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Subject: **RPU Wholesale & Retail Load Forecasting Methodologies**

2016 Interim Report

Participant: **City of Riverside, Riverside Public Utilities (RPU)**

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1. Overview & Introduction

RPU uses regression based econometric models to forecast both its total expected GWh system load and system MW peak on a monthly basis. Regression based econometric models are also used to forecast expected monthly retail loads (GWh) for our four primary customer classes. These models are calibrated to historical load and/or sales data extending back to January 2003. The following input variables are used in one or more of these econometric models: (a) various monthly weather summary statistics, (b) specific calendar effects, (c) unplanned for (but verified) expansion of industrial loads, (d) long-term econometric input variables for the Riverside – San Bernardino – Ontario metropolitan service area; i.e., annual per capita personal income (PCPI) and monthly non-farm employment (EMP) estimates, and (e) the cumulative load loss effects associated with retail customer solar PV installations and all of our measured Energy Efficiency programs. These models are used to project RPU wholesale gross and peak monthly loads and monthly retail sales twenty years into the future.

Due to a lack of AMI and load research survey data, RPU does not currently produce forecasts of coincident or non-coincident peak loads associated with any specific customer class, or future electrical rates for any customer class and/or tier rate structure. However, our current wholesale and retail forecasting models do explicitly capture and account for the effects of all active RPU Energy Efficiency programs at their current funding and implementation levels, along with the impacts of customer installed solar PV distributed generation within our service territory. This document describes our statistical methodology used to account for these EE and solar PV effects in detail. The interested reader should refer to our SB1037/AB2021 report for more detailed information about RPU's various EE / rebate programs, and our SB1 report for more general information about solar PV installation trends within the RPU service territory.

RPU does not currently administer any type of long-term, dispatchable Demand Response program in its service territory. In response to the 2012 SONGS closure, RPU has implemented a Power Partners voluntary load curtailment program to call upon up to 10 MW of commercial and industrial load shedding capability during any CAISO Stage 3 emergency situation. For large TOU customers, we use commercial time-of-use rate structures to encourage and incentivize off-peak energy use. Finally, we have no ESP's in our service territory and we do not anticipate either losing any existing load or gaining any new service territory over the next ten years.

2. Forecasting Approach

2.1. General modeling methodology

The following load based metrics are modeled and forecasted by the RPU Power Resources Division:

- Hourly system loads (MW),
- Total monthly system load (GWh),
- Maximum monthly system peak (MW),
- Total monthly retail loads for our Residential, Commercial, Industrial and Other customer classes (GWh).

Additionally, dynamic-regression (time series) models are used to simulate the following seasonal weather information (UCR CIMIS Weather Station data) for the Riverside electrical service area:

- Riverside average daily temperature (°F)
- Riverside max-min temperature differential (°F)

These daily weather data simulation models are calibrated to historical data and are used in our hourly system load equations (to produce prospective, simulated hourly system loads). These corresponding average historical values are also used as prospective weather input values for our monthly load forecasting equations, respectively.

All primary monthly forecasting equations are statistically developed and calibrated to 13 years of historical monthly load data. The parameter estimates for each forecasting equation are updated every 6 to 12 months; if necessary, the functional form of each equation can be updated or modified on an annual basis. Please note that this report only summarizes the methodology and statistical results pertaining to our monthly forecasting equations. Section 3 of this report describes our monthly system load and system peak equations, while section 4 discusses our class-specific, retail load models.

2.2. Input variables

The various weather, calendar, economic and structural input variables used in our monthly forecasting equations are defined in Table 2.1. Note that all weather variables represent functions of the average daily temperature (ADT, °F) expressed as either daily cooling degrees (CD) or extended heating degrees (XHD), where these indices are in turn defined as

$$CD = \max[ADT-65, 0] \qquad \text{Eq. 2.1}$$

$$XHD = \max[55-ADT, 0]\ . \qquad \text{Eq. 2.2}$$

Thus, two days with average temperatures of 73.3° and 51.5° would have corresponding CD indices of 8.3 and 0 and XHD indices of 0 and 3.5, respectively.

The “structural” variables shown in Table 2.1 represent calculated cumulative load and peak impacts associated with the following programs and mandates:

- Additional, new industrial load that relocated into the RPU service territory in the 2011-2012 time frame, in response to a two year, city-wide economic incentive program. (Note that some load later migrated out of our service territory in the 2014-2015 time frame; the impact of this load loss is also incorporated into this “new load” structural variable.)
- Avoided energy use directly attributable to RPU energy efficiency programs and rebates.
- Avoided energy use directly attributable to customer installed solar PV systems within the RPU service territory.

The calculations associated with each of these load and peak impact variables are described in greater detail below. More specifically, section 2.4 describes the amount and timing of the new industrial load that relocated into our service territory in 2011 and 2012, and out of our service territory in 2014 and 2015. Likewise, sections 2.5 and 2.6 describe how we calculate the cumulative avoided load and peak energy usage associated with RPU energy efficiency programs and rebates, and customer installed solar PV systems within the RPU service territory, respectively.

Finally, low order Fourier frequencies are also used in the regression equations to help describe structured seasonal load (or peak) variations not already explained by other predictor variables. These Fourier frequencies are formally defined as

$$Fs(n) = \text{Sine}[\, n \times 2\pi \times [(m\text{-}0.5)/12\} \,], \qquad \text{Eq. 2.3}$$

$$Fc(n) = \text{Cosine}[\, n \times 2\pi \times [(m\text{-}0.5)/12\} \,], \qquad \text{Eq. 2.4}$$

where m represents the numerical month number (i.e., 1 = Jan, 2 = Feb, .., 12 = Dec).

Table 2.1 Economic, calendar, weather, structural and miscellaneous input variables used in RPU monthly forecasting equations (SL = system load, SP = system peak, RL = retail load(class specific)).

Effect	Variable	Definintion	Forecasting Eqns.		
			SL	SP	RL
Economic	PCPI	Per Capita Personal Income ($1000)	X	X	X
	EMP	Non-farm Employment (100,000)	X	X	X
Calendar	SumMF	# of Mon-Fri (weekdays) in month	X		
	SumSS	# of Saturdays and Sundays in month	X		
	Xmas	Retail (residential) indicator variable for Christmas effect (DEC = 1, JAN = 1.5, all other months = 0)			X
Weather	SumCD	Sum of monthly CD’s	X		X
	SumXHD	Sum of monthly XHD’s	X		X
	MaxCD3	Maximum concurrent 3-day CD sum in month		X	
	CDImpact	Interaction between SumCD and MaxCD3	X	X	
	MaxHD	Maximum single XHD value in month		X	
Structural (Indst, EE, PV)	New.Indst.Load	New Industrial load (GWh: calculated)	X		X
	New.Indst.Peak	New Industrial peak (MW: calculated)		X	
	Avoid.EE.Load	Cumulative avoided EE load (GWh: calculated)	X		X
	Avoid.EE.Peak	Cumulative avoided EE peak (MW: calculated)		X	
	Avoid.PV.Load	Cumulative avoided PV load (GWh: calculated)	X		X
	Avoid.PV.Peak	Cumulative avoided PV peak (MW: calculated)		X	
Fourier terms	Fs(1)	Fourier frequency (Sine: 12 month phase)	X	X	X
	Fc(1)	Fourier frequency (Cosine: 12 month phase)	X	X	X
	Fs(2)	Fourier frequency (Sine: 6 month phase)	X	X	X
	Fc(2)	Fourier frequency (Cosine: 6 month phase)	X	X	X
	Fs(3)	Fourier frequency (Sine: 4 month phase)		X	
	Fc(3)	Fourier frequency (Cosine: 4 month phase)		X	
Lag function	Lag(X[i])	Produces value of X for month i-1			X

2.3. Historical and forecasted inputs: economic and weather effects

The annual values of our historical and forecasted economic indices are reported on Demand Form 2.1 in our 2017 CEC IEPR submission packet. Annual PCPI data have been obtained from the US Bureau of Economic Analysis (http://www.bea.gov), while monthly employment statistics have been obtained from the CA Department of Finance (http://www.labormarketinfo.edd.ca.gov). As previously stated, both sets of data correspond to the Riverside-Ontario-San Bernardino metropolitan service area.

