as follows:

1. *Billing Month HDD and CDD:*
   Daily HDD and CDD are added by billing cycle to determine the HDD and CDD for each cycle and month. Once we have an HDD and CDD value for each cycle and month, all the cycles are combined into one billing month, averaging the cycle HDD and the cycle CDD. A HDD value and a CDD value for each billing month have now been created.

   Next, we calculate Normal Billing HDD and CDD. **These values are used in the sales forecast model.** They are calculated by averaging 20 years of monthly billing HDD and CDD.

2. *Calendar Month HDD and CDD:*
   Daily HDD and CDD are added by calendar month to calculate the HDD and CDD for each calendar month.

   Normal Calendar HDD and CDD are next calculated. **These values are used in the sales forecast.** They are calculated by averaging 20 years of monthly Calendar HDD and CDD.

OTP's sales forecast uses weather normalization principally to compare the sales forecast to weather normalized historical data. HDD and CDD are used in all models with the exception of street and area lighting. All of OTP's classes have some level of weather sensitivity.

c) Woods & Poole Economics, Inc.

Data: *Attachment A-35 Woods and Poole Data.xlsx*

Adjustments Made: None

Detailed Information:

OTP uses economic data from Woods & Poole Economics, Inc. in its sales forecasts. Woods & Poole's database contains economic and demographic data. OTP downloads this information by county for use in its meter and UPM models.

OTP does not serve the entire load in the counties within its service territory, which is especially problematic when OTP does not serve a large city (e.g. Fargo, Moorhead, Grand Forks and Minot) that has a significant impact on the economy of the county. OTP does not serve these larger cities, but it does serve small communities surrounding these larger cities. To reflect this fact, OTP used econometric data only from counties where OTP serves at least 10 percent of the population of the county. County population data is downloaded from www.census.gov. The percentage of the population served by OTP in each county was determined by dividing the sum of populations of towns served by OTP in each county by the total population of the county. Town populations were obtained from an internal database of towns served. The data is then summed to the state level and graphed as a reasonability check. Annual Woods & Poole data is converted from annual data to monthly data by interpolating between annual values with a flat line.

As OTP serves three states with economic differences, using econometric models makes it possible to utilize the different economic data for each state and determine whether particular variables are drivers for each state.

4. CALENDAR MONTH CALCULATION

Because historical usage data is, in its purest form, in billing month format, OTP created all models using billing month data. After creating billing month sales models, these models were adapted to calendar month by substituting billing month days with the calendar month days. As weather generally only affects UPM or kWh, not the number of meters, the calendar month conversion is only applied to the UPM or kWh models. To create the calendar month UPM or kWh forecasts, the calendar month HDD and CDD (from *Attachment A-34 HDD CDD By Division.xlsx*) are substituted for the billing month HDD and CDD resulting in a calendar month UPM or kWh forecast.

5. INDICATOR VARIABLES

All sales forecast models utilize indicator variables. Monthly indicator variables that account for seasonal differences are the most common. Annual indicator variables are used to account for the deviations in growth or consumption that are not expected in the test year. For example, the Residential UPM Model uses a indicator variable starting in 2011 to account for the change from a growth trend that occurred prior to a slow decline occurring after 2010. Other indicator variables were utilized as necessary to improve the fit of the model and statistical significance of the economic and weather variables. Trend variables were also used to predict sales where they were significant.

6. USE OF SALES FORECAST IN REVENUE FORECAST

As noted earlier, OTP develops sales forecasts for each class within each jurisdiction. However, to develop an accurate revenue forecast, the sales forecasts need to be allocated to a more detailed rate code level. In this manner, OTP can apply appropriate billing determinants to compute the forecasted revenues. With the Large Commercial class forecast using a kWh sales model, rather than a UPM and meter model, the forecasted meter counts for this class is created using an exponential smoothing model within MetrixND using historical meter data. Meter counts for manually forecast customers are manually added to the class meter totals. Meter counts are not required for the Area or Street Lighting classes as revenue for these classes is determined on a per fixture basis. More detail can be found in the Revenue Forecast section at B.3.b).

To allocate the forecasted sales and meters to each rate code, the most current 24 months of billing sales and meter counts for each state/year/month/revenue class/rate code and state/year/month/revenue class are summed and input into separate Excel spreadsheets for each class. A percent for each rate code in each class is calculated by state/year/month, then a two-year average of these percentages is computed.

See *Attachment A-36 Res Sales by Rate Code.xlsx* as an example of this process. The worksheets contained in this spreadsheet are found in Table 4:

Table 4

Res Sales to Rate Code	
Worksheet	**Description**
MN / ND / SD	Two years of sales by rate code, by month
MN Ratios / ND Ratios / SD Ratios	Two years of ratios per rate code, by month
MN_2_Year_Ratios / ND_2_Year_Ratios / SD_2_Year_Ratios	Average percentage of sales by month, rate code (assigned to a indicator year)
Res_Calendar Forecast	2024 monthly calendar forecast by month
Res_Calendar by Rate Code	2024 monthly calendar forecast by month, rate code

This same process is followed for each of the following classes for all kWh sales and meter counts: Residential, Farm, Small Commercial, Large Commercial and OPA. These monthly percentages are then applied to the sales and meter forecasts to allocate sales and meter counts to the rate code level.

