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2016 IID Load Forecast Report



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Section 1: Summary

The Resource Planning and Acquisition unit of the Energy Department at the Imperial Irrigation District (IID) has prepared the system 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 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 2014 load forecast as well as the 2016 forecast. Since the 2016 forecast is based upon most of the 2014 methodology, this document serves as a supplement to the original 2014 load forecast report to explain the exact process and modifications for this updated forecast.

The 2016IID Load Forecast basically uses the same methodology as the 2014 IID Load Forecast as provided to IID 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 for a 20-year period, beginning 2016 through 2035. In total, there were 24 categories of forecast. The table below summarizes those categories:

2016 Load Forecast Categories							
Forecast Type	Forecast Category	Base/Expected Case (Weather Normalized)	Severe Weather Case	Mild Weather Case	High EE/PV Case (MWh)	Zero Net Energy Case	
Gross	Peak Load (MW)	4	4	4	NA	NA	
	NEL(MWh)	1	√	√	NA	NA	
	Energy Sales (MWh)	1	1	1	NA	NA	
Net of EE/PV Programs	Peak Load (MW)	1	4	1	1	1	
	NEL(MWh)	1	4	4	4	1	
	Energy Sales (MWh)	1	4	4	4	4	

Table 1-1 2016 Load Forecast Results Categories

The Net Energy for Load (NEL) forecast was derived from the total retail sales forecast based on recent averages of distribution losses; Coincident Peak (CP) forecast was derived from NEL forecast and historical representative load factors. The forecast also incorporated the load impact resulting from IID Energy Efficiency (EE) and IID Rooftop Photo Voltaic (PV) Solutions Programs. The forecast results will be presented as the Gross of EE and PV program's basis (Gross Sales, Gross NEL and Gross CP), followed by the Net of EE and PV programs basis (Net Sales, Net NEL, and Net CP). Retail customer counts and sales by major customer classification as well as hourly load data generally from 2000 through 2015 (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.

While IID's load forecast focuses primarily on the overall impact of any and all solar rooftop installations, the Net Energy Metering/SB1 targets are a good benchmark to estimate future activity. With rapid growth of PV installations in recent years, the current PV installations and the registered PV installations in process has surpassed the current NEM capacity cap of 50.2MW within the IID footprint. A new NEM capacity cap re-vote is expected in the near future to reach 100.4MW. In response to this change, the 2016 IID Load Forecast changes the assumptions to develop a realistic estimate of the future PV penetration on the IID system. In 2014, per California Assembly Bill 2021's requirement, the Imperial Irrigation District Board of Directors adopted revised annual electric energy efficiency program targets for energy savings and demand reduction for years 2014-2023. The 2016 IID Load Forecast uses the board approved energy efficiency program targets as assumptions to estimate the future impact of Energy Efficiency (EE) programs on the IID system. Due to the above changes regarding PV and EE programs, as well as the future regulatory uncertainties, the 2016 IID Load Forecast created a high case and a Zero Net Energy (ZNE) case in addition with an expected case to reflect both the high estimate of PV+EE impact and the most reasonable estimate of PV+EE impact. This will provide a necessary range of potential load and energy consumption possibilities in order to be fully aware of the costs and benefits of all IID energy supply resources relative to the demand of power and energy.

Even though the historical load over the last 15 years had an average growth rate of 1.9%, as Figure 1-2 shows, the load of the IID System over 2009-2015 maintained a fairly flat trend. Compared to the 2014 Load Forecast, the 2016 Load Forecast has a lower average annual growth rate of 1.4% for the first ten years (2016-2025), and a higher average annual growth 1.9% for the second ten years (2026-2025). The lower average annual growth rate 1.4% in the first ten forecast years (2016-2025) is mainly due to fast growth of PV+EE impact, which takes away some growth rate of IID system load. 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 from 1.8% in 2014 Load Forecast to 1.9% in 2016 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 1-3 shows, the CP during historical period (2001-2015) has a higher average annual growth rate reaching to 2.4%, however during the latest 6 years 2009-2015, the peak of the IID system stayed flat too. Compared to the 2014 Load Forecast, the 2016 Load Forecast has a lower CP average annual growth rate 1.5% for the first 10 years (2016-2025), a higher average CP annual growth rate 1.9% for the second 10 years (2026-2035). The tables below illustrate this comparison of the 2014 load forecast and the 2016 load forecast:



Figure 1-2 Net IID System NEL Requirements in 2014 Load Forecast vs 2016 Load Forecast

Figure 1-3 Net Coincident Peak Demand in 2014 Load Forecast vs 2016 Load Forecast



Due to the unpredictability of weather temperature for the long term forecast, and the fact that that weather has an important impact on energy consumption, the 2016 IID Load Forecast provides retail

sales, NEL and CP forecasts under three weather scenarios: Normal (basecase/expected), Mild and Severe. These weather scenarios are used to estimate the load under the normal, abnormally severe and abnormally mild weather conditions. In previous load forecast, only some months of the year are assumed to have severe and mild weather, but In the 2016 Load Forecast, severe and mild weather scenarios are expanded to all the 12 months of the year so that the range between mild and normal, and the range between normal and severe are wider than the previous 2014 load forecast. Figure 1-4 below depicts the projection of NEL under three weather scenarios in 2014 Load Forecast: the blue dash line is net NEL under normal weather scenario; the green dash line is net NEL under severe weather scenario; and the red dash line is net NEL under mild weather scenario. The average range between normal and severe scenarios is 101 MWh in the forecasted 20 years; the average range between normal and severe scenarios is 92 MWh.



