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2018 IID Load Forecast Report

April 2018 – Energy Optimization & Procurement Section: Resource Planning & Acquisition unit

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Section 1: Summary

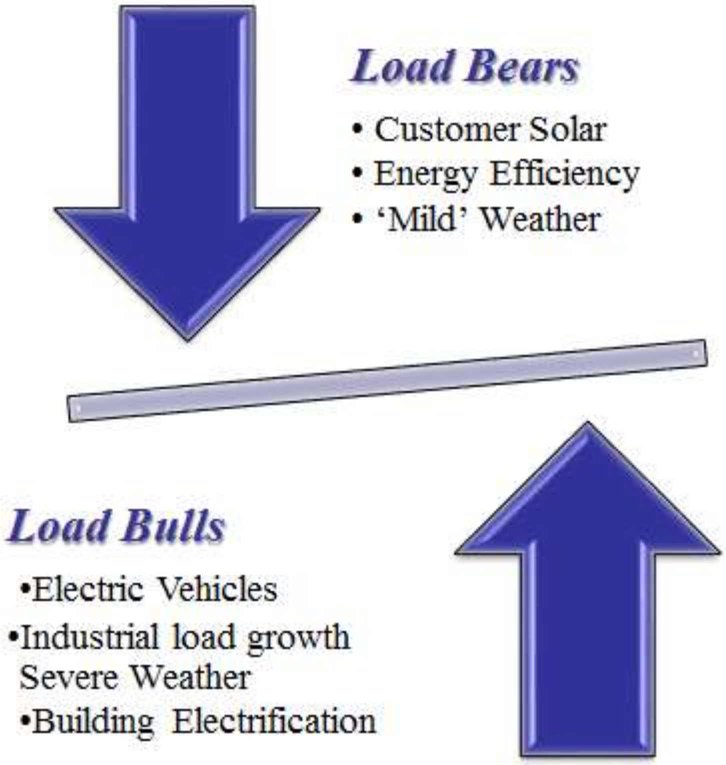
Energy Optimization & Procurement of the Energy Department at the Imperial Irrigation District (IID) has prepared the system load term load forecast of peak demands, net energy requirements and energy sales to customers within the IID service territory. This forecast will be used for district wide long term planning purposes in current planning activities for the next 20 years. In 2014, IID completed a Request for Proposals (RFP) to acquire load forecasting services as well as the tools and training to allow IID staff to complete all future forecasts. The load forecast is an integral part of District planning activities, so a forecasting process that relies on industry accepted standards of practice, as well as rigorous, detailed and thorough analysis is critical to obtaining results that are both realistic and statistically sound. This approach holds true for both the 2016 load forecast as well as the 2018 forecast. Since the 2018 forecast is based upon most of the 2016 methodology, this document serves as a supplement to the original 2016 load forecast report to explain the exact process and modifications for this updated forecast.

The 2018 IID Load Forecast basically uses the same methodology as the 2016 IID Load Forecast with some modifications to reflect the current economic, weather and regulatory changes. In this load forecast study, econometric approach was utilized to forecast IID's total retail sales. The Net Energy for Load (NEL) forecast was derived from the total retail sales forecast and the average difference of NEL and retail sales in historical years; Coincident Peak (CP) forecast was derived from NEL forecast and historical representative load factors. The forecast is primarily driven by several key variables that have an impact on hourly/daily/monthly/yearly loads and the forecast incorporated the load impact resulting from these variables including, but not limited to:

- Weather changes
- IID Energy Efficiency (EE) programs
- IID Rooftop Photo Voltaic (PV) Solutions Programs
- Electric Vehicles programs (EV)
- New industrial load impact
- Regulatory requirement changes

Since these variables are uncertain the severity of their impact on load depends on how each of these variables transpire. Generally, these variables can either encourage load growth or deter it. Below is a diagram that illustrates which variables encourage load growth and which variables deter load growth:

Figure 1-1: Load Impact Variables



As a result of this fact, several scenarios were created for each variable. These different variables have different scenarios each based on different assumptions and the interactions and combinations of these different variables and their own cases can provide many load forecast results.

For purposes of the 2018 forecast, three main cases were selected to represent the majority of the most common ranges of potential outcomes. Those 3 cases are as follows:

1. **High Case** – Combining severe weather conditions, high industrial growth, high electric vehicle impact and low energy efficiency and rooftop/customer solar impacts
2. **Mid (Expected) Case** - Combining normal weather, normal industrial growth, average electric vehicle impact and average energy efficiency and rooftop/customer solar impacts
3. **Low Case** – Combining mild weather conditions, normal economic industrial growth, low electric vehicle impact and high energy efficiency and rooftop/customer solar impacts

Furthermore, there are numerous potential combinations of the key significant variables that can essentially create a new forecast. These are called "Other Observations". For example, some of these combinations are combining normal weather with high industrial growth and normal energy efficiency, rooftop/customer rooftop solar. Or, as another example is combining the Mid Case variables with a much higher view of energy efficiency/rooftop solar impacts. Below is a table that describes the three main cases along with the 'other observations" and the forecast results provided from each process:

Figure 1-2 2018 Load Forecast Categories

2018 Load Forecast Categories					
		CASE			OTHER OBSERVATIONS
Forecast Type	Forecast Category	Base/Expected	HIGH CASE (Severe weather, high industrial, High EV, Low EE/PV)	LOW CASE (Mild weather, normal economic industrial growth, high EE/PV, Low EV impacts)	Various results from combining High/Mid/Low projections of: EE, PV, EV, Industrial Load, Weather Regulatory Requirements & Zero Net Energy
Gross	Peak Load (MW)	✓	✓	✓	
	NEL(MWh)	✓	✓	✓	
	Energy Sales (MWh)	✓	✓	✓	
Net of EE/PV Programs	Peak Load (MW)	✓	✓	✓	
	NEL(MWh)	✓	✓	✓	
	Energy Sales (MWh)	✓	✓	✓	

Retail customer counts and sales by major customer classification as well as hourly load data generally from 2001 through 2017 (the study period) were provided by IID. The historical data regarding IID Energy Efficiency Programs and IID PV solutions Programs were provided internally by IID also. Historical and projected economic and demographic data were provided by Woods & Poole Economics, Inc. Weather data was provided by Weather Underground, Inc.

Even though the historical Net Energy for Load had an average growth rate of 1.7% over the last 17 years, as Figure 1-1 shows, the load of the IID System over 2009-2016 maintained a fairly flat trend. And the flat trend in the historical load growth lasted two years longer than that in 2016 Load Forecast (2016 and 2017), that is the main reason to explain why the overall average annual growth rate in 2018 load forecast declined a little compared to that of the 2016 Load Forecast. Moreover, the 2018 Load Forecast has a lower average annual growth rate of 1.2% for the first ten years (2018-2027), and a higher average annual growth 1.7% for the second ten years (2028-2037). The lower average annual growth rate 1.2% in the first ten forecast years (2018-2027) is mainly due to fast growth of PV+EE impact, which takes away some growth rate of IID system load. It is also due to the weather normalization impacts when bringing weather for 2018 and beyond back to normal as compared to the last several years that are considered severe weather years. With PV+EE impact reaching market saturation and an optimistic growth in economic forecast data by Woods & Poole Economics, Inc. during the second ten years, the average annual growth rate increased to 1.7% in 2018 Load Forecast. The same applies for CP's average annual growth rate in the next 20 forecast years since CP forecast is derived from NEL forecast and load factor. As Figure 1-2 shows, the CP during historical period (2001-2017) has a higher average annual growth rate reaching to 2.6%, this is due to that in the recent two years 2016 and 2017, the peak of the IID system jumped historically high to 1,073MW due to historically record high temperature in peak day. The tables below illustrate this comparison of the 2016 load forecast and the 2018 load forecast:

Figure 1-3 Net IID System NEL Requirements in 2016 Load Forecast vs 2018 Load Forecast

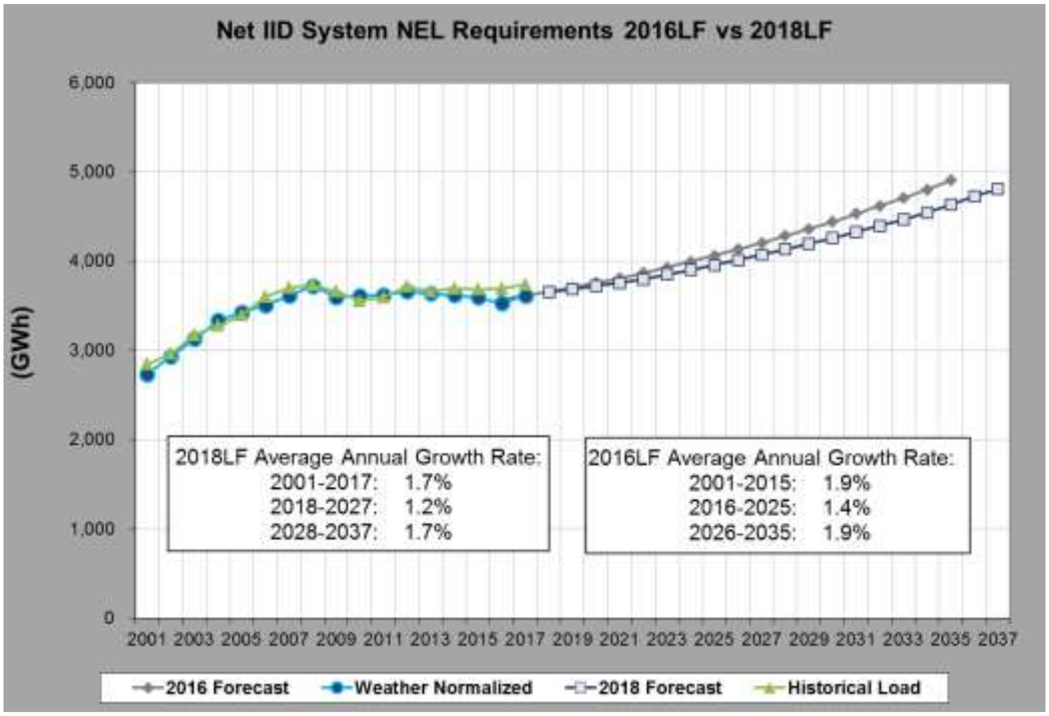
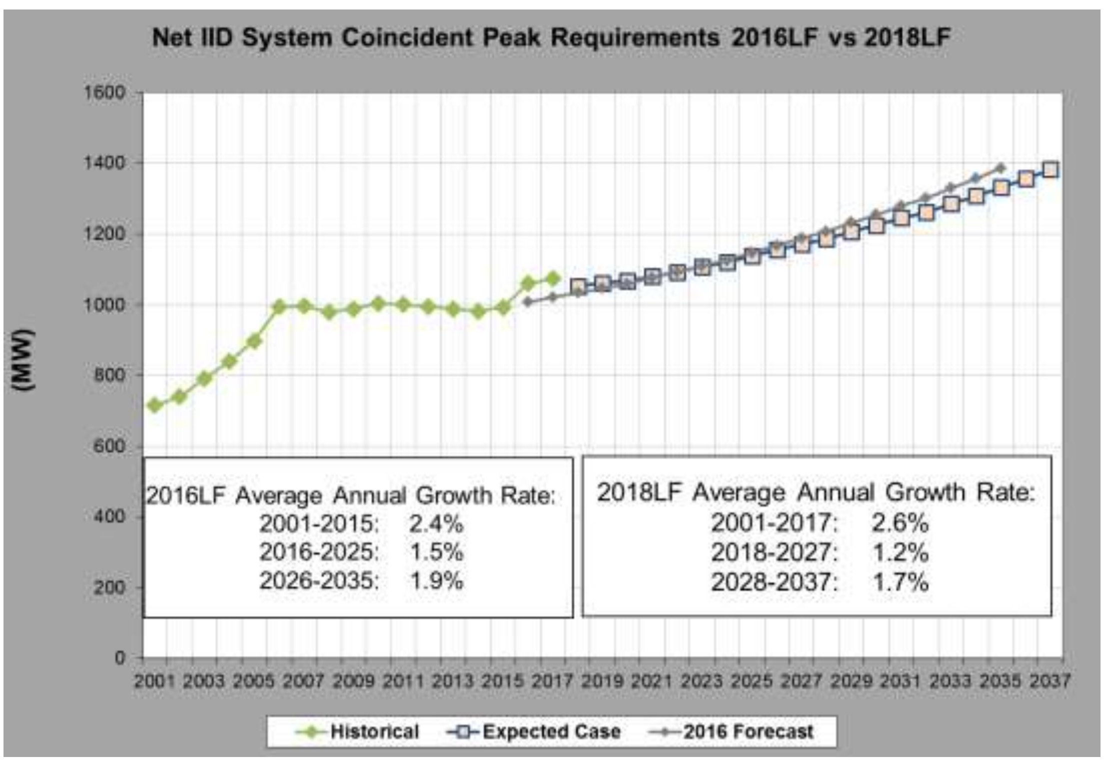


Figure 1-4 Net Coincident Peak Demand in 2016 Load Forecast vs 2018 Load Forecast



Due to the unpredictability of weather temperature for the long term forecast, and the fact that weather has an important impact on energy consumption, the 2018 IID Load Forecast provides retail sales, NEL and CP forecasts under three weather scenarios: Normal (base/expected), Mild and Severe. These weather scenarios are used to estimate the load under the normal, abnormally severe and abnormally mild weather conditions and are combined with several other variables to create three cases.

Figure 1-3 below depicts the projection of NEL under three scenarios in 2016 Load Forecast: the blue line is net NEL under normal weather and expected EE_PV scenario; the green dash line is net NEL under severe weather scenario and expected EE_PV; and the red dash line is net NEL under mild weather and high EE_PV scenario.

Figure 1-5 Net IID System NEL Requirements in 2016 Load Forecast

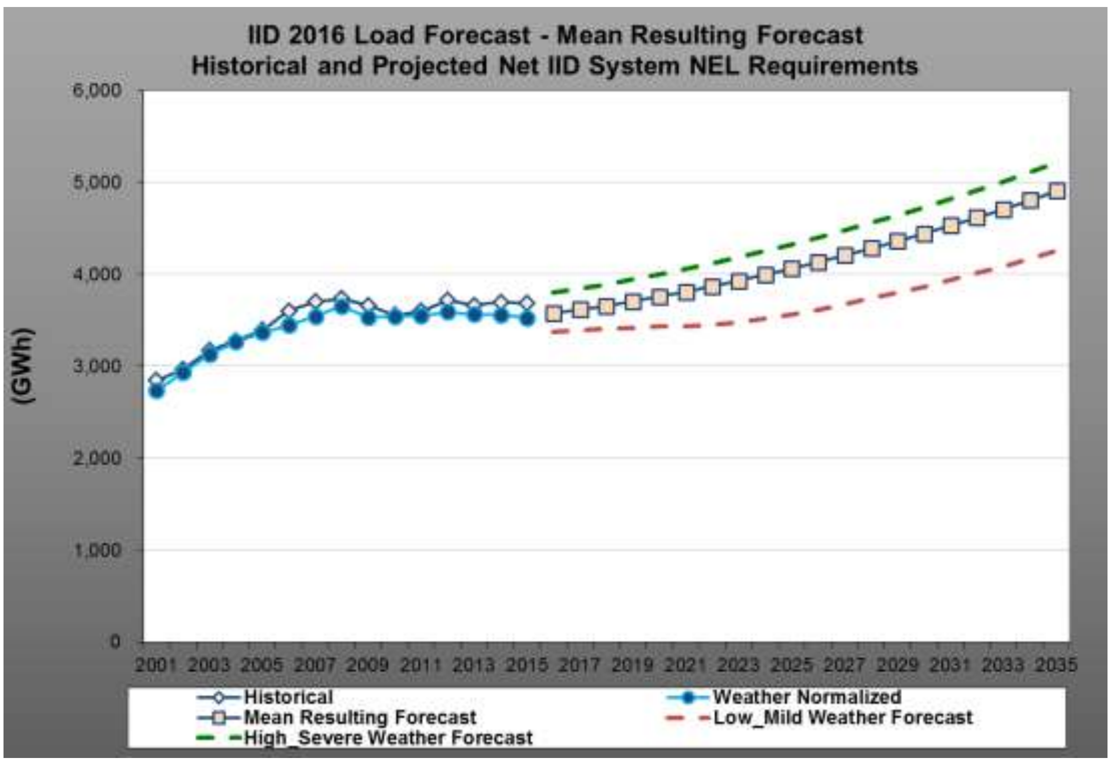
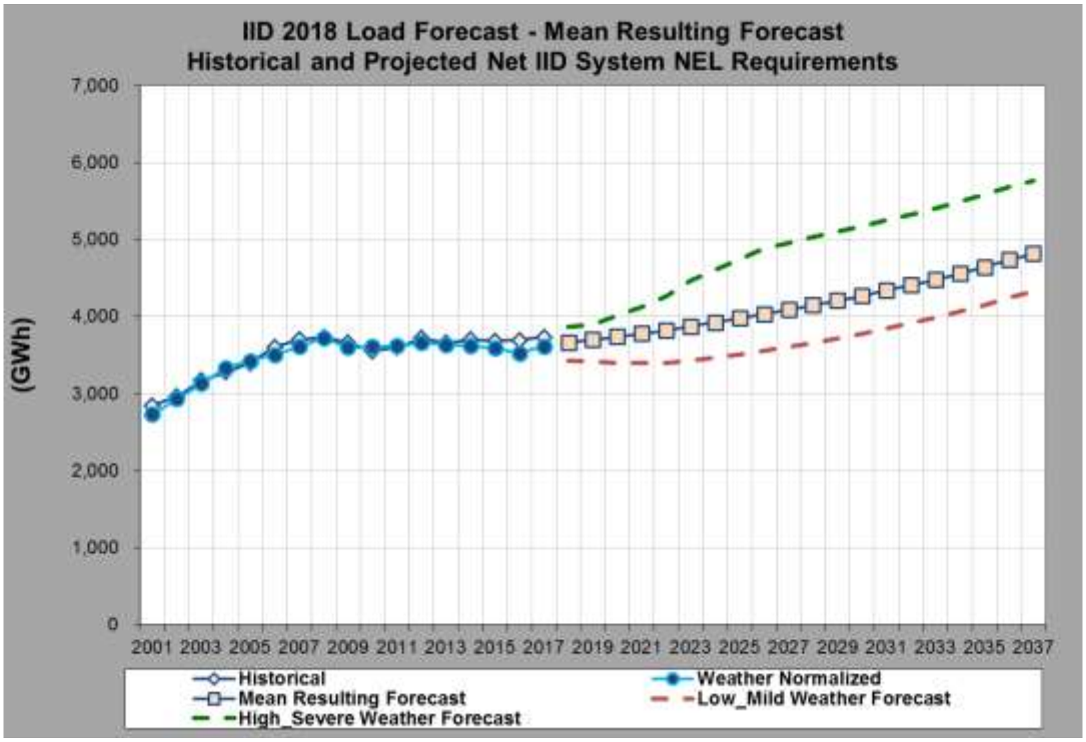


Figure 1-4 below depicts the projection of NEL under three scenarios in 2018 Load Forecast. The blue line is Mid (Expected) senario combining normal weather, normal industrial growth, average electric vehicle impact and average energy efficiency and rooftop/customer solar impacts; the green dash line is the High_Severe Weather Forecast scenario combining severe weather conditions, high industrial growth, high electric vehicle impact and low energy efficiency and rooftop/customer solar impacts; and the red dash line is the Low_Mild Weather Forecast scenario combining mild weather conditions, normal economic industrial growth, low electric vehicle impact and high energy efficiency and rooftop/customer solar impacts

Figure 1-6 Net IID System NEL Requirements in 2018 Load Forecast



Similarly, Figure 1-5 depicts the projection of coincident peak under three scenarios in 2016 Load Forecast and Figure 1-6 depicts the projection of coincident peak under three scenarios in 2018 Load Forecast.

