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Form 4 Demand Forecast Methods and Models

Form 4 is for LSEs to document the electricity demand forecast methods, models, and data used to develop the submitted forecast forms. LSEs may include existing forecast model reports as an appendix to this form if this report includes the following required information.

LSEs should begin Form 4 by defining the area for which the forecast is developed identifying isolated loads and resale customers and describe how they are included or excluded from the forecast. Provide definitions of customer classes, including which rate classes are included in the categories for which forecasts are submitted.

Each of the rate classes for MID's customer consumption is described as follows:

Residential- This schedule is applicable to individual family accommodations devoted primarily to residential, household and related purposes (as distinguished from commercial, professional and industrial purposes), to general farm service on a farm, where the residence on such farm is supplied through the same meter, and to public dwelling units. Service to public dwelling units for residential occupancy is limited by special provisions described in the rate tariff.

Commercial- This schedule is applicable to general commercial customers having a demand of 1,000 kilowatts or less and multiple units for residential occupancy. Service to public dwelling units for residential occupancy is limited by special provisions described in the rate tariff. A demand rate schedule is applied to those customers that are greater than 20 kilowatts. A voluntary time of use rate schedule is also available to commercial customers with a 12 month period of an instantaneous demand of 500-1,000 kilowatts.

Industrial- This schedule is applicable to industrial customers having demands of 1,000 kilowatts or greater in any month during the previous twelve months. For customers above 25,000 kilowatts, a separate industrial rate is available.

Agriculture- This schedule is applicable to separately metered water well pumping, reclamation service, and farm use. Lighting and farm use will be provided to the extent permitted by special provisions as described in the rate tariff. This schedule does not apply to commercial food or agricultural processing operations, machine shops, or any other service not connected with the individual farm operations.

Public Lighting- This Schedule is applicable to all night lighting on the public streets, alleys, highways and parks for cities, lighting districts or other public bodies.

Following is an excerpt from MID's Integrated Resource Plan (Chapter VI) which describes MID's Long-Term Demand and Energy Forecast (LTDEF) used in this IEPR submittal. This narrative addresses the topics of discussions requested for the 2019 IEPR's Form 4 and Form 6.

Energy Demand and Peak Forecasts

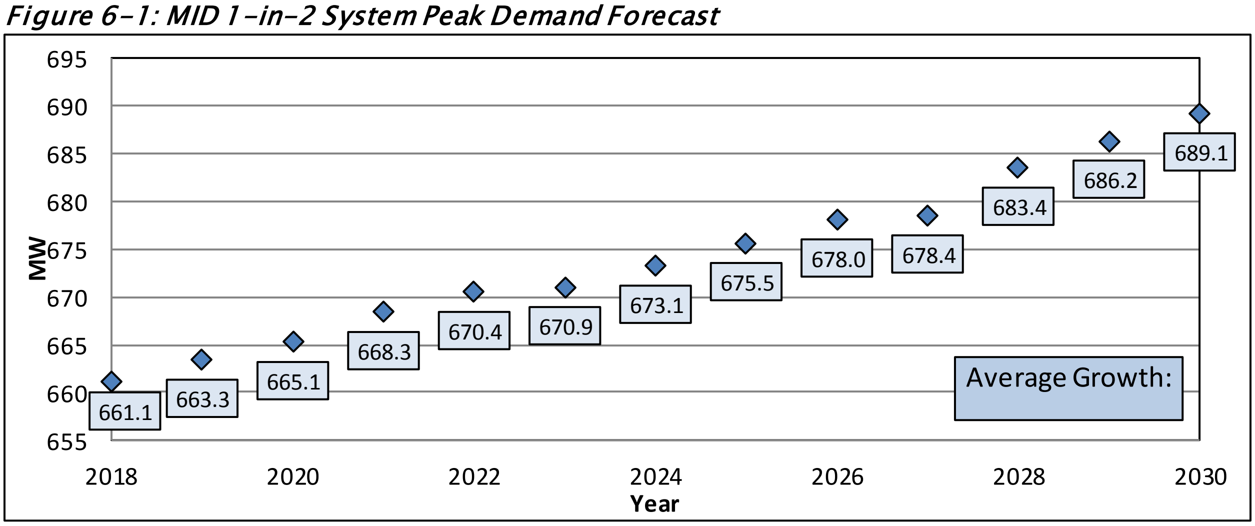
Overview of IRP Energy and Peak Forecasts

POUs are required to address Energy Demand and Net Peak Forecasts in the IRPs adopted and submitted to the Energy Commission pursuant to SB 350. MID is the sole load serving entity of the greater Modesto area (north of the Tuolumne River, Waterford and Salida); and has been serving load in the northern expansion area, defined as "a 400 square mile area in Southern San Joaquin County, Northern Stanislaus County, and Western Tuolumne County", often referred as "four-city area" "including Ripon, Escalon, Oakdale and Riverbank", on a competitive basis, since 1996. Additionally, MID has been the sole load serving entity in the community of Mountain House since 2001. MID is also a non-exclusive load serving entity for load migrated to the northern expansion area, referred as "Greenfield load", since 2007. The MID in-house 2018 Long-Term Demand and Energy Forecast (LTDEF) for the MID region and out of MID territory cities (OFT) serves as the input for determining the POU's resource procurement needs. This chapter includes discussion of the methodology, assumptions, and data used to create the Energy Demand and Peak Forecasts. The forecast horizon is from 2018 through 2030.

MID's Energy Demand and Peak Forecasts are based on a set of econometric models describing the hourly load in the region as a function of a number of weather variables (e.g., surface temperature, solar irradiance level), calendar variables (e.g., day of week, holidays), and demographic variables (e.g., labor force data). The LTDEF utilizes regional demographic data obtained from the U.S. Department of Labor. The weather data utilized in the LTDEF is thirty years of historical weather data provided by the Weather Company for two weather stations. This LTDEF also incorporates demand side forecast models, which include projections for customer solar, energy efficiency and electric vehicle charging.