Figure 1-4 Net IID System NEL Requirements in 2014 Load Forecast

In comparison, Figure 1-5 below depicts the projection of NEL under three weather scenarios in 2016 Load Forecast: The average range between normal and severe scenarios is 267MWh in the forecast 20 years; the average range between normal and mild scenarios is 232MWh. We can see that both the mean-severe range and the mean -mild range in 2016 Load Forecast are a lot wider than the ranges in 2014 Load Forecast. This change is due to that in 2016 Load Forecast three weather scenarios are expanded to all the 12 months of the year instead of only the 7 months in the 2014 Load Forecast.



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

Similarly, Figure 1-6 depicts the projection of coincident peak under three weather scenarios in 2014 Load Forecast and Figure 1-7 depicts the projection of coincident peak under three weather scenarios in 2016 Load Forecast. The average mean-severe range (75MW) and the average mild-severe range (65MW) in the 2016 Load Forecast are a lot wider than the average mean-severe range (27MW) and the average mean-mild range (25MW) in the 2014 Load Forecast.



Figure 1-6 Net IID System CP Demand Requirements in 2014 Load Forecast



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

In the following sections, detailed descriptions on methodology modifications in the 2016 Load Forecast compared with 2014 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 2016 Load Forecast. Finally, the limitations of the 2016 Load Forecast we came across during the study process and future recommendations will be discussed.

Section 2: Methodology and Models Design

Model Specification

The 2016 Load Forecast continues to use econometric forecasting methodology to forecast retail sales based on the historical monthly sales by rate classifications for the IID system. The econometric models basically keep the same explanatory variables as those in 2014 Load Forecast with minor changes. The model specifications are discussed as below:

- Residential classes (Residential and Residential Energy Assistance): In the 2014 Load Forecast, it was assumed that the average usage per residential customer keep flat at 2012 levels in the forecast years, and subject to no weather variations changes. In 2016 load forecast, analysis was completed comparing the relationship between historical weather temperature and the average usage per residential customer (refer to Figure 2-1) The key findings are that the average usage per residential customer did change from year to year and did not stay flat as assumed in the 2014 Load Forecast. When adding historical Cooling Degree Days (CDD) in Figure 2-1, the average usage per residential customer did subjected to weather variation changes from year to year with some exceptions in only a few years. This means that during a hot year, the average usage per residential customers went up; and during a cool year, the average usage per residential customers went up; and during a cool year, the average usage per residential usage model and residential energy Assistance model, which were created in 2014 Load Forecast but was not used in the ultimate 2014 Load Forecast, should, in fact, be used in the 2016 Load Forecast. The residential usage model and residential energy assistance model include the following independent variables:
 - Weather terms that capture monthly weather variability,=
 - Seasonality terms that capture additional variations not due to weather in certain key months
 - A limited number of terms intended to address level shifts in the usage data.

Similar to the 2014 Load Forecast, the residential modeling framework combines residential average usage and residential customer counts to get the total residential sales in the 2016 Load Forecast. This is due to the relative homogeneity of the residential energy consumption patterns. The residential customer counts model and the residential energy assistance customer counts model include these independent variables:

- Blended population in IID service territory
- Some limited trend terms to capture unexplained shifts in customer counts (some trend terms are newly added in 2016 Load Forecast to capture the unexplained shifts during 2013-2015)



Figure 2-1 Historical average usage per residential customer and CDD

- Mobile home/recreational vehicle class sales model is a function of blended personal income and monthly weather variables.
- Agricultural class sales model is a function of the number of agricultural customer counts, monthly weather variables and some limited terms to address anomalous level shifts in the usage data.
- Commercial class sales model is a function of blended Gross Regional Product (GRP), monthly weather variables and autoregressive terms.
- Industrial class sales model is a function of trend variable and autoregressive terms.
- Lighting class sales model is a function of blended total employment 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 and monthly weather variables and certain limited trend terms intended to capture otherwise unexplained level shifts in the data.

Rooftop Photo-Voltaic Solutions Program Impacts

Similar with 2014 Load Forecast, a Bass Diffusion Model approach was adopted to estimate IID PV program Impact (which captures all 'behind the meter' installations) to IID system load in terms of annual capacity and energy impact in 2016 Load Forecast. However, under Federal and IID's monetary incentives as well as lower cost of solar panels during 2013-2015, IID customers who participated in IID's PV program surpassed expectations. Net Energy Metering (NEM) is 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 is 50.2MW and reaches 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 is way above the current IID NEM capacity cap 50.2MW. In the 2014 Load Forecast, the market saturation point for PV installations. Therefore, in 2016 Load forecast, the Bass Diffusion Model was modified from linear to non-linear. To estimate the parameters in the non-linear Bass Diffusion model, a market saturation point needs to be assumed. The

assumption of PV market saturation point in the expected case is to double the current NEM program capacity cap from 50.2MW to 100.4MW, which is the most possible result of NEM re-volt in the near future, as most utilities advocate. Figure 2-2 depicts different PV impact in 2014 Load and 2016 PV impact:



Figure 2-2 PV new and accumulated installations capacity in 2016 Load Forecast and 2014 Load Forecast

The dashed red line is the new annual PV installations capacity in the 2014 Load Forecast; the red solid line is the accumulated PV installations capacity annually in the 2014 Load Forecast; the dashed blue line is the new annual PV installations capacity in the 2016 Load Forecast; the blue solid line is the accumulated PV installations capacity annually in 2016 Load Forecast. Both the new PV installations capacity and accumulated PV installations capacity are significantly higher in the 2016 Load Forecast than in the 2014 Load Forecast. This is due to the different NEM capacity cap assumptions in the 2014 vs the 2016 Load Forecast.

The assumption of PV market saturation point 239MW in the high case is derived from the market driven mechanism instead of NEM capacity cap. 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 2016 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, IID rates and the output efficiency of panels. Figure 2-3 depicts different PV impact in expected case and high case:



Figure 2-3 PV new and accumulated installations capacity in Expected Case and High Case in 2016 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 green dash line is the new PV installations capacity annually in high case scenario; the green solid line is the accumulated PV installations capacity annually in high case scenario. Both the new 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: 100.4MW in the expected case and 239MW in high case.