Figure 1-7 Net IID System CP Demand Requirements in 2016 Load Forecast

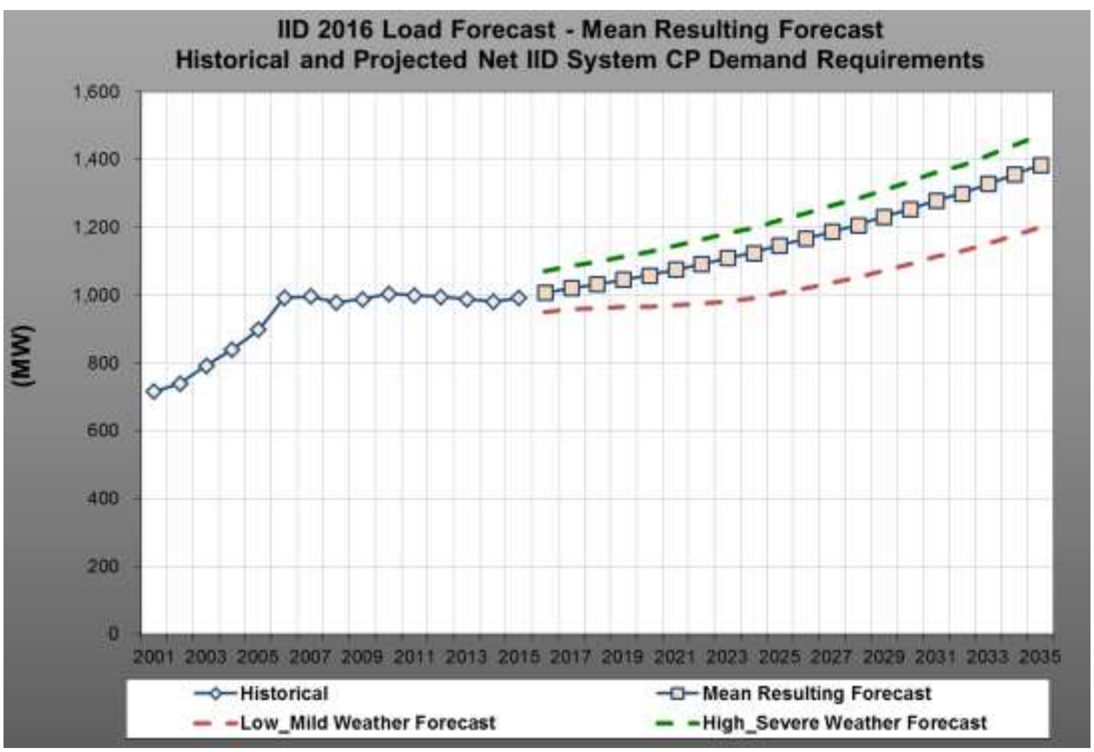
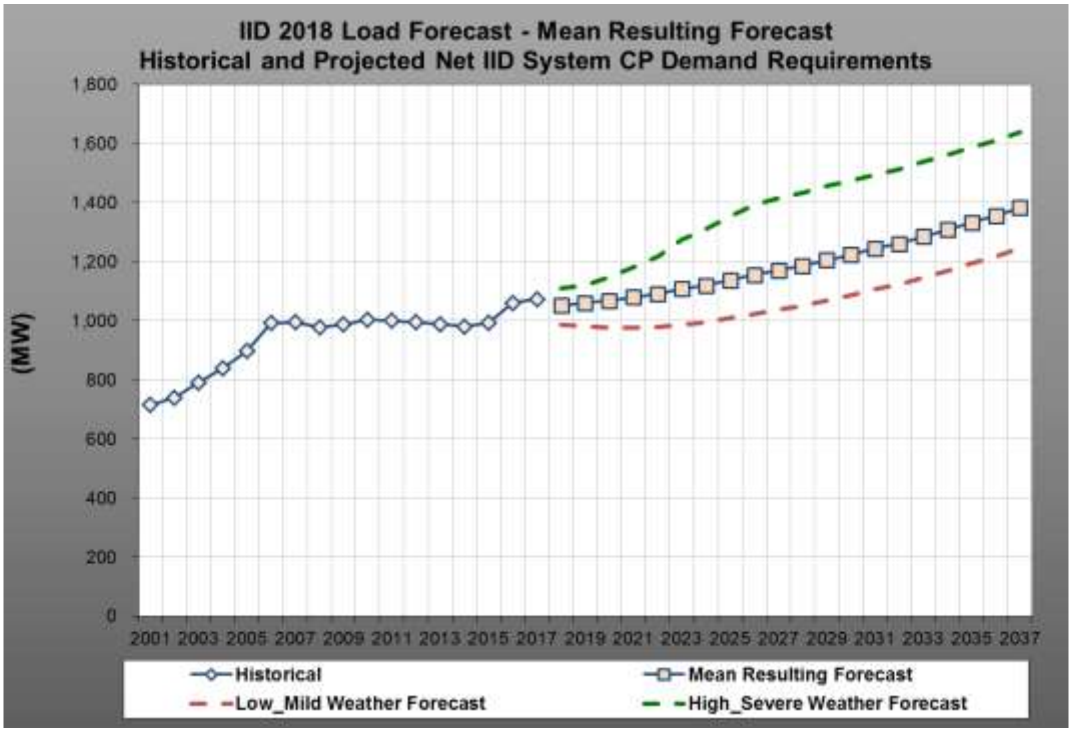
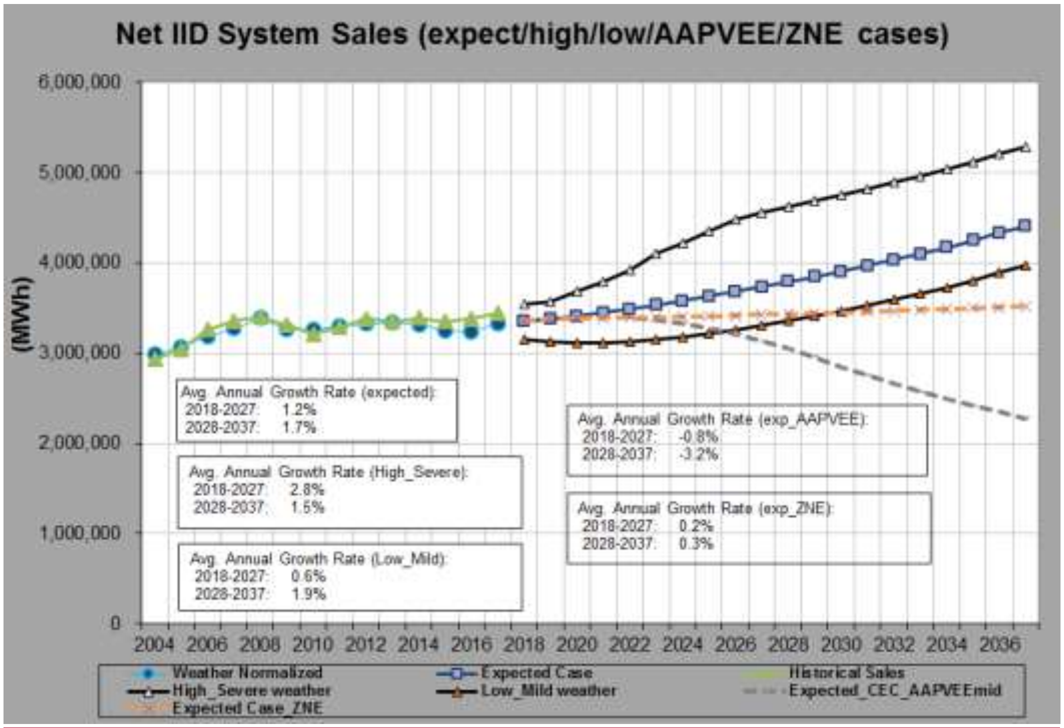


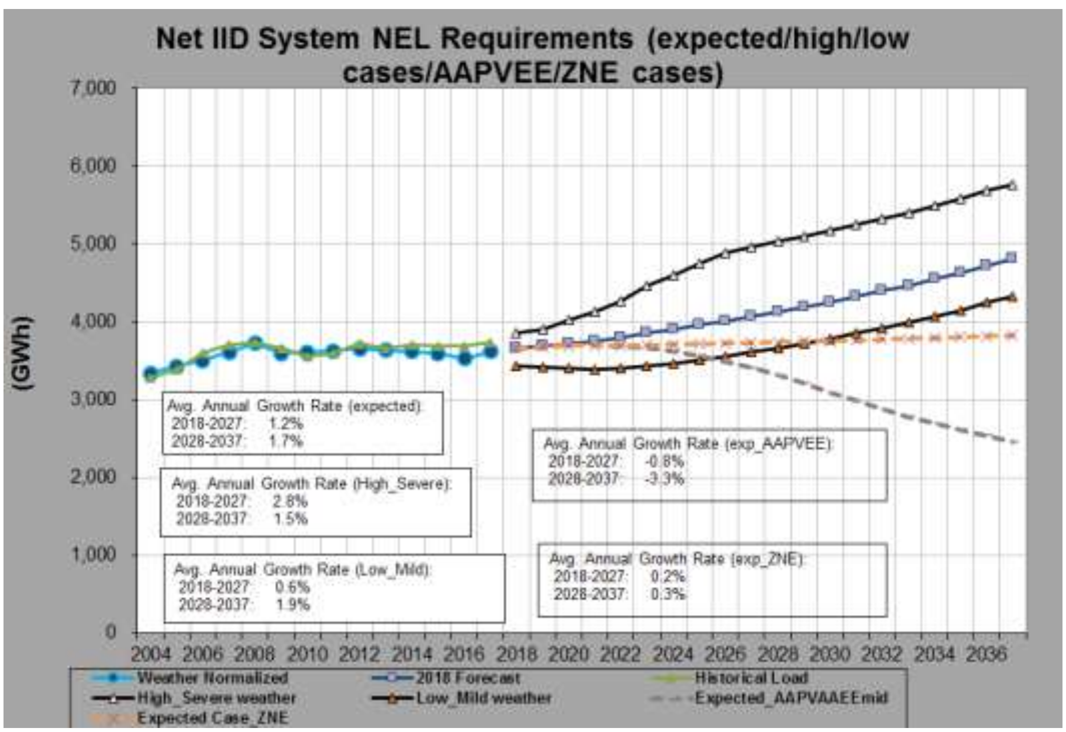
Figure 1-8 Net IID System CP Demand Requirements in 2018 Load Forecast

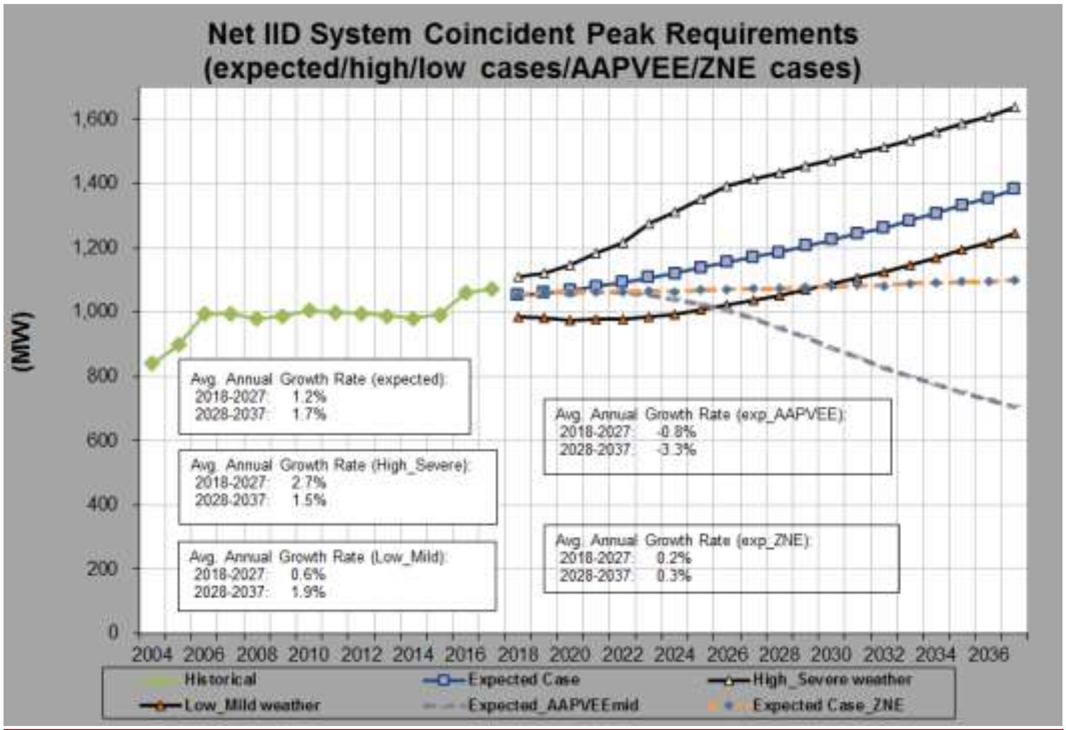


It is important to note that IID closely observed the California Energy Commission's (CEC) process in state demand forecasting. In reponse to the savings beyond "traditional"AAEE estimated in support of SB350 and additional achievable PV adoption, manifested through the 2019 Title 24 residential building standards update insupport of Zero Nero Net Energy goals, IID 2018 load forecast adds cases of other observations to account for the two additional elements: AAEE (additional achievable energy efficiency savings) and AAPV (additional achievable PV adoption).

The three Figures below added two cases for the additional observations to address Title 20 and Title 24 AAEE and AAPV impact on IID system load (NEL), IID system sales and IID system CP. The orange color dash line assumes that all the new forecasted energy sales after 2020 are replaced by rooftop solar, besides the 110MW rooftop solar installations by IID's current customers (PV expected case), so the total sales after 2020 is pretty flat. The grey color dash line is another case to address AAEE and AAPV. The system impact data were provided by CEC staff. The assumption is that Title 24 regulations will induce 80 percent of single family homes to be built with a PV system after 2020.The impacted savings braught by the regulations Title 20 and Title 24 is a lot more aggressive in the AAPV +AAEE mid case pluging the data provided by CEC


Net IID System Sales (expect/high/low/AAPVEE/ZNE cases)
(MWh)
Avg. Annual Growth Rate (expected):
2018-2027: 1.2%
2028-2037: 1.7%
Avg. Annual Growth Rate (High_Severe):
2018-2027: 2.8%
2028-2037: 1.5%
Avg. Annual Growth Rate (Low_Mild):
2018-2027: 0.6%
2028-2037: 1.9%
Avg. Annual Growth Rate (exp_AAPVEE):
2018-2027: -0.8%
2028-2037: -3.2%
Avg. Annual Growth Rate (exp_ZNE):
2018-2027: 0.2%
2028-2037: 0.3%
Weather Normalized
Expected Case
Historical Sales
High_Severe weather
Low_Mild weather
Expected_CEC_AAPVEEmid
Expected Case_ZNE


Net IID System NEL Requirements (expected/high/low cases/AAPVEE/ZNE cases)
(GWh)
Avg. Annual Growth Rate (expected):
2018-2027: 1.2%
2028-2037: 1.7%
Avg. Annual Growth Rate (High_Severe):
2018-2027: 2.8%
2028-2037: 1.5%
Avg. Annual Growth Rate (Low_Mild):
2018-2027: 0.6%
2028-2037: 1.9%
Avg. Annual Growth Rate (exp_AAPVEE):
2018-2027: -0.8%
2028-2037: -3.3%
Avg. Annual Growth Rate (exp_ZNE):
2018-2027: 0.2%
2028-2037: 0.3%
Weather Normalized
2018 Forecast
Historical Load
High_Severe weather
Low_Mild weather
Expected_AAPVAAEEmid
Expected Case_ZNE



In the following sections, detailed descriptions on methodology modifications in the 2018 Load Forecast compared with 2016 Load Forecast and the rationale of the modifications will be given. Sample size and data sources selections will be described in more details. The regression results will be analyzed and discussed in order to lay a solid foundation for the conclusions of the 2018 Load Forecast. Finally, the limitations of the 2018 Load Forecast that have been come across during the study process and future recommendations will be discussed.

Section 2: Methodology and Models Design

Model Specification

The 2018 Load Forecast continues to use econometric forecasting methodology to forecast retail sales based on the historical monthly sales by different customers' billings categories. The econometric models basically keep the same explanatory variables as those in 2016 Load Forecast with minor changes and modifications. The changes and modifications of the 2018 load forecast models are all based on ex-post model evaluation approach. That means plugging in actual data into the different available models with different choices of independent variables, comparing the forecasted load obtained from the models and the actual load, the models which have the lowest MAPE were selected as 2018 load forecast models. The model specifications are discussed as below:

- The residential sales model includes the following independent variables:
  - Weather terms that capture monthly weather variability,
  - Month dummy variables that capture additional variations not due to weather in every month of the year
  - A limited number of terms intended to address level shifts in the sales data.
  - Blended population in IID service territory
- Similar to the 2016 Load Forecast, the residential energy assistance modeling framework combines residential average usage and residential customer counts to get the total residential energy assistance sales in the 2018 Load Forecast. This is due to the relative homogeneity of the residential energy consumption patterns. The residential energy assistance sales model include these independent variables:
  - Blended low income population in IID service territory
  - Blended personal income in IID service territory
  - Month dummy variables that capture additional variations not due to weather in every month of the year
  - Weather terms that capture monthly weather variability,
  - A limited number of terms intended to address level shifts in the sales data.
  - Autoregressive terms
- Mobile home/recreational vehicle class sales model is a function of blended personal income, blended GRP, monthly weather variables, seasonal dummies, trend variable and autoregressive term.
- Agricultural class sales model is a function of blended farm employment, the number of agricultural customer counts, monthly weather variables and some limited terms to address anomalous level shifts in the usage data and autoregressive term.
- Commercial class sales model is a function of blended Gross Regional Product (GRP), blended farm employment, monthly weather variables, month dummy variables that capture additional variations not due to weather in every month of the year and autoregressive term
- Industrial class sales model is a function of trend variable and autoregressive terms.
- Added industrial load growth scenarios are a function of internal discussion and information from various internal sections of the Energy Department.