The following attachments create the monthly sales and meter forecasts by rate code:

- *Attachment A-36 Res Sales to Rate Code.xlsx*
- *Attachment A-37 Res Meters to Rate Code.xlsx*
- *Attachment A-38 Farm Sales to Rate Code.xlsx*
- *Attachment A-39 Farm Meters to Rate Code.xlsx*
- *Attachment A-40 SCom Sales to Rate Code.xlsx*
- *Attachment A-41 SCom Meters to Rate Code.xlsx*
- *Attachment A-42 LCom Sales to Rate Code.xlsx*
- *Attachment A-43 LCom Meters to Rate Code.xlsx*
- *Attachment A-44 OPA Sales to Rate Code.xlsx*
- *Attachment A-45 OPA Meters to Rate Code.xlsx*

A similar process is used to create monthly rate code allocations for Street Light and Area Light sales using the most current 24 months of billing data. These monthly percents are then applied to the sales forecasts to allocate sales to the rate code level. Area Light sales are then added to their respective class totals. A set of worksheets for each class, similar to the Res sales example above, can be found in the following attachments:

- *Attachment A-46 ALT Sales to Rate Code.xlsx*
- *Attachment A-47 SLT Sales to Rate Code.xlsx*

This process is not necessary for the Pipeline class, as its sales and meter counts are manually added to the applicable rate code forecast.

The kWh sales forecast and meter count forecast at the rate code level are key inputs into the revenue forecast model for pricing.

The output of the sales forecast, including a meter count forecast, is found in *Attachment A-48 Sales and Meter Count Forecasts to Revenue Forecast.xlsx*. This workbook contains four worksheets. The first, titled *Sales Input to Revenue Forecast*, contains the entire non-company use sales forecast, by state and rate code. It includes the manually forecasted customers' sales. The next worksheet, *Meter Input to Revenue Forecast* contains the forecast of meter counts, by state and rate code, including manually forecasted customer meter counts. The next tab, *Manually Forecasted Customers*, contains the manually forecasted customer sales data. The Pipeline data within these worksheets goes into the revenue model to be priced separately. Finally, the last worksheet, *Unclassified* contains OTP's forecasted company use sales.

B. REVENUE FORECAST

1. OVERVIEW

Section B is a description of the process used to develop OTP's revenue forecast. The revenue forecast used up to three years of historical customer data from CIS/A and Excel workbooks containing OTP's current rate code prices, one contains light rates and the other contains all other rates. There are also four SAS programs and numerous Excel workbooks attached that provide the inputs and a transparent view of OTP's revenue model.

OTP developed its revenue forecast[6] by applying rate code pricing to the applicable billing determinants[7] derived from the sales forecast. OTP uses actual historical billing

[6] OTP forecasts retail revenue excluding small power producers.
[7] Billing Determinants are units needed for billing. OTP's billing determinants used in the revenue forecast include sales (kWh), demand (kW), ratcheted demand (ratcheted kW), and meter count.

determinants to develop demand ratios, ratcheted demand[8] ratios, and forecasted meter counts. The demand and ratcheted demand ratios are multiplied by the sales forecast to acquire the demand and ratcheted demand for each rate code. When all billing determinants at the rate code level were computed, they were multiplied by the corresponding price to compute revenues for each rate code. Subsequently, OTP rolled up the rate code level revenues to their respective cost of service class level revenues by state.

The cost of service classes are as follows:

- Residential
- Farms
- Small General Service
- Large General Service
- Irrigation
- Outdoor Lighting
- Other Public Authority (OPA)
- Controlled Service Water Heating/Deferred Load
- Controlled Service Interruptible
- Controlled Services Off Peak

Section B of this document will cover the information needed to develop the North Dakota revenue forecast.