Zero-Net Energy building is defined as one where the net of the amount of energy by on-site renewable energy resources is equal to the value of the energy consumed annually by the building. Zero-Net Energy (ZNE) building policies have been supported by the CPUC, the California Air Resources Board (ARB) and Governor Brown's Executive Order B-18-12. California Energy Commission updated the California Building Energy Efficiency Standards for 2016 and 2019 with clear orientation toward the upcoming ZNE targets for low-rise residential buildings (three stories or fewer) in 2020 and nonresidential buildings in 2030. The 2016 load forecast combines ZNE targets with PV program scenarios design to develop a PV ZNE case with the straightforward assumption that all the new residential energy demand after 2020 and all the new commercial energy demand after 2030 are supplied by distributed PV solar rooftops in order to meet ZNE targets. Before ZNE targets take effect in 2020 for residential and in 2030 for commercial, the PV ZNE case assumes that PV installations are driven by market payback years as the PV high case assumes. Figure 2-4 depicts different PV impact in high case and ZNE case.



Figure 2-4 PV new and accumulated installations capacity in High Case and ZNE Case in 2016 Load Forecast

The green dashed line is the new annual PV installations capacity in the high case scenario; the green solid line is the accumulated PV installations capacity annually in high case scenario; the orange dashed line is the new annual PV installations capacity in ZNE case scenario; the orange solid line is the accumulated PV installations capacity annually in ZNE case scenario. Both the new PV installations capacity and accumulated PV installations capacity are the same before 2024 and higher in the ZNE case than in high case after 2024. This is attributable to the fact that before 2024 PV installations driven by market payback years have more significant impact, and after 2024 PV installations driven by the ZNE policy have more significant impact.

After deriving the new annual installations and the annual accumulated installations capacity from Bass Diffusion model approach as well as ZNE targets, an annual peak impact and energy impact have been estimated for the expected case, the high case and the ZNE case based on the following assumptions:

- A useful life of 20 years
- An annual degradation factor of 0.75 percent
- A capacity factor of 20.25 percent for a given installation

Energy Efficiency Portfolio Impacts

The Energy Efficiency (EE) program impact projection is based on EE activities over the historical period 2006-2015. In the 2016 Load Forecast, EE was named Demand Side Management (DSM). Similar to the 2014 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 5% degradation rate per year. Different from the 2014 Load Forecast, the annual EE program impact in the forecast years in the 2016 Load Forecast is projected based on IID Board of Directors adopted annual electric energy efficiency program targets for the years 2014-2023 (refer to Table 2-1). In the expected case, 85% of the target amount is assumed 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 2023; a 5% degradation rate is applied to project the annual EE program impact after 2023, as the blue solid line in the Figure 2-4 below shows.

Year	MWh
2014	14508
2015	14986

Table 2-1 IID board adopted Energy Saving Targets for 2014-2023

Figure 2-4 EE annual accumulated degrade energy impact in 2014 and 2016 Load Forecast



The red line in the Figure 2-4 depicts the annual EE program impact projection based on the assumptions that EE program ends in 2012; no targets needed to be met; and with a 10% degradation rate annually in the 2014 Load Forecast. In the high case, 100% of the target amount is assumed to be met in the years 2016-2023. After 2023, the program requirements maintain at the average growth rate of 2014-2023 and with no market saturation point, as the Figure 2-5 below shows.



Figure 2-5 EE annual accumulated degrade energy impact in the expected and high cases

PV + EE Impact to Net and Gross NEL and CP

In the 2016 Load Forecast, the impact of PV and EE on theNEL increases significantly compared with 2014 Load Forecast caused by changes in assumptions described above in the expected case, high case and ZNE case. In Figure 2-6, 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 3.6% of the gross NEL in 2014 Load Forecast.



Figure 2-6 Gross/ Net NEL and EE&PV impact in 2014 Load Forecast

In Figure 2-7, the average EE&PV impact in the forecast years makes 8.1% of the gross NEL in 2016 Load Forecast (Expected Case), which increased a lot compared with that in the 2014 Load Forecast.



Figure 2-7 Gross/Net NEL and EE&PV impact in 2016 Load Forecast (Expected Case)

In Figure 2-8, the average EE&PV impact in the forecast years makes 13% of the gross NEL in 2016 Load Forecast (High Case), which increased a lot compared with that in the 2016 Load Forecast (Expected case).





In Figure 2-9, the average EE&PV impact in the forecast years makes 16% of the gross NEL in 2016 Load Forecast (ZNE Case), which is higher compared with that in the 2016 Load Forecast (high case).



Figure 2-9 Gross/Net NEL and EE&PV impact in 2016 Load Forecast (ZNE Case)

Likewise, in the 2016 Load Forecast, PV and EE CP impact increases significantly compared with 2014 Load Forecast since CP is derived from NEL and Load Factor. In Figure 2-10, 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 3.3% of the gross CP in 2014 Load Forecast.

In Figure 2-11, the average EE&PV impact in the forecast years makes 7.7% of the gross CP in 2016 Load Forecast (Expected Case).

Figure 2-11 Gross/Net CP and EE&PV impact in 2016 Load Forecast (Expected Case)

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

Figure 2-12 Gross/Net CP and EE&PV impact in 2016 Load Forecast (High Case)

In Figure 2-13, the average EE&PV impact in the forecast years makes 15.4% of the gross CP in 2016 Load Forecast (ZNE Case).