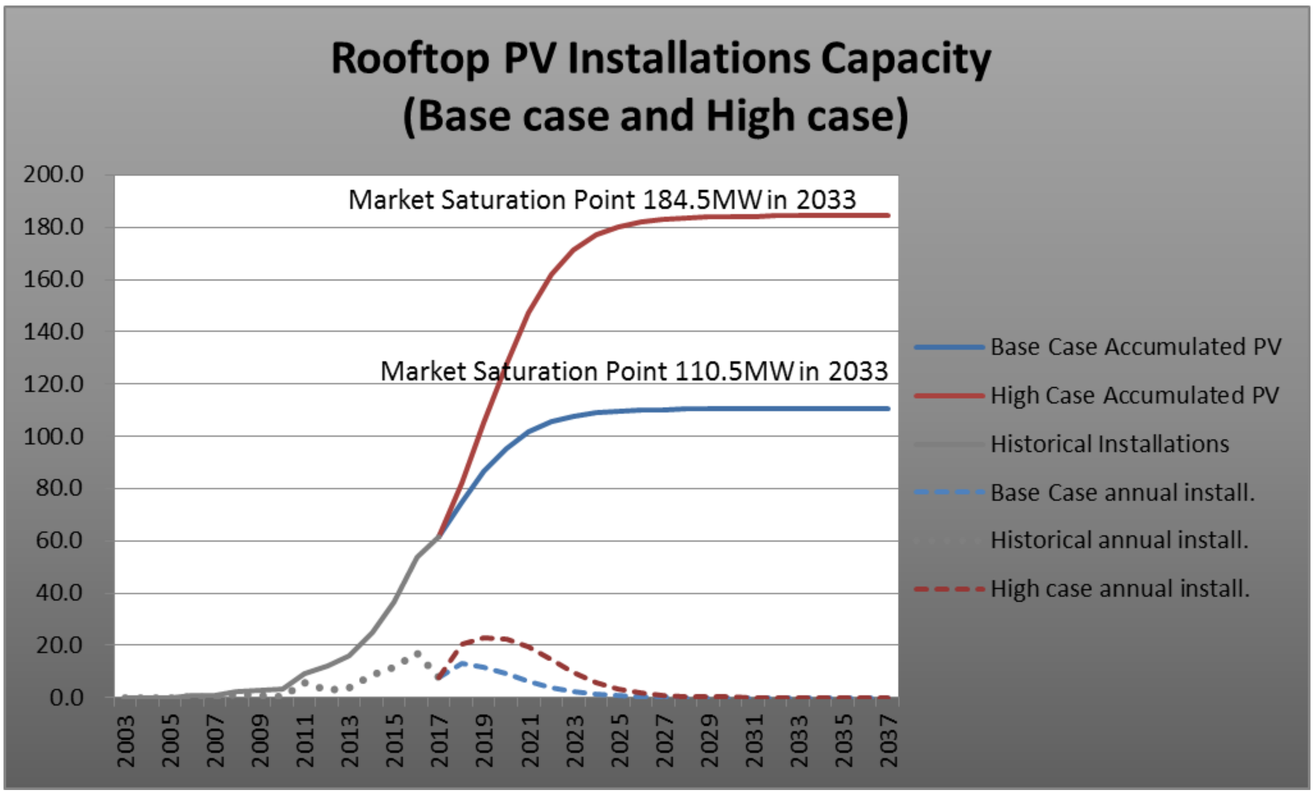
- Lighting class sales model is a function of blended total employment in the IID service area, blended GRP in the IID service area, some limited trend terms and autoregressive terms.
- Municipal class sales model is a function of blended personal income in the IID service territory , blended GRP in the IID service area, monthly weather variables and certain limited trend terms intended to capture otherwise unexplained level shifts in the data.
- Electric Vehicle information was provided by the CEC's demand forecast groups. The CEC also provided a calculator to estimate high, low and expect impact levels by assuming various levels of meeting the targets of EXECUTIVE ORDER B-48-18.

Rooftop Photo-Voltaic Impacts

Similar with 2016 Load Forecast, a Bass Diffusion Model approach was adopted to estimate the rooftop PV Impact (which captures all 'behind the meter' installations) to IID system load in terms of annual capacity and energy impact in 2018 Load Forecast. However, under Federal and IID's monetary incentives as well as lower cost of solar panels during 2013-2017, IID customers who participated in IID's PV program surpassed expectations. Net Energy Metering (NEM) was a program designed to benefit IID customers who generate their own electricity (and sometimes electricity for the IID grid) using solar, wind, biogas, fuel cell or a hybrid of these technologies. IID's NEM program capacity cap was 50.2MW and reached 5% of IID's peak demand. At the end of 2015, the existing PV installations and the registered PV installations in process have reached up to 64.5MW, which was way above the IID NEM capacity cap 50.2MW. In 2016 Load forecast, the Bass Diffusion Model was modified from linear to non-linear The assumption of PV market saturation point in the expected case was to double the original NEM program capacity cap from 50.2MW to 100.4MW, which was the most possible result of NEM re-volt in the near future, as most utilities advocated at that time. But doubling the original NEM program capacity cap has not happened as assumed in 2016 load forecast. In July 2016, IID made a policy decision to change its Net Metering Program to ensure that everyone pays their fair share for their use of the energy grid, including customers who choose to install rooftop solar systems on their homes. The new Net Billing Program, which was approved by the board July 2016 after extensive discussion, now aligns prices with the actual cost of providing power for all customers. This was a necessary solution that balances the interests of every customer IID serves in order to continue to deliver on IID's obligation to providing the greatest value at the lowest cost. Under the new Net Billing Program, the IID no longer provides the incentive to the customers who install rooftop PV. And there is no program capacity cap either.

In 2018 Load Forecast, since there is no NEM program capacity cap to control people's decision in rooftop PV installations in IID service territories, the market driven mechanism is the only consideration in estimating the market saturation point in IID service territories. National Renewable Energy Laboratory (NREL) published a market survey and study on the PV market penetration percentage and payback years (NREL, 2014). The results of the survey were used to estimate the market saturation point within the IID service territory in the 2018 Load Forecast according to the estimated payback years of PV installations. The payback years of PV installations are estimated by considering the cost of panels, Federal and IID's incentives, solar panel imports tariff, IID rates and the output efficiency of panels. The PV installation cost decreased by 20%-30% compared with that of 2016 Load Forecast. Moreover, it is assumed that the federal incentive and the solar panel imports tariff balanced each other and the PV installation cost keeps no changes in the forecast years. It was also assumed that 50% of commercial customers and 46% of residential customers rent their properties and are excluded from the customers who have the possibility to install rooftop PV. Then two cases for rooftop PV Impacts forecast were coming out: the expected case and the high case. The expected case assumes that IID will no long provide incentive for the customers who install rooftop PV in the forecast years, so the calculated market saturation point is 110.5MW for the total rooftop PV installation capacity in IID service area. The high case assumes that IID provides incentive for the customers who install rooftop PV again in the forecast years, also IID rate is increased by 7%, so the calculated market saturation point is 184.5MW for the total rooftop PV installation capacity in IID

Figure 2-1 PV new and accumulated installations capacity in Expected Case and High Case in 2018 Load Forecast



The blue dashed line is the new PV installations capacity annually in expected case scenario; the blue solid line is the accumulated PV installations capacity annually in expected case scenario; the red dash line is the new PV installations capacity annually in high case scenario; the red solid line is the accumulated PV installations capacity annually in high case scenario. Both the new PV installations capacity and accumulated PV installations capacity are a lot higher in the high case than in expected case. This is mainly a due to the different market saturation points assumptions: 110.5MW in the expected case and 184.5MW in high case.

Energy Efficiency Portfolio Impacts

The Energy Efficiency (EE) program impact projection is based on EE activities over the historical period 2006-2017. In the 2018 Load Forecast, similar with the 2014 and 2016 Load Forecast, several discounting factors are used to degrade long-term cumulative EE program impact and they are as follows:

- End-use degradation factor
- Market Saturation factor
- End-of-life impact factor
- Baseline shift impact factor and contingency factor.

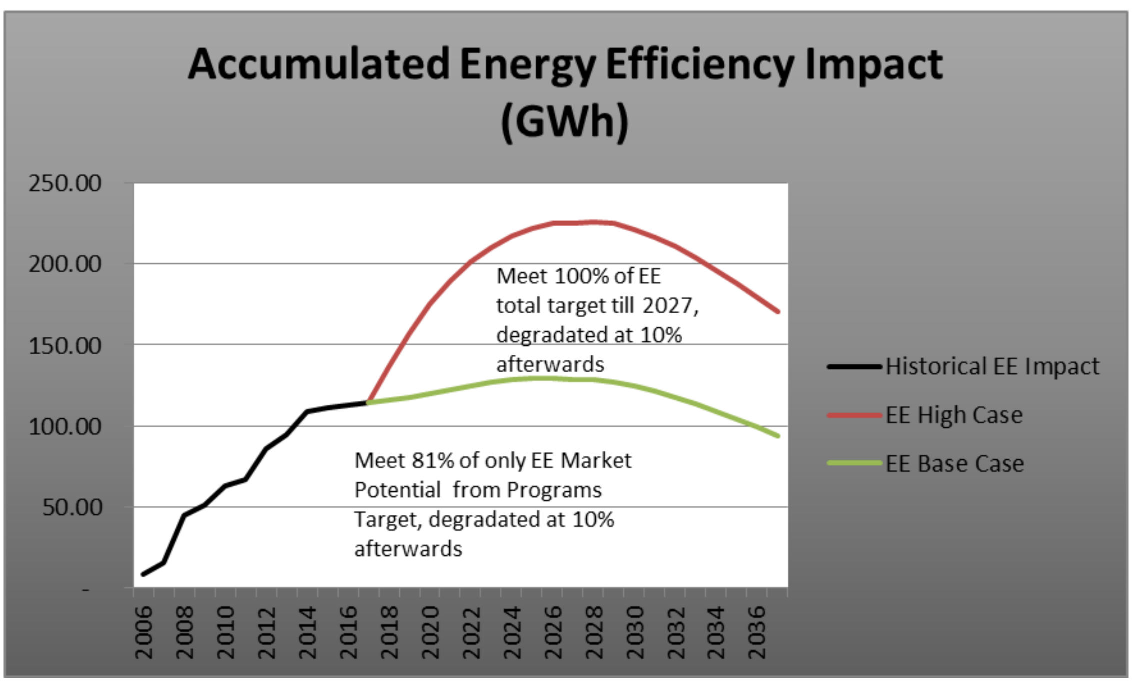
All these factors are added up to 10% degradation rate per year. The annual EE program impact in the forecast years in the 2018 Load Forecast is projected based on IID Board of Directors adopted annual electric energy efficiency program targets for the years 2018-2027 (refer to Table 2-2). Different from the previous IID Board of Directors adopted annual electric energy efficiency program targets, which only has one Energy Savings targets, in the new adopted Energy Savings Target for 2018-2027, as Table 2-2 below shows, there are two categories: Market Potential from Programs and Codes and Standards. After consulting with IID staff who is working on EE programs, the Market Potential from Programs in the Energy Savings Target is consistent with the old Energy Savings Target, the Codes and Standards includes the savings from other areas and programs which are not included before. Therefore, in the expected case, we assume that the energy savings under Market Potential from Programs are the EE target we are most likely to hit. Moreover, we assume only 81% of the target amount to be met in the forecast years according to IID's historical performance during the program execution years. The market saturation point is reached in 2027; a 10% degradation rate is applied to project the annual EE program impact after 2027, as the green solid line in the Figure 2-3 below shows; Other the other hand, in the high case, we assume that the energy savings targets are the sum of the two categories: Market Potential from Programs and Codes and Standards in the forecast years, and the market saturation point is reached also in 2027 and a 10% degradation rate is applied to project the annual EE program impact after 2027, as the red solid line in Figure 2-3 below shows.

Table 2-2 IID board adopted Energy Saving Targets for 2018-2027

Year	MWh (Market Potential from Programs)	MWh (Codes and Standards)	New EE Targets (MWh)
2018	15674	17801	33475
2019	16075	17685	33760
2020	17209	16743	33952
2021	18051	14181	32232
2022	18225	12669	30894
2023	17917	10751	28668
2024	17432	10253	27685
2025	16930	9778	26708
2026	15703	9324	25027
2027	15658	6777	22435

The green line in the Figure 2-3 depicts the annual EE program impact projection based on the assumptions that EE program ends in 2027; only 81% of the target amount to be met in the forecast years according to IID's historical performance during the program execution years, no targets needed to be met after 2027; and with a 10% degradation rate annually. In the high case, 100% of the target amount is assumed to be met in the years 2018-2027. After 2027, no targets needed to be met; and with a10% degradation rate annually. as the Figure 2-3 below shows.

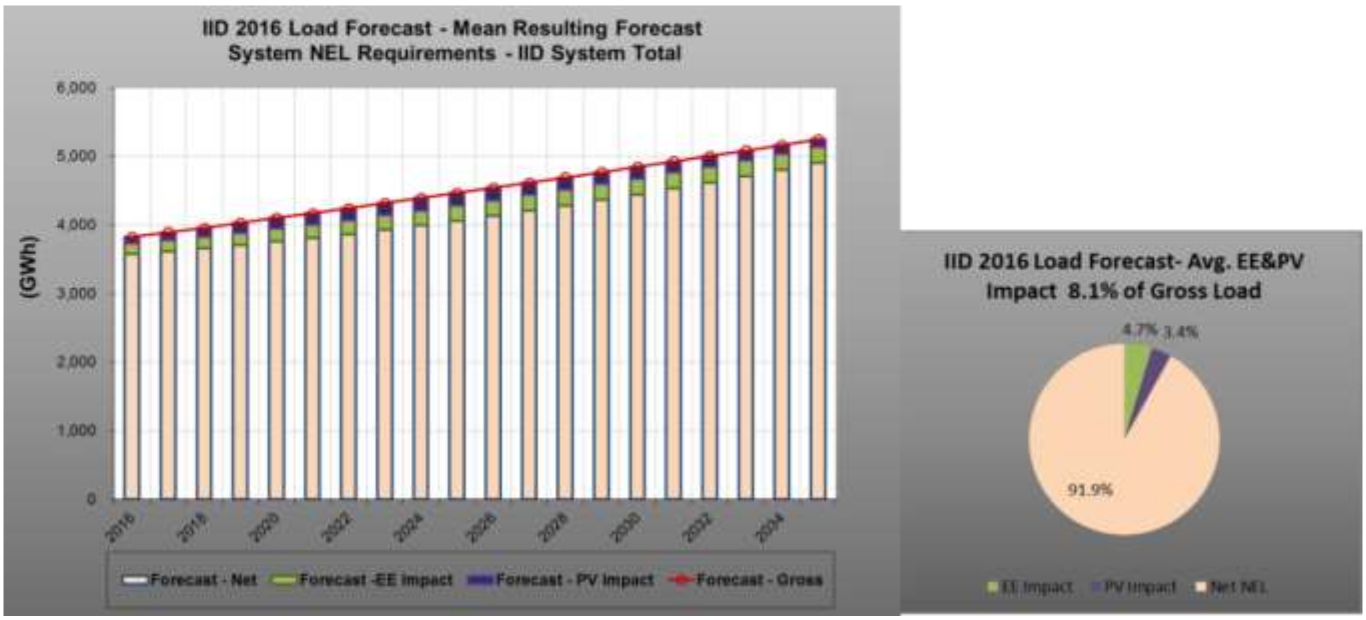
Figure 2-3 EE annual accumulated degrade energy impact in the expected and high cases



PV + EE Impact to Net and Gross NEL and CP

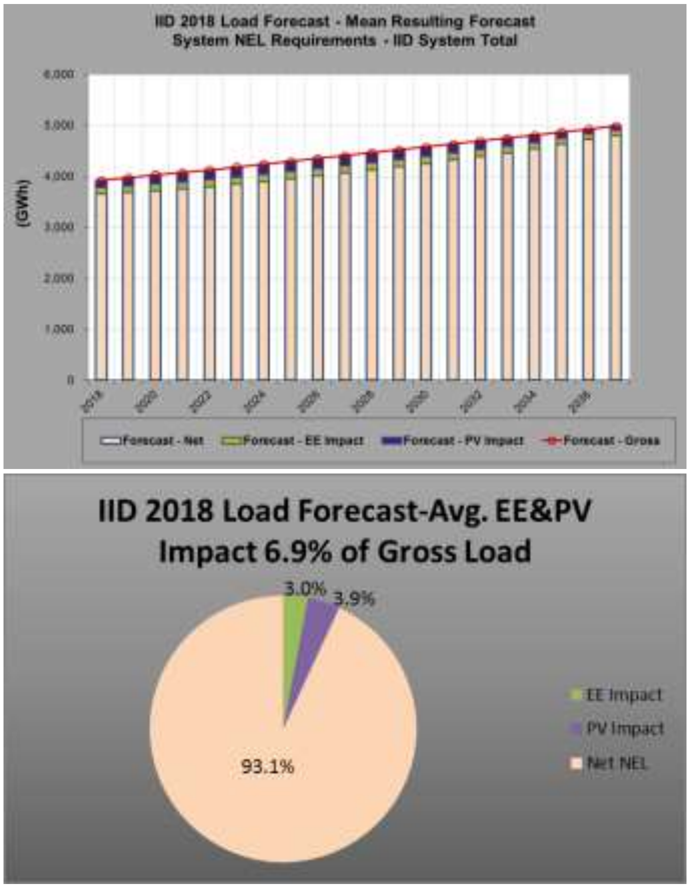
In the 2018 Load Forecast, the impact of PV and EE on the NEL changes in some degree compared with 2016 Load Forecast caused by the changes in the assumptions described above in the expected case and high case. In Figure 2-4, the columns and lines chart on the left depicts the relationship of net NEL, PV impact, EE impact and gross NEL in the forecast years; the pie chart on the right depicts that the average EE&PV impact in the forecast years makes 8.1% of the gross NEL in 2016 Load Forecast.

Figure 2-4 Gross/ Net NEL and EE&PV impact in 2016 Load Forecast



In Figure 2-5, the average EE&PV impact in the forecast years makes 6.9% of the gross NEL in 2018 Load Forecast (Expected Case), which declined compared with that in the 2016 Load Forecast. The main reason to explain the declines of EE&PV impact in 2018 Load Forecast is the assumption of EE expected case only considering the EE savings target from the category Market Potential from Programs, which declines yearly.