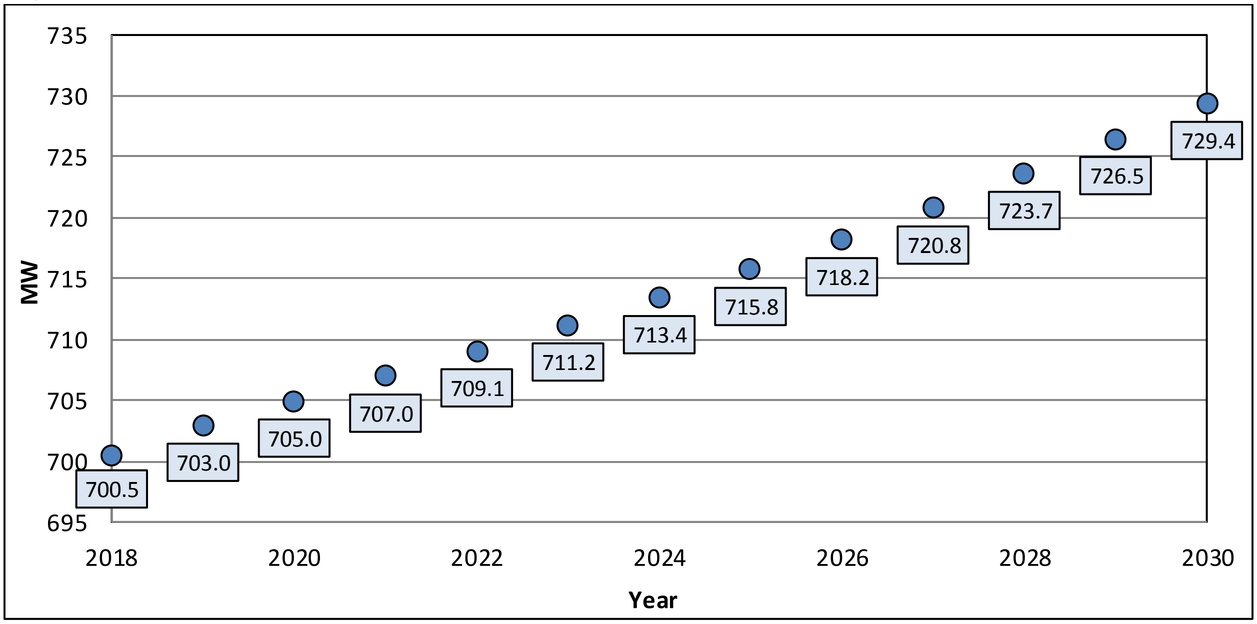
Overview of Forecast Results

Figure 6-1: MID 1-in-2 System Peak Demand Forecast



As shown in Figure 6-1, the 2018 LTDEF projects a system 1 in 2 non-coincident peak[1] demand growing at an average annual rate of approximately 0.4% from 2018 to 2030. Historically, peak demand annual growth rate was 0.8% from 2008-2017. The slower growth rate from 2018 to 2030 is mostly attributable to a slower annual growth in demographic variables.

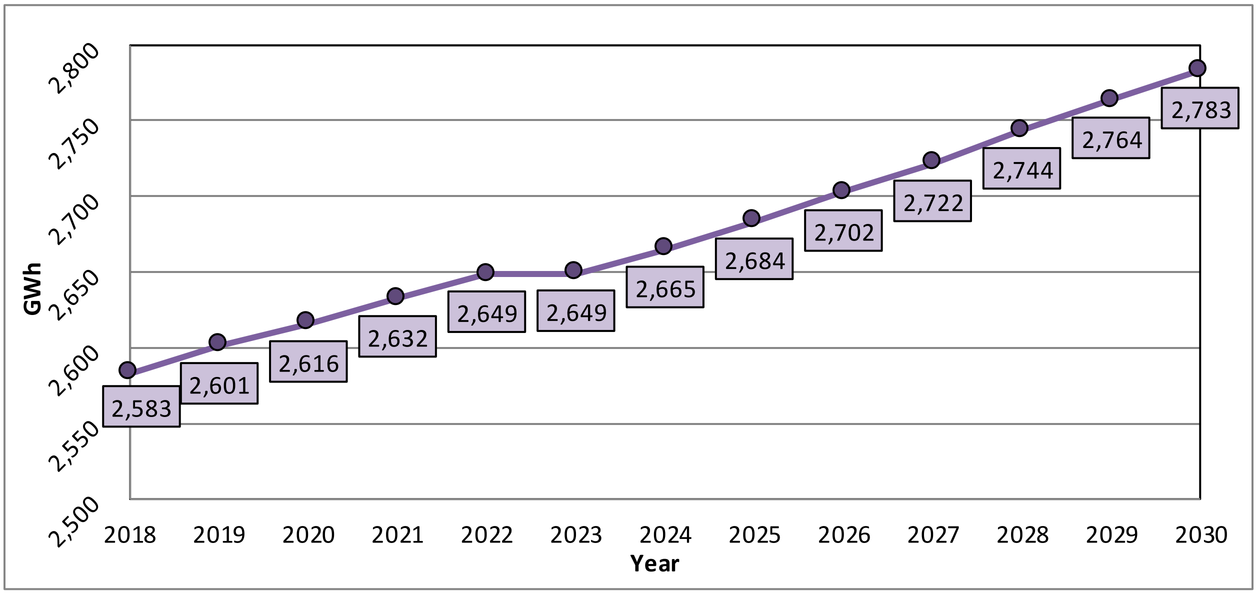
Figure 6-2: MID 1-in-10 System Peak Demand Forecast



As shown in Figure 6-2, the 2018 LTDEF projects a system 1 in 10 non-coincident peak demand growing at an average annual rate of approximately 0.3% from 2018 to 2030.