Figure 2-13 Gross/Net CP and EE&PV impact in 2016 Load Forecast (ZNE Case)

Mild, Base and Severe Weather Scenarios and Range Forecast

In the 2014 Load Forecast, in addition to Base Case forecast assuming normalized weather conditions, Severe and Mild weather scenarios were developed to capture the load volatility resulting from weather variations. January, February, June, July, August, September and December are considered into Normal, Severe and Mild weather scenarios. For the remaingmonths (March, April, May, October and November), only normalized weather conditions apply (as Table 2-2 shows) assuming that severe and mild weather won't happen in these months. However, according to actual historical data, severe and Mild weather can happen in any months of the year. During May 2015, for example, the weather temperature was unusually low and fell into the mild weather range. Therefore, in the 2016 Load Forecast, Severe and Mild weather scenarios were expanded to all the 12 months of the year (as Table 2-3 shows). The result of this change contributes to higher variations of the ranges between mild-base and severe-base in the 2016 Load Forecast than those in the 2014 Load Forecast.

Table 2-2 Base/Mild/Severe Weather HDDs and CDDs in 2014 Load Forecast

StationDesert Resorts Regional ArptCountyRiverside

Computed Normal						
Average of all Complete						
Months	over entire	data set				
Month	Month HDD CDD					
1	325	3				
2	191	12				
3	90	67				
4	22	193				
5	1	421				
6	0	633				
7	0	830				
8	0	790				
9	0	607				
10	7	297				
11	127	38				
12	334	2				
Annual	1,096	3,893				

Computed Mild							
Average of all Complete							
Months	Months over entire data set						
Month	Month HDD CDD						
1	214	3					
2	126	12					
3	90	67					
4	22	193					
5	1	421					
6	0	460					
7	0	603					
8	0	574					
9	0	441					
10	7	297					
11	127	38					
12	220	2					
Annual	807	3,111					

Con	Computed Severe							
Averag	Average of all Complete							
Months	Months over entire data set							
Month	Month HDD CDD							
1	435	3						
2	255	12						
3	90	67						
4	22	193						
5	1	421						
6	0	806						
7	0	1,057						
8	0	1,006						
9	0	773						
10	7	297						
11	127	38						
12	447	2						
Annual	1,385	4,674						

Table 2-3 Base/Mild/Severe Weather HDDs and CDDs in 2016 Load Forecast

Station	Imperial County Arpt (KIPL)
County	Imperial

Computed Normal						
Average of all Complete						
Months	over entire	data set				
	NormalHD	NormalCD				
Month	D	D				
1	294	3				
2	165	14				
3	81	72				
4	22	187				
5	2	402				
6	0	635				
7	0	831				
8	0	821				
9	0	639				
10	6	329				
11	101	50				
12	299	3				
Annual	969	3,984				

Computed Mild							
Average of all Complete							
Months	over entire	data set					
Month	MildHDD	MildCDD					
1	136	2					
2	77	12					
3	37	62					
4	10	162					
5	1	348					
6	0	551					
7	0	721					
8	0	712					
9	0	554					
10	3	285					
11	47	43					
12	12 138 2						
Annual	448	3,456					

Computed Severe							
Average of all Complete							
Months over entire data set							
	SevereH SevereC						
Month	DD	DD					
1	451	3					
2	254	16					
3	125	81					
4	33	211					
5	3	455					
6	0	719					
7	0	941					
8	0	930					
9	0	724					
10	9	372					
11	155	56					
12	460	3					
Annual	1,490	4,513					

Section 3: Data sources and Samples Design

In the 2016 Load Forecast study, 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 2000 through December 2015 (Study Period); NEL and CP data were also from January 2000 through December 2015; Energy Efficiency programs impact data was available and analyzed from January 2006 through December 2015 (Note: Energy Efficiency programs impact data on December 2015 was not yet available at the time of doing the study, so estimated data was used only for that month, all the other data was actual); PV installation capacity data was available and analyzed from January 2003 through December 2015.

Weather Data

In the 2014 Load Forecast, historical weather data has been provided by the National Climatic Data Center, a subsidiary of the National Oceanic and Atmospheric Administration (NOAA). The weather station selected was Desert Resorts Regional Arpt., which was located in Riverside County. But after completing an hourly load vs hourly weather temperature analysis, 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. Therefore, in the 2016 Load Forecast Imperial County Arpt. Weather Station was selected as weather data source. 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, which 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).

Sixty-five historical years' temperatures, which aredownloaded from Underground Weather website, were used as the weather data (1950-2015) inputs in the 2016 Load Forecast study. The raw weather data is the daily average temperature, which need to be 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).

From an annual perspective, the normalized CDD is getting higher based on the more recent sample years' temperatures. Figure 3-2 below illustrates the normalized CDD based on 65 historical sample years is the lowest, the normalized CDD based on recent 20 sample years is higher and the normalized CDD based on the recent five sample years is the highest.

Figure 3-3 Historical CDD vs Normalized CDDs Based on Different Sample Years

However, from monthly perspective, different sample years have different weather patterns for normalized, severe and mild CDDs and HDDs. Figure 3-4 depicts Normalized, mild and severe monthly CDD and HDD based 65 historical sample years. The peak CDD is July;

Figure 3-4 Monthly Norm/Mild/Severe CDD and HDD based on 65 years weather data

Figure 3-5 depicts Normalized, mild and severe monthly CDD and HDD based 20 historical sample years. The peak CDD is August;

Figure 3-5 Monthly Norm/Mild/Severe CDD and HDD based on 20 years weather data

Figure 3-6 depicts Normalized, mild and severe monthly CDD and HDD based on five historical sample years. The peak CDD is August.

Figure 3-6 Monthly Norm/Mild/Severe CDD and HDD based on 5 years weather data

Sixty five sample years of weather data was used in the 2016 Load Forecast even though the annual normalized CDD is the lowest since from a monthly perspective, as analyzed above, the monthly Norm/Mild/Severe CDD and HDD pattern with largest sample size (65 years) represents the most significant pattern, and is more statistically sound.