Figure 2-5 Gross/Net NEL and EE&PV impact in 2018 Load Forecast (Expected Case)



In Figure 2-6, the average EE&PV impact in the forecast years makes 13% of the gross NEL in 2016 Load Forecast (High Case); in Figure 2-7, the average EE&PV impact in the forecast years makes 12% of the gross NEL in 2018 Load Forecast (Low_mild case)

Figure 2-6 Gross/Net NEL and EE&PV impact in 2016 Load Forecast (High Case)

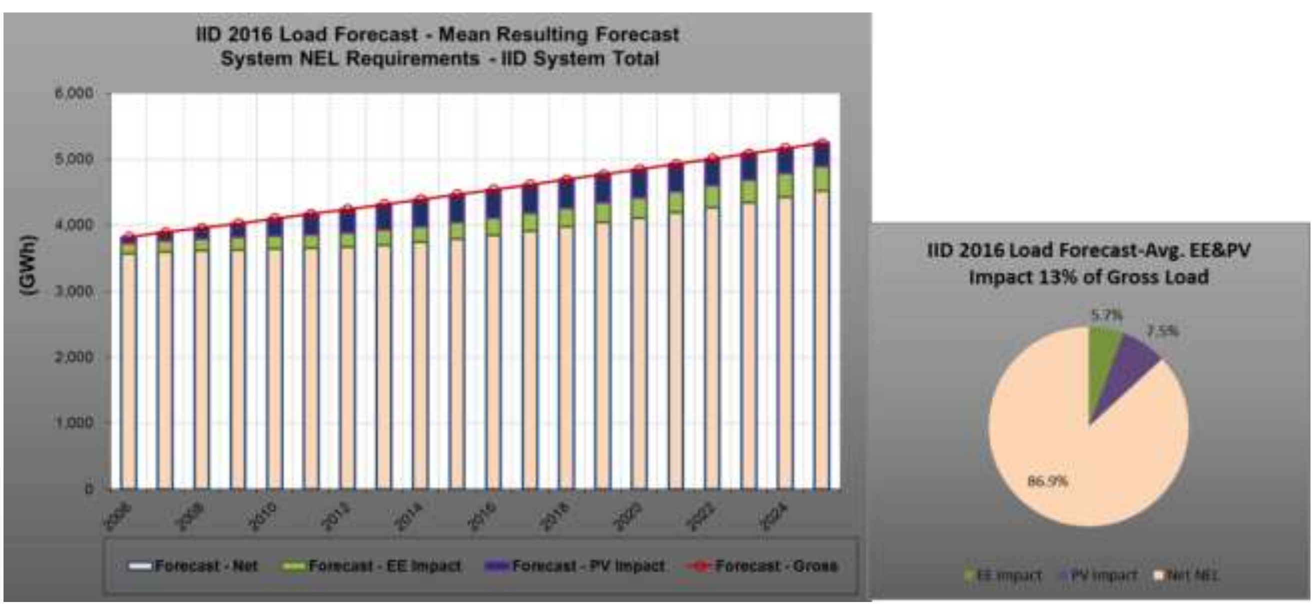
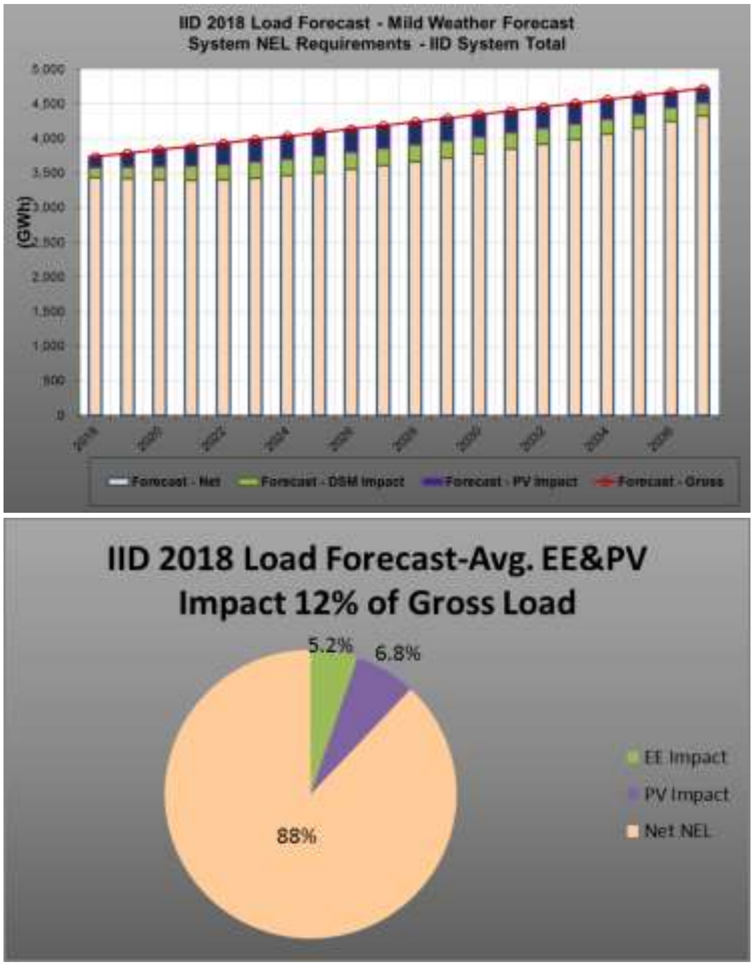
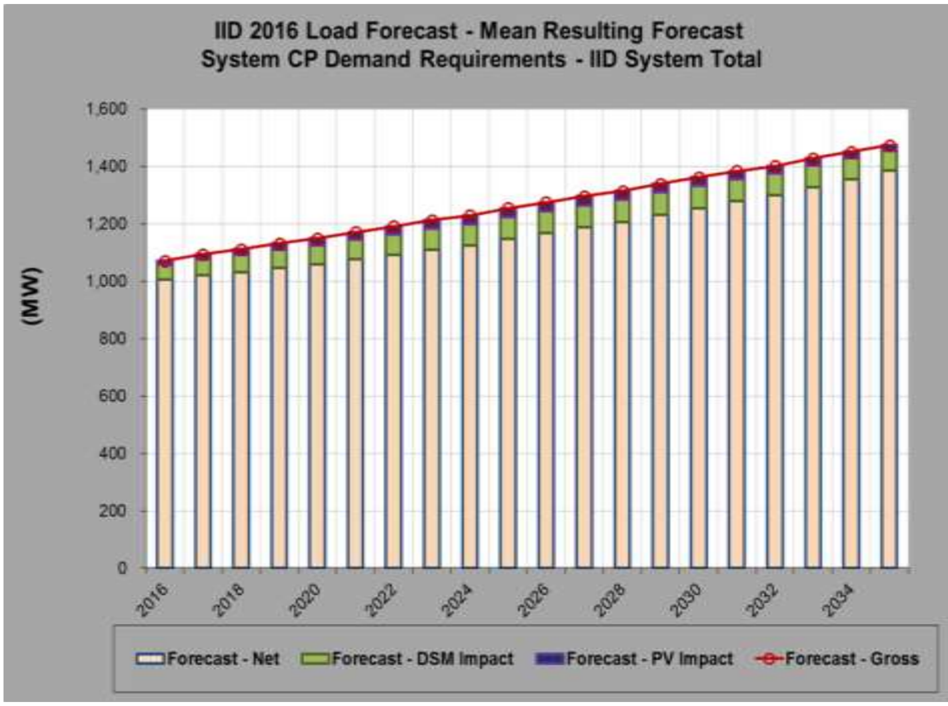


Figure 2-7 Gross/Net NEL and EE&PV impact in 2018 Load Forecast (Low-mild Case)



Likewise, in the 2018 Load Forecast, PV and EE CP impact changed in the same trend as that in NEL compared with 2016 Load Forecast since CP is derived from NEL and Load Factor. In Figure 2-8, the columns and lines chart on the left depicts the relationship of net CP, PV impact, EE impact and gross CP in the forecast years; the pie chart on the right depicts that the average EE&PV impact in the forecast years is approximately 7.7% of the gross CP in 2016 Load Forecast (Expected Case). In Figure 2-9, the columns and lines chart on the left depicts the relationship of net CP, PV impact, EE impact and gross CP in the forecast years; the pie chart on the right depicts that the average EE&PV impact in the forecast years is approximately 6.5% of the gross CP in 2018 Load Forecast (Expected Case).

Figure 2-8 Gross/Net CP and EE&PV impact in 2016 Load Forecast (Expected Case)



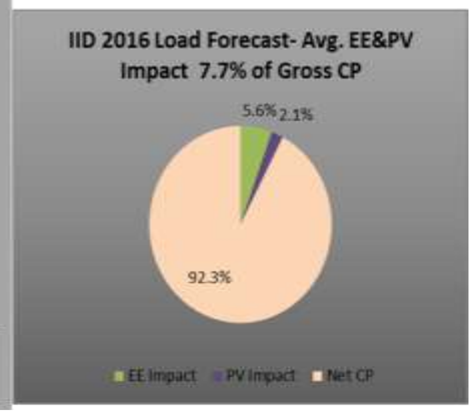
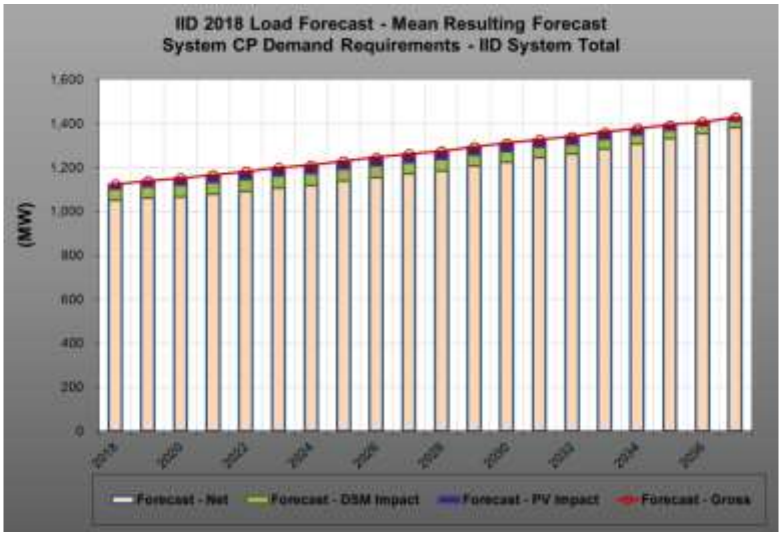
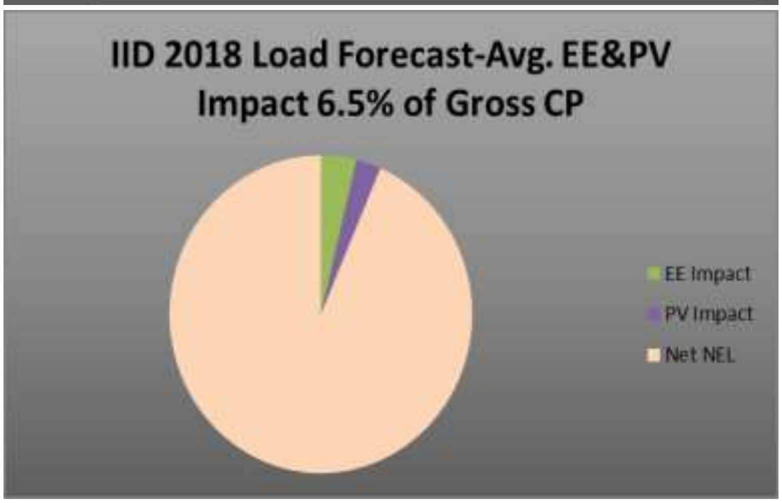


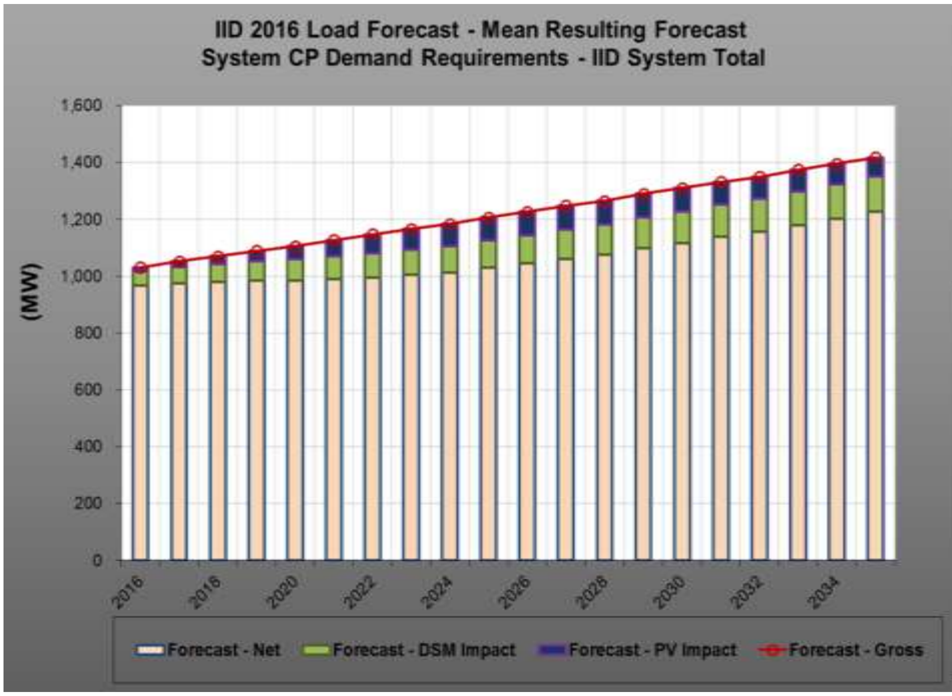
Figure 2-9 Gross/Net CP and EE&PV impact in 2018 Load Forecast (Expected Case)





In Figure 2-10, the average EE&PV impact in the forecast years makes 13% of the gross CP in 2016 Load Forecast (High Case). In Figure 2-11, the average EE&PV impact in the forecast years makes 12% of the gross CP in 2018 Load Forecast (High Case).

Figure 2-10 Gross/Net CP and EE&PV impact in 2016 Load Forecast (High Case)



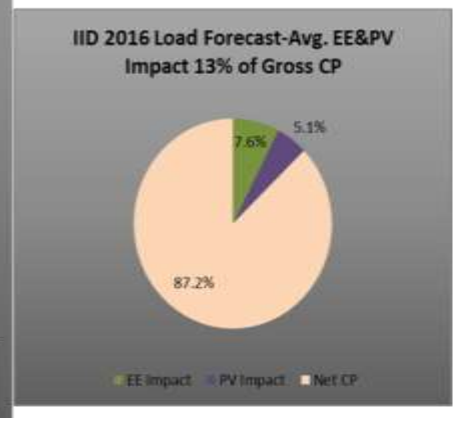
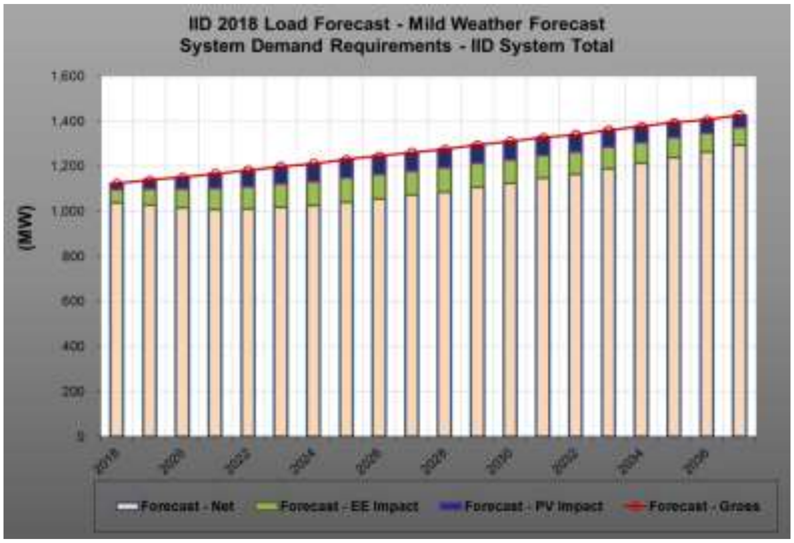
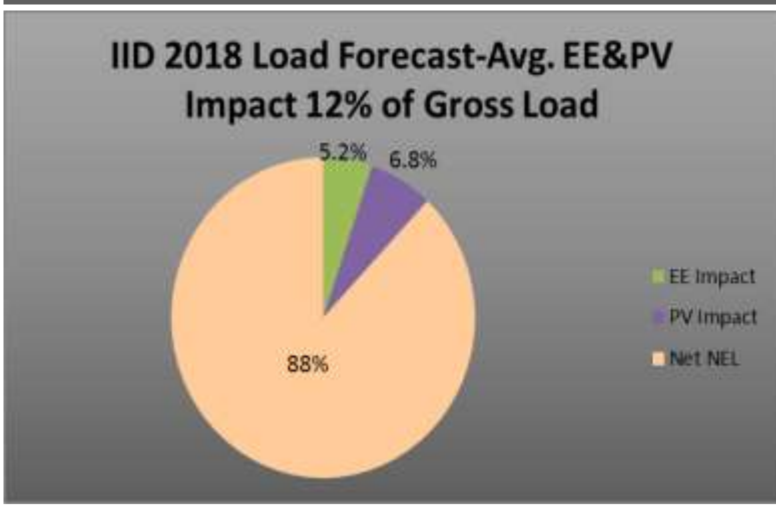


Figure 2-11 Gross/Net CP and EE&PV impact in 2018 Load Forecast (Low-mild Case)





Mild, Base and Severe Weather Scenarios and Range Forecast

Since weather cannot be forecasted further than 14 days ahead under the current technology, and weather temperature is an important variable to affect the load, weather normalization methodology has to be applied to long term load forecast, which is an industry standard methodology. In old IID long term load forecast, 65 years of historical weather temperature was used to calculate normalized weather temperature. But we also observed that using longer historical weather temperatures, the calculated normalized temperatures are lower, using shorter historical weather temperatures, the calculated normalized temperatures are higher. When using ex-post evaluation method to test both 30 years normalized weather temperatures and 67 years normalized weather temperature, the test result supports 30 years normalized weather temperatures. Moreover, 30 years normalized weather temperatures seem to be industry standard to be widely used in the long term load forecast in the energy industry. Therefore, in 2018 Load Forecast, 30 years normalized weather temperatures are used instead of the 67 years, as that in 2016 Load Forecast. Table 2-12 depicts the calculated normalized weather temperatures in 2016 Load Forecast; table 2-13 depicts the calculated normalized weather temperatures in 2018 Load Forecast.