All SumCD, SumXHD, MaxCD3 and MaxHD weather indices for the Riverside service area are calculated from historical average daily temperature levels recorded at the UC Riverside CIMIS weather station (http://wwwcimis.water.ca.gov/cimis). Forecasted average monthly weather indices are based on historical averages; these forecasted monthly indices are shown in Table 2.2. Note that these average monthly values are used as weather inputs for all forecasts on/after 2016.

Table 2.2. Expected average values (forecast values) for future monthly weather indices; see Table 2.1 for weather index definitions.

Month	SumCD	SumXHD	MaxCD3	MaxHD
JAN	1.6	98.3	1.4	11.6
FEB	2.2	66.8	2.0	9.9
MAR	7.4	41.4	5.4	7.9
APR	26.8	14.4	13.9	4.6
MAY	88.7	2.1	28.2	1.1
JUN	212.1	0.1	45.5	0.1
JUL	340.8	0.0	57.0	0.0
AUG	362.4	0.0	59.8	0.0
SEP	243.7	0.1	50.2	0.0
OCT	93.0	2.7	30.9	1.3
NOV	14.6	27.4	10.4	6.7
DEC	2.7	77.1	2.5	10.4

2.4 New 2011-2012 Industrial Load

In January 2011, in response to the continuing recession within the Inland Empire, the City of Riverside launched an economic incentive program to attract new, large scale industrial business to relocate within the city boundaries. As part of this incentive program, RPU launched a parallel program for qualified relocating industries to receive a two year, discounted time-of-use (TOU) electric rate. In response to this program, approximately 10-12 new industrial businesses relocated to within the city's electric service boundaries over an 18 month period.

Table 2.3 below quantifies the approximate, industrial MW load additions that RPU experienced between January 2011 and July 2012, in response to this program. These forecasted load additions were later verified (in 2013) by examining the recorded meter readings of industrial TOU energy use patterns for these new customers. It should be noted that RPU's discounted TOU incentive program was closed to new subscriptions in December 2012. The additional load growth experienced since that time can be attributed to the general improvement in our local economic conditions.

Given that the load additions quantified in Table 2.3 are directly attributable to the above mentioned incentive program, we have isolated this effect in our econometric models via the use of calculated "New.Indst.Load" and "New.Indst.Peak" input variables. These input variables define the calculated, cumulative amounts of incentivized new monthly peak MW and retail GWh load volumes impacting our service territory, beginning in January 2011. Hence, in the econometric forecasting models discussed in sections 3 and 4 of this report, the corresponding parameter estimates associated with these input variables have been restricted to pre-specified positive coefficients; i.e., +1.05 for the system equations and +1.00 for the retail equations, respectively. Note that the system coefficients (+1.05) are designed to account for both the retail load impacts and the corresponding distribution losses (estimated to be approximately 5%). Note also that since all of these businesses are large industrial entities with stable, constant base-load energy patterns, the expected cumulative GWh load volumes can and are calculated directly from the corresponding cumulative MW peaks; i.e.,

$$\text{GWh load} = (\text{MW peak} \times 24 \text{ hours} \times \text{days-in-month})/1000 \qquad \text{Eq. 2.5}$$

Finally, beginning early 2015 there has been a steady reduction of this relocated Industrial MW load due to various reasons. Table 2.3.2 shows the approximate load loss pattern that began in early 2015. As of now, the Industrial MW load is standing at 3 MW and appears to have stabilized. Since RPU does not anticipate re-opening the economic incentive program at any point in the near future, the cumulative future MW peak impact is assumed to be a constant 3 MW throughout the 2016-2027 forecast horizon.

Table 2.3.1 Industrial MW load additions in direct response to RPU's 2011-2012 discounted TOU incentive program.

Year	Month	Load Addition (MW/hour)	Cumulative Peak Addition (MW)	Cumulative Load Addition (GWh)
2011	January	0.5 MW/hour	0.5 MW	0.37 GWh
2011	April	3.0 MW/hour	3.5 MW	2.52 GWh
2011	July	1.0 MW/hour	4.5 MW	3.35 GWh
2011	October	0.5 MW/hour	5.0 MW	3.72 GWh
2012	July	1.0 MW/hour	6.0 MW	4.46 GWh
Program closed in December 2012 to new participants				

Table 2.3.2 Industrial MW load deductions (i.e., load loss pattern since early 2015).

Year	Month	Load Deduction (MW/hour)	Cumulative Peak Deduction (MW)	Cumulative Load Deduction (GWh)
2015	April	0.75 MW/hour	0.75 MW	0.54 GWh
2015	July	0.75 MW/hour	1.5 MW	1.12 GWh
2015	October	0.75 MW/hour	2.25 MW	1.67 GWh
2016	January	0.75 MW/hour	3.0 MW	2.23 GWh
RPU's new Industrial MW loads are projected to stay at 3 MW				

2.5 Cumulative Energy Efficiency savings since 2005

RPU has been tracking and reporting SB-1037 annual projected EE savings since 2006. These reported values include projected net annual energy savings and net coincident peak savings for both residential and non-residential customers, for a broad number of CEC program sectors. Additionally, these sector specific net energy and peak savings can be classified into "Baseload", "Lighting" and "HVAC" program components, respectively**.**

In the fall of 2014, we reviewed all of our EE saving projections going back to fiscal year 2005/06, in order to calculate our cumulative load and peak savings attributable to efficiency improvements and rebate programs. The steps we performed in this analysis were as follows:

1. We first computed the sum totals of our projected net annual energy and coincident peak savings for the three program components (Baseload, Lighting, and HVAC) for each fiscal year, for both residential and non-residential customers.
2. Next, we calculated the cumulative running totals for each component from July 2005 through December 2014 by performing a linear interpolation on the cumulative fiscal year components.

3. We then converted these interpolated annual totals into monthly impacts by multiplying these annual values by the monthly load and peak scaling/shaping factors shown in Table 2.4.
4. Finally, we summed these three projected monthly program components together to estimate the cumulative projected monthly load and peak reduction estimates, directly attributable to measured EE activities.

It should be noted that these represent interpolated engineering estimates of energy efficiency program impacts. Figure 2.2 shows a graph of the cumulative impact of the projected retail load savings due to EE impacts over time (along with projected load savings attributable to solar PV installations; see section 2.6). Likewise, Figure 2.3 shows a graph of the cumulative impact of the projected retail peak energy savings due to EE impacts over time.

In theory, if such estimates are unbiased and accurate, then when one introduces a regression variable containing these observations into an econometric forecasting model, the corresponding parameter estimate should be approximately equal to -1.0 (to reflect the anticipated load or peak energy reduction over time, etc.). In practice, this parameter estimate may differ from -1.0 in a statistically significant manner, due to inaccuracies in the various EE program sector savings projections.