Economic Data

Historical and projected economic and demographic data were provided by Woods & Poole Economics. (Note: at the time of doing 2016 load forecast study, Woods & Poole Economics' latest available data set is based on historical years' data from 1970 through 2013, the forecast years' data is from 2014-2040. That means 2 years lagged behind the 2016 Load Forecast, of which the forecast years are from 2016-2035.) 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 2016 Load Forecast. Therefore, the data for each county was blended using a weighted average derived from 2015 energy sales data (Riverside County 58%; Imperial County 42%).

Figure 3-7 2015 IID Energy Sales by Customer Categories

As illustrated above, residential sales make 45% of 2015 IID total energy sales; commercial sales make 44% of 2015 IID total energy sales. All the rest customer categories only make 11% of 215 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 3-8 demonstrates that blend population growth has similar trend as residential sales growth from 2003 through 2035.

Figure 3-8 IID Residential Sales Growth Rate vs Blend Population Growth Rate

For the historical period (2003-2015), avg. population growth rate is 2.4%; avg. residential sales growth rate is 2.7%. During the first 10 forecast years (2016-2025), avg. population growth rate is 1.9%; avg. residential sales growth rate is 1.8%. During the second 10 forecast years (2026-2035), avg. population growth rate is 1.8%; avg. residential sales growth rate is 1.7%. In the commercial regression model, blend Gross Regional Product (GRP) is an important independent variable. This signifies that the commercial load growth can be mainly explained by blend GRP growth. Figure 3-9 demonstrates that blend GRP growth has similar trend as commercial sales growth from 2003 through 2035.

For the historical period (2003-2015), avg. GRP growth rate is 2.8%; avg. commercial sales growth rate is 2.2%. During the first 10 forecast years (2016-2025), avg. GRP growth rate is 3.5%; avg. commercial sales growth rate is 2.0%. During the second 10 forecast years (2026-2035), avg. GRP growth rate is 2.9%; avg. commercial sales growth rate is 1.8%.

Section 4: Limitations and Future Recommendations

The 2016 Load Forecast methodology and model specifications basically keep the same as 2014 Load Forecast with some modifications and improvements, which have been discussed in the previous sections of this report. Some limitations are found during the 2016 Load Forecast study process, subjected to either the current technical limits 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 2016 Load Forecast is monthly Energy Sales, NEL and CP from 2016 through 2035. 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.

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 2015 energy sales data (Riverside County 58%; Imperial County 42%). 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 42% for Imperial Valley and 58% 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 2016 load forecast study, Woods & Poole Economics' latest available data set is based on historical years' data from 1970 through 2013; the forecast years' data is from 2014-2040. That means 2 years lagged behind the 2016 Load Forecast, of which the forecast years are from 2016-2035. Some major assumptions might change during the 2 years (2013-2015), 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 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 2016 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 Residential Customer Counts Regression Model

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	Averaae	llsaae	Rearession N	Indel
rigure	J-2	Residentia	customer	Average	Usuge	Regression iv	louer

					a
Dependent Variable	e: LOG(RES	USE)			Forecast: RESUSEF_EVALUATION
Method: Least Squa	res				Actual: RESUSE
Date: 01/13/16 Tim	ie: 13:43				2,000 Forecast sample: 2004M01 2015M09
Sample: 2004M0120	D15M12				Included observations: 141
Included observation	ons: 144				1,600 Root Mean Squared Error 72.87799
					Mean Abs. Percent Error 4.217830
Variable	Coefficier	Std. Error	t-Statistic	Prob.	1.200 Theil Inequality Coefficient 0.030117
					Bias Proportion 0.000391
<u>C</u>	<u>6.5044</u>	0.030709	211.8074	<u>0</u>	800 Variance Proportion 0.001614
@SEAS(2)	-0.13995	0.02502	-5.593706	0	Covariance Proportion 0.99/995
@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	RESUSEF_EVALUATION ± 2 S.E.
@SEAS(11)	-0.12084	0.027324	-4.422301	0	
@SEAS(12)	-0.09067	0.033789	-2.683245	0.0082	2
W_CDD_N	0.000667	3.28E-05	20.36671	0	
W_HDD_N	0.000304	0.000122	2.501642	0.0136	5
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	7
TREND(11:2004)=0	-0.37222	6.00E-02	-6.201306	0	
R-squared	0.983802	Mean de	pendent var	6.912123	
Adjusted R-squared	0.982452	S.D. dep	endent var	0.428153	
S.E. of regression	0.056718	Akaike ir	nfo criterion	-2.821811	
Sum squared resid	0.424628	Schwarz	criterion	-2.574327	7
Log likelihood	215.1704	Hannan-	Quinn criter.	-2.721248	3
F-statistic	728.8095	Durbin-V	Vatson stat	2.084694	
Prob(F-statistic)	0				

Figure 5-2 shows residential average usage model. 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 these two models are the most important models in the 2016 Load Forecast.

Commercial Sales Model

Another important IID customer category is commercial customer, which makes 44% of total IID system sales. Figure 5-3 shows commercial sales 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 4.64%.