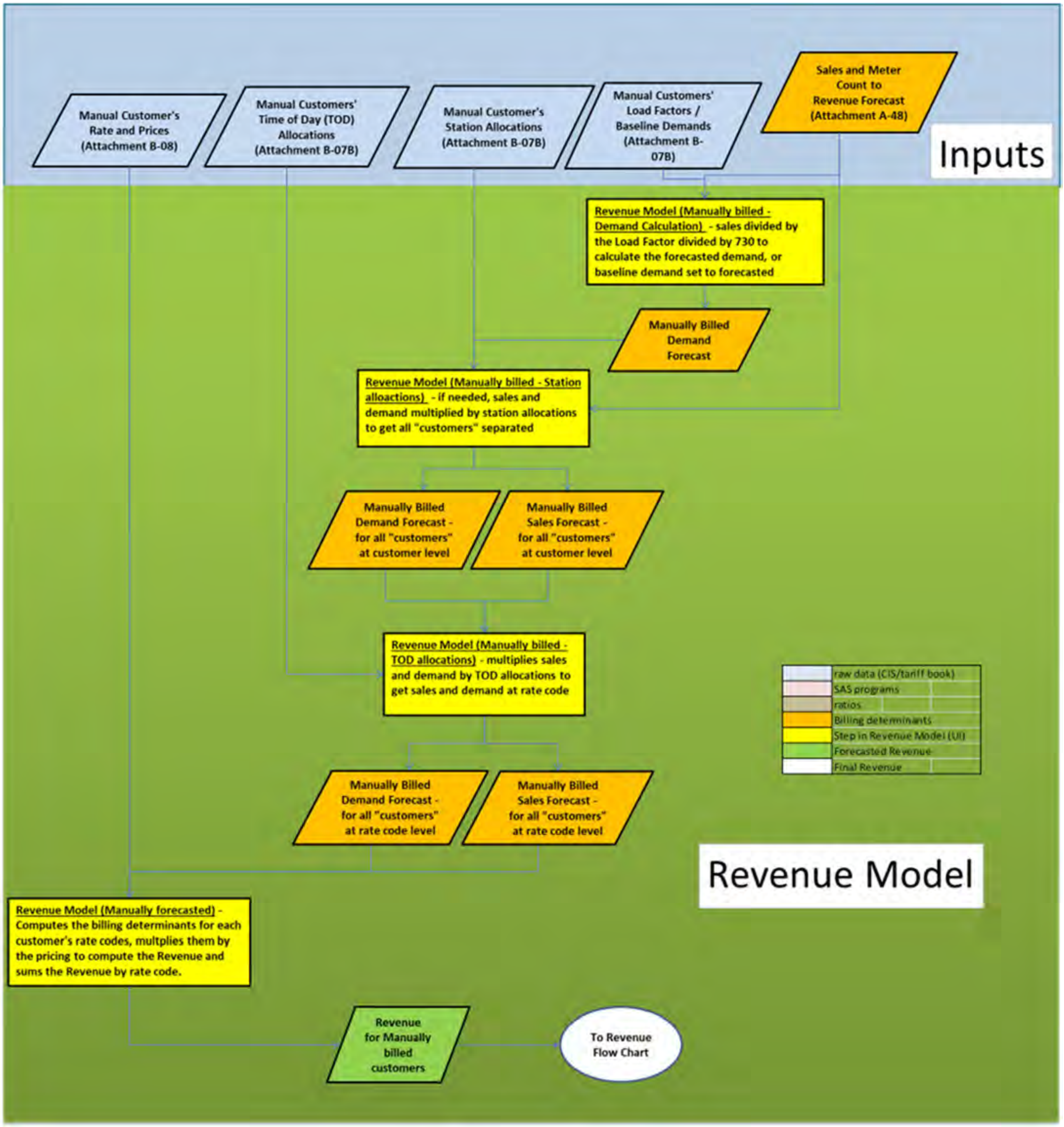
2. REVENUE FORECAST DESCRIPTION

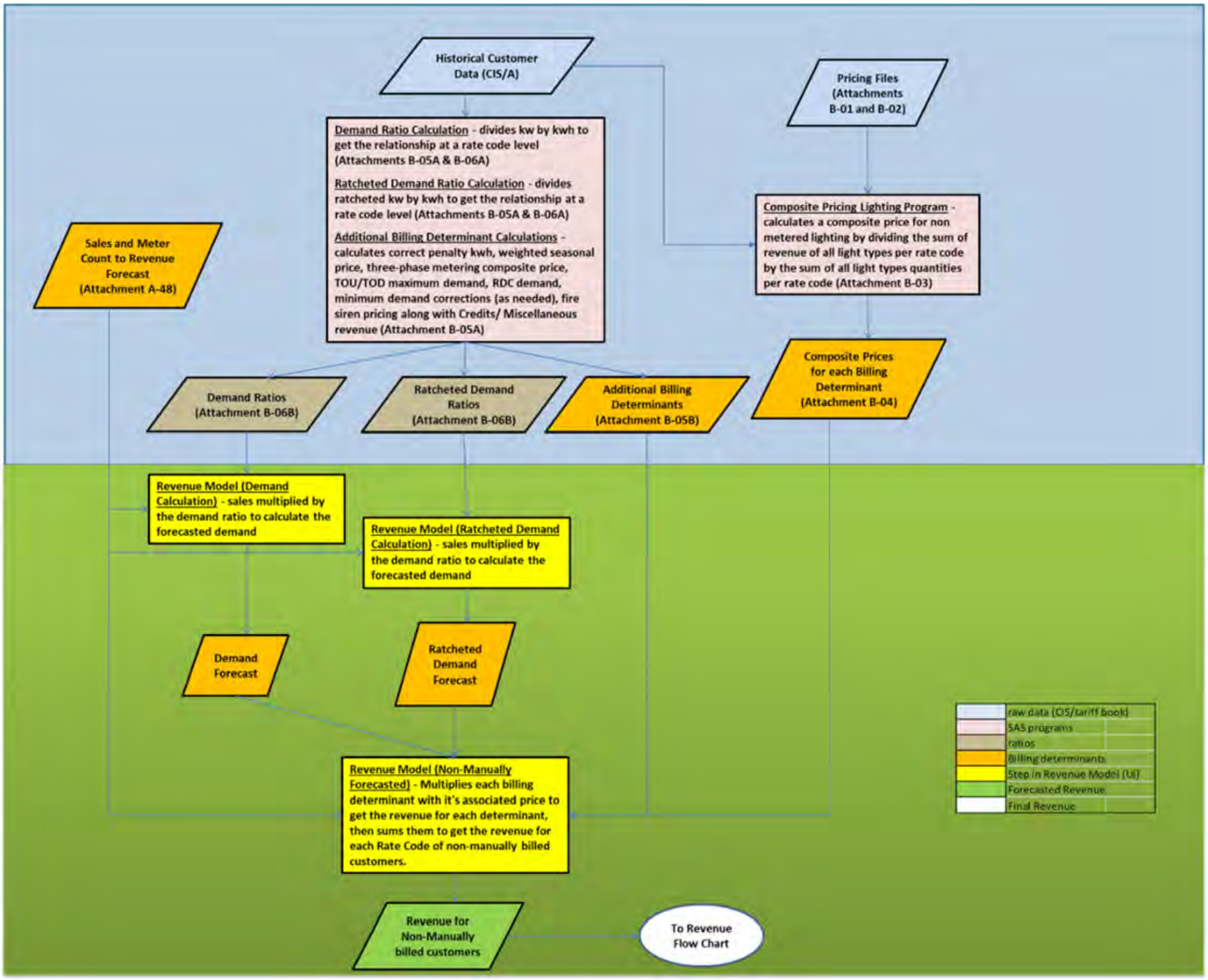
The following flowcharts describe the process OTP used to create its revenue forecast. The remainder of section B of this document is laid out in two main sections: Inputs and Revenue Model.