[1] Non-coincident Peak: MID regional peak usually does not coincide with statewide peak. MID forecasts its own peak demand irrespective of coincidence to statewide demand.

Figure 6-3: MID Forecasted Energy Requirement



As shown in Figure 6-3, the 2018 LTDEF projects system energy growing at an average annual rate of approximately 0.6% from 2018-2030. Historically, the annual energy growth rate was -(0.2)% from 2008-2017. The energy forecast grows at a quicker pace compared to Peak Demand mostly due to the regional economic recovery post 2014 and its impact to energy consumption.

2018 LTDEF Methodology and Assumptions

This chapter provides a high level overview of the 2018 LTDEF. The assumptions and methodology discussed in this chapter depict MID's current understanding of the region, the regulations and technology developments and their impacts to energy consumption. Later chapters in this IRP present a comparison of earlier long term energy forecasts and the 2018 LTDEF. This chapter focuses on the 2018 LTDEF.

Modeling Framework

The 2018 LTDEF is a linear regression model. The model accounts for the impacts of weather, economics, demographics and seasonal trends. The 2018 LTDEF also incorporates demand side forecasts including hourly photovoltaic, energy efficiency, and electric vehicle projections. Impacts from existing interruptible and demand response programs to the energy and peak demand forecast are not modelled in the 2018 LTDEF. Those resources are dispatchable and are instead considered part of MID's resource mix.

The MID LTDEF is comprised of load from two geographic regions: MID base territory and MID OFT. Forecasts for both territories share a similar methodology.

The LTDEF model building process consists of four steps:

- Variable selection

- Econometric model building
- Weather scenario building
- Model results adjustments

Model Variable Selection

The LTDEF was developed using a combination of the following variables. While each of these variables was considered, the final model was based only on the most statistically relevant variables.

- Weather Variables
  - Surface Temperature
  - Solar Irradiance
  - Rainfall (not used in the final model)
  - Humidity (not used in the final model)
  - Lagged Temperature (1-4 hours)
  - 24 Hour Temperature Moving Average

- Economic and Demographic Variables
  - Labor Force Data
  - Inflation (not used in the final model)
  - Population (not used in the final model)
- Categorical Variables
  - Month
  - Day Type (day of week, holiday)
  - Hour
- Cross-Reference Variables
  - Temperature and Hour
  - Temperature and Month
  - Lagged Temperature and Hour
  - Lagged Temperature and Month
  - 24 Hour Temperature Moving Average and Hour
  - 24 Hour Temperature Moving Average and Month
  - Hour and Day Type
  - Hour and Month

Econometric Model Building Process

During the model building process, historical hourly demand, temperature, economic and demographic data from 1/1/2008 – 12/31/2017 were used. All variables were tested and evaluated. Only statistically significant variables were selected to build the econometric model.

The initial stage of building the forecast model was to run a set of regressions using actual data from previous years. This is the "sliding simulation" stage. All variables were regressed with actual values that functioned as either independent variables or cross-related variables (X variables). Year 2013 to 2017 load functioned as the dependent variables (Y variables). These five rolling test result years (2013-2017) were projected using the actual data from the prior four years. By benchmarking the regression's projected Y variable to the actual load of those years (2013-2017), the X variables that had material impact to the resulting projections were identified. Any immaterial X variables were excluded from the model. For example, rainfall data was determined to be an immaterial variable in the econometric model. After multiple sliding simulations and additional testing, a preliminary econometric model was built with the material variables.

During the 2nd stage of building the econometric model, a series of rolling regressions were conducted to determine the best regression period. After benchmarking the results of these rolling regressions to the actual load, it was determined that actual load was best represented (fit) by the econometric model and its coefficients derived from the most recent four-year period. This is consistent with the intuition that the current year's electricity consumption pattern has most similarities to its adjacent historical years.

The table below demonstrates the test result year's relationship to its sliding regression data.

Table 6-1: Simulation Years and Forecast Years

O - Test Result Year		**Econometric Model Simulation Years**								
X - Historical Regression Data		$Year_1$	$Year_2$	$Year_3$	$Year_4$	$Year_5$	$Year_6$	$Year_7$	$Year_8$	$Year_9$
Forecast Model	$Regression_1$	**X**	**X**	**X**	**X**	**O**				
	$Regression_2$		**X**	**X**	**X**	**X**	**O**			
	$Regression_3$			**X**	**X**	**X**	**X**	**O**		
	$Regression_4$				**X**	**X**	**X**	**X**	**O**	
	$Regression_5$					**X**	**X**	**X**	**X**	**O**

The final econometric regression model is then fitted and adjusted for data abnormalities. For example, this current version of the econometric model does not handle holidays very well. So, manual adjustments on those special occasions would help remove some time related forecast errors.