Figure 5-3 Commercial Sales Model

All the rest of IID customer categories only make up about 11% of IID total system sales. Statistically, all the models used in 2016 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 higher CDD, the more energy consumption for agricultural customer sales. Figure 5-4 shows agricultural sales model:

Figure 5-4 Agricultural Sales Model

Dependent Variable	: LOG(AG)							
Method: Least Squar	res							
Date: 01/12/16 Time	e: 16:31							
Sample: 2004M01 20	15M12							
Included observatio	ns: 144							
Variable	Coefficier	Std. Error t	-Statistic	Prob.				
<u>C</u>	<u>-0.75198</u>	0.870004	-0.864342	<u>0.3889</u>				
LOG(C_AGF2)	1.402205	0.129378	10.83802	0			Forecast AGF_EVALUATION	1
W_CDD_N	0.00032	3.71E-05	8.632476	0	1	4 J	Actual: AG	
W_HDD_N(-1)	-0.00122	0.000111	-10.99404	0	к ААААА	ñ a Al-	Forecast sample: 2004M01	2015M12
TREND(2:2007)=0	0.114713	1.42E-01	0.806119	0.4216	VALAA AZZ	$\Lambda \Lambda \Lambda$	Included observations: 144	
TREND(2:2008)=0	0.442635	0.160906	2.7509	0.0067	N IAN IAN IAN IAN I		Root Mean Squared Error	671.3348
					MANDAN JAN AN	NIANA)	Mean Absolute Error	492.5562
R-squared	0.845162	Mean de	pendent var	8.714455	*****	N// W// W	Mean Abs. Percent Error	8.270818
Adjusted R-squared	0.839552	S.D. depe	endent var	0.290632	V V V V V	V V I	Bias Proportion	0.003176
S.E. of regression	0.116416	Akaike in	fo criterion	-1.42253	r v v v V		Variance Proportion	0.050248
Sum squared resid	1.870255	Schwarz o	criterion	-1.29879			Covariance Proportion	0.946576
Loglikelihood	108.422	Hannan-(Quinn criter.	-1.37225				
F-statistic	150.6507	Durbin-W	/atson stat	2.122171	09 10 11 12 1	3 14 15		
Prob(F-statistic)	0				EVALUATION ± 2 S.E.			

Overview of Study Results and Conclusions

As described earlier, there are 24 total forecast categories. Results of IID 2016 Load Forecast are presented in two types (Gross and Net) under three weather scenarios (Base, Severe and Mild) and three Energy Efficiency program and PV program scenarios (Expected, High case and ZNE case).

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 which are experienced over lengths of transmission and distribution lines using the basic formula below:

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 2014 Load Forecast, the 2016 Load Forecast has lower net NEL value in base weather case for each of the same forecast year (as Table 4-2 shows).

IID 2	2014 Load Foreca	st	IID 2016 Load	Forecast (expe	cted case)
Year	Net NEL (GWh)	Growth Rate	Year	Net NEL (GWh)	Growth Rate
2003	3173		2003	3173	
2004	3280	3.38%	2004	3280	3.38%
2005	3395	3.48%	2005	3395	3.48%
2006	3604	6 16%	2006	3604	6.16%
2000	3703	2 75%	2007	3703	2.75%
2007	3703	2.75%	2008	3736	0.89%
2008	3730	0.69%	2009	3662	-1.98%
2009	3662	-1.98%	2010	3555	-2.92%
2010	3555	-2.92%	2011	3599	1.25%
2011	3599	1.25%	2012	3719	3.34%
2012	3719	3.34%	2013	3662	-1.55%
2013	3753	0.90%	2014	3699	1.02%
2014	3786	0.87%	2015	3687	-0.33%
2015	3852	1.75%	2016	3577	-2.99%
2016	3917	1.68%	2017	3616	1.10%
2017	3988	1 83%	2018	3656	1.10%
2018	4062	1.83%	2019	3706	1.37%
2010	4002	1.04/0	2020	3760	1.45%
2019	4154	1.70/0	2021	3811	1.36%
2020	4207	1.77%	2022	3868	1.51%
2021	4281	1.76%	2023	3930	1.58%
2022	4357	1.77%	2024	3995	1.66%
2023	4433	1.75%	2025	4063	1.70%
2024	4510	1.74%	2026	4133	1.73%
2025	4588	1.73%	2027	4206	1.77%
2026	4668	1.74%	2028	4284	1.86%
2027	4748	1.73%	2029	4362	1.82%
2028	4832	1.77%	2030	4441	1.81%
2029	4916	1.74%	2031	4000	2.00%
2030	5002	1.75%	2032	4018	1.8/%
2031	5100	1 95%	2033	4700	2.06%
2031	5100	1.55%	2034	4803	2.06%
2052	5194	1.00%	2035	4906	2.15%

Table 5-2 Net NEL in 2014 LF vs Net NEL in 2016 LF

Using year 2016 as an example, NEL is 3917 GWh in 2016 load forecast, but net NEL is 3577 GWh in 2016 load forecast, which is 340GWh less .Compared to the 2014 Load Forecast, the 2016 Load Forecast base weather case has lower net CP value too for each of the same forecast year, as Table 5-3 shows.

IID	2014 Load Foreca	st	IID 2016 Load	l Forecast (expe	cted case)
Year	Net Peak (MW)	Growth Rate	Year	Net Peak (NW)	Growth Rate
2003	792		2003	792	
2004	840	6.06%	2004	840	6.06%
2005	898	6.90%	2005	898	6.90%
2006	993	10 58%	2006	993	10.58%
2000	996	0.30%	2007	996	0.30%
2007	930	1 71%	2008	979	-1.71%
2000	979	-1.71%	2009	988	0.92%
2009	988	0.92%	2010	1004	1.62%
2010	1004	1.62%	2011	1000	-0.40%
2011	1000	-0.40%	2012	995	-0.50%
2012	995	-0.50%	2013	988	-0.70%
2013	1018	2.27%	2014	982	-0.61%
2014	1026	0.87%	2015	992	1.02%
2015	1044	1.75%	2016	1007	1.55%
2016	1059	1.40%	2017	1021	1.38%
2017	1081	2.11%	2018	1033	1.10%
2018	1101	1 84%	2019	1047	1.37%
2019	1121	1.78%	2020	1059	1.1/%
2015	1121	1.70%	2021	1076	1.64%
2020	1150	2.04%	2022	1092	1.51%
2021	1101	2.04/0	2023	1110	1.58%
2022	1181	1.77%	2024	1125	1.39%
2023	1202	1.75%	2025	1147	1.90%
2024	1219	1.46%	2020	1107	1.73%
2025	1244	2.01%	2027	1207	1.77%
2026	1266	1.74%	2028	1737	2.09%
2027	1287	1.73%	2025	1252	1 81%
2028	1307	1.49%	2030	1234	2.06%
2029	1333	2.01%	2032	1301	1.60%
2030	1356	1.75%	2032	1329	2 19%
2031	1383	1.95%	2033	1356	2.06%
2032	1404	1.58%	2035	1386	2.15%
			2000	1300	2.13/0