Table 2.4. Monthly load scaling and peak shaping factors for converting interpolated SB 1037 cumulative annual net load and coincident peak EE program impacts into cumulative monthly impacts.

Month (i)	Load Scaling Factors			Peak Shaping Factors		
	Baseload	Lighting	HVAC	Baseload	Lighting	HVAC
Jan	0.0833 for all months	0.0970	$SumCD_{(i)}/1390$	1.0 for all months	1.164	$SumCD_{(i)}/362.4$
Feb		0.0933			1.119	
Mar		0.0858			1.030	
Apr		0.0784			0.940	
May		0.0746			0.896	
Jun		0.0709			0.851	
Jul		0.0709			0.851	
Aug		0.0746			0.896	
Sep		0.0784			0.940	
Oct		0.0858			1.030	
Nov		0.0933			1.119	
Dec		0.0970			1.164	

2.6 Cumulative Solar PV installations since 2001

RPU has been tracking annual projected load and peak savings due to customer solar PV installations for the last five years. Additionally, since the enactment of SB1, RPU has been encouraging the installation of customer owned solar PV through its solar rebate program. Figure 2.1 shows the calculated total installed AC capacity of customer owned solar PV in the RPU service territory since 2002.

Based on the installed AC capacity data, we can estimate the projected net annual energy savings and net coincident peak savings for both residential and non-residential customers, respectively. In the summer of 2016, we reviewed all of our solar PV saving projections going back to calendar year 2002, in order to calculate our cumulative load and peak savings attributable to customer installed PV systems within our service territory. These calculations were performed by converting the installed AC capacity data into monthly load and peak energy reduction impacts by multiplying these capacity values by the monthly load and peak scaling/shaping factors shown in Table 2.5. (These scaling and shaping factors are based on a typical south-facing roof-top solar PV installation with a 20% annual capacity factor, and assume that our distribution peaks occur in HE19 from November through February, and HE16 in March through October.) We then summed these projected monthly components together to estimate the cumulative projected monthly load and peak reduction estimates, directly attributable to solar PV distributed generation (DG) activities.

Once again, it should be noted that these represent interpolated engineering estimates of solar PV DG impacts. Figure 2.2 shows a graph of the cumulative impact of the projected retail load savings due to both EE and solar PV-DG impacts over time. Likewise, Figure 2.3 shows a graph of the cumulative impact of the projected retail peak energy savings due to EE and PV-DG impacts over time. As before, if such estimates are unbiased and reasonably accurate, then when one introduces a regression variable containing these observations into an econometric forecasting model, the corresponding parameter estimate should be approximately equal to -1.0 (to reflect the anticipated load or peak energy reduction over time, etc.). In practice, this parameter estimate may once again differ from -1.0 in a statistically significant manner, due to inaccuracies in the various solar PV-DG savings calculations.

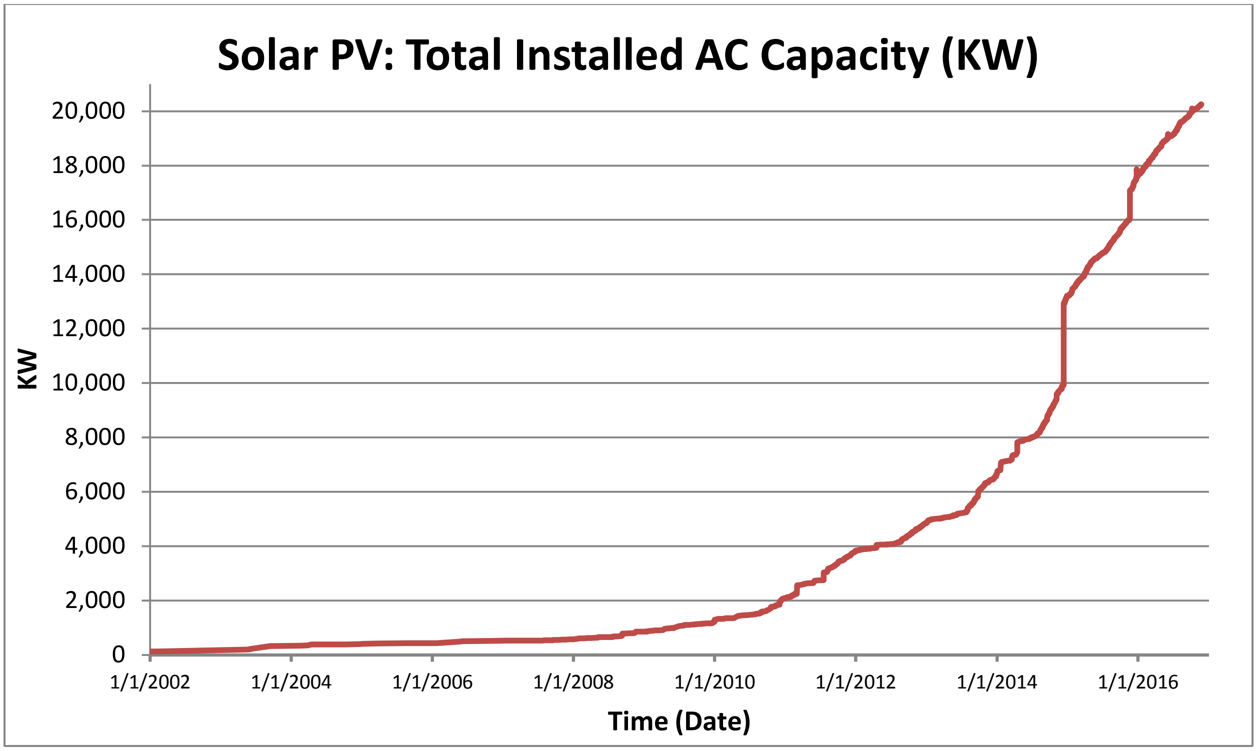

Figure 2.1. Total installed AC capacity of customer owned solar PV in the RPU service territory since 2002.

Table 2.5. Monthly load scaling and peak shaping factors for converting cumulative solar AC capacity into monthly net load and peak PV-DG impacts.

Month	Load Scaling Factors	Peak Shaping Factors
Jan	0.172	0
Feb	0.181	0
Mar	0.195	0.359
Apr	0.211	0.403
May	0.225	0.434
Jun	0.232	0.442
Jul	0.229	0.425
Aug	0.217	0.389
Sep	0.203	0.342
Oct	0.188	0.298
Nov	0.176	0
Dec	0.170	0