<u>Weather Scenarios Building</u>

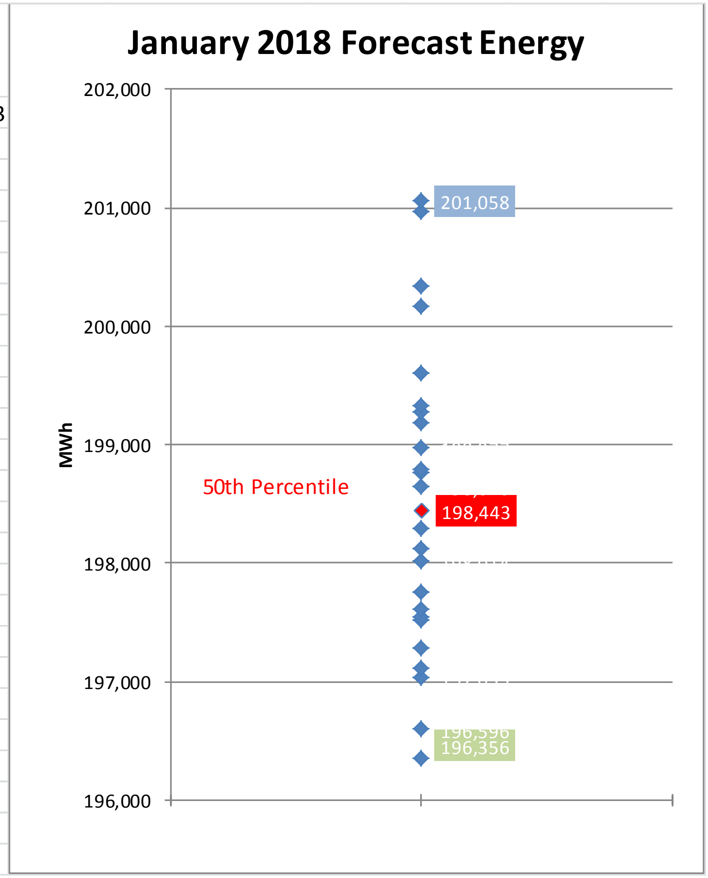
After deriving the final econometric regression model, weather scenarios were used to derive the final energy and peak load forecast. The weather scenarios used in the model are based on 25 years of historical weather data (1/1/1993-12/31/2017). Each year's observed weather pattern is considered an individual weather scenario. For example, the historical weather data from 1997, including solar irradiance, temperature, 24 hour moving average temperature and the other relevant weather variables, is referred to as the "1997 Weather Scenario" in the model.

For each forecast year (2018-2030), those 25 historical weather patterned scenarios were plugged into the econometric regression model to generate approximately 525 sets of load forecasts for 2018-2030. The resulting load forecasts were then fitted and adjusted for special days (holidays), combined with demographic growth, to derive each forecast year's final energy and peak demand projection. Each year's final energy forecast is determined by the result that represents the 50th percentile value of that year's weather patterned model results. Each year's 1 in 2 peak forecast is the 50th percentile value of that year's weather patterned peak model results, and each year's 1 in 10 peak forecast is the 90th percentile value of that year's weather patterned peak model results.

Table 1-2 uses January 2018 as an example to show how the monthly energy forecast was derived. By ranking the forecast results from the 25 weather scenarios from highest to lowest, it was determined that a monthly energy value of 198,443 MWh represents the 50th percentile result, which was derived from weather scenario 1998.

Table 6-2: Energy Forecast Sample

Forecast Year	Month	Weather Scenario	Forecast Energy (MWh)	P 50 (MWh)
2018	1	2014	196356	198443
2018	1	2003	196596.1	
2018	1	2015	197034.7	
2018	1	1994	197116.9	
2018	1	2016	197285.4	
2018	1	1999	197515.3	
2018	1	2010	197542.5	
2018	1	2000	197604.1	
2018	1	2009	197749.3	
2018	1	2012	198013.8	
2018	1	1993	198126.3	
2018	1	2004	198287.7	
2018	1	1998	198443.1	
2018	1	2005	198646.5	
2018	1	2011	198769.6	
2018	1	2007	198788.3	
2018	1	1996	198977.4	
2018	1	2006	199179.9	
2018	1	2001	199274.5	
2018	1	1997	199329.2	
2018	1	1995	199605.9	
2018	1	2002	200171.5	
2018	1	2013	200338.2	
2018	1	2017	200970.3	
2018	1	2008	201058.4	



Final Results Adjustments

Due to day of the week impact and leap year influence, the sum of the individual 12 month 50th percentile energy forecast results is slightly different than the 50th percentile result for the entire year. It was determined that the 12-month sum provides a more accurate result than the single annual figure given the inaccuracies in the annual historical data from billing cycle changes and loss factor calculation errors.

Out of Territory (OFT) Load Forecast Scenarios

OFT (Out of Territory) load represents a small portion of the MID total demand. Due to lack of historical metered data, the OFT load forecast was derived from 2009-2016 end-of-year billing data for individual cities and their billed rate classes.

Historically, the northern expansion area represents 6.09% percent of MID's total retail sales and Mountain House represents 1.62% of MID's total retail sales. This ratio to the system total load changes over time, but the difference is considered negligible and is not varied in this forecast.

Greenfield load is also considered in the forecast at the same growth rate of the entire system. It accounts for approximately 2% of MID retail load.

Economic Assumptions and Demographic Data

During the variable testing stage, several economic and demographic variables were tested, including population, employment rate, unemployment rate, seasonal employment and regional population growth. None of these variables was determined to be a good fit to the linear econometric model. The most significant variable was determined to be the regional labor force data published by the U.S. Department of Labor. The monthly labor force data was distributed evenly throughout the entire month and then added to the econometric model. Because a forecast of labor force data is not available, it is assumed that labor force will grow at a rate equal to the average historical growth rate of the past 10 years. This labor force data is then included in the econometric model as an independent variable.

Retail Sales Forecast and Retail Class Forecast

The retail sales forecast is projected by assuming a fixed average transmission loss in the system. After considering the impact of customer solar generation, the average loss factor on the MID system since 2015 is 2.5%. The difference between the system total demand and retail sales is attributed to transmission and distribution losses. Retail class forecasts are derived from historical billing ratios, which are the ratios of historical billed demand in each retail class to the total retail load, and the set of average historical billing ratios was applied to the 2018 LTDEF retail forecast to derive each class' retail forecast respectively. The monthly and annual ratios vary, but overall each retail class maintains a consistent ratio over time.