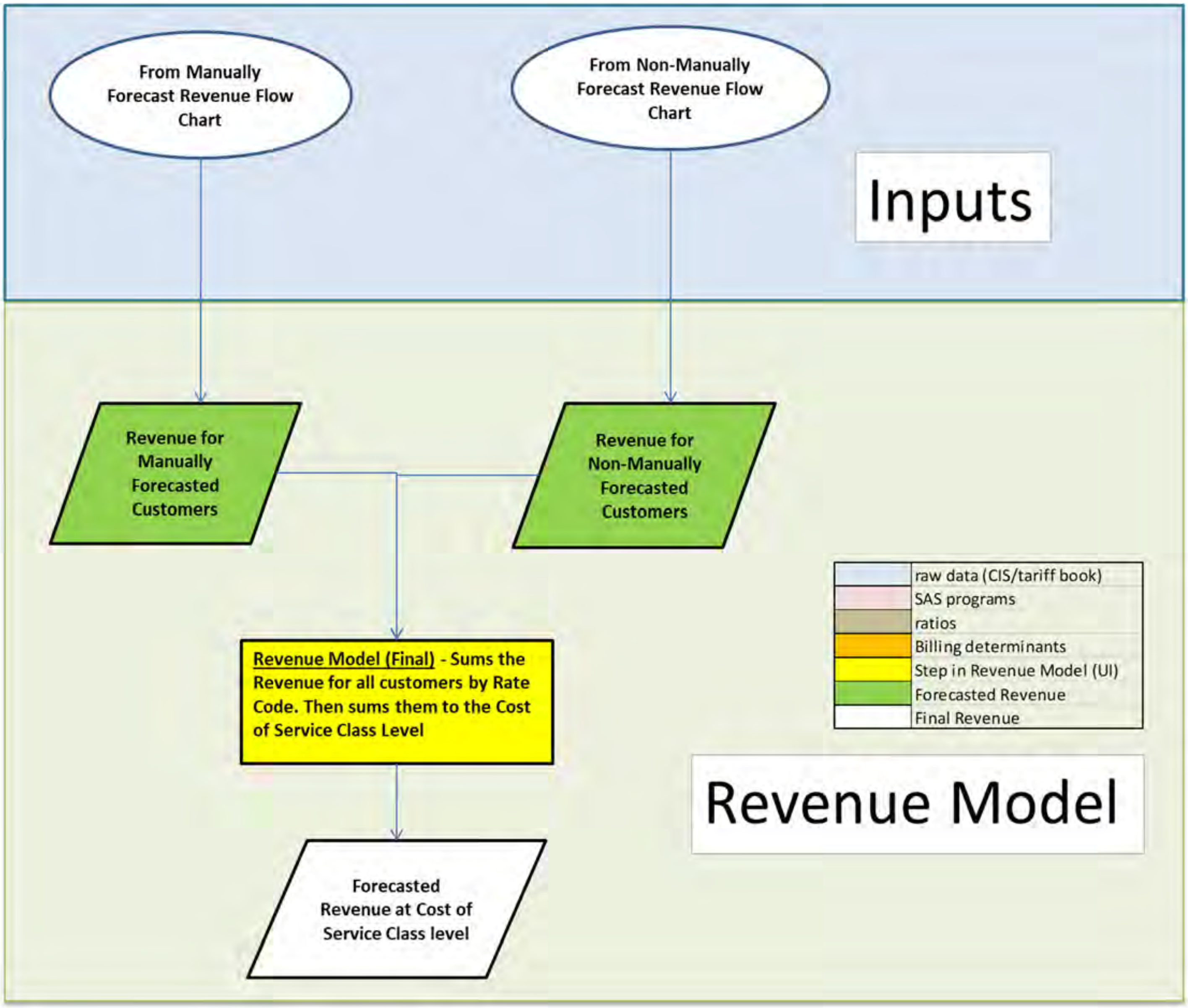
Inputs: This section explains how each input to the revenue model is calculated. The initial sections of each input can be read alone, or you can use the SAS sections as a companion to the SAS programs, which are attached in pdf format.

Revenue Model: This section is a description of OTP's revenue model and is the link between the inputs and the final revenue forecast results.

[8] Ratcheted demand is the maximum demand over the last 12 months, primarily used for calculating the facilities demand.


Inputs
Manual Customer's Rate and Prices (Attachment B-08)
Manual Customers' Time of Day (TOD) Allocations (Attachment B-07B)
Manual Customer's Station Allocations (Attachment B-07B)
Manual Customers' Load Factors / Baseline Demands (Attachment B-07B)
Sales and Meter Count to Revenue Forecast (Attachment A-48)
Revenue Model (Manually billed - Demand Calculation) - sales divided by the Load Factor divided by 730 to calculate the forecasted demand, or baseline demand set to forecasted
Manually Billed Demand Forecast
Revenue Model (Manually billed - Station alloactions) - if needed, sales and demand multiplied by station allocations to get all "customers" separated
Manually Billed Demand Forecast - for all "customers" at customer level
Manually Billed Sales Forecast - for all "customers" at customer level
Revenue Model (Manually billed - TOD allocations) - multiplies sales and demand by TOD allocations to get sales and demand at rate code
Manually Billed Demand Forecast - for all "customers" at rate code level
Manually Billed Sales Forecast - for all "customers" at rate code level
raw data (CIS/tariff book)
SAS programs
ratios
Billing determinants
Step in Revenue Model (UI)
Forecasted Revenue
Final Revenue
Revenue Model
Revenue Model (Manually forecasted) - Computes the billing determinants for each customer's rate codes, multplies them by the pricing to compute the Revenue and sums the Revenue by rate code.
Revenue for Manually billed customers
To Revenue Flow Chart