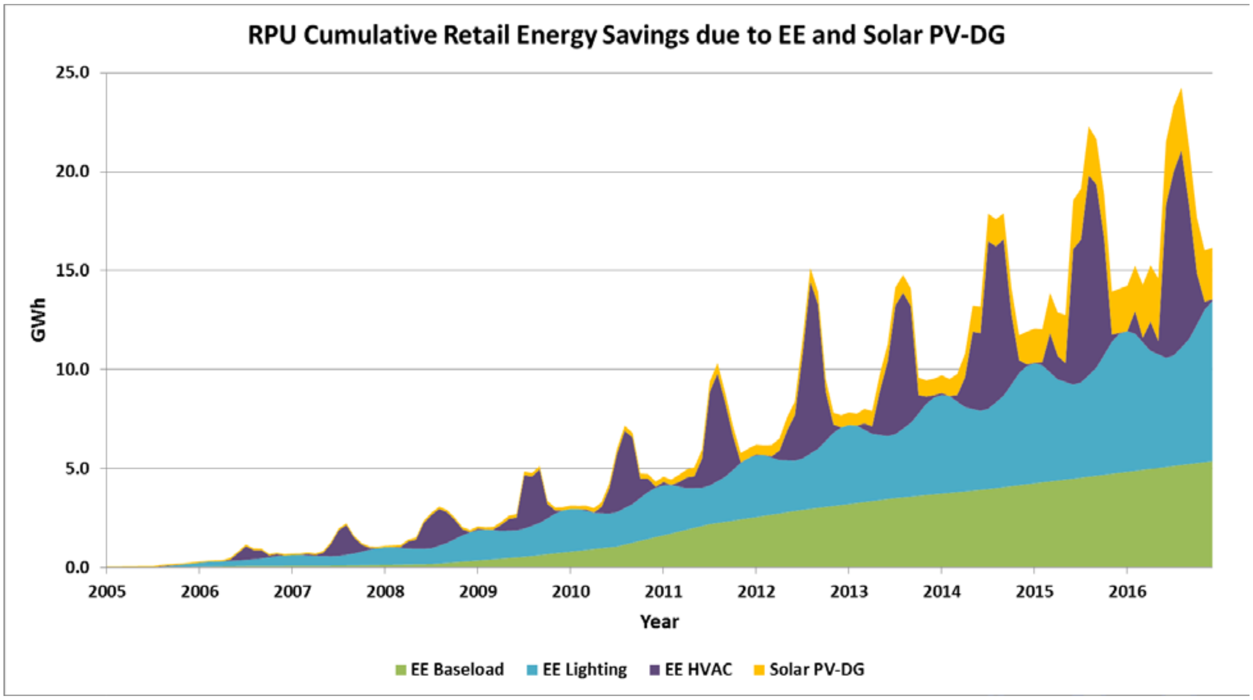

Figure 2.2. Calculated cumulative projected retail energy savings in the RPU service territory due to both EE program and solar PV distributed generation impacts over time.

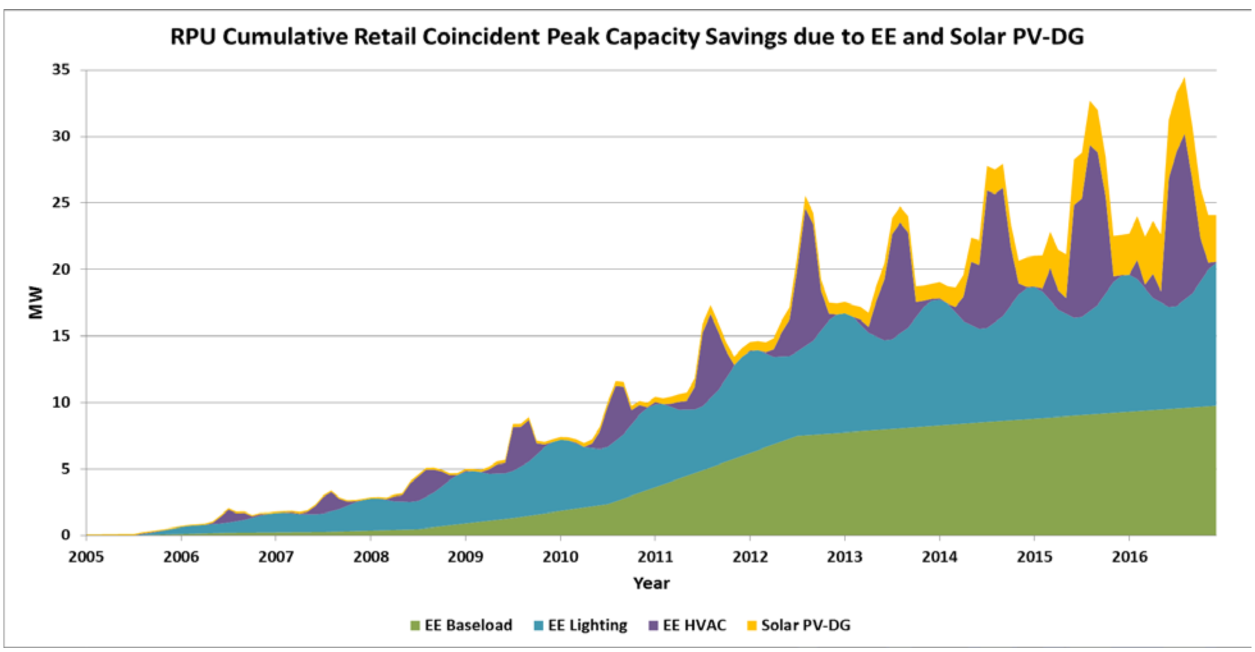

Figure 2.3. Calculated cumulative projected coincident peak capacity savings in the RPU service territory due to both EE program and solar PV distributed generation impacts over time.

3. System Load and Peak Forecast Models

3.1 Monthly system total load model

The regression component of our monthly total system load forecasting model is a function of our two economic drivers (PCPI and EMP), two calendar effects that quantify the number of weekdays (SumMF) and weekend days (SumSS) in the month, three weather effects that quantify the total monthly cooling and extended heating degrees (SumCD and SumXHD) and the interactive effect of the maximum three-day heatwave impact (MaxCD3), four low order Fourier frequencies (Fs(1), Fc(1), Fs(2) and Fc(2)), one constrained new Industrial load effect (Load.Indst), and one initially unconstrained effect that captures the combined impacts of avoided load due to EE and PV-DG impacts. Additionally, the heterogeneous residual variance (mean square prediction error) component is defined to be seasonally dependent; i.e., larger for the summer months (May through October) than the winter months (November through April). Mathematically, the model is defined as

$$y_t = \beta_0 + \beta_1[PCPI_t] + \beta_2[EMP_t] + \beta_3[SumMF_t] + \beta_4[SumSS_t] + \beta_5[SumCD_t] + \beta_6[SumXHD_t] +$$

$$\beta_7[SumCD_t][MaxCD3_t]/100 + \beta_8[Fs(1)_t] + \beta_9[Fc(1)_t] + \beta_{10}[Fs(2)_t] + \beta_{11}[Fc(2)_t] +$$

$$1.05[Load.Indst_t] + \theta_1[EE_t+PV.DG_t] + \varepsilon_{jt} \qquad \text{Eq. 3.1}$$

where

$$\varepsilon_{jt \text{ for } j=1(\text{summer}),\, 2(\text{winter})} \sim N(0, \sigma_j^2). \qquad \text{Eq. 3.2}$$

In Eq. 3.1, y_t represents the RPU monthly total system load (GWh) for the calendar ordered monthly observations and forecasts (t=1 → Jan 2003) and the seasonally heterogeneous summer and winter residual errors are assumed to be Normally distributed and temporally uncorrelated. Eqs. 3.1 and 3.2 were initially optimized using restricted maximum likelihood estimation (SAS MIXED Procedure). After determining the approximate variance ratio for the seasonal errors and verifying that the θ_1 parameter estimate was negative and statistically significant, Eq. 3.1 was refit using weighted least squares (SAS REG Procedure).