Forecast for Electric Vehicles, Customer Solar and Energy Efficiency

The 2018 LTDEF incorporates the California Energy Commission electric vehicle forecast and assumptions, which were published in December, 2017 in the "Light-Duty Plug-in Electric Vehicle Energy and Emission Calculator". By the end of 2030, the projected electric vehicle (EV) contribution to MID load is projected to be 19 GWh of energy consumption, with an annual growth rate of 18%.

MID projects that regional customer solar generation grows 4% each year and offsets 126 GWh of system energy consumption by the end of 2030. An hourly profile for customer solar generation was applied to all customer solar projections. The aggregated generation of all the customer solar programs is shaped by this hourly profile. The 8760 hourly profile is the average generation profile derived from two MID customer solar sites, which were determined to be representative samples of typical customer systems. The demand reduction from customer solar programs coincident to the MID system peak is estimated to range from 2 to 10 MW during summer 2018. This model will be updated as more meter data becomes available.

The 2018 LTDEF incorporates the latest energy efficiency targets approved by the MID board. This forecast is consistent to MID's 2017 spring EE forecast submitted to the CEC. MID developed an hourly profile for energy efficiency programs, which is similar to the profiles published in the 2016 CEC staff report CEC-200-2017-007. This hourly profile was used to determine the net hourly consumption.

Forecast Scenarios

The 2018 LTDEF incorporates multiple weather scenarios to each year's forecast. Instead of providing one forecast value for each time interval, MID models weather scenarios and provides a range of forecast results covering historical extreme weather conditions.

Macroeconomic and demographic changes are also significant drivers of MID regional load. Several macroeconomic and demographic variables were studied for significance; however, only the labor force variable was determined to be significant enough to be included in the forecast model. This variable is a composite of many drivers and can also be a dependent variable to other economic and demographic variables. The economic downturn in 2009 created a significant impact to MID electricity demand and also created so much volatility in the economic variables, such as inflation, GDP growth and employment, that their significance to the load forecast was reduced. Due to their reduced significance, these variables were not included in this forecast.

Net Demand Profile

MID's summer and winter net demand profiles have unique characteristics. Situated in the heart of California's central valley, MID's net demand is primarily driven by heating, air conditioning, and seasonal agricultural loads. These factors also drive a large difference between winter peak demand and summer peak demand. MID's winter and summer net peak hour is coincident to the winter and summer gross peak hour, respectively.

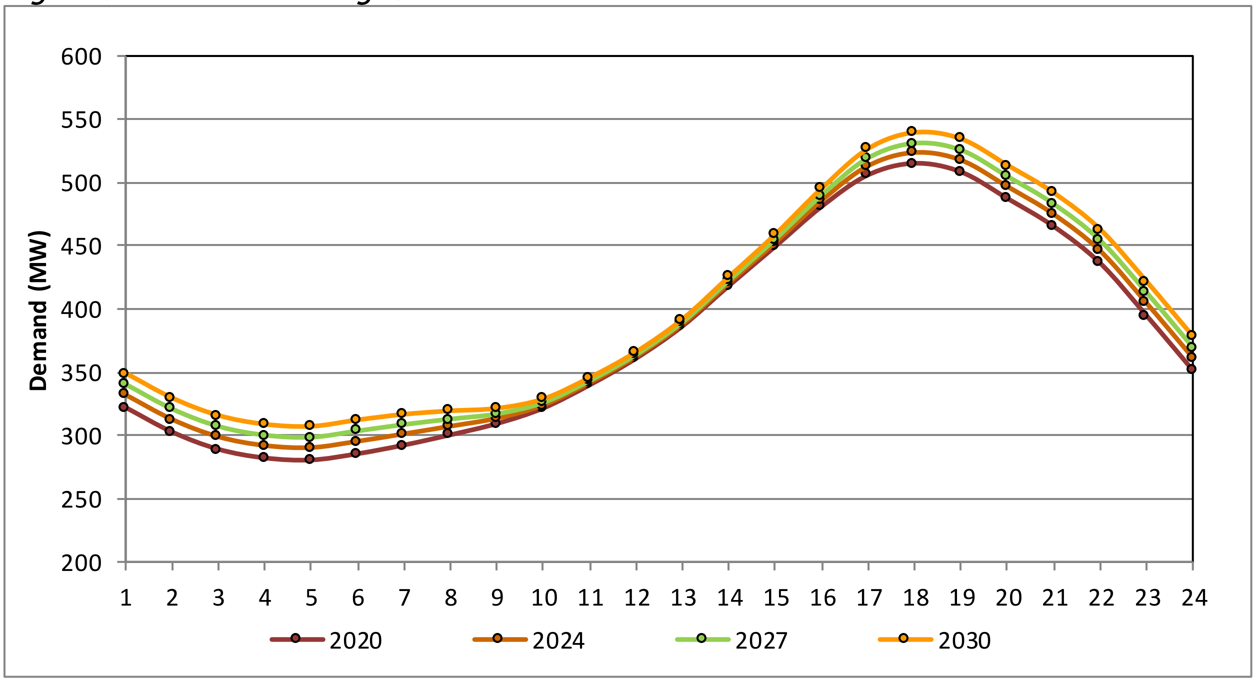
Summer Net Demand Profile

MID's summer net demand is largely driven by weather dependent residential load and seasonal agricultural load. It is common for MID to have days when the daily peak demand doubles the daily minimum. Due to the volatility of the summer demand, MID has to maintain flexible energy supplies to maintain reliability.