Table 2-12 Base/Mild/Severe Weather HDDs and CDDs in 2016 Load Forecast (65 years)

Computed Normal			Computed Mild			Computed Severe		
Average of all Complete Months over entire data set			Average of all Complete Months over entire data set			Average of all Complete Months over entire data set		
Month	NormalHDD	NormalCDD	Month	MildHDD	MildCDD	Month	SevereHDD	SevereCDD
1	294	3	1	136	2	1	451	3
2	165	14	2	77	12	2	254	16
3	81	72	3	37	62	3	125	81
4	22	187	4	10	162	4	33	211
5	2	402	5	1	348	5	3	455
6	0	635	6	0	551	6	0	719
7	0	831	7	0	721	7	0	941
8	0	821	8	0	712	8	0	930
9	0	639	9	0	554	9	0	724
10	6	329	10	3	285	10	9	372
11	101	50	11	47	43	11	155	56
12	299	3	12	138	2	12	460	3
Annual	969	3,984	Annual	448	3,456	Annual	1,490	4,513

Table 2-13 Base/Mild/Severe Weather HDDs and CDDs in 2018 Load Forecast (30 years)

Computed Normal			Computed Mild			Computed Severe		
Average of all Complete Months over entire data set			1 in 20 cases of all Complete Months over entire data set			1 in 20 cases of all Complete Months over entire data set		
Month	NormalHDD	NormalCDD	Month	MildHDD	MildCDD	Month	SevereHDD	SevereCDD
1	294	1	1	135	1	1	452	1
2	157	12	2	72	11	2	242	14
3	60	97	3	28	83	3	93	110
4	16	210	4	7	181	4	24	240
5	1	434	5	0	373	5	1	495
6	0	669	6	0	576	6	0	763
7	0	864	7	0	743	7	0	985
8	0	865	8	0	743	8	0	986
9	0	668	9	0	575	9	0	762
10	5	334	10	2	287	10	7	380
11	106	47	11	49	40	11	163	54
12	332	1	12	153	1	12	511	1
Annual	970	4,202	Annual	446	3,613	Annual	1,493	4,791

Since cooling degree days have the heaviest influence on IID's total energy use, below a chart comparing cooling degree days in the normal/mild/sever weather scenarios:

Table 2-14 Weather Scenarios (30 years vs 67 years): Normal/Mild/Severe

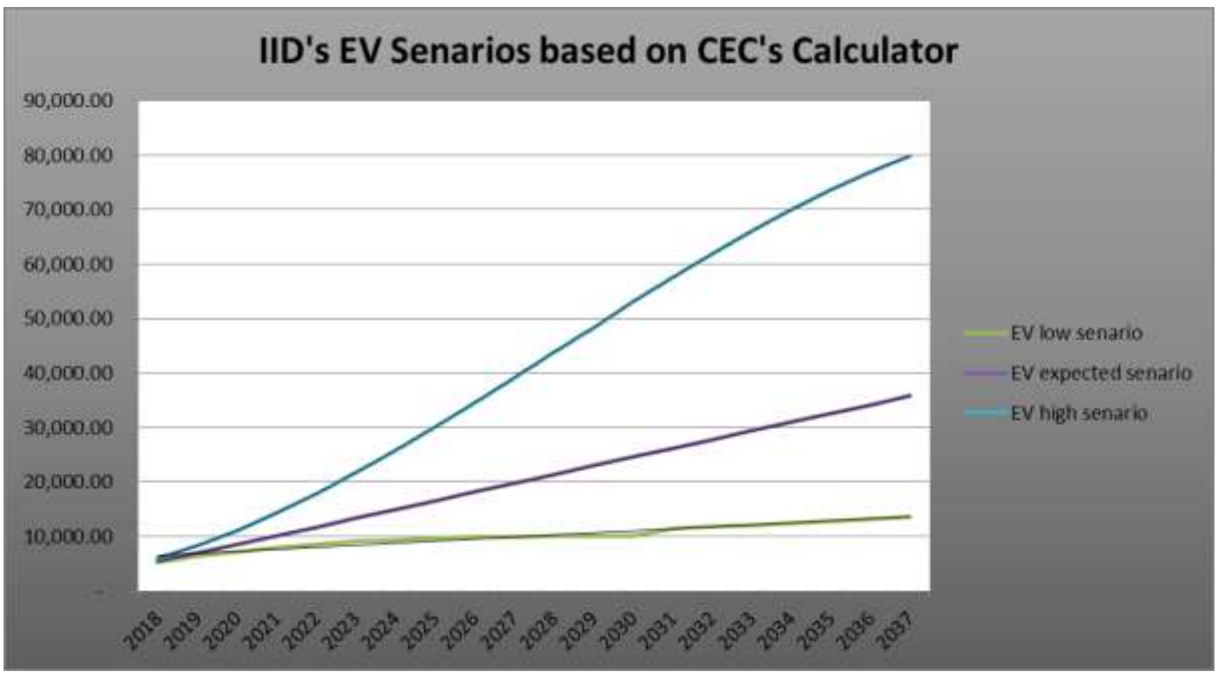
Essentially, the most recent 30 years show greater volatility in weather and this volatility is reflected in the load forecast by providing a wider range of potential outcomes and it also affects the starting point of the first year of the projection. More specifically, since the recent two years 2016 and 2017 are extremely hot years, the actual heating degree days are even much higher than the severe weather range, which only happens under small probability of 1 in 20 cases in the past 30 years. Both the Net Energy for Load (NEL) growth and the Coincident Peak growth are greatly impact by the extreme hot weather in the years 2016 and 2017. However, by using normalized weather temperatures in the 20 years of projection in expected case, the projected NEL in the first forecast year drops.

Electric Vehicles

POUs are required to address transportation electrification in the IRPs adopted and submitted to the Energy Commission pursuant to SB 350. California Energy Commission staff has developed a spreadsheet-based tool to assist POUs in estimating and reporting on the energy and emissions impact of light-duty plug-in electric vehicle (LD PEV) deployment in their service territories. According to the introduction of the calculator, the tool was developed in consultation with Air Resources Board, California Public Utilities Commission, and California's privately owned utilities. It uses data from various sources to estimate energy and emissions over time associated with displacing a gasoline-powered light-duty vehicle with a PEV in any year from 2017 to 2030. This tool captures nominal vehicle population decline after its first sale, and travel decline as the vehicle ages. Concurrently, improving gasoline and PHEVs fuel economy and declining carbon intensity gasoline and power generation use in future years are also quantified (CAFE standards), yielding more accurate estimates. Additional data is used to project the annual electricity consumption over time of the representative ("composite") PEVs deployed in a given year.

As a POU, IID addressed transportation electrification in 2018 load forecast by using CEC's calculator (version 3.5-3). For purposes of this calculator, the POUs are not required to make specific assumptions about the number of PEVs deployed in any year. However, utilities do need to choose the future statewide PEV deployment scenario goal. In IID's electric vehicles energy consumption projections of 2018 load forecast, three scenarios have been created according to CEC's EV policy drivers assumptions: EV low scenario, EV expected scenario and EV high scenario. IID's EV low scenario uses CEC's business as usual scenario (the green line in the graph below). Business as usual trajectory keeps the historic Federal, State, Local incentives and consumer acceptance. IID's EV expected scenario (the purple line in the graph below) is based on Executive Order B-16-12, Senate Bill 1275 (2014) which set a goal of achieving 1 million Zero-emission vehicles by 2023 and achieving 1.5 million ZEVs by 2025, including required infrastructure. IID's EV high scenario (the blue line in the graph below) is based on Governor 5 million PEV goal by 2030. Since the calculator only does projection till 2030, and the forecast years in IID's 2018 load forecast is till 2037, the projection of EV energy consumption during 2031-2037 is using trend/regression method.

Table 2-15: IID's EV Scenarios based on CEC's calculator



New Industrial Load (Cannabis)

Please add brief description here. Explain the process of working with the Distribution section and the management decision to use "typical industrial load growth" for the expected case, but we also have other observations that include faster industrial load growth. Please put that rate of growth assumptions and our assumptions for peak and energy application here. Section B-1 (Page 168) of the CEC demand forecast (X:\BACKOFFICE\2018\RESOURCE PLANNING\Load Forecast\2018 Forecast\CEC IEPR Commissioner Workshop Dec.15 presentations) is a great reference for general info

On November 8, 2016, Californians approved Proposition 64, the California Marijuana Legalization Initiative that made it legal for individuals to grow and consume marijuana for recreational purposes on and after November 9, 2016. Proposition 215 in 1996 had already legalized the medical use of marijuana in California. Proposition 64 made it legal for persons of age 21 and older to grow and consume marijuana for recreational purposes in a private home or a licensed business establishment. Individuals could also share limited amounts of marijuana with each other. The sale of recreational marijuana became legal on January 1, 2018, although consumption of marijuana in public places remains illegal. California is the fifth state to legalize the recreational use of marijuana after Colorado, Washington, Oregon, and Alaska. Legalization creates concerns from an energy point of view because cultivation can be quite energy intensive.

For IID, it is realized that the projection of cannabis energy usage is important in the long term load forecast since it is known that production of marijuana is quite energy intensive especially for indoor production. However, historical data on the production and consumption of marijuana is scarce because of the illegal nature of these activities in the past. The only information can be obtained regarding to cannabis load is from IID's Distribution Planning & Engineering section. According to the information they provided, the city of Coachella has designated an undeveloped land east of Grapefruit Blvd and South of Ave. 48 as a cannabis growing area. Electrical Load requested from individual cultivators varies from 3 to 40 MW per parcel. Based on the total projected load for the area (245MW), the need of 2 substations (120MW each) and a 230 KV transmission line have been identified. The city of Coachella is setting up a community facility district (CFD) to provide local city backed bonds for the capital necessary for all of the infrastructure needs for this new industrial park. Table 2-15 shows total projected electrical load within the Cannabis Zone by IID's Distribution Planning & Engineering staff.

Table 2-16: Total Projected Electrical Load Within the Cannabis Zone

TOTAL PROJECTED ELECTRICAL LOAD WITHIN THE CANNABIS ZONE

Due to the uncertainty nature of cannabis production, and it is newly passed law in California and there are still different opinions on this issue between federal's level and state's level, when doing cannabis load projection in IID's 2018 Load Forecast, three scenarios for cannabis load have been created to capture the uncertainties: business as usual case, new industrial load (med case), new industrial load (high case). For the business as usual case for cannabis load, which is used in the expected case of 2018 Load Forecast, we assume that cannabis load growth has been included in the economic growth projection, so not considered as a separated energy sales category. For the new industrial load (med case), we use the low projection provided from IID's Distribution Planning & Engineering section. For the new industrial load (high case), we use the high projection provided from IID's Distribution Planning & Engineering section. Figure 2-16 below shows new industrial peak impact and energy impact for both med case and high case in 2018 Load Forecast. Cannabis load business as usual case peak impact and energy impact are not available since it is assumed to combined into other energy sales categories.

Figure 2-17: New Industrial Peak Impact and Energy Impact (med case, high case)

	New Industrial Med Case		New Industrial High Case	
Year	Peak Imapct(MW)	Energy Impact (KWh)	Peak Imapct(MW)	Energy Impact (KWh)
2018	-	-		-
2019	-	-		-
2020	10	35,345	20	76,373
2021	15	52,125	41	144,743
2022	20	69,089	62	223,816
2023	25	86,184	104	352,812
2024	30	103,639	127	427,610
2025	35	122,956	150	502,149
2026	45	156,079	173	570,041
2027	50	173,886	177	581,693
2028	55	189,972	180	592,882
2029	55	189,358	180	591,567
2030	55	189,148	180	591,494
2031	55	189,065	180	591,876
2032	55	189,257	180	593,067
2033	55	188,599	180	591,581
2034	55	188,393	180	591,547
2035	55	188,231	180	591,654
2036	55	188,489	180	593,141
2037	55	187,817	180	591,580

Note: since the load factor of New Industrial is not available, it is assumed that New Industrial's load factors are the same as IID's total system load factors.

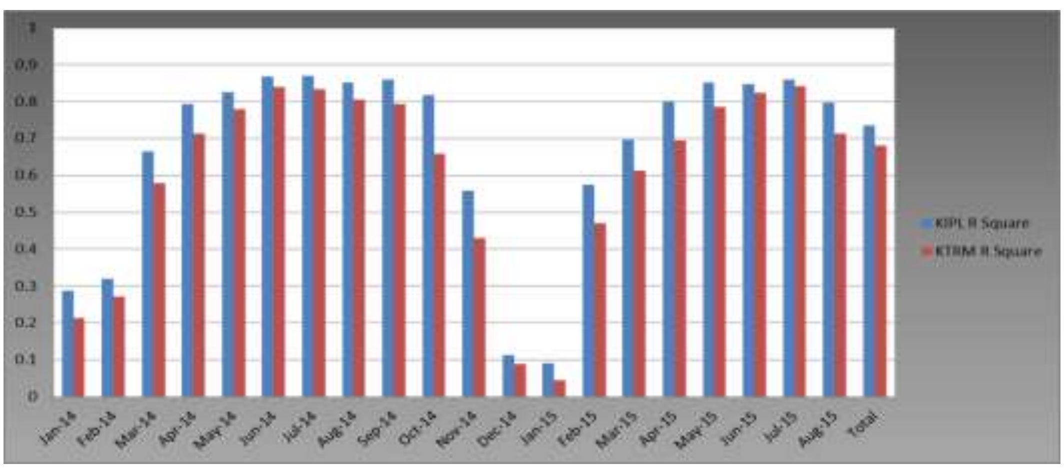
Section 3: Data sources and Samples Design

In the 2018 Load Forecast study, the data for number of customer accounts, energy sales, NEL,CP, PV installation capacity, and Energy Efficiency programs impact was collected and maintained by IID staff. Energy sales data was generally available and analyzed over January 2001 through December 2017 (Study Period); NEL and CP data were also from January 2001 through December 2017; Energy Efficiency programs impact data was available and analyzed from January 2006 through December 2016 (Note: Energy Efficiency programs impact data on 2017 was not yet available at the time of doing the study, so estimated data was used for 2017, and the estimation is based on 2017 IID EE target and 2016 target achieving percentage); PV installation capacity data was available and analyzed from January 2003 through December 2017.

Weather Data

In IID service territories, there are two weather stations, Imperial County Airport (KIPL) weather station is located in Imperial County, Desert Resorts Regional Airport (KTRM) weather station is located in Riverside County. In the 2018 Load Forecast, the weather station KIPL in Imperial County is still selected as a weather data source. But after completing an hourly load vs hourly weather temperature analysis in 2016, it was determined that the weather data from Imperial County Arpt. Weather Station (KIPL) in Imperial County is more correlated to the IID system load. Figure 3-1 depicts the R squared results after processing a correlation regression analysis of hourly load vs hourly weather temperature from January 2014 to August 2015.

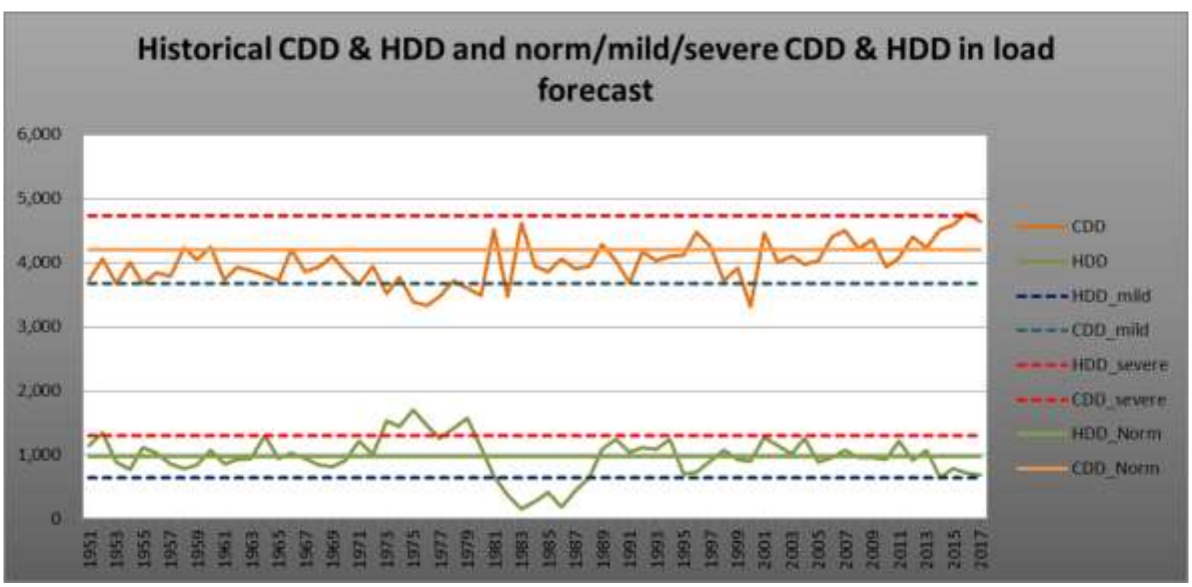
Figure 3-1 Correlation between IID system load and KTRM vs KIPL weather data



The red columns are the R Squared of the regression models by each month for the weather station KTRM, which is located in Riverside County (independent variable is hourly weather temperature from KTRM by each month, dependent variable is hourly IID system net load by each month); the blue columns are the R Squared of the regression models by each month for the weather station KIPL, which is located in Imperial County (independent variable is hourly weather temperature from KIPL by each month, dependent variable is hourly IID system net load by each month). It can be seen that blue columns are significantly higher than red columns in all months of the test period. It indicates that the weather data from KIPL is more significantly correlated with IID system load. Therefore, it was decided to change the weather station from Desert Resorts Regional Arpt. (KTRM) into Imperial County Arpt. (KIPL).

30 historical years' temperatures, which are downloaded from Underground Weather website, were used as the weather data (1988-2017) inputs in the 2018 Load Forecast study. The raw weather data is the daily average temperature, which is converted into Heating Degree Days (HDD) and Cooling Degree Days (CDD). HDD is defined as the number of degrees that a day's average temperature is below 65° Fahrenheit , the temperature below which buildings need to be heated; CDD is defined as the number of degrees that a day's average temperature is above 65° Fahrenheit, and people start to use air conditioning to cool their buildings. 1-in-20 (Level of significance: 5% on each tail) two tails t-Distribution test was used to estimate the normalized HDD and CDD, severe HDD and CDD (right tail), mild HDD and CDD (left tail). Figure 3-2 below demonstrates historical actual annual CDDs and HDDs (1951-2017), the orange solid line is the actual CDDs, the red dash line is the calculated severe CDDs, the orange solid line is the calculated normal CDDs, the blue dash line is the calculated mild CDDs. We can see that basically the actual annual CDDs line move up and down randomly around the calculated normal CDDs line, the calculated severe-normal-mild range tries to cover all the movement, still there are a few chances when the actual orange line move outside of the range. Likewise, the green solid line is the actual HDDs, the red dash line is the calculated severe HDDs, the green solid line is the calculated normal HDDs, and the blue dash line is the calculated mild HDDs. We can see that similarly the actual annual HDDs line move up and down around the normal HDDs line randomly, the calculated severe-normal-mild range tries to cover all the movement, but still there are a few chances when the actual green line moves outside of the range. Therefore, even though the load forecast is the range forecast due to the randomness of weather temperatures, there is still 5% probability when the range can't capture the actual weather temperature changes.

Figure 3-2 Historical CDD & HDD nad norm/mild/severe CDD & HDD in 2018 load forecast



Economic Data

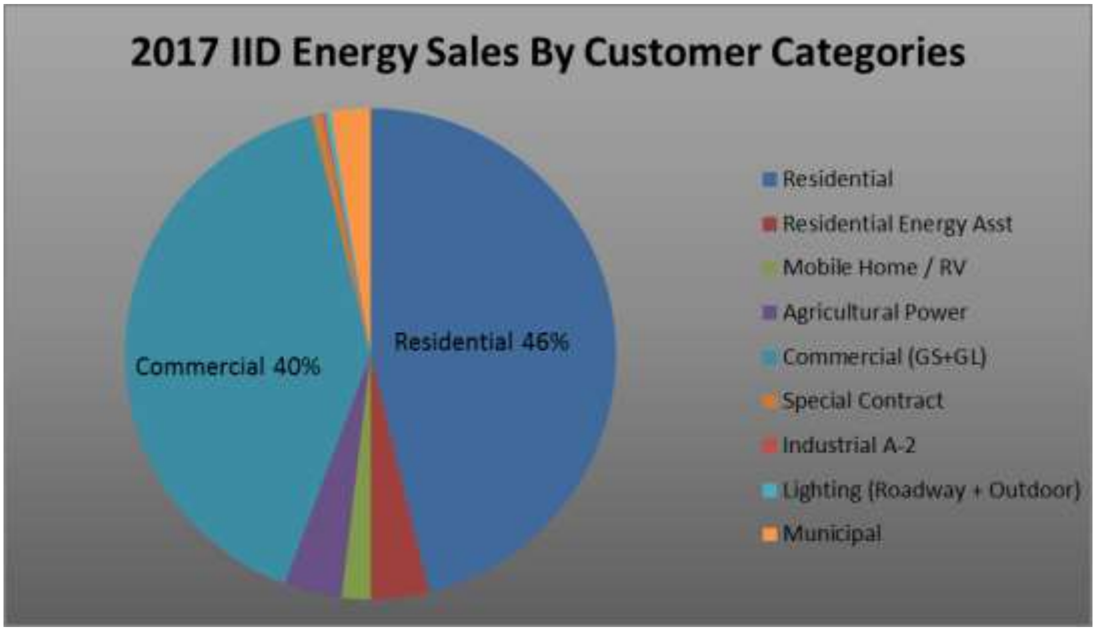
Historical and projected economic and demographic data were provided by Woods & Poole Economics. (Note: at the time of doing 2018 load forecast study, Woods & Poole Economics' latest available data set is based on historical years' data from 1970 through 2015, the forecast years' data is from 2016-2050.That means 2 years lagged behind the 2018 Load Forecast, of which the forecast years are from 2018-2037.) The IID service territory covers both Imperial County and part of Riverside County. The two counties have very different economic and demographic attributes in terms of county population, households, employment, personal income and gross domestic product, which are used as independent variables in the 2018 Load Forecast. Therefore, the data for each county was blended using a weighted average derived from 2017 energy sales data (Riverside County 59%; Imperial County 41%).