All input observations that reference historical time periods are assumed to be fixed (i.e., measured without error) during the estimation process. For forecasting purposes, we treated the forecasted economic indices and structural effects (New.TOU, EE, and PV-DG) as fixed variables and the forecasted weather indices as random effects. Under such an assumption, the first-order Delta method estimate of the forecasting variance becomes

$$Var(\hat{y}_t) = \sigma_m^2 + Var\{\ \beta_5[SumCD_t] + \beta_6[SumXHD_t] + \beta_7[SumCD_t][MaxCD3_t]/100\ \} \qquad \text{Eq. 3.3}$$

where σ_m^2 represents the model calculated mean square prediction variance and the second variance term captures the uncertainty in the average weather forecasts. Note that the second variance term is approximated via simulation, once the parameters associated with the SumCD and SumXHD weather effects have been estimated.

3.2 System load model statistics and forecasting results

Table 3.1 shows the pertinent model fitting and summary statistics for our total system load forecasting equation, estimated using weighted least squares. The equation explains about 99% of the observed variability associated with the monthly 2003-2016 system loads and nearly all input parameter estimates are statistically significant below the 0.01 significance level. Eqn. 3.1 was initially fit using the SAS MIXED procedure via a restricted maximum likelihood estimation procedure. The summer and winter variance parameters converged to an approximate 2:1 variance ratio and thus were restricted to this ratio during the weighted least squares analysis.

As shown in Table 3.1, the estimate for the winter seasonal variance component is 10.77 GWh; the corresponding summer component is twice this amount (21.54 GWh). An analysis of the variance adjusted model residuals suggests that the model errors are also Normally distributed, devoid of outliers and approximately temporally uncorrelated; implying that our modeling assumptions are likewise reasonable. Additionally, the θ_1 parameter estimate for the combined EE and PV-DG avoided load effects converged to -1.076 (std.error = 0.091), which is not statistically different from -1.05. Thus, we can conclude that all of the engineering calculated avoided load effect is accounted for in this econometric model.

The remaining regression parameter estimates shown in the middle of Table 3.1 indicate that monthly system load increases as either/both weather indices increase (SumCD and SumXHD), and the interaction between the SumCD and MaxCD3 is positive and statistically significant. Additionally, weekdays contribute slightly more to the monthly system load, as opposed to Saturdays and Sundays (i.e., the SumMF estimate is > than the SumSS estimate). Finally, our RPU system load is expected to increase as either the area wide PCPI and/or employment indices improve over time (i.e., both economic parameter estimates are > 0, although the PCPI index exerts the dominate influence). Likewise, our load growth will grow more slowly if future EE and/or PV-DG trends increase above their current forecasted levels.

Figure 3.1 shows the observed (blue points) versus calibrated (green line) system loads for the 2003-2016 timeframe. Nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines) and the observed versus calibrated load correlation exceeds 0.995. Figure 3.2 shows the forecasted monthly system loads for 2016 through 2028, along with the corresponding 95% forecasting envelope. This forecasting envelope encompasses both model and weather uncertainty, while treating the projected economic indices as fixed inputs. There is considerable uncertainty associated with summer forecasts due to the increased uncertainty surrounding summer weather patterns. Note also that these forecasts assume that our future PV-DG installation rates will stabilize at approximately 2 MW of AC capacity per year, and that our future calculated EE savings rate will continue to be approximately equal to 1% of our total annual system loads. Under these assumptions, our system loads are forecasted to grow at 1.1% per year over the next ten years.

Table 3.1 Model summary statistics for the monthly total system load forecasting equation.

Gross Monthly Demand Model (Jan 2003 - Jun 2016): GWh units
Forecasting Model: includes Weather & Economic Covariates, Fourier Effects,
new TOU (constrained), and Avoided Load (Solar PV and EE)

Final Forecasting Equation: assumes 2/1 varaince pattern

Dependent Variable: GWhload Load (GWh)
Number of Observations Used: 162
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	148623	12385	1149.55	<.0001
Error	149	1605.32228	10.77398		
Corrected Total	161	150228			

Root MSE	3.28237	R-Square	0.9893
Dependent Mean	183.58443	Adj R-Sq	0.9885
Coeff Var	1.78794		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	-129.82154	12.94915	-10.03	<.0001	0
PCPI	PCPI ($1,000)	1	4.24920	0.36776	11.55	<.0001	8.81999
Emp_CC	Labor (100,000)	1	0.48452	0.70786	0.68	0.4947	7.36996
SumMF		1	5.41898	0.35923	15.09	<.0001	1.73806
SumSS		1	4.64536	0.41399	11.22	<.0001	1.63160
SumCD		1	0.14921	0.01361	10.96	<.0001	52.07005
CDImpact		1	0.06377	0.01822	3.50	0.0006	32.78173
SumXHD		1	0.05637	0.01007	5.60	<.0001	2.44714
Fs1		1	-4.71738	0.67698	-6.97	<.0001	3.44161
Fc1		1	-6.18440	0.92379	-6.69	<.0001	6.41590
Fs2		1	1.39411	0.56267	2.48	0.0143	2.38021
Fc2		1	1.48087	0.43198	3.43	0.0008	1.40295
avoided_load	EE+PV.DG	1	-1.07626	0.09148	-11.76	<.0001	4.25588
extra_tou	New.TOU	1	1.05000	0	Infty	<.0001	0

Durbin-Watson D	1.596
Number of Observations	120
1st Order Autocorrelation	0.190

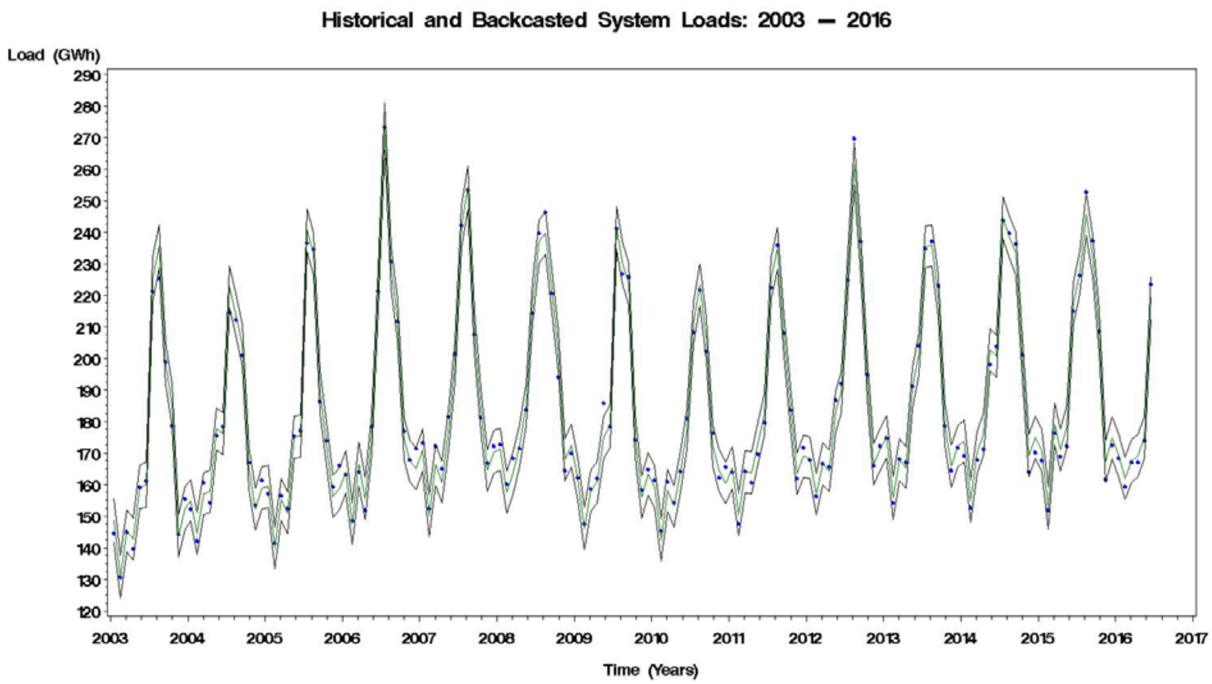

Figure 3.1. Observed and predicted total system load data (2003-2016), after adjusting for known weather conditions.