Summer Profile changes

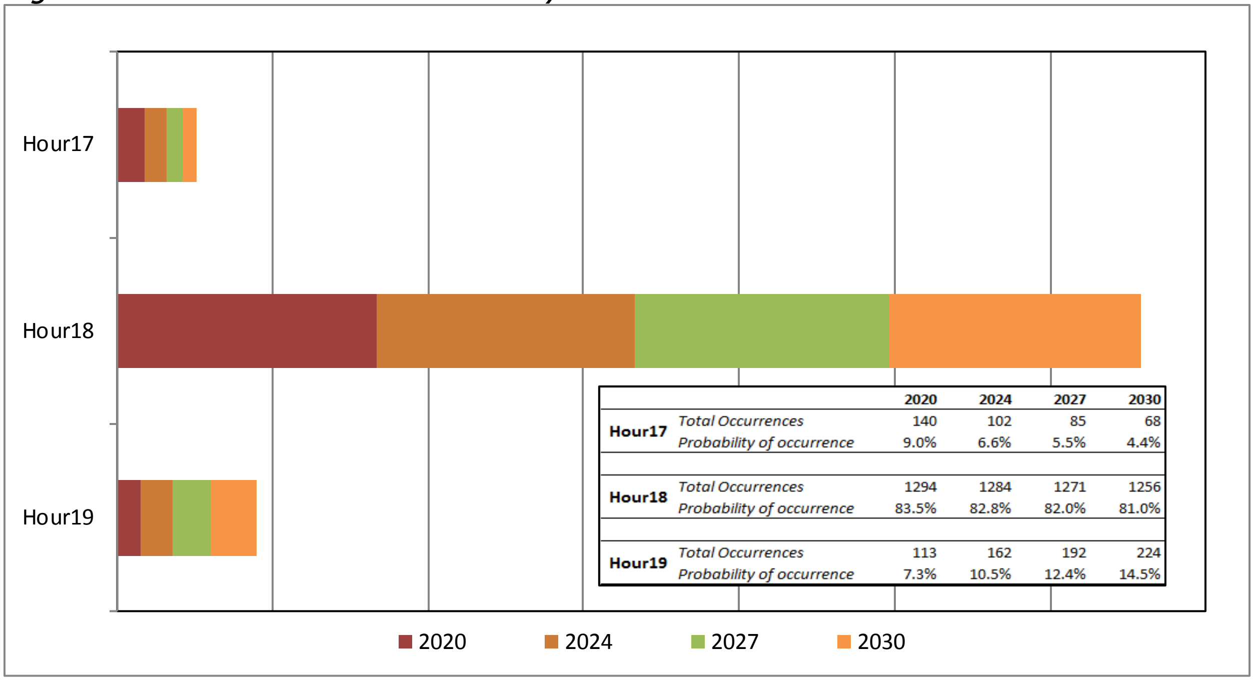
Similar to many utilities in California, MID is experiencing summer load profile changes. In a summer demand profile study from MID's 2018 Long-term Demand and Energy Forecast, a potential pattern change between 2019's summer demand profile and 2030's summer demand profile was noticed.

Figure 6-4: Forecast Average Summer Demand



Twenty-five load scenario simulations were conducted in the study. From the results of these 25 load scenarios, it was concluded that the summer peak might shift to the later evening in the observed planning horizon. The probability of the peak occurring at each hourly interval is calculated by dividing the total count of peak occurring in each hourly interval in all 25 scenarios by the total occurrences of daily peak events in July and August. For example, the total count of daily peaks happening in 2019 in HE (hour-ending) 17 in the 25 load scenarios is 140, and total count of daily peak events in July and August is 1,550 (25scenarios*62 days), so the HE 17 probability of peak occurrence is 9.0%. The results of the study are explained in Figure 6-5.

Figure 6-5: Summer Peak Hour Probability of Occurrence



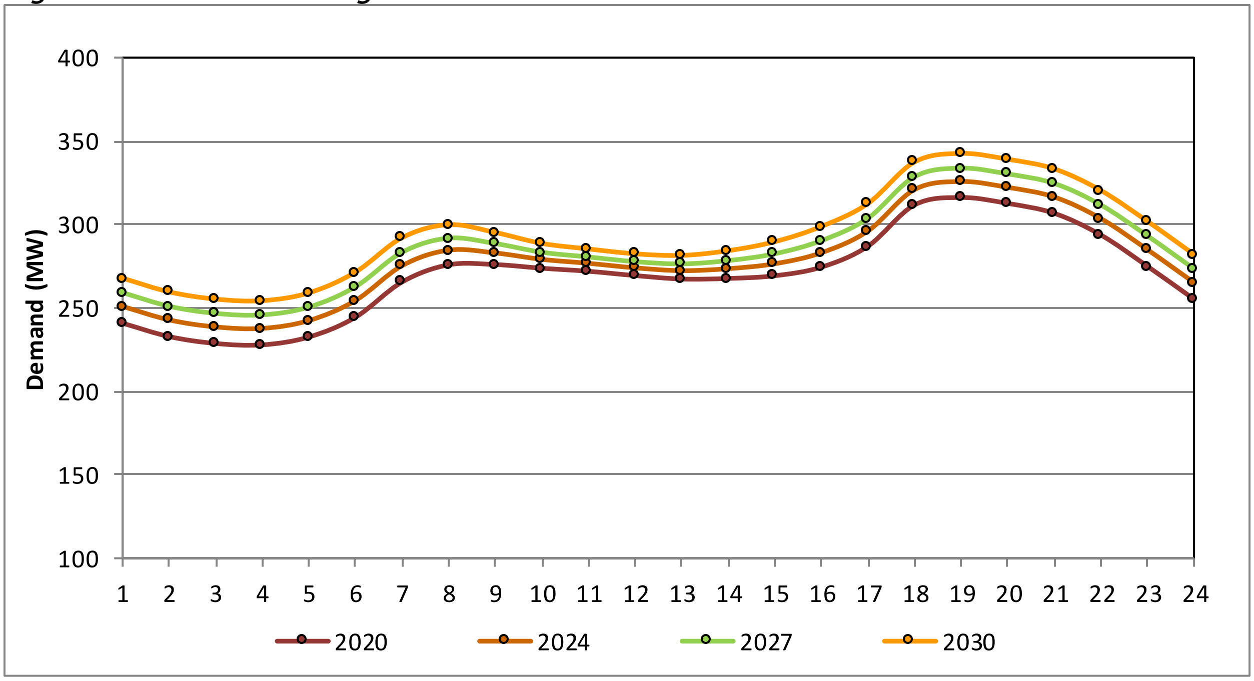
		2020	2024	2027	2030
Hour17	*Total Occurrences*	140	102	85	68
	Probability of occurrence	9.0%	6.6%	5.5%	4.4%
Hour18	*Total Occurrences*	1294	1284	1271	1256
	Probability of occurrence	83.5%	82.8%	82.0%	81.0%
Hour19	*Total Occurrences*	113	162	192	224
	Probability of occurrence	7.3%	10.5%	12.4%	14.5%