The economic data used in 2018 load forecast regression models are: population, total employment, farm employment, retail employment, personal income and gross regional product/GRP. The below is a comparison table of the annual growth rate of these economic variables in 2018 load forecast vs 2016 load forecast. In order to do a fair comparison, the table compares the first 10 years' annual growth rate and the second 10 years' annual growth rate in both 2018 load forecast and 2016 load forecast. The table shows that almost all the variables have positive growth rate, except the variable of farm employment, which has negative annual growth rate. For 2018 load forecast, some of them have faster annual growth rate (indicated in red color), some of them have slower annual growth rate (indicated in green color), compared with 2016 load forecast. Especially for the variables population, gross regional product and farm employment which are the variables used to forecast the two main IID customer categories residential and commercial customers, they have slower growth rate. This can be another reason to explain why 2018 load forecast results have a little bit slower annual growth rate, compared with 2016 load forecast results.

Figure 3-3 Average Annual Growth Rate of Load Forecast Economic Data 2018 vs 2016

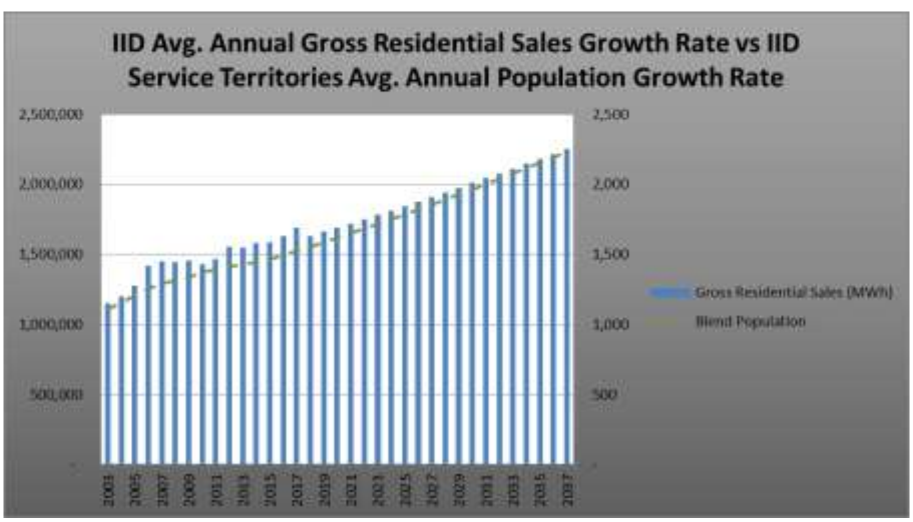
		Population	Total Employment	Farm Employment	Retail Employment	Personal Income	Gross Regional Product
2018 LF Economic Data	2018-2027	1.97%	2.30%	-0.06%	3.14%	3.39%	3.01%
	2028-2037	1.84%	1.96%	-0.33%	2.84%	2.81%	2.67%
2016 LF Economic Data	2016-2025	1.99%	2.23%	0.54%	2.68%	3.41%	3.05%
	2026-2035	1.64%	2.29%	0.43%	2.72%	3.47%	3.09%

Figure 3-4 2017 IID Energy Sales by Customer Categories



As illustrated above, residential sales make 46% of 2017 IID total energy sales; commercial sales make 40% of 2017 IID total energy sales. The entire rest customer categories only make 14% of 2017 IID total energy sales. That means the total IID system load growth is mainly driven by residential customers and commercial customers. In the residential regression model, blend population is an important independent variable. This indicates that the residential load growth can be mainly explained by blend population growth. Figure 3-5 demonstrates that blend population growth has the similar trend as residential sales growth from in both the first ten forecast years and the second ten forecast years.

Figure 3-5 IID Gross Residential Sales Growth Rate vs Blend Population Growth Rate

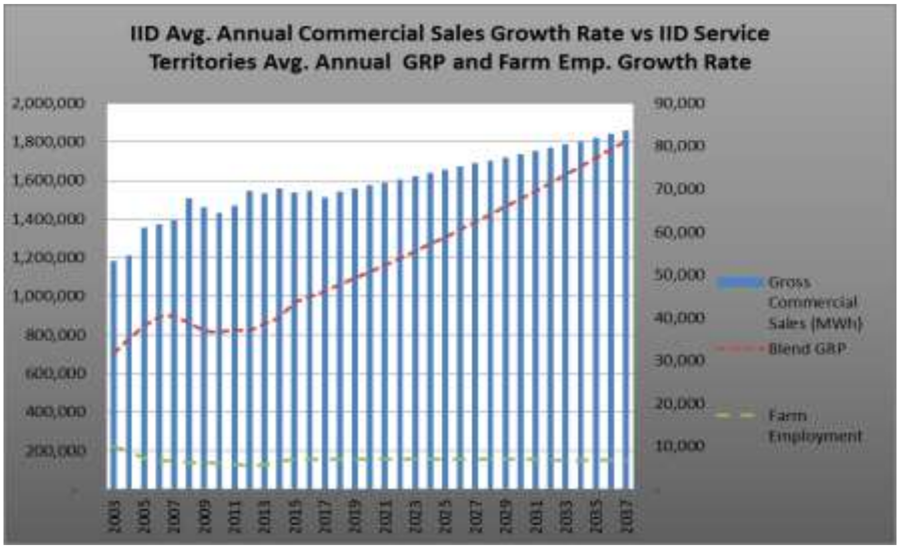


Year	Gross Residential Sales	Blend Population
2003-2017	2.8%	2.3%
2018-2027	1.8%	2.0%
2028-2037	1.6%	1.8%

For the historical period (2003-2017), avg. population growth rate is 2.3%; avg. residential sales growth rate is 2.8%. During the first 10 forecast years (2018-2027), avg. population growth rate is 2.0%; avg.

residential sales growth rate is 1.8%. During the second 10 forecast years (2028-2037), avg. population growth rate is 1.8%; avg. residential sales growth rate is 1.6%.

Figure 3-6 IID Commercial Sales Growth Rate vs Blend GRP Growth Rate



Year	Gross Comm. Sales	Blend GRP	Blend Farm Emp.
2003-2017	1.8%	2.7%	-2.6%
2018-2027	1.0%	3.0%	-0.1%
2028-2037	1.0%	2.7%	-0.3%

In the commercial regression model, blend Gross Regional Product (GRP) used to be an important independent variable in commercial sales model in old load forecast. But from the Figure 3-6 above, we can observe that the Blend GRP has a way faster growth rate than commercial sales during the historical period 2011-2017. Therefore, in 2018 Load Forecast commercial sales model, farm employment was added as another independent variable besides Blend GRP. It is observed from Figure 3-6 that for the historical period (2003-2017), avg. GRP growth rate is 2.7%; avg. commercial sales growth rate is 1.8%; avg. farm employment is -2.6%; during the first 10 forecast years (2018-2027), avg. GRP growth rate is 3.0%, avg. commercial sales growth rate is 1.0%, avg. farm employment is -0.1%; During the second 10 forecast years (2028-2037), avg. GRP growth rate is 2.7%, avg. commercial sales growth rate is 1.0%, avg. farm employment is -0.3%. Figure 3-6 demonstrates that Blend GRP has too much faster annual growth rate during all periods than Gross Commercial Sales. Adding the variable Blend Farm Employment with a flat or negative growth rate can make the growth rate of the regression result of Gross Commercial Sales much slower and more realistic. That's why the ex-post model evaluation test of adding the variable farm employment has less error.

Section 4: Limitations and Future Recommendations

The 2018 Load Forecast methodology and model specifications basically keep the same as 2016 Load Forecast with some modifications and improvements, which have been discussed in the previous sections of this report. Some limitations are found during the 2018 Load Forecast study process, subjected to either the current technical limits, data availability or current knowledge limits. Future recommendations are given in this section in order to improve IID load forecast accuracy.

8760 Hourly Load Forecast

The output of 2018 Load Forecast is monthly Energy Sales, NEL and CP from 2018 through 2037. However, the main input data of the load forecast econometric models are the historical monthly sales by rate classifications for the IID system. Also, the Historical and projected economic and demographic data used as independent variables in the models are also monthly based. But in reality, some of IID's planning activities require the level of granularity to hourly. So, changing the monthly output into the hourly could result in a drastic improvement of understanding the load and, eventually, load forecast accuracy. The approach of changing the monthly level into the hourly level is to use the historical hourly vs daily, daily vs monthly rate to allocate the monthly value into hourly without changing the hourly load shapes. However, the issue of this changing process is that in order to exactly match the forecasted monthly energy and the forecasted coincident peak load at the same time minor adjustments to the load shapes have to be done. One way to solve this issue is to obtain the hourly input data. Currently, subject to the limitations of IID's metering system, hourly energy consumption data by customer categories is not available yet. IID load forecasting staff is dedicated to continuing to learn various approaches and methodology in load forecasting and this will be reflected in future load forecasts as the data input for any new methodology is available.

Lack of Monthly Meter Data by Customer Categories

Currently only monthly energy sales billing data by customer categories is available to forecast energy sales, NEL and CP are calculated based on the forecasted results of energy sales, no monthly meter data by customer categories is available, this is an important source of load forecast error besides the error resulted from weather temperatures. As we know that NEL and CP are meter data based on calendar months, while energy sales billing data is based on billing cycles, and billing cycles are different from calendar months, normally several days lagged behind calendar months and the billing cycles changed from time to time depending on the availability of the customer side meter data. Due to lacks of monthly meter data by customer categories, we have to use forecasted energy sales plus the loss to forecast the NEL. The loss basically is the difference between energy sales and NEL, includes the losses which are experienced over lengths of transmission and distribution lines, the energy consumed in the stations services and most importantly, the difference between the energy sales' billing cycle readings and the meters' calendar cycle readings, and etc. Therefore, the loss is not just loss; it is the general difference between energy sales and NEL. And the loss is estimated based on a general approach too. It is estimated based on historical average loss percentage. When forecasted energy sales is available, estimated loss percentage is available, the NEL can be calculated by using the formula NEL=energy sales/(1-loss percentage). The CP forecast is calculated based on NEL forecast. This general approach of getting NEL and CP from energy sales and a general difference percentage can lead to the load forecast error. Therefore, if monthly meter data by customer categories are available in the near future, NEL regression models can be created based directly on the monthly meter data by customer categories to forecast NEL directly to avoid the substantial error analyzed above and therefore to improve load forecast accuracy.

Blended Economic and Demographic Data

IID service territory predominantly resides in Imperial Valley (Imperial County) and Coachella Valleys (Riverside County). Imperial Valley and Coachella Valley have different economic and demographic attributes. However, the system load information (NEL and CP) does not separate into the two areas and the load forecast models does not separate into two areas' load forecast as well. So the economic and demographic data for each area was blended using a weighted average derived from 2017 energy sales data (Riverside County 59%; Imperial County 41%). But this weighted average blend data approach has some limits and can be biased in some degree. Take blend population variable as an example. Blend population is an important independent variable to forecast residential customer counts. The average population growth rate in Riverside County during 2006-2015 was 1.89%, the average population growth rate in Imperial County during 2006-2015 was 1.28%, and the blend population growth rate during 2006-2015 was 1.86% using the above mentioned weighted average approach. So we can see that the blend growth rate is closer to the growth rate of Riverside County. However, the average growth rate of IID residential customer counts during 2006-2015 was 1.18%, which was closer to the average population growth rate in Imperial County rather than Riverside County. In other words, if we use Imperial County population as independent variable to forecast the residential customer counts instead of using blend population, we might get more accurate forecast. In the future load forecast, the 41% for Imperial Valley and 59% for Coachella Valley approach needs to be improved to reflect more representative economic and demographic attributes of the two areas and to avoid the bias exemplified above.

Lag of Economic Data

At the time of processing the 2018 load forecast study, Woods & Poole Economics' latest available data set is based on historical years' data from 1970 through 2015; the forecast years' data is from 2016-2050.That means 2 years lagged behind the 2018 Load Forecast, of which the forecast years are from 2018-2037. Some major assumptions might change during the 2 years (2015-2017), which could influence economic data, and thereby the load forecast results. Updated load forecast is recommended when a new version of economic data is available and if there are significant changes from the current version.

As mentioned previously in this report, the load forecast is based on the information of forecasting the direction of both the nation's and specifically IID service territory's economy, which is impossible to predict accurately. Accordingly, a forecast must be viewed as a reference only in various planning activities. Moreover, regular reviews of the updated economic projections, system loads, and retail customer data are required to update load forecast periodically in order to reflect the new and unforeseen changes in the load forecast.

Section 5: Analysis of regression results and Conclusions

The 2018 Load Forecast methodology basically uses econometric models analyzing historical data and make estimates of future data. However, there is always the possibility of an unanticipated shock to the economy, or of some other event that was not foreseen based on an analysis of historical data. One statistic used to evaluate the projections is Mean Absolute Percent Error (MAPE) which provides a valid and reliable method to evaluate the effectiveness of a projection method as to compare previous projection to current data. Although, such a comparison does not indicate the potential accuracy of current or future projections, it can be useful to measure the magnitude of error of previous projections.

Using the statistical software, EViews, and Ordinary Lease Squares (OLS) Regression techniques, each category of customer sales and customer counts was developed as a statistically significant model. Sample Equations for forecasting IID's main customer sales are exemplified as the figures below.

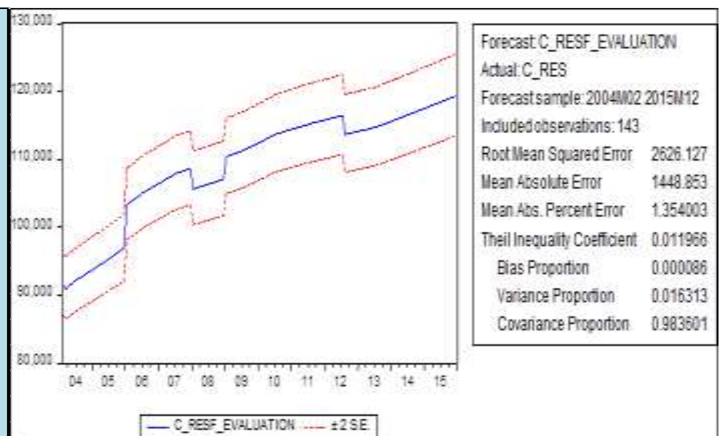
Residential Sales Model

Figure 5-1 2016 Residential Customer Counts Regression Model

Dependent Variable: LOG(C_RES)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 01/14/16 Time: 14:06
Sample (adjusted): 2004M02 2015M12
Included observations: 143 after adjustments
Convergence achieved after 5 iterations

Variable	Coefficier	Std. Error	t-Statistic	Prob.
C	5.002744	0.329407	15.1871	0
LOG(BLENDPOP)	0.921193	0.045871	20.08244	0
TREND(12:2005)<=0	-0.05563	0.006924	-8.034016	0
@YEAR=2008	-0.02895	0.005268	-5.495619	0
TREND(8:2012)>=0	-0.01907	0.005048	-3.777091	0.0002
TREND(7:2014)>=0	-0.02242	0.005383	-4.163807	0.0001
AR(1)	-0.3835	0.07909	-4.848854	0

R-squared	0.923301	Mean dependent var	11.6001
Adjusted R-squared	0.919917	S.D. dependent var	0.079548
S.E. of regression	0.022511	Akaike info criterion	-4.70188
Sum squared resid	0.068919	Schwarz criterion	-4.55685
Log likelihood	343.1846	Hannan-Quinn criter.	-4.64295
F-statistic	272.8607	Durbin-Watson stat	1.861312
Prob(F-statistic)	0		
Inverted AR Roots	-0.38		



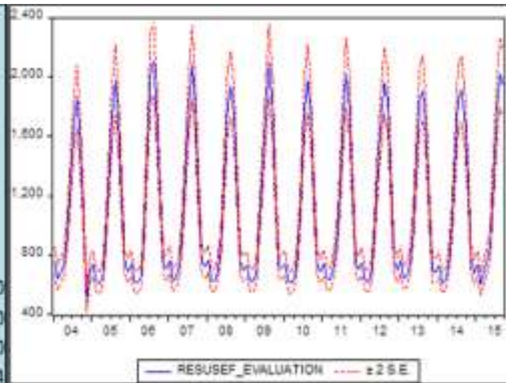
In the 2016 Load Forecast, total Residential Energy Sales is derived by residential customer counts multiplying residential average usage. Figure 5-1 shows residential customer counts model. The model is statistically significant from R-squared, t-statistic, F-statistic, and etc. All the signs of the coefficients meet expectations. When historical data (2004-2015) is input into the model, MAPE is 1.35%.

Figure 5-2 Residential Customer Average Usage Regression Model

Dependent Variable: LOG(RESUSE)
Method: Least Squares
Date: 01/13/16 Time: 13:43
Sample: 2004M01 2015M12
Included observations: 144

Variable	Coefficier	Std. Error	t-Statistic	Prob.
C	6.5044	0.030709	211.8074	0
@SEAS(2)	-0.13995	0.02502	-5.593706	0
@SEAS(3)	-0.14758	0.027632	-5.340893	0
@SEAS(4)	-0.14645	0.0277	-5.28689	0
@SEAS(5)	-0.06181	0.025654	-2.409217	0.0174
@SEAS(11)	-0.12084	0.027324	-4.422301	0
@SEAS(12)	-0.09067	0.033789	-2.683245	0.0082
W_CDD_N	0.000667	3.28E-05	20.36671	0
W_HDD_N	0.000304	0.000122	2.501642	0.0136
W_CDD_N(-1)	0.000567	3.88E-05	14.5975	0
W_HDD_N(-1)	7.08E-05	1.14E-04	0.619505	0.5367
TREND(11:2004)=0	-0.37222	6.00E-02	-6.201306	0

R-squared	0.983802	Mean dependent var	6.912123
Adjusted R-square	0.982452	S.D. dependent var	0.428153
S.E. of regression	0.056718	Akaike info criterion	-2.821811
Sum squared resid	0.424628	Schwarz criterion	-2.574327
Log likelihood	215.1704	Hannan-Quinn criter.	-2.721248
F-statistic	728.8095	Durbin-Watson stat	2.084694
Prob(F-statistic)	0		



Forecast: RESUSEF_EVALUATION
Actual: RESUSE
Forecast sample: 2004M01 2015M09
Included observations: 141

Root Mean Squared Error	72.87799
Mean Absolute Error	50.19625
Mean Abs. Percent Error	4.217830
Theil Inequality Coefficient	0.030117
Bias Proportion	0.000391
Variance Proportion	0.001614
Covariance Proportion	0.997995

Figure 5-2 shows the residential average usage model in 2016 Load Forecast. The model is statistically significant from R-squared, t-statistic, F-statistic, and etc. All the signs of the coefficients meet expectation. When historical data (2004-2015) is input into the model, MAPE is 4.21%. Residential sales make up to 45% of total IID system sales. So combining the error of the two models which were used to forecast residential energy sales, the total error is 5.57%.