Table 5-3 Net CP in 2014 LF vs Net CP in 2016 LF

Using year 2016 as an example once again, CP is 1059MW in 2014 Load Forecast, but CP is 1007MW in 2016 Load Forecast, which is 52MW less. This change can be explained as follows: The load of the IID System over 2013-2015 was experiencing negative growth. The NEL annual growth rate was -1.55% in 2013 and was -0.33% in 2015 as Table 5-2 shows. The CP annual growth rate was -0.70% in 2013 and was -0.61% in 2014 as Table 5-3 shows. Another explanation of this change is the sudden growth of distributed rooftop PV impact, which took away some of IID system load during 2013-2015, and the PV impact is expected to grow in the forecast years, which can take away some of IID system load growth too as the analysis at the beginning of this report. Energy sales have the same trend as NEL because NEL forecast is derived from energy sales forecast. Table 5-4 shows the PV peak impact (CP) and energy impact (NEL) on total IID system load under three different scenarios. Each scenario has different assumptions based on policy possibilities and market drivers as analyzed in previous part of the report.

	PV Exp	ected Case	PV H	igh Case	PV ZNE Case		
Year	Peak Imapct(MW)	Energy Impact (KWh)	Peak Imapct(MW)	Energy Impact (KWh)	Peak Imapct(MW)	Energy Impact (KWh)	
201	6 18.14	84,250,561	19.05	88,565,353	19.05	88,565,353	
201	7 22.12	102,458,670	25.15	116,758,532	25.15	116,758,532	
201	8 25.77	118,981,647	32.69	151,569,734	32.69	151,569,734	
201	9 28.80	132,387,245	41.55	192,349,644	41.55	192,349,644	
202	0 31.16	142,575,786	51.23	236,703,259	51.23	236,703,259	
202	1 32.98	150,110,517	60.85	280,408,903	60.85	280,408,903	
202	2 34.34	155,404,303	69.37	318,606,581	69.37	318,606,581	
202	3 35.34	158,999,630	76.08	347,949,262	76.08	347,949,262	
202	4 36.07	161,263,846	80.86	367,956,620	81.79	372,354,478	
202	5 36.56	162,376,122	84.01	380,148,139	88.10	399,460,251	
202	6 36.81	162,436,496	85.97	386,626,073	94.61	427,343,587	
202	7 37.01	162,183,913	87.55	391,272,395	100.91	453,962,026	
202	8 36.43	158,727,086	87.51	388,616,681	107.03	479,976,821	
202	9 36.28	156,980,548	87.73	386,884,480	113.51	507,237,238	
203	0 36.13	155,241,047	88.06	385,723,085	125.92	562,264,860	
203	1 33.48	143,314,009	85.58	372,867,895	138.26	618,196,240	
203	2 32.48	138,242,616	84.59	366,074,848	151.09	674,978,929	
203	3 30.97	131,061,326	83.18	357,670,866	163.87	731,368,489	
203	4 27.76	117,021,449	79.97	341,931,416	176.52	787,839,073	
203	5 23.39	98,324,710	75.59	321,547,853	188.98	843,757,248	

Table 5-4 PV Peak Impact and Energy Impact (expected case, high case, ZNE case)

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

		EE Exp	ected Case	EE High Case		
Year		Peak Imapct(MW)	Energy Impact (KWh)	Peak Imapct(MW)	Energy Impact (KWh)	
	2016	58.01	141,173,200	58.78	143,478,343	
	2017	59.88	148,303,505	61.44	152,960,426	
	2018	61.47	154,530,386	63.75	161,326,405	
	2019	63.26	161,286,732	66.28	170,261,085	
	2020	65.27	168,618,479	69.03	179,821,031	
	2021	67.47	176,450,855	72.00	189,920,979	
	2022	69.66	184,171,031	74.92	199,843,930	
	2023	71.68	191,352,710	77.64	209,091,734	
	2024	73.33	197,355,794	80.43	218,490,187	
	2025	74.63	202,280,188	83.29	228,051,290	
	2026	75.62	206,218,753	86.23	237,787,067	
	2027	76.33	209,257,761	89.25	247,709,581	
-	2028	76.77	211,477,321	92.35	257,830,957	
	2029	76.98	212,951,781	95.54	268,163,394	
	2030	76.98	213,750,102	98.81	278,719,191	
-	2031	76.79	213,936,211	102.18	289,510,756	
	2032	76.42	213,569,334	105.65	300,550,630	
	2033	75.90	212,704,304	109.21	311,851,503	
	2034	75.23	211,391,854	112.88	323,426,228	
	2035	74.45	209,678,888	116.66	335,287,842	

Table 5-5 shows the Energy Efficiency program peak impact (CP) and energy impact (NEL) on total IID system load under two different scenarios. Each scenario reflects the different achieving performance

on IID board approved energy savings targets as well as policy possibilities on future energy savings targets, which are already analyzed in previous part of the report.

Figure 5.1 IID Net NEL Growth Rate (Expected/High/ZNE Cases)

Figure 5.1 depicts IID total system net NEL growth rate under three different scenarios: expected case, EE high case and EE ZNE case. The Expected case has highest growth rate, EE high case has medium growth rate, and EE ZNE case has lowest growth rate.