In 2020 there is a 91.5% probability that the peak would occur between HE 17 and HE 18 and 7.3% probability in HE 19. In 2030, the probability the peak would occur between HE 17 and HE 18 reduces to 85.4% and increases to 14.3% in HE 19.

<u>Winter Net Demand Profile</u>

MID's winter demand profile remains relativity flat throughout all hours. Unlike summer demand, seasonal loads are not active during the winter months leading to a lower base load. The majority of volatility in the winter pattern is contributed by changes from lighting loads from residential and commercial customers; and a smaller amount is contributed by changes of electric heating load. The shift of peak hours is not observed in the winter load pattern according to the load scenario study.

Figure 6-6: Forecast Average Winter Demand



<u>Distributed Energy Resources (DER's) Impacts to Net Demand</u>

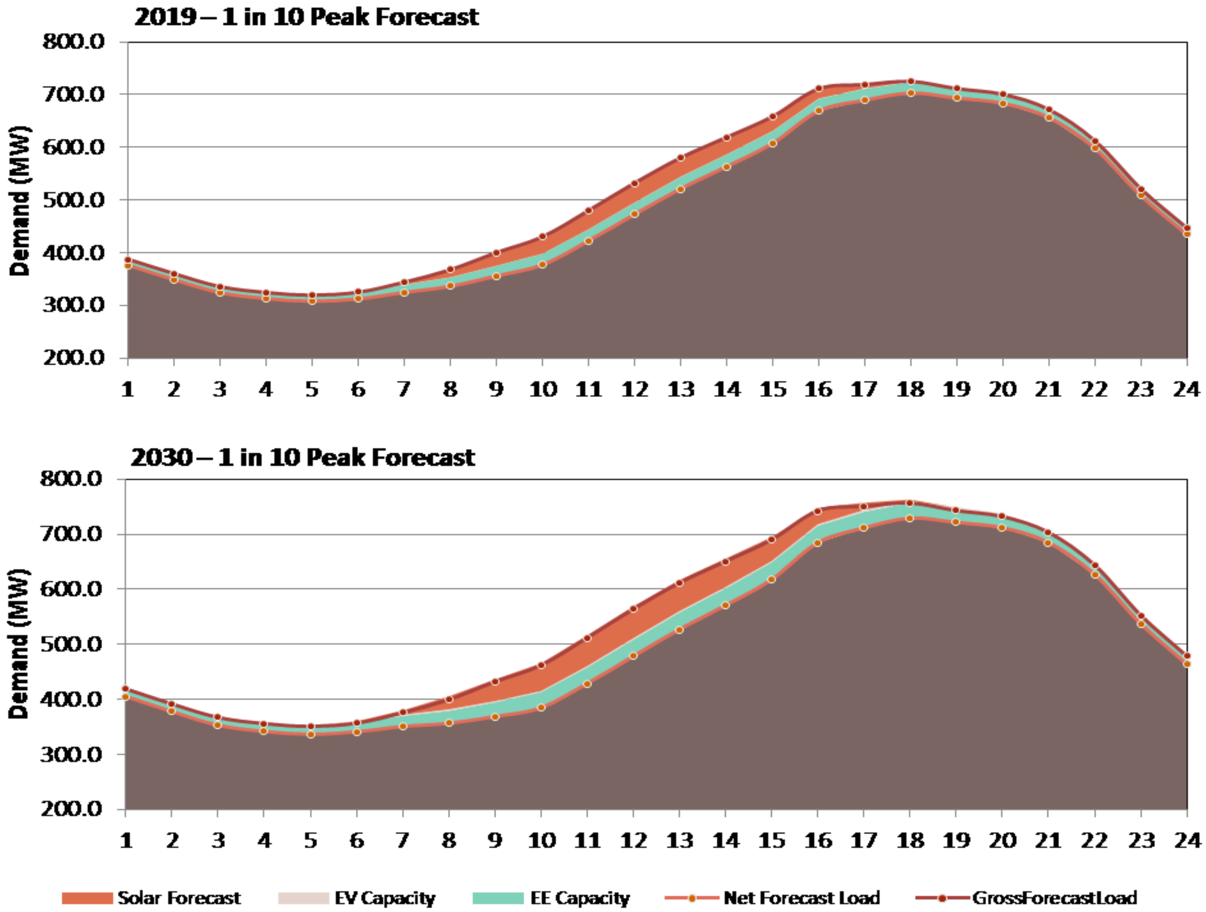
MID currently considers three Distributed Energy Resources (DER's) programs when forecasting net demand; behind-the-meter solar, electric vehicles, and energy efficiency. In addition to these programs, MID manages a demand response program; however this program is considered a supply side resource.