Historical Customer Data (CIS/A)
Pricing Files (Attachments B-01 and B-02)
Demand Ratio Calculation - divides kw by kwh to get the relationship at a rate code level (Attachments B-05A & B-06A)
Ratcheted Demand Ratio Calculation - divides ratcheted kw by kwh to get the relationship at a rate code level (Attachments B-05A & B-06A)
Additional Billing Determinant Calculations - calculates correct penalty kwh, weighted seasonal price, three-phase metering composite price, TOU/TOD maximum demand, RDC demand, minimum demand corrections (as needed), fire siren pricing along with Credits/ Miscellaneous revenue (Attachment B-05A)
Composite Pricing Lighting Program - calculates a composite price for non metered lighting by dividing the sum of revenue of all light types per rate code by the sum of all light types quantities per rate code (Attachment B-03)
Sales and Meter Count to Revenue Forecast (Attachment A-48)
Demand Ratios (Attachment B-06B)
Ratcheted Demand Ratios (Attachment B-06B)
Additional Billing Determinants (Attachment B-05B)
Composite Prices for each Billing Determinant (Attachment B-04)
Revenue Model (Demand Calculation) - sales multiplied by the demand ratio to calculate the forecasted demand
Revenue Model (Ratcheted Demand Calculation) - sales multiplied by the demand ratio to calculate the forecasted demand
Demand Forecast
Ratcheted Demand Forecast
Revenue Model (Non-Manually Forecasted) - Multiplies each billing determinant with it's associated price to get the revenue for each determinant, then sums them to get the revenue for each Rate Code of non-manually billed customers.
Revenue for Non-Manually billed customers
To Revenue Flow Chart
raw data (CIS/tariff book)
SAS programs
ratios
Billing determinants
Step in Revenue Model (UI)
Forecasted Revenue
Final Revenue


From Manually Forecast Revenue Flow Chart
From Non-Manually Forecast Revenue Flow Chart
Inputs
Revenue for Manually Forecasted Customers
Revenue for Non-Manually Forecasted Customers
raw data (CIS/tariff book)
SAS programs
ratios
Billing determinants
Step in Revenue Model (UI)
Forecasted Revenue
Final Revenue
Revenue Model (Final) - Sums the Revenue for all customers by Rate Code. Then sums them to the Cost of Service Class Level
Revenue Model
Forecasted Revenue at Cost of Service Class level

3. INPUTS

Several inputs to the revenue model are necessary in order to calculate the revenue forecast. They include: (1) forecasted sales; (2) composite pricing for lighting; (3) demand ratios; (4) ratcheted demand ratios, (5) additional billing determinants, (6) forecasted meter counts; and (7) manually forecasted customer inputs.

a) Forecasted Sales

The sales forecast[9] described above in section A is the foundation for the revenue forecast. The sales forecast is provided at the rate code level by state for all non-manually forecasted customers. Once the state/month/rate code level forecasted sales were computed (see section A.6.), they were input into the revenue model. The manually forecasted customers' sales were also input into the revenue model, however at the customer level.

b) Composite Pricing (CP) for Lighting

To compute the revenue forecast for lighting, allocation of the sales forecast to rate code level is necessary, due to different types of fixtures per rate code (*Attachment A-48 Sales Forecast to Revenue Forecast.xlsx*). To develop actual pricing derived by rate design, the rate codes were allocated to their most granular level of fixture types per rate code.

Consequently, to compute each rate code's revenue forecast, each rate code needs a weighted composite rate to price the sales at the rate code level. Since OTP is converting lighting fixtures from non-LED to LED, OTP uses the frequencies of fixture kinds to compute the composite rates based on the most current calendar month of CIS/A data, starting at a customer level and building up to rate code level based on each customer's fixture type(s), fixture replacement allocations and fixture kWh allocations. OTP used one full calendar year of historical data to reflect the usage trends of current lighting customers with kWh charges. This program excludes the manually forecasted customers from the sales forecast and the non-lighting customers from the CP process.

This program excludes the manually forecasted customers from the sales forecast.

The CP Lighting SAS program develops the following composite billing determinants:

- fixture charges (N730, N741, N749)
- kWh charges (N408, N744, N748)
- fixture counts (N730, N741, N749)
- kWh sales (N408, N744, N748)

[9] Calendar month sales are used to compute the Revenue Forecast.

The SAS program and Excel workbook that create the composite rates (*Attachment B-03 Annual_Lighting_Counts.pdf* and *Attachment B-04 Composite Pricing_Lighting.xlsx*) is described in more detail below.