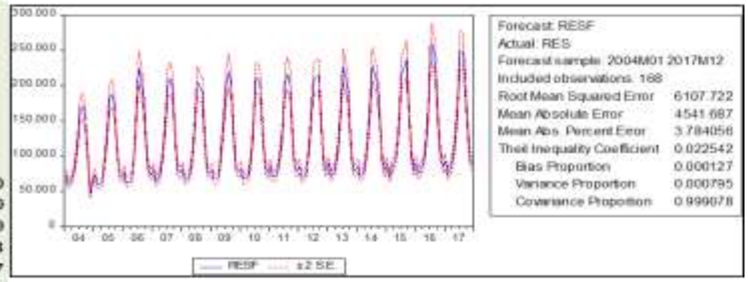
In 2018 Load Forecast, only one model used to forecast residential sales as figure 5-3 shows below.

Figure 5-3 2018 Load Forecast Residential Sales Regression Model

Dependent Variable: LOG(RES)
Method: Least Squares
Date: 01/16/18 Time: 10:19
Sample: 2004M01 2017M12
Included observations: 168

Variable	Coefficier	Std. Error	t-Statistic	Prob.
C	4.802465	0.405174	11.85285	0
@MONTH=2	-0.17695	0.025275	-7.00085	0
@MONTH=3	-0.17591	0.037982	-4.63141	0
@MONTH=4	-0.17974	0.048286	-3.72237	0.0003
@MONTH=5	-0.10218	0.058105	-1.75852	0.0807
@MONTH=6	-0.06413	0.073368	-0.87408	0.3835
@MONTH=7	-0.01467	0.090447	-0.16221	0.8714
@MONTH=8	-0.13454	0.097591	-1.37865	0.1701
@MONTH=9	-0.07656	0.08891	-0.86112	0.3905
@MONTH=10	-0.11233	0.069744	-1.61058	0.1094
@MONTH=11	-0.17936	0.050111	-3.57917	0.0005
@MONTH=12	-0.14344	0.033536	-4.27725	0
W_CDD_N	0.000615	7.47E-05	8.228975	0
W_HDD_N	0.000287	0.000121	2.365956	0.0193
W_CDD_N(-1)	0.000665	7.50E-05	8.875355	0
W_HDD_N(-1)	-4.66E-06	0.00012	-0.03887	0.969
TREND(11:2004)=0	-0.40339	0.054767	-7.36555	0
LOG(BLENDPOP)	0.894492	0.054076	16.54148	0

R-squared	0.988107	Mean dependent	11.62321
Adjusted R-square	0.986759	S.D. dependent va	0.440794
S.E. of regression	0.050722	Akaike info criteri	-3.02397
Sum squared resid	0.385901	Schwarz criterion	-2.68926
Log likelihood	272.0139	Hannan-Quinn crit	-2.88813
F-statistic	733.0902	Durbin-Watson sta	2.164059
Prob(F-statistic)	0		



To eliminate the combined error due to two regression models were used to forecast residential sales, in 2018 load forecast, only one regression model is used to forecast residential sales. And the MAPE is 3.78% when the historical data (2004-2017) is input into the model, which is much lower than the MAPE of 5.57% in 2016 load forecast

Commercial Sales Model

Another important IID customer category is commercial customer, which makes 40% of total IID system sales in 2017. Figure 5-4 shows commercial sales model used in 2016 Load forecast. The model is statistically significant from R-squared, t-statistic, F-statistic, and etc. All the signs of the coefficients meet expectations. When historical data (2004-2015) is input into the model, MAPE is 4.64%.

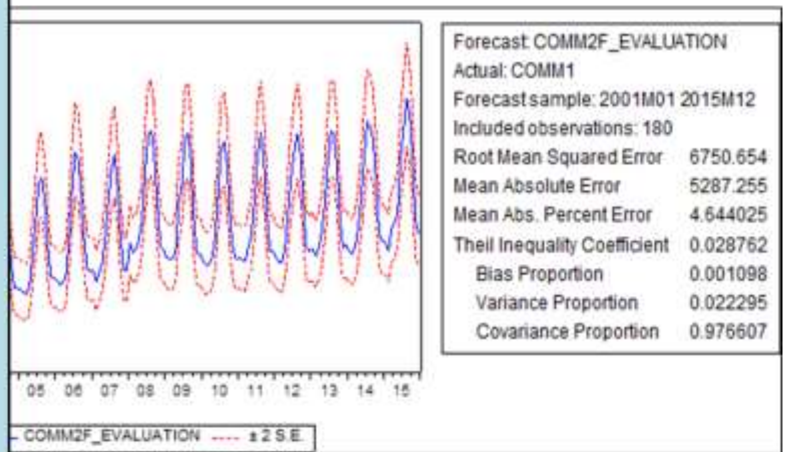
Figure 5-4 Commercial Sales Model in 2016 Load Forecast

Dependent Variable: LOG(COMM1)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 01/12/16 Time: 16:55
Sample: 2001M01 2015M12
Included observations: 180
Convergence achieved after 5 iterations

Variable	Coefficier	Std. Error	t-Statistic	Prob.
C	4.929961	0.545414	9.038941	0
LOG(BLENDGRP)	0.627834	0.051781	12.12487	0
@YEAR<2008	-0.12746	0.011962	-10.65477	0
W_CDD_N	0.000352	2.38E-05	14.82517	0
W_HDD_N	0.000175	4.59E-05	3.810644	0.0002
W_CDD_N(-1)	0.000132	2.27E-05	5.811573	0
AR(3)	0.166605	7.52E-02	2.214868	0.0281

R-squared	0.911983	Mean dependent var	11.63615
Adjusted R-squarec	0.90893	S.D. dependent var	0.198145
S.E. of regression	0.059796	Akaike info criterion	-2.757654
Sum squared resid	0.618566	Schwarz criterion	-2.633483
Log likelihood	255.1888	Hannan-Quinn criter.	-2.707308
F-statistic	298.7533	Durbin-Watson stat	2.151031
Prob(F-statistic)	0		

Inverted AR Roots	0.55	-.28+.48	-.28-.48



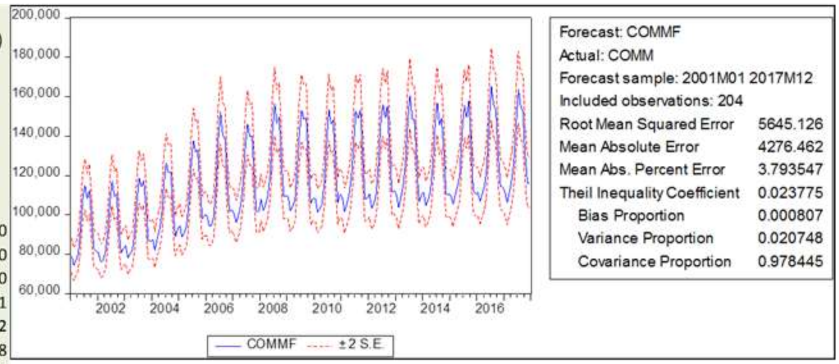
In 2018 Load Forecast, some modifications were made to improve the commercial sales model. One important change of the model is to add another economic variables farm employment as independent variable in the regression model. The reason for adding this variable is due to that GRP forecast have a way faster growth rate than the growth rate of IID commercial sales. By using GRP as the only economic variable in the regression model, the forecast result of commercial sales tends to be a lot higher than the actual commercial sales in the recent years. Moreover, by adding farm employment as another economic variable in the regression model, when plugging historical data (2001-2017) into the model, the MAPE is 3.79% as Figure 5-5 shows, which is much lower than the MAPE of 4.64% of the commercial sales model in 2016 load forecast.

Figure 5-5 Commercial Sales Model in 2018 Load Forecast

Dependent Variable: LOG(COMM)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 01/11/18 Time: 10:28
Sample: 2001M01 2017M12
Included observations: 204
Convergence achieved after 4 iterations

Variable	Coefficier	Std. Error	t-Statistic	Prob.
C	8.587562	0.487247	17.62465	0
LOG(BLENDGRP)	0.331055	0.042283	7.829564	0
LOG(BLENDEMP_FR	-0.24842	0.037117	-6.692878	0
@MONTH=2	-0.07671	0.022894	-3.350778	0.001
@MONTH=3	-0.08062	0.031077	-2.594362	0.0102
@MONTH=4	-0.08747	0.035908	-2.436001	0.0158
@MONTH=5	-0.06057	0.045474	-1.331979	0.1845
@MONTH=6	-0.01104	0.061598	-0.179228	0.858
@MONTH=7	-0.01509	0.078406	-0.192411	0.8476
@MONTH=8	-0.10559	0.085644	-1.232889	0.2192
@MONTH=9	-0.04717	0.077911	-0.605391	0.5457
@MONTH=10	-0.09246	0.059103	-1.564375	0.1194
@MONTH=11	-0.10577	0.035853	-2.950163	0.0036
@MONTH=12	-0.0029	0.018773	-0.154708	0.8772
@YEAR<2008	-0.06464	0.013372	-4.83365	0
W_CDD_N	0.000218	6.84E-05	3.193727	0.0017
W_HDD_N	-0.00011	0.000106	-1.053069	0.2937
W_CDD_N(-1)	0.000205	6.79E-05	3.02503	0.0028
AR(3)	0.158013	0.074186	2.129963	0.0345

R-squared	0.935275	Mean dependent var	11.64799
Adjusted R-squarec	0.928978	S.D. dependent var	0.196504
S.E. of regression	0.052368	Akaike info criterion	-2.97252
Sum squared resid	0.507352	Schwarz criterion	-2.663479
Log likelihood	322.197	Hannan-Quinn criter.	-2.847507
F-statistic	148.5144	Durbin-Watson stat	2.130792
Prob(F-statistic)	0		
Inverted AR Roots	0.54	-.27+.47i	-.27-.47i



All the rest of IID customer categories only make up about 14% of IID total system sales. Statistically, all the models used in 2018 Load Forecast are significant. However, models are more reliable the larger the customer population. Small customer categories are subject to more error because of the small sample size.

Agricultural Sales Model

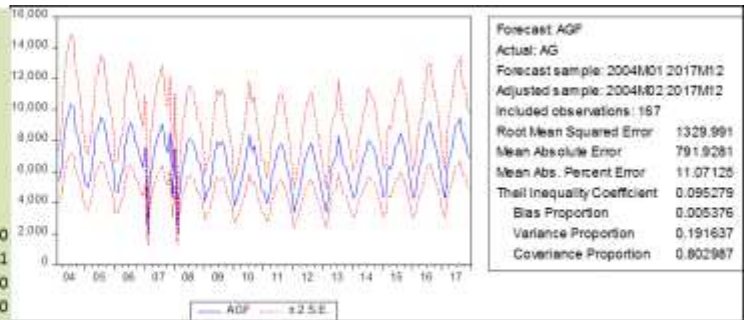
A very interesting finding during the 2016 Load Forecast study is within the agricultural customer sales model. The sign of the coefficient of weather variable HDD is different from other customer sales models and is different from our expectation as well. It is expected to have a positive sign. That means the higher CDD, the more energy consumption. However, the actual equation shows a negative sign even though all the other statistic values are significant. After consulting IID customer account billing staff, it was learned that the farmers in IID service territory do not work all four seasons of the year due to the extremely hot summer temperature and the extremely mild winter temperature in this area. The winter provides perfect temperature for the crops to grow in IID service territory, therefore winter is the busy season for the farmers in this area. This is why the lower HDD, the better temperature for crops to grow, the more energy consumption for agricultural customer sales. The same pattern is true for agricultural sales in 2018 Load Forecast. Figure 5-6 shows agricultural sales model in 2018 Load Forecast.

Figure 5-6 Agricultural Sales Model in 2018 Load Forecast

Dependent Variable: LOG(AG)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 04/25/18 Time: 09:51
Sample (adjusted): 2004M02 2017M12
Included observations: 167 after adjustments
Convergence achieved after 10 iterations

Variable	Coefficier	Std. Error	t-Statistic	Prob.
C	6.944817	0.380154	18.26845	0
LOG(BLENDEMP_FRM)	0.332204	0.206686	1.607287	0.11
C_AGF	0.00139	0.000175	7.927391	0
W_CDD_N	0.000323	5.68E-05	5.680113	0
W_HDD_N(-1)	-0.00123	0.000153	-8.02766	0
TREND(2:2007)=0	-0.21376	0.167597	-1.27547	0.204
TREND(2:2008)=0	-0.04109	0.17973	-0.22859	0.8195
AR(1)	0.497642	0.072527	6.861503	0

R-squared	0.804365	Mean dependent	8.767545
Adjusted R-squared	0.795752	S.D. dependent va	0.327326
S.E. of regression	0.147931	Akaike info criteri	-0.93742
Sum squared resid	3.4795	Schwarz criterion	-0.78806
Log likelihood	86.27454	Hannan-Quinn crit	-0.8768
F-statistic	93.39087	Durbin-Watson sta	2.321513
Prob(F-statistic)	0		
Inverted AR Roots	0.5		



Overview of Study Results and Conclusions

Results of IID 2018 Load Forecast are presented in three types (Net Energy for Load or NEL, Energy Sales, Coincident Peak or CP) for both gross and net values under three weather scenarios (base, severe and mild), three Energy Efficiency program scenarios (expected, high, AAEE), three rooftop PV program scenarios (expected, high, AAPV), two new industrial scenarios (expected, high) and three electrical vehicles scenarios (low, expected, high). Since the combinations of different scenarios can have so many different load forecast results due to volatilities of the market, uncertainties of the policies and variations of people's decisions and behaviors and etc, IID 2018 Load Forecast comes out with three cases as the main cases among so many cases of combinations of difference scenarios: expected case (base weather, expected EE and PV, expected EV), low case (mild weather, high EE and PV, low EV) and high case (severe weather, low EE and PV, high new industrial, high EV).

The following is a brief description of each of the various types of forecasts:

- Energy Sales are representative of the energy sold to all IID customers. It is the actual energy consumption for all IID customers and appeared in the monthly billing accounts.

- Net Energy for Load (NEL) is representative of the energy consumption plus the losses. The losses include not only the losses which are experienced over lengths of transmission and distribution lines, but also include the energy consumed in the stations services and most importantly, the difference between the sales' billing cycle and the meter' calendar cycle. NEL is the monthly data from the meters which are calculated based on the calendar months while energy sales is the monthly data from the billing data which are calculated based on finance's billing cycles, normally, billing cycles are lagged behind the calendar months. This is the reason why in some months the losses could be a negative number. For example, the meter data is from the month September, but the billing data available in the month September normally is the energy consumption starting from some days in August till some days in September. Since the weather temperature is much higher in August than in September, so the energy sales billing data could be higher than the meter data on September, hence the losses could be negative on that month.

$$NEL = Energy\ Sales + Losses$$

- Coincident Peak (CP) is representative of the energy demand among all categories of customers that coincides with the highest total demand on the system at one particular hour.
- Gross results are representative of the load levels for energy demand that is grossed up assuming that the estimated impacts of EE and PV programs were not exists.
- Net results are representative of the load levels for energy demand that is net of the estimated load impacts regarding EE and PV programs. It is the energy demand that need to be met by IID system central resources rather than distributed generating resources such as rooftop PV. The following equations are the basic premise of the gross forecast calculations:

$$Gross\ NEL - Net\ NEL = (DSM + PV) \times \frac{1}{(1 - Loss\ Rate)}$$

$$Gross\ CP - Net\ CP = (DSM + PV) \times \frac{1}{(1 - Loss\ Rate)}$$

Note: There is a loss rate included in the Gross and Net difference calculation. This denotes that losses would be associated with supply side resources (e.g., a central generating station), while DSM or distributed PV would imply a reduction in losses because those resources would be located at the point of usage and therefore avoid the losses which would otherwise be experienced over lengths of transmission and distribution lines.

Compared to the 2016 Load Forecast, the 2018 Load Forecast has a little bit lower net NEL value in the expected case for each of the same forecast year (as Table 5-7 shows).

Figure 5-7 Net NEL in 2016 LF vs Net NEL in 2018 LF (Expected Cases)

IID 2016 Load Forecast (expected case)		
Year	Net NEL (GWh)	Growth Rate
2003	3173	
2004	3280	3.38%
2005	3395	3.48%
2006	3604	6.16%
2007	3703	2.75%
2008	3736	0.89%
2009	3662	-1.98%
2010	3555	-2.92%
2011	3599	1.25%
2012	3719	3.34%
2013	3662	-1.55%
2014	3699	1.02%
2015	3687	-0.33%
2016	3577	-2.99%
2017	3616	1.10%
2018	3656	1.10%
2019	3706	1.37%
2020	3760	1.45%
2021	3811	1.36%
2022	3868	1.51%
2023	3930	1.58%
2024	3995	1.66%
2025	4063	1.70%
2026	4133	1.73%
2027	4206	1.77%
2028	4284	1.86%
2029	4362	1.82%
2030	4441	1.81%
2031	4533	2.06%
2032	4618	1.87%
2033	4706	1.91%
2034	4803	2.06%
2035	4906	2.15%

IID 2018 Load Forecast		
Year	Gross NEL(G	Growth Rate
2003	3173	
2004	3280	3.37%
2005	3395	3.51%
2006	3604	6.16%
2007	3703	2.75%
2008	3736	0.89%
2009	3662	-1.98%
2010	3555	-2.92%
2011	3599	1.24%
2012	3719	3.33%
2013	3662	-1.53%
2014	3699	1.01%
2015	3687	-0.32%
2016	3695	0.22%
2017	3738	1.16%
2018	3658	-2.14%
2019	3687	0.79%
2020	3722	0.95%
2021	3754	0.86%
2022	3798	1.17%
2023	3850	1.37%
2024	3902	1.35%
2025	3957	1.41%
2026	4014	1.44%
2027	4072	1.44%
2028	4133	1.50%
2029	4194	1.48%
2030	4256	1.48%
2031	4328	1.69%
2032	4396	1.57%
2033	4467	1.62%
2034	4546	1.77%
2035	4631	1.87%
2036	4726	2.05%
2037	4805	1.67%

Using year 2018 as an example, NEL is 3656 GWh in 2016 load forecast, but net NEL is 3558 GWh in 2018 load forecast, which is pretty close.

Compared to the 2016 Load Forecast, the 2018 Load Forecast expected case has pretty close net CP value too for almost each of the same forecast year, as Table 5-8 shows.