<u>DERs Impact to Net Peak</u>

The DER peak shaving contribution coincident to the forecasted net system peak is estimated to be 23.5 MW in 2019 in HE 18. By 2030 DERs are expected to shave an additional 10.4 MW coincidental to the system peak hour for a total of 33.9 MW peak reduction.

The DER peak shaving contribution varies during the day and has different impacts to the net system demand in different hourly intervals. The observed maximum contribution of DERs is expected to occur during HE 12. The DER peak shaving contribution at HE 12 in 2019 is estimated to be 60MW. By 2030, the DER peak shaving contribution is estimated to grow to 91 MW at HE 12. The largest growth in DERs is expected to come from behind-the-meter solar resources, with energy efficiency being the second-largest contributor.

Figure 6-7: DER Impacts



<u>Electric Vehicle's Impact to Net Peak</u>

MID's Electric Vehicle demand coincident to system peak is expected to be 0.6MW in 2019 at HE 18. This demand is expected to increase to 3.2 MW in 2030 at HE 18.

Table 6-3 shows the forecasted peak coincident demand through 2030.

Table 6-3: Electric Vehicle Peak Coincident Demand

	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
EV Peak Coincident Demand (MW)	0.6	0.8	1.0	1.2	1.4	1.7	1.9	2.2	2.4	2.7	2.9	3.2

<u>Energy Efficiency's Impact to Net Peak</u>

Energy Efficiency's (EE) peak shaving contribution coincident to net system peak is estimated to be 21.1 MW in 2019. By 2030, the figure is expected to grow to 28 MW. The maximum demand reduction from energy efficiency is forecast to occur at HE 15, which is before the expected net system peak demand. The EE demand reduction at HE 15 is estimated to be 23.1 MW in 2019 and 31.2 MW in 2030.

Table 6-4 shows the forecasted peak-coincident EE capacity.

Table 6-4: Energy Efficiency Peak Coincident Demand Reduction[2]

	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
AAEE Peak Coincident Demand Reduction (MW)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
EE Peak Coincident Demand Reduction (MW)	21.1	22.0	22.9	23.7	24.6	25.4	26.1	26.7	27.2	27.5	27.8	28.0

Behind-the-Meter Solar 's Impact to Net Peak

Behind-the-meter solar peak shaving contribution coincident to the net system peak for 2019 is estimated at 1.7 MW. By 2030 this figure is expected to grow to 2.6 MW. Behind-the-meter solar has a small impact on MID's net peak demand. The maximum output from behind-the-meter solar occurs during the middle of the day (HE 12), with an estimated maximum output of 37.9 MW in 2019 and 58.3 MW by 2030. As figure 6-7 illustrates, this output declines dramatically by hour-ending 18.

Table 6-5: Behind-the-Meter Solar Peak Coincident Capacity

	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Solar Peak Coincident Capacity (MW)	1.7	1.8	1.9	1.9	2.0	2.1	2.2	2.3	2.3	2.4	2.5	2.6

Demand Response and Interruptible Programs

MID operates a demand response and interruptible program with a total capacity of 28 MW. The demand response (DR) program is a one-way paging system with load controller receivers (LCRs) that temporarily interrupts the operation of enrolled customer's air conditioning units. This program is called Shave the Energy Peak (STEP). The program currently has an estimated enrolled capacity of 30 MW, although STEP is typically dispatched by interrupting one-third of the enrolled devices at a time in order to achieve a continuous demand reduction of 10 MW. The STEP program can be dispatched by MID system operators when needed. Due to its dispatch ability the STEP program is considered a supply resource and is not included in the load forecast.

[2] No demand reduction estimate for AAEE is included since the nature of those future measures is not yet known.

In addition to the STEP program, MID also has a commercial interruptible program with a capacity of about 18 MW. MID can call on enrolled customers to reduce the demand they've committed to the program when needed. It is also considered a supply side resource.

<u>2018 LTDEF VS 2017 Forecast and Accuracy Tracking Results</u>

As noted in MID's LTDEF, in terms of the forecast comparison to the previous forecast, the 2018 LTDEF model is much different than the 2017 Forecast model. The matrix table below identifies the major differences of the two models:

Table 2-1: Forecasting Model Comparison

Category	Attributes	2018 Load Forecast Model	2017 Load Forecast Model
Model Characteristics	Frequency of Input Data	Hourly	Annual
	Regression Method	Simple Linear Regression	Simple Linear Regression
	Historical Data Range (Years)	4	19
	Observations Per Regression	35040	19
	Observation Per Variable	37.5	6.3
	Weather Variables	15	1
	Macro Economics variables	0	1
	Demographic variables	1	1
	Categorical Dummy Variables	39	0
	Variable Cross-Effects	879	0
	Variables per Regression	934	3
MAPE*	Monthly Peak	2.3%	6.4%
	Monthly Energy	1.4%	4.6%
	2018 Annual 1-in-2 Peak (MW)	661	681
	2018 Annual Energy (GWh)	2,583	2,580
Output Results	Models Required to Maintain	1	3
	Forecast Sensitivity	Range	Single Value
	Forecast Profile	Hourly	Annual
* MAPE is explained in the following sections of this chapter			

MID tracks its model accuracy by conducting rolling backcasts. Historical values of the independent variables were plugged into the forecast model to retroactively forecast results from 2014 to 2017.

To benchmark the rolling backcast, MID uses a well-known error measurement statistic, MAPE (Mean Absolute Percent Error), to benchmark the model accuracy. MAPE is a more applicable measurement to calculate the load forecast error. It measures the size of the error in percentage terms, in comparison to the actual value. The new forecast model achieves greater accuracy compared to the previous models, as evidenced by the lower resulting MAPE values.