SAS Program: CP Lighting

The CP Lighting program (*Attachment B-03 Annual_Lighting_Counts.pdf)* imports one year of customer billing data from the CIS/A database. We assign rate code fixtures to each customer based on their rate code and fixture counts. All manually forecasted customers are excluded from the customer billing data. The Excel workbooks *Attachment B-01 Rates.xlsx and Attachment B-02 Light Rates.xlsx* contain the pricing and is used to determine what billing determinants are needed to calculate the revenue for each rate. From this, the program determines any necessary tier thresholds and splits the kWh or fixture counts accordingly. The program uses one year of customer data and was summed by state/month/rate code/fixture type, as well as by state/month/rate code. The billing determinants for each fixture type were then multiplied by the appropriate fixture's pricing schedule. Then the total one-year revenue for each determinant was divided by the corresponding rate code determinant resulting in the weighted rate code price. OTP sums the weighted fixture price to the rate code level composite price, exports them from the SAS program and includes them in *Attachment B-04 Composite Pricing_Lighting.xlsx*. These prices are imported into the revenue model.

c) Demand Ratios

The Business Planning Department provides a kWh sales forecast for each rate code. For pricing purposes we also need to compute a forecasted demand amount. Using SAS (*Attachment B-05A Billing Determinant Ratio Calculations_Not_Public.pdf)*, a ratio is developed at a state/month level to relate historical kWh to kW. The demand ratio is determined based on three years of CIS/A data, starting at the customer level and building up to rate codes, regardless of their revenue class. This still allowed OTP to factor in some degree of weather normalization. The forecasted demand is calculated, via SAS (*Attachment B-06 Demand_Ratcheted Demand_ratio_Not_Public.pdf),* by multiplying the forecasted sales by the calculated ratio per state/month/rate code. The manually forecasted customers from the sales forecast are handled differently and are excluded from these programs. The details within the SAS program for the Demand Ratios is described in more detail below.

SAS Program: Demand Ratios

The SAS program, *Attachment B-05A Billing Determinant Ratio Calculations_Not_Public.pdf*, imports three years of individual customer historical data and assigns each customer to a rate code. It also imports *Attachment B-01 Rates.xlsx* to determine if kW is needed for billing and if there is a minimum kW. The manually forecasted customers are excluded from this program. If a customer is on the Residential Demand Control (RDC) rate, then the ratcheted kW is set to the kW, since the billing demand is a coincident demand and functions like a ratcheted kW. If a rate requires kW, the actual kW is compared to the minimum kW, and the greater of the two is used in the customer's bill. This is needed since the CIS/A data records actual (not billing) kW, and for pricing we need to have the entire amount of billing kW. The kWh and kW are summed by state/year/month/rate code for three calendar years of data. The summed kW is then divided by the summed kWh to get the demand ratios for each state/year/month/rate code. Once we have every year's ratios, the average ratio is found and exported from the SAS program (*Attachment B-005B Billing Determinant Ratios_ND_Not_Public.xlsx*). With the Irrigation rate having highly fluctuating customer counts in the months from November through April, the average of the other months is found and applied to these months. The rate code level demand ratios are imported into the revenue model.

d) Ratcheted Demand Ratios

Along with the kWh and kW, ratcheted kW is also needed for pricing. Using the same SAS program that is used to calculate the demand ratios, (*Attachment B-05A Billing Determinant Ratio Calculations_Not_Public.pdf)*, a ratio is developed at the state/month level to relate historical kWh to ratcheted kW. It is based on three years of CIS/A data, starting at a customer level, and building up to rate codes regardless of revenue class combination. This still allowed OTP to factor in weather normalization. The forecasted ratcheted demand is calculated, via SAS (*Attachment B-06 Demand_Ratcheted Demand_ratio_Not_Public.pdf),* by multiplying the forecasted sales by the calculated ratcheted demand ratio per state/month/rate code. The manually forecasted customers from the sales forecast are handled differently and are excluded from these programs. The SAS program for the Ratcheted Demand Ratios is described in more detail below.

SAS Program: Ratcheted Demand Ratios

The SAS program imports three years of individual customer historical data and assigns each customer to a rate code. *Attachment B-01 Rates.xlsx* is also imported to determine if the ratcheted kW is needed for billing (primarily used for calculating the facilities charge) and if there is a minimum ratcheted kW. The manually forecasted customers are excluded from this program. If any rate requires a ratcheted kW, the ratcheted kW is compared to the minimum kW, and the greater of the two is used in the customer's bill. This is needed since the CIS/A data records actual (not billing) kW, and for pricing we need to have the entire amount of billing kW. Due to the ratcheted kW being the maximum kW over a 12-month period, the maximum kW for all rate codes on a Time of Use (TOU)/Time of Day (TOD) rate must be found and the others deleted. Therefore, if a customer is on a TOU/TOD rate, the maximum ratcheted kW is found among the multiple rate codes for each customer's monthly bill.

Once we have the maximum for each customer's monthly bill, if the corresponding rate code's ratcheted kW for that month is not the max, it is set to zero. Then the kWh and ratcheted kW are summed by state/month/rate code for reporting purposes. The kWh and ratcheted kW are summed by state/year/month/rate code for three calendar years of data. The summed ratcheted kW is divided by the summed kWh to get the ratcheted demand ratios for each state/year/month/rate code. Once we have every year's ratio, the average ratio is found and exported from the SAS program (*Attachment B-005B Billing Determinant Ratios_ND_Not_Public.xlsx*) to be imported into the revenue model.

e) Additional Billing Determinant Calculations

Some additional billing determinants are needed for the final revenue calculation in order to determine the correct prices or calculate accurate revenue. *Attachment B-05A Billing Determinant Ratio Calculations_Not_Public.pdf* provides the calculations for these determinants and Attachment B-05B Billing Determinant Ratios_ND_Not_Public.xlsx contains the results. They are listed below with detailed descriptions to follow.