Figure 5-8 Net CP in 2016 LF vs Net CP in 2018 LF (Expected Cases)

IID 2016 Load Forecast (expected case)		
Year	Net Peak (NW)	Growth Rate
2003	792	
2004	840	6.06%
2005	898	6.90%
2006	993	10.58%
2007	996	0.30%
2008	979	-1.71%
2009	988	0.92%
2010	1004	1.62%
2011	1000	-0.40%
2012	995	-0.50%
2013	988	-0.70%
2014	982	-0.61%
2015	992	1.02%
2016	1007	1.55%
2017	1021	1.38%
2018	1033	1.10%
2019	1047	1.37%
2020	1059	1.17%
2021	1076	1.64%
2022	1092	1.51%
2023	1110	1.58%
2024	1125	1.39%
2025	1147	1.98%
2026	1167	1.73%
2027	1188	1.77%
2028	1207	1.58%
2029	1232	2.09%
2030	1254	1.81%
2031	1280	2.06%
2032	1301	1.60%
2033	1329	2.19%
2034	1356	2.06%
2035	1386	2.15%

IID 2018 Load Forecast		
Year	Gross Peak(I	Growth Rate
2003	792	
2004	840	6.06%
2005	898	6.90%
2006	993	10.61%
2007	996	0.23%
2008	979	-1.66%
2009	988	0.92%
2010	1004	1.61%
2011	1000	-0.37%
2012	995	-0.55%
2013	988	-0.65%
2014	982	-0.68%
2015	992	1.07%
2016	1060	6.84%
2017	1073	1.24%
2018	1052	-1.95%
2019	1061	0.80%
2020	1068	0.67%
2021	1080	1.15%
2022	1093	1.16%
2023	1108	1.37%
2024	1120	1.08%
2025	1138	1.67%
2026	1155	1.43%
2027	1171	1.46%
2028	1186	1.22%
2029	1206	1.75%
2030	1224	1.49%
2031	1245	1.68%
2032	1261	1.30%
2033	1285	1.89%
2034	1308	1.77%
2035	1332	1.87%
2036	1356	1.77%
2037	1382	1.95%

Using year 2018 as an example once again, CP is 1033MW in 2016 Load Forecast, CP is 1052MW in 2018 Load Forecast, which is 19MW more, this difference can be explained by using 30 years normalized weather data which is a little bit higher than using 65 years normalized weather data. Energy sales have the same trend as NEL because NEL forecast is derived from energy sales forecast.

As it was discussed in this reprot, the long term load forecast is a range forecast instead of an exact point forecast due to the fact that long-term weather temperatures can't be reliably predicted. Three different weather scenarios (base, severe, mild) create a ranged forecast. Although, the expected forecast may be used as a single point of reference for various activities, it is recommended that the ranged forecast is considered in all long term planning activities to capture the unpredictable impact of weather changes on load. Consider the forecast as a range helps long term planning activities capture the varying possibilities of needs as a result of uncontrollable risks and the relationship of demand and supply. The weather impact (mild/expected/severe) on the gross result of the load forecast expected case is as table 5-9 shows,

Table 5-9 2018 Load Forecast Expected Case Gross CP and NEL in Base/Severe/Mild Weather Cases

	LF Expected Case (mild weather)		LF Expected Case (expected weather)		LF Expected Case (severe weather)	
Year	Gross CP(MW)	Gross NEL (MWh)	Gross CP(MW)	Gross NEL (MWh)	Gross CP(MW)	Gross NEL (MWh)
2018	1,070.80	3,740,593	1,124.60	3,928,541	1,183.30	4,133,568
2019	1,085.20	3,791,058	1,139.70	3,981,267	1,199.30	4,189,437
2020	1,096.90	3,842,420	1,152.00	4,035,339	1,212.30	4,246,598
2021	1,112.50	3,886,383	1,168.20	4,081,084	1,229.30	4,294,454
2022	1,126.70	3,935,798	1,183.20	4,133,184	1,245.10	4,349,672
2023	1,142.30	3,990,609	1,199.70	4,190,873	1,262.60	4,410,674
2024	1,154.00	4,042,513	1,212.00	4,245,549	1,275.70	4,468,523
2025	1,172.20	4,094,756	1,231.00	4,300,459	1,295.80	4,526,503
2026	1,187.10	4,146,929	1,246.70	4,355,303	1,312.30	4,584,406
2027	1,202.50	4,200,600	1,262.90	4,411,860	1,329.50	4,644,229
2028	1,214.70	4,254,971	1,275.80	4,469,148	1,343.10	4,704,805
2029	1,233.60	4,309,259	1,295.70	4,526,350	1,364.10	4,765,285
2030	1,249.20	4,363,703	1,312.10	4,583,747	1,381.50	4,825,976
2031	1,264.70	4,418,196	1,328.60	4,641,267	1,398.90	4,886,819
2032	1,276.90	4,472,874	1,341.50	4,699,019	1,412.50	4,947,928
2033	1,296.10	4,527,784	1,361.70	4,757,006	1,434.00	5,009,279
2034	1,311.90	4,582,942	1,378.40	4,815,224	1,451.60	5,070,861
2035	1,327.80	4,638,443	1,395.20	4,873,768	1,469.30	5,132,781
2036	1,340.20	4,694,599	1,408.30	4,933,023	1,483.20	5,195,460
2037	1,360.00	4,750,767	1,429.10	4,992,362	1,505.20	5,258,250

The weather impact (mild/expected/severe) on the net result of the load forecast expected case is as table 5-10 shows,

Table 5-10 2018 Load Forecast Expected Case Net CP and NEL in Base/Severe/Mild Weather Cases

Year	LF Expected Case (mild weather)		LF Expected Case (expected weather)		LF Expected Case (severe weather)	
	Net CP(MW)	Net NEL (MWh)	Net CP(MW)	Net NEL (MWh)	Net CP(MW)	Net NEL (MWh)
2018	998.10	3,469,748	1,052.20	3,657,696	1,111.20	3,862,723
2019	1,005.80	3,496,590	1,060.60	3,686,799	1,120.40	3,894,969
2020	1,012.40	3,528,897	1,067.70	3,721,817	1,128.30	3,933,075
2021	1,024.00	3,559,692	1,080.00	3,754,393	1,141.40	3,967,762
2022	1,035.70	3,600,407	1,092.50	3,797,793	1,154.80	4,014,281
2023	1,049.90	3,649,889	1,107.50	3,850,153	1,170.80	4,069,954
2024	1,061.20	3,699,218	1,119.50	3,902,255	1,183.40	4,125,229
2025	1,079.00	3,750,856	1,138.20	3,956,560	1,203.20	4,182,603
2026	1,094.60	3,805,127	1,154.50	4,013,501	1,220.40	4,242,604
2027	1,110.50	3,860,354	1,171.30	4,071,614	1,238.10	4,303,983
2028	1,124.10	3,918,510	1,185.60	4,132,687	1,253.20	4,368,345
2029	1,144.00	3,976,799	1,206.40	4,193,891	1,275.20	4,432,826
2030	1,161.10	4,036,257	1,224.40	4,256,301	1,294.10	4,498,530
2031	1,180.90	4,104,991	1,245.00	4,328,062	1,315.70	4,573,614
2032	1,196.30	4,170,005	1,261.20	4,396,151	1,332.60	4,645,059
2033	1,219.00	4,237,665	1,285.00	4,466,887	1,357.50	4,719,160
2034	1,240.90	4,313,732	1,307.70	4,546,014	1,381.30	4,801,651
2035	1,264.40	4,395,529	1,332.10	4,630,854	1,406.60	4,889,867
2036	1,287.30	4,487,196	1,355.70	4,725,621	1,431.00	4,988,057
2037	1,312.60	4,562,907	1,382.10	4,804,501	1,458.60	5,070,390

In order to improve the understanding of IID load weather related risk and volatility. The expected range that future IID systems load is likely to fall within using 90 percent confidence interval. However, to improve the accuracy of the forecast, regular updates to adjust for changes in the underlying assumptions are required.

Besides weather impact, rooftop PV installations, energy efficiency programs, electric vehicles and new industrial load are variables can impact load. Some of them can add some load such as electric vehicles, new industrial load; some of them can take away some load such as rooftop PV installations and energy efficiency programs. The impact of these variables can be determined by government policies, market mechanism, people's decision making process and behaviors, all of which can have lots of possibilities. 2018 IID Load Forecast results have different scenarios of each of these different variables to capture the trend of these possibilities. The below tables list the energy impact and peak impact of each of these variables under different variables. Figure 5-11 depicts PV peak impact and energy impact under both PV expected case and PV high case; figure 5-12 depicts EE peak impact and energy impact under both EE expected case and EE high case; figure 5-13 depicts EV peak impact and energy impact under EV expected case, EV low case and EV high case; figure 5-14 depicts new industrial peak impact and energy impact under new industrial med case and new industrial high case.

Figure 5-11 PV Peak Impact and Energy Impact (expected case, high case)

Year	PV Expected Case		PV High Case	
	Peak Imapct(MW)	Energy Impact (KWh)	Peak Imapct(MW)	Energy Impact (KWh)
2018	28.09	129,918,713	30.86	143,045,573
2019	32.46	149,631,547	39.43	182,511,669
2020	35.83	164,472,635	47.90	221,218,779
2021	38.13	174,125,513	55.21	254,154,237
2022	39.56	179,565,718	60.69	278,134,603
2023	40.39	182,142,781	64.28	293,058,464
2024	40.85	182,978,466	66.42	300,977,417
2025	41.07	182,640,100	67.57	304,190,587
2026	40.97	180,983,658	67.98	304,019,052
2027	40.99	179,762,195	68.28	303,166,227
2028	40.51	176,457,792	67.94	299,645,854
2029	40.28	174,246,123	67.82	297,001,645
2030	40.08	172,127,493	67.67	294,221,336
2031	38.01	162,428,573	65.64	283,775,237
2032	36.94	156,864,829	64.63	277,553,286
2033	35.44	149,567,597	63.17	269,570,850
2034	32.19	135,202,245	59.91	254,305,476
2035	27.76	116,170,899	55.49	234,380,856
2036	21.27	88,910,729	49.00	206,234,111
2037	18.31	76,180,726	46.04	192,624,183

Figure 5-12 EE Peak Impact and Energy Impact (expected case, high case)

Year	EE Expected Case		EE High Case	
	Peak Imapct(MW)	Energy Impact (KWh)	Peak Imapct(MW)	Energy Impact (KWh)
2018	46.34	115,959,592	52.77	136,719,179
2019	45.75	117,404,355	57.96	156,807,260
2020	45.50	119,624,590	62.69	175,078,532
2021	45.49	122,305,870	66.41	189,802,682
2022	45.52	124,860,176	69.34	201,716,411
2023	45.47	126,909,187	71.29	210,212,771
2024	45.31	128,359,848	72.74	216,876,494
2025	45.04	129,258,198	73.75	221,896,845
2026	44.48	129,071,318	74.13	224,734,161
2027	43.97	128,866,621	73.67	224,695,744
2028	43.52	128,700,644	73.66	225,957,171
2029	42.71	127,279,197	72.91	224,719,352
2030	41.63	124,855,036	71.58	221,469,525
2031	40.34	121,642,911	69.78	216,622,476
2032	38.90	117,824,665	67.63	210,530,137
2033	37.34	113,553,639	65.21	203,490,041
2034	35.70	108,958,568	62.60	195,752,662
2035	34.01	104,146,974	59.86	187,527,860
2036	32.31	99,208,118	57.04	178,990,492
2037	30.61	94,215,560	54.18	170,285,319

Figure 5-13 EV Peak Impact and Energy Impact (expected case, high case)

	EV low case		EV expected case		EV high case	
Year	Peak Imapct(MW)	Energy Impact (KWh)	Peak Imapct(MW)	Energy Impact (KWh)	Peak Imapct(M	Energy Impact (KWh)
2018	1.68	5,328	1.75	5,556	1.89	6,012
2019	1.99	6,324	2.20	6,996	2.62	8,316
2020	2.26	7,200	2.68	8,520	3.49	11,100
2021	2.50	7,944	3.18	10,092	4.50	14,292
2022	2.69	8,556	3.68	11,700	5.62	17,856
2023	2.85	9,048	4.20	13,332	6.84	21,732
2024	2.96	9,420	4.70	14,952	8.11	25,836
2025	3.05	9,684	5.22	16,584	9.49	30,144
2026	3.10	9,864	5.73	18,216	10.89	34,584
2027	3.14	9,984	6.24	19,824	12.32	39,132
2028	3.16	10,056	6.73	21,420	13.73	43,728
2029	3.18	10,104	7.24	23,016	15.23	48,372
2030	3.18	10,116	7.74	24,600	16.69	53,028
2031	3.58	11,376	8.25	26,196	18.10	57,492
2032	3.69	11,748	8.73	27,792	19.42	61,848
2033	3.82	12,120	9.25	29,400	20.78	66,024
2034	3.94	12,504	9.76	30,996	22.02	69,948
2035	4.05	12,876	10.26	32,604	23.17	73,596
2036	4.16	13,248	10.74	34,200	24.15	76,920
2037	4.29	13,620	11.27	35,796	25.13	79,848

Note: since the load factor of EV is not available, it is assumed that EV's load factors are the same as IID's total system load factors.

As it was discussed previously, although there are many different combinations of scenarios due to interactions of different variables such as EE, PV, EV, New industries and weather, three main cases among them are considered as the main load forecast results: expected case (base weather, expected EE and PV, expected EV), low case (mild weather, high EE and PV, low EV) and high case (severe weather, low EE and PV, high new industrial, high EV). The load forecast high case of is the highest load level among all the load forecast results; the load forecast low case of the load forecast result is the lowest load level among all the load forecast results; the load forecast expected case is the combination of all the expected cases of all variables. Figure 5.15 depicts IID total system net NEL growth rate under three main cases: expected, high and low; Figure 5.16 depicts IID total system net CP growth rate under the three main cases: expected, high and low; Figure 5.17 depicts IID total energy sales growth rate under the three main cases: expected, high and low.

Figure 5.14 IID 2018 Load Forecast Net NEL Growth Rate (Expected/High/Low Cases)

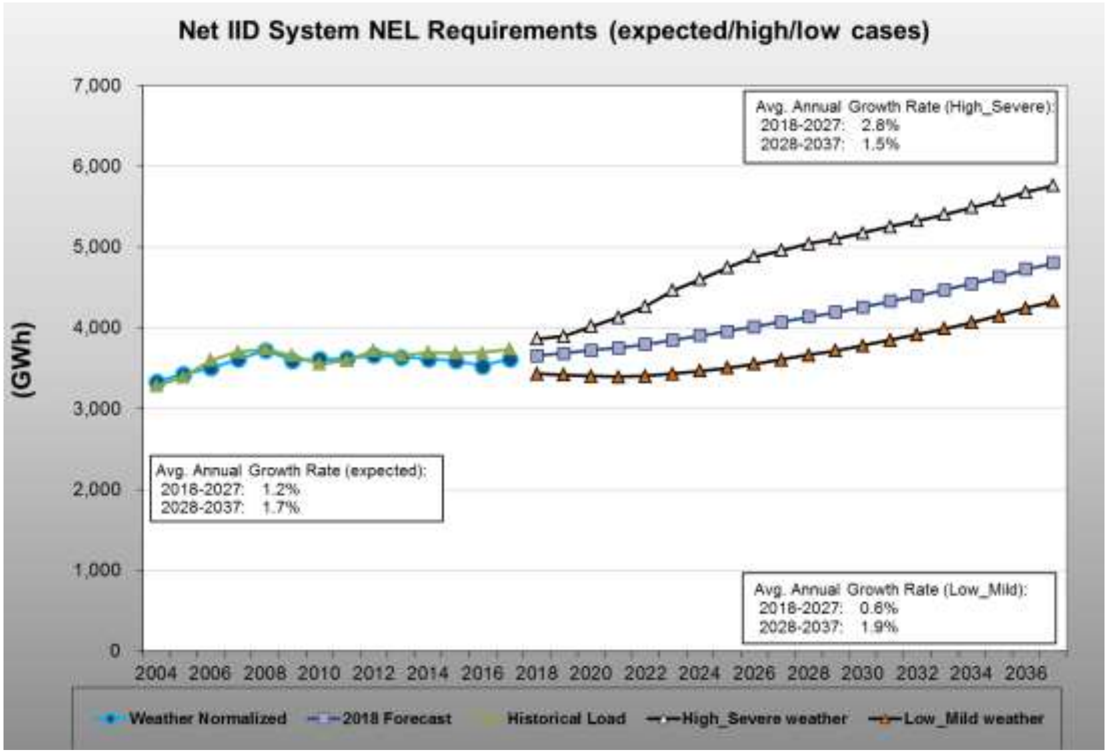


Figure 5.15 IID 2018 Load Forecast Net CP Growth Rate (Expected/High/Low Cases)

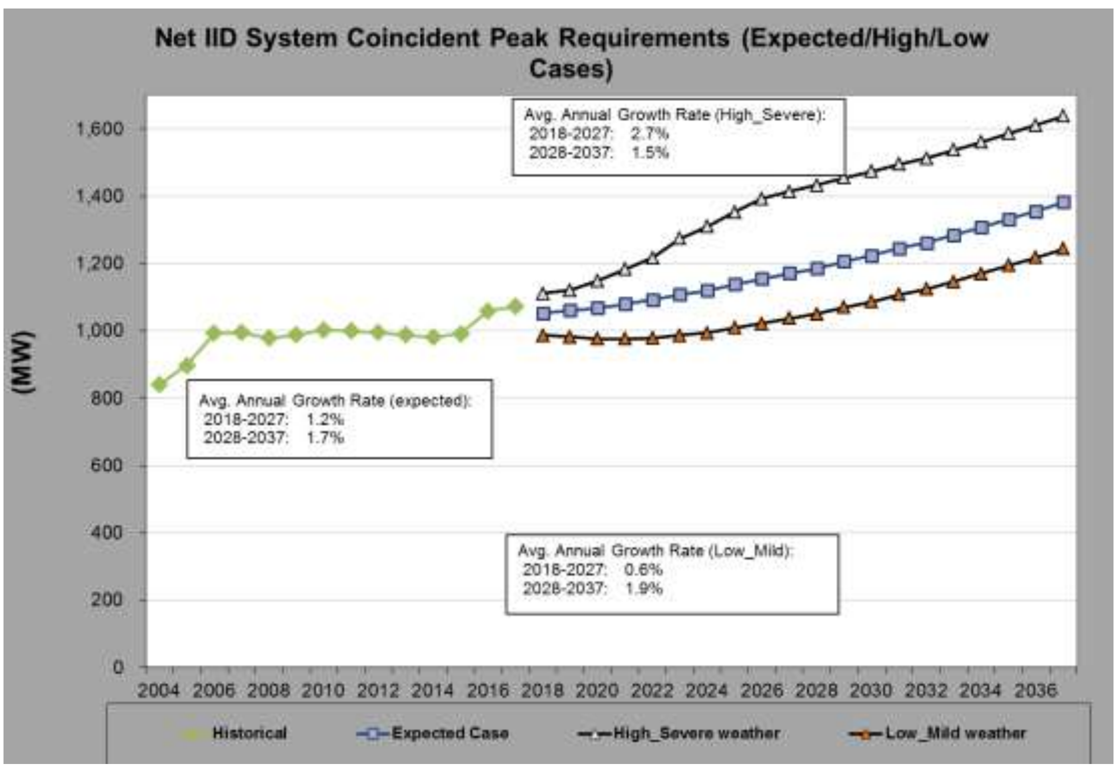


Figure 5.16 IID 2018 Load Forecast Energy Sales Growth Rate (Expected/High/Low Cases)