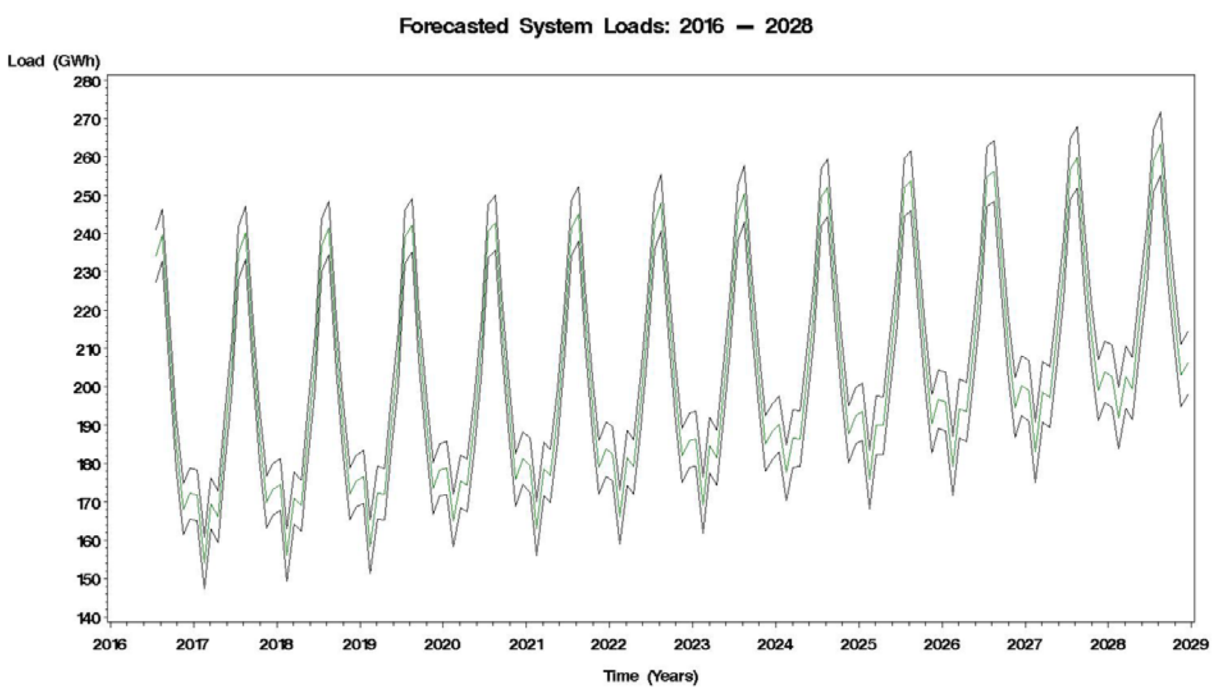

Figure 3.2. Forecasted monthly total system loads for 2016-2028; 95% forecasting envelopes encompass both model and weather uncertainty.

Table 3.2 shows the forecasted monthly RPU system loads for 2017, along with their forecasted standard deviations. Once again, these standard deviations quantify both model and weather uncertainty. The 2017 forecasts project that our annual system load should be 2269.4 GWh, assuming that the RPU service area experiences typical weather conditions throughout the year.

Table 3.2. 2017 monthly total system load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Load (GWh)	Std.Dev (GWh)
JAN	171.8	4.04
FEB	154.0	3.97
MAR	169.6	4.06
APR	166.1	5.10
MAY	185.8	8.20
JUN	205.6	11.17
JUL	234.8	12.51
AUG	240.2	12.47
SEP	210.7	11.92
OCT	187.8	8.52
NOV	169.9	4.39
DEC	173.3	3.98
Annual TOTAL	2269.40	

3.3 Monthly system peak model

The regression component of our monthly system peak forecasting model is a function of our primary economic driver (employment: EMP), three weather effects that quantify the maximum three-day cooling requirements (i.e., 3-day heat waves), the interaction of this effect with the monthly cooling degrees and the maximum single day heating requirement (MaxCD3, SumCD and MaxHD, respectively), six lower order Fourier frequencies (Fs(1), Fc(1), Fs(2), Fc(2), Fs(3) and Fc(3)), one constrained new Industrial peak effect (Peak.Indst), and one initially unconstrained effect that captures the combined impacts of avoided peak-load due to EE and PV-DG impacts. Note that only one economic driver is used in our peak forecasting model because this model was found to be unstable when both economic variables were incorporated into the equation. The heterogeneous residual variance (mean square prediction error) component is again defined to be seasonally dependent, but now where the summer period is defined to be one month longer (April through October). Mathematically, the model is defined as

$$y_t = \beta_0 + \beta_1[EMP_t] + \beta_2[MaxCD3_t] + \beta_3[SumCD_t][MaxCD3_t]/100 + \beta_4[MaxHD_t] +$$

$$\beta_5[Fs(1)_t] + \beta_6[Fc(1)_t] + \beta_7[Fs(2)_t] + \beta_8[Fc(2)_t] + \beta_9[Fs(3)_t] + \beta_{10}[Fc(3)_t] +$$

$$1.05[Peak.Indst_t] + \theta_1[EE_t+PV.DG_t] + \varepsilon_{jt} \qquad \text{Eq. 3.4}$$

where

$$\varepsilon_{jt\text{ for } j=1(\text{summer}),\, 2(\text{winter})} \sim N(0, \sigma_j^2). \qquad \text{Eq. 3.5}$$

In Eq. 3.4, y_t represents the RPU monthly system peaks (MW) for the calendar ordered monthly observations and forecasts (*t*=1 → Jan 2003) and the seasonally heterogeneous summer and winter residual errors are assumed to be Normally distributed and temporally uncorrelated. Eqs. 3.4 and 3.5 were again initially optimized using restricted maximum likelihood estimation (SAS MIXED Procedure), before being refit using weighted least squares.

As in the total system load equation, all input observations that reference historical time periods were assumed to be fixed. Likewise, we again treated the forecasted economic indices as fixed variables and the forecasted weather indices as random effects. Under such an assumption, the first-order Delta method estimate of the forecasting variance becomes

$$Var(\hat{y}_t) = \sigma_m^2 + Var\{ \beta_2[MaxCD3_t] + \beta_3[SumCD_t][MaxCD3_t]/100 + \beta_4[MaxHD_t] \} \qquad \text{Eq. 3.6}$$

where σ_m^2 represents the model calculated mean square prediction variance and the second variance term captures the uncertainty in the average weather forecasts. As before, the second variance term was approximated via simulation after the parameters associated with the weather effects were estimated.

3.4 System peak model statistics and forecasting results

Table 3.3 shows the pertinent model fitting and summary statistics for our system peak forecasting equation. This equation explains approximately 97% of the observed variability associated with the monthly 2003-2016 system peaks.