- (1) Penalties
- (2) Seasonal Charges
- (3) Three-Phase Metering
- (4) Time of Use/Time of Day Rates (TOU/TOD)
- (5) Residential Demand Control Demand
- (6) Minimum Billing Demand/Facilities Demand
- (7) Fire Sirens
- (8) Credits/Miscellaneous

(1) Penalties

Rates for certain customers, such as large and small dual fuel customers, include penalty rates that are assessed when there is measured usage during a period in which the customer is intended to fully shed its load. This could happen when the customer's system fails to respond to a control signal and/or completely shed its load when control is initiated. These customers have a separate penalty register on their meters, so if the customer has usage during the penalty period, the kWh is counted on both the regular register and the penalty register and the data stored in the CIS system for billing purposes.

Adding both kWh values would result in double-counting the total kWh. Therefore, we first subtract the penalty kWh value from the regular kWh value to determine the appropriate kWh to charge at the standard (non-penalty) price. Since the kWh on the penalty meter is charged at the standard price as well as the penalty price, we add the standard rate price to the penalty rate price in *Attachment B-01 Rates.xlsx* before calculating the penalty kWh price.

(2) Seasonal Charges

There are various rates where customers have the option for seasonal usage. This allows customers to receive a bill only in the months they are active, rather than all year. To recover the customer charges that the customer would incur during their inactive months, a seasonal charge is applied to their first bill each year. The pricing workbook (*Attachment B-01 Rates.xlsx*) is used to determine if a seasonal charge is applicable to each rate. If it is, the first bill for each of the seasonal customers is found, and for each month the number of first bills is counted by state/month/rate group/rate code. The number of customers on any rate is counted by state/month/rate group. The number of seasonal customers for each rate code is divided by the number of all customers in that state/month/rate group level to get the percentage of seasonal customers with their first bill in each month. That percentage is then multiplied by the fixed seasonal charge to get the weighted seasonal price for each month and is exported with the other weighted prices. This is added to the customer charge weighted price before it is imported into the revenue model.

(3) Three-Phase Metering

OTP's Farm rate has a facility charge that is based on either single-phase metering or three-phase metering. *Attachment B-01 Rates.xlsx* is used to determine if three-phase charges are applicable. Using three years of historical data, all three-phase service customers are counted by state/month/rate group/rate code/tier. In addition, a count of all customers (single-phase and three-phase) is determined by state/month/rate group/rate code. The three-phase customer count is multiplied by the corresponding price and then divided by the total customer count for the rate code. This is the composite rate that will be used in the final revenue forecast calculation.

(4) Time of Use/Time of Day Rates

TOU/TOD rates have differing rates based on the time of the customer's usage. Because the TOU/TOD rates have multiple registers on their meter, one for each TOU/TOD rate code, and all the registers together account for the total usage for a single day. The ratcheted demand, which is needed in order to calculate the facilities demand, needs to be the maximum of the multiple registers. For each customer, we determine the maximum ratcheted kW for each division/premise/bill date/meter number.[10] If the ratcheted kW does not equal the maximum ratcheted kW for each rate code, it is set to zero, leaving only the maximum ratcheted kW. A variable is created to identify if the ratcheted kW was set to zero so that it will not be overridden when the minimum demand is applied, described below (Minimum Billing Demand/Facilities Demand).

(5) Residential Demand Control Demand

Customers on the RDC rate have their ratcheted kW set to the billing kW, since the billing demand functions like a ratcheted kW.

(6) Minimum Billing Demand/Facilities Demand

OTP has several rates where a minimum demand is required. *Attachment B-01 Rates.xlsx* is input to identify what the minimum kW or ratcheted kW is for each rate code, if any. If the actual kW or ratcheted kW is less than this minimum requirement, the actual kW or ratcheted kW is replaced by the minimum required amount.[11] This is necessary because CIS/A data contains actual kW and ratcheted kW, not billing kW or billing ratcheted kW.

(7) Fire Sirens

The Fire Sirens price is based on horsepower (HP) rather than kWh. These are set up in CIS as area light types, and a separate type is created for each HP. Thus, in *Attachment B-02 Light Rates.xlsx,* each siren size has its own price with the customer charge added to the per HP amount since the customer charge is by siren. These are handled below in section (8) Credits/Miscellaneous.

---

[10] That calculation must occur at the meter level because it is possible for a customer to have multiple TOU/TOD rates, however for each rate sequence (ex. M611) the meter number is the same followed by a suffix – which for this program's purposes are deleted.

[11] Only the maximum TOU/TOD rate code for the ratcheted kW are included to avoid overriding the non-maximum ratcheted kW being set to zero on page 28, section (4) Time of Use/Time of Day (TOU/TOD) Rates.

(8) Credits/Miscellaneous

OTP has rates and credits that are not based on metering consumption. They are the Air Conditioning credit, Water Heating credit, Closed Non-Standard Lighting, Fire Sirens and Tail*W*inds (wind energy). Since these rates are not directly based on metered kWh, they are handled differently in the program. The program identifies customers on these rates and sums up the quantity by state/month/rate code of three years of historical data. To get the quantity for Tail*W*inds, the kWh is first divided by 100 since the price they pay is per 100 kWh. The total quantity by state/month/ rate code is multiplied by the price for that rate code to get the total revenue for that rate code. Once we have the total Credits/Miscellaneous revenue it is exported from the SAS program and imported into the revenue model and added to the calculated revenue for the non-manually forecasted customers.

f) Meter Count Forecast

A meter count is needed to calculate the fixed charges such as a fixed facilities charge, seasonal charge or customer charge. OTP forecasts meter counts, excluding manually forecasted customers, for each state/class/year/month within MetrixND using a combination of historical meter counts, economic data and indicator variables as described in detail in Sections A.2. to A.5. above. The noted attachments, specific for meters, provide information of the modeling inputs and results. Section A.6. describes how the meter forecasts are divided into the proper rate code designation. *Attachment A-48 Sales and Meter Count Forecasts to Revenue Forecast.xlsx* contains the forecast of meter counts, by state and rate code, including manually forecasted customer meter counts.