Figure 5.2 IID Net CP Growth Rate (Expected/High/ZNE Cases)

Figure 5.2 depicts IID total system net CP growth rate under the three different scenarios. Similarly, the expected case has highest, EE high case has medium growth rate, and EE ZNE case has lowest growth rate. The same is true for IID energy sales growth rate, as Figure 5.3 shows.

Figure 5.3 IID Energy Sales Growth Rate (Expected/High/ZNE Cases)

Finally, three different weather scenarios (base, severe, mild) create a ranged forecast instead of an exact forecast. Although, the expected forecast may be used as a single point of reference for various activities, RP&A recommends that the ranged forecast is considered in all planning activities to capture the unpredictable impact of weather variations on load. Consider the forecast as a range helps planning activities capture the varying possibilities of needs as a result of uncontrollable risks and the relationship of demand and supply. The gross result on IID system load is as table 5-6 shows,

Table 5-6 Gross C	P and NEL in	Base/Severe	/Mild Weather	Cases
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		Base We	eather Case	Severe V	/eather Case	Mild Weather Case		
Year		Gross CP(MW)	Gross NEL (MWh)	Gross CP(MW)	Gross NEL (MWh)	Gross CP(MW)	Gross NEL (MWh)	
	2016	1,072.08	3,825,577	1,135.77	4,052,829	1,016.69	3,627,939	
	2017	1,093.86	3,892,635	1,158.72	4,123,453	1,037.49	3,692,020	
	2018	1,112.08	3,957,464	1,177.97	4,191,934	1,054.81	3,753,673	
	2019	1,132.47	4,030,030	1,199.67	4,269,178	1,074.06	3,822,180	
	2020	1,149.92	4,103,329	1,218.16	4,346,831	1,090.61	3,891,684	
	2021	1,172.09	4,171,019	1,241.46	4,417,898	1,111.78	3,956,402	
	2022	1,192.33	4,243,046	1,262.85	4,494,012	1,131.02	4,024,863	
	2023	1,212.88	4,316,170	1,284.59	4,571,363	1,150.53	4,094,300	
	2024	1,230.47	4,390,766	1,303.20	4,650,287	1,167.23	4,165,123	
	2025	1,254.82	4,465,421	1,328.93	4,729,168	1,190.37	4,236,087	
	2026	1,275.81	4,540,129	1,351.10	4,808,059	1,210.34	4,307,140	
	2027	1,297.18	4,616,158	1,373.69	4,888,437	1,230.64	4,379,374	
	2028	1,315.15	4,692,940	1,392.69	4,969,617	1,247.72	4,452,318	
	2029	1,340.52	4,770,412	1,419.52	5,051,519	1,271.82	4,525,922	
	2030	1,362.44	4,848,418	1,442.69	5,133,969	1,292.65	4,600,049	
	2031	1,384.48	4,926,848	1,465.98	5,216,868	1,313.59	4,674,577	
	2032	1,402.82	5,005,783	1,485.36	5,300,311	1,331.02	4,749,576	
	2033	1,428.97	5,085,174	1,513.01	5,384,227	1,355.87	4,825,017	
	2034	1,451.43	5,165,071	1,536.74	5,468,669	1,377.20	4,900,945	
	2035	1,474.06	5,245,613	1,560.66	5,553,783	1,398.71	4,977,494	

The net (EE+PV expected case) result on IID system load is as table 4-7 shows.

		Base W	eather Case	Severe W	eather Case	Mild Weather Case	
Year		Net Expected CP(MW)	Net Expected NEL (MWh)	Net Expected CP(MW)	Net Expected NEL (MWh)	Net Expected CP(MW)	Net Expected NEL (MWh)
	2016	1,007.39	3,576,743	1,071.39	3,803,995	951.72	3,379,104
	2017	1,021.25	3,616,064	1,086.44	3,846,882	964.60	3,415,450
	2018	1,032.51	3,655,924	1,098.73	3,890,394	974.96	3,452,133
	2019	1,046.61	3,705,854	1,114.15	3,945,002	987.91	3,498,004
	2020	1,058.88	3,759,566	1,127.46	4,003,069	999.27	3,547,921
	2021	1,076.20	3,810,615	1,145.92	4,057,494	1,015.59	3,595,998
	2022	1,092.49	3,868,314	1,163.37	4,119,280	1,030.87	3,650,131
	2023	1,109.78	3,929,522	1,181.85	4,184,716	1,047.12	3,707,653
	2024	1,125.17	3,994,922	1,198.26	4,254,443	1,061.62	3,769,278
	2025	1,147.46	4,062,922	1,221.94	4,326,668	1,082.69	3,833,588
	2026	1,167.33	4,133,278	1,242.99	4,401,208	1,101.52	3,900,290
	2027	1,187.93	4,206,233	1,264.83	4,478,512	1,121.06	3,969,449
	2028	1,206.69	4,284,380	1,284.62	4,561,057	1,138.92	4,043,758
	2029	1,231.96	4,362,150	1,311.35	4,643,257	1,162.91	4,117,660
	2030	1,254.29	4,441,207	1,334.94	4,726,758	1,184.15	4,192,838
	2031	1,280.11	4,532,628	1,362.02	4,822,648	1,208.86	4,280,357
	2032	1,300.54	4,617,573	1,383.49	4,912,101	1,228.38	4,361,366
	2033	1,329.03	4,705,857	1,413.49	5,004,910	1,255.56	4,445,699
	2034	1,356.39	4,802,727	1,442.13	5,106,324	1,281.80	4,538,600
	2035	1,385.51	4,905,833	1,472.55	5,214,003	1,309.79	4,637,715

Table 5-7 Net (Expected EE &PV) CP and NEL in Base/Severe/Mild Weather Cases

As discussed before in the report, the range in 2016 Load Forecast is much wider than that in 2014 Load Forecast, in order to improve the understanding of IID load 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.