Eqn. 3.4 was initially fit using the SAS MIXED procedure via a restricted maximum likelihood estimation procedure. The summer and winter variance parameters converged to an approximate 4:1 (summer:winter) ratio and were thus constrained to this ratio in the weighted least squares analysis. An analysis of the variance adjusted model residuals suggests that the model errors were also Normally distributed, devoid of outliers and temporally uncorrelated; implying that our modeling assumptions are likewise reasonable.

As shown in Table 3.3, the θ_1 parameter estimate for the combined EE and PV-DG avoided peak effects converged to -0.408 (std.error = 0.318). In contrast to the load model, the avoid peak parameter estimate was not found to be statistically significant. However, the negative value is consistent with an interpretation that approximately 41% of the engineering calculated, avoided peak load effects due to EE and PV-DG activities translate into measureable system peak reductions.

The remaining regression parameter estimates shown in the middle of Table 3.3 imply that monthly system peaks increases as each of the weather indices increase, but the peaks appear to be primarily determined by the MaxCD3 index. (Recall that this index essentially quantifies the maximum cooling degrees associated with 3-day summer heat waves.) RPU system peaks are also expected to increase as the PCPI index improves over time (i.e., PCPI parameter estimate is > 0). Likewise, our peak growth will grow more slowly if future EE and/or PV-DG trends increase above their current forecasted levels. Additionally, not every individual Fourier frequency parameter estimate is statistically significant, although their combined effect significantly improves the forecasting accuracy of the model.

Figure 3.3 shows the observed (blue points) versus calibrated (green line) system peaks for the 2003-2016 timeframe. Nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines) and the observed versus calibrated load correlation exceeds 0.985. Figure 3.4 shows the forecasted monthly system peaks for 2016 through 2028, along with the corresponding 95% forecasting envelope. This forecasting envelope again encompasses both model and weather uncertainty, while treating the projected economic and structural indices as fixed inputs. As with the system loads, there is considerable uncertainty associated with summer peak forecasts due to the increased uncertainty surrounding summer weather patterns. Note that our system peaks are forecasted to grow at 0.6% per year over the next ten years.

Table 3.3 Model summary statistics for the monthly system peak forecasting equation.

Gross Monthly Peak Model (Jan 2003 - Jun 2016): MW units
Forecasting Model: includes Weather & Economic Covariates, Fourier Effects, new TOU (constrained), and Avoided Peak (Solar PV and EE)

Final Forecasting Equation: assumes 4/1 varaince pattern

Dependent Variable: peak Peak (MW)

Number of Observations Read	456
Number of Observations Used	162
Number of Observations with Missing Values	294

Weight: season_wght (summer and winter, 4:1 ratio)

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	1829351	166305	443.39	<.0001
Error	150	56261	375.07623		
Corrected Total	161	1885612			

Root MSE	19.36688	R-Square	0.9702
Dependent Mean	396.83148	Adj R-Sq	0.9680
Coeff Var	4.88038		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	161.17374	43.89884	3.67	0.0003	0
PCPI	PCPI ($1,000)	1	4.67821	1.52285	3.07	0.0025	4.34414
MxCD3		1	2.84669	0.21545	13.21	<.0001	10.16918
CDimpact		1	0.22608	0.06171	3.66	0.0003	10.80435
MxHD1		1	1.80259	0.35860	5.03	<.0001	1.89375
Fs1		1	-23.39705	3.61872	-6.47	<.0001	2.82476
Fc1		1	-41.16086	4.59631	-8.96	<.0001	4.56230
Fs2		1	2.73909	3.18677	0.86	0.3914	2.19315
Fc2		1	-1.89124	2.49382	-0.76	0.4494	1.34306
Fs3		1	9.79449	2.34076	4.18	<.0001	1.18308
Fc3		1	8.19761	2.21039	3.71	0.0003	1.05512
tou_peak	New.TOU	1	1.05000	0	Infty	<.0001	0
avoided_peak	EE+PV.DG	1	-0.40806	0.31784	-1.28	0.2012	4.22224

Durbin-Watson D	1.933
Number of Observations	162
1st Order Autocorrelation	0.016

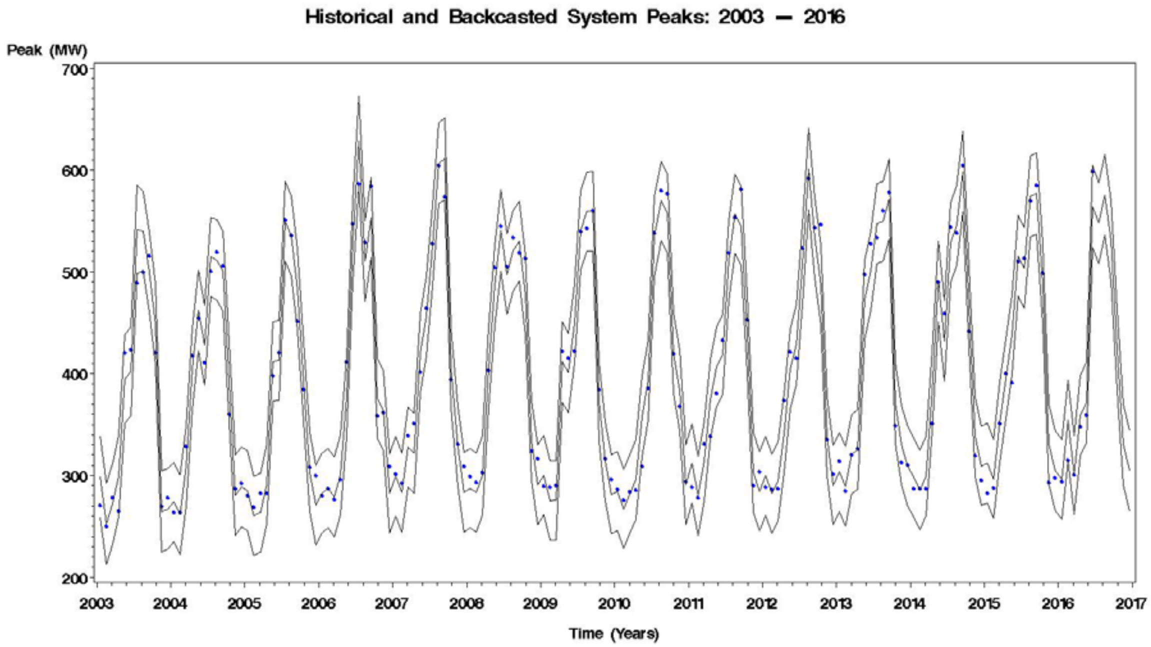

Figure 3.3. Observed and predicted system peak data (2003-2016), after adjusting for known weather conditions.