The resulting forecasted meter counts are imported into the revenue model.

g) Manually Forecasted Customer Inputs

As described in the sales forecast, OTP has some manually forecasted customers. The sales for these customers are imported into the revenue model separately from the rest of the sales. The revenue forecast for these customers is calculated manually, as well. To calculate the revenue for the manually forecasted customers we use the following inputs for each customer:

- Forecasted sales
- Estimated load factor or baseline demand
- Station allocation (if they have multiple stations - used for a Pipeline Customer)
- Time of Day allocation (if they are on a TOD Rate)
- Pricing for each necessary rate code’s billing determinant

These inputs, excluding pricing, are based on historical data, and are modified based on information obtained from customers themselves.

SAS Program: LF and Allocations

The SAS program (Attachment B-07A LF and Allocations_Not_Public.pdf) imports three years of individual customer historical data and assigns each manually forecasted customer a weighted average load factor, Time-of-Day allocations, where applicable, and the percent of usage distribution per Enbridge station in Minnesota. The load factor is calculated by dividing the usage by the product of demand and total number of hours in a given period. The Time-of-Day allocations determine the percentage of usage in the three TOD periods of On-Peak, Mid-Peak and Off-Peak. The percent of usage distribution displays the proportion of usage between the Minnesota Enbridge stations. The results are exported to an Excel file (Attachment B-07B LF and Allocations_Not_Public.xlsx).

4. REVENUE MODEL

Once all the inputs have been determined, they are imported into the revenue model. The manually forecasted customers' revenue is computed by customer/year/month, and the non-manually forecasted customers' revenue is computed by state/year/month/rate code. They are added together, along with the Credit/Miscellaneous revenue, at a state/year/month/rate code level. The rate code revenues are then summed to the 10 classes corresponding to the cost of service study. The calculations are discussed in more detail below.

a) Manually Forecasted Customers

The manually forecasted customers' forecasted sales, load factor/baseline demand, station allocations, time-of-day allocations, system marginal energy pricing (SMEP) allocations, and price for each billing determinant are imported into the revenue model. If the account has a load factor charge, their monthly sales is divided by the load factor divided by 730 resulting in the kW for each customer.[12] If the customer has a baseline demand, it is used as the kW. **[PROTECTED DATA BEGINS…**

… PROTECTED DATA ENDS]

If the customer is on a Time of Day rate, the Time of Day allocator is multiplied by the customer's total sales to get the sales for each rate code. If the customer has elected SMEP, the rate code sales are multiplied by the appropriate baseline and incremental

[12] 730 is the number of hours in the average year divided by 12 to get the average number of hours in a month.

percentages to determine the baseline and incremental sales. The demand also has a Time of Day allocator which is handled in the same manner as the kWh; however, if the customer has a baseline, the demand allocators are set to 100 percent since the baseline is the same for all hours of the day. If a facilities (ratcheted) kW is needed for the account, the annual maximum kW for the test year is found and applied to each month for that year as the ratcheted kW.[13] Thus for each account, we now have the kWh, kW, and ratcheted kW for each of the customer's rate codes. Each rate code is multiplied by the corresponding price and summed by determinant and then by customer.

b) Non-Manually Forecasted Revenue

Once the sales, demand ratios, ratcheted demand ratios, pricing and meter forecasts are imported into the revenue model, a series of calculations take place to find the revenue for each rate code. The state/month/rate code level kWh is first multiplied by both the corresponding demand ratios and the ratcheted demand ratios. This will give the needed billing kW and ratcheted kW for each rate code. Thus, we now have all the forecasted billing determinants for each rate code. The pricing files (*Attachment B-01 Rates.xlsx and Attachment B-04 Composite Pricing_Lighting.xlsx*) contains monthly prices for the following: kWh tier 1, kWh tier 2, kW, facilities kW tier 1, facilities kW tier 2, fixed facilities charge, and customer charge. Then the following calculations are made by state/year/month/rate code:

Tier 1 kWh revenue	= kWh tier 1 charge*Forecasted kWh
Tier 2 kWh revenue	= kWh tier 2 charge*Forecasted kWh
kW revenue	= kW charge*Forecasted kW
Tier 1 ratcheted kW revenue	= Facilities kW tier 1 charge*Forecasted ratcheted kW
Tier 2 ratcheted kW revenue	= Facilities kW tier 2 charge*Forecasted ratcheted kW
Fixed facilities revenue	= Fixed facilities charge*Forecasted meter count
Customer revenue	= Customer charge[14]*Forecasted meter count

Once each of these pieces has been calculated, the Credits/Miscellaneous revenue is added into their respective state/year/month/rate code resulting in the non-manually forecasted customer revenue.

As the last step of the Revenue Forecast, the non-manually forecasted customer revenue and manually forecasted customer revenue are summed by rate code, and then to the cost of service class revenue by state.

---

[13] This is not a "true" ratchet as the value may be pulled from a future month.
[14] At this point the customer charge includes both the customer charge and the annual seasonal charge.

C. METER TO CUSTOMER TRANSLATION

The test year sales forecast in OTP's last rate case was based on Use Per Customer (UPC) models. This required OTP to develop forecasts for the number of customers and then develop a process to translate customers to meters because pricing is done at the meter, not customer level. OTP has since changed its sales forecasting process to utilize UPM in the sales forecast, thereby avoiding the need to translate customers to meters when moving from the sales forecast to the revenue model. OTP does still use customers in the development of allocation factors.