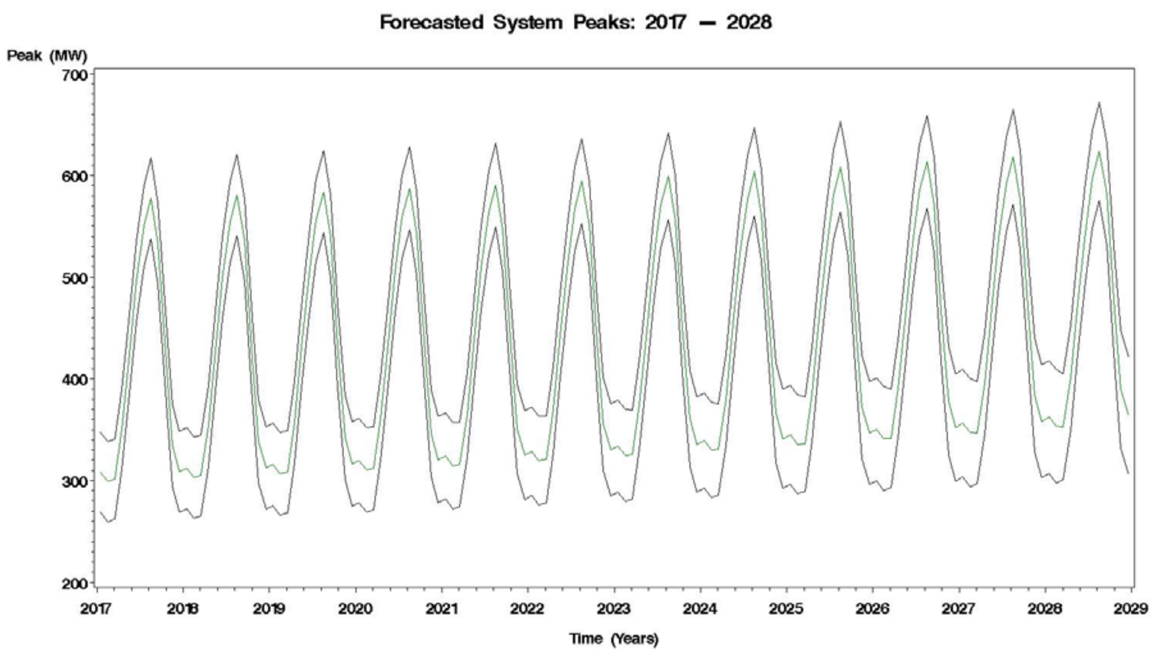

Figure 3.4. Forecasted monthly system peaks for 2017-2028; 95% forecasting envelopes encompass both model and weather uncertainty.

Table 3.4 shows the forecasted monthly RPU system peaks for 2016, along with their forecasted standard deviations. Once again, these standard deviations quantify both model and weather uncertainty. The 2016 forecasts project that our maximum monthly system peak should be about 573.4 MW and occur in August, assuming that the RPU service area experiences typical weather conditions throughout the year. Note that this represents a 1-in-2 peak forecast, respectively.

Table 3.4. 2017 monthly system peak forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Peak (MW)	Std.Dev (MW)
JAN	308.2	22.41
FEB	298.9	23.27
MAR	301.4	27.10
APR	350.6	32.79
MAY	424.5	37.42
JUN	495.9	38.06
JUL	550.1	38.89
AUG	577.7	38.44
SEP	533.1	40.36
OCT	426.5	37.90
NOV	334.3	31.74
DEC	308.7	24.29

3.5 Peak demand weather scenario forecasts

After calculating all of the 2017-2028 monthly peak forecasts and their corresponding standard deviation estimates (that incorporate weather uncertainty), additional peak demand forecasts for more extreme weather scenarios can be produced. Under the assumption that these $\hat{y}_t$ forecasts can be probabilistically approximated using a Normal distribution, the following formulas can be used to calculate 1-in-5, 1-in-10, 1-in-20 and 1-in-40 forecast scenarios:

1-in-5 Peak: $\hat{y}_t + 0.842[\,\mathrm{Std}(\hat{y}_t)\,]$ Eq. 3.7

1-in-10 Peak: $\hat{y}_t + 1.282[\,\mathrm{Std}(\hat{y}_t)\,]$ Eq. 3.8

1-in-20 Peak: $\hat{y}_t + 1.645[\,\mathrm{Std}(\hat{y}_t)\,]$ Eq. 3.9

1-in-40 Peak: $\hat{y}_t + 1.960[\,\mathrm{Std}(\hat{y}_t)\,]$ Eq. 3.10

In Eqs. 3.7 through 3.10, the scale multiplier terms applied to the standard deviation represent the upper 80% (1-in-5), 90% (1-in-10), 95% (1-in-20) and 97.5% (1-in-40) percentiles of the Standard Normal distribution, respectively.

In the RPU service area, our maximum weather scenario peaks are always forecasted to occur in the month of August. Thus, for 2017, our forecasted 1-in-5, 1-in-10, 1-in-20 and 1-in-40 peaks are 610.1, 627.0, 640.9 and 653.0, respectively.

4. Class-specific Retail Load Forecast Models

Our RPU retail load forecasting models are described in this section. However, before discussing each equation in detail, the following modeling issues require clarification. First, it is important to note that our retail sales data span overlapping 30-day billing cycles and are subject to post-billing invoice corrections. As such, our retail load models tend to be inherently less precise and thus subject to significantly more forecasting uncertainty. Additionally, all retail model variance terms are assumed to be constant (i.e., homogeneous) across the calendar year, since seasonal variance effects are difficult to identify and estimate in the presence of these increased signal-to-noise effects.

Second, RPU cannot currently analyze and estimate individual Commercial and Industrial forecasting models, because our Commercial versus Industrial classification schema was changed (over 2005 through 2007) by our Finance/Billing department. Instead, we have estimated a combined Commercial + Industrial load equation, produced combined forecasts using this equation and then split these forecasts into separate Commercial and Industrial predictions using monthly Commercial/Industrial load ratio metrics (historically derived from Jan 2007 through Dec 2013 billing data; see Table 4.3). This issue is discussed in more detail in section 4.3.

Third, and again due to the higher signal-to-noise effects in our billing data, the avoided EE and PV-DG structural terms in our retail models cannot be reliably estimated with reasonable precision. Instead, we have chosen to restrict these parameter estimates to pre-specified values that are consistent with the corresponding fitted parameters derived from our system load equation, after removing the distribution loss components. These structural constraints are discussed in more detail in sections 4.1 and 4.3, respectively.

Finally, it is important to note that we also constrain the annual sum of our class specific, retail forecasts to be equal to 94.6% of our forecasted annual wholesale loads. (RPU internal distribution losses have averaged 5.4% over the last 15 years.) This constraint is applied by determining a post-hoc, annual adjustment factor (f_R) computed as

$$f_R = [\,0.946(W) - O\,] \,/\, [\,R + C + I\,] \qquad \text{Eq. 4.1}$$

where *R*, *C*, *I* and *O* represent our forecasted annual Residential, Commercial, Industrial and Other retail loads, and *W* represents our forecasted annual wholesale system load. Our final monthly residential, commercial and industrial load forecasts are then adjusted by this annual factor, to ensure that the sum of all our annual retail load forecasts are exactly equal to 94.6% of our annual system load forecasts. Note that this process is done to force our (less accurate) retail load forecasts to align with our loss adjusted system load forecasts, after accounting for the fact that we expect 0% growth in our Other retail load class for the foreseeable future.

4.1 Monthly residential load model (retail sales)

Our monthly residential load forecasting model is a function of one economic driver (prior month EMP), two current and prior weather effects that quantify the total monthly cooling and extended heating degrees (SumCD and SumXHD), an indicator variable that quantifies an increase in residential load due to late December / early January holiday effects, four low order Fourier frequencies (Fs(1), Fc(1), Fs(2) and Fc(2)), and an a-priori constrained effect that captures the combined impacts of avoided load due to residential EE and solar PV-DG activities. Mathematically, the model is defined as

$$y_t = \beta_0 + \beta_1[EMP_{t-1}] + \beta_2[(SumCD_t + SumCD_{t-1})/2] + \beta_3[(SumXHD_t + SumXHD_{t-1})/2] + \beta_4[XMas_t] +$$

$$\beta_5[Fs(1)_t] + \beta_6[Fc(1)_t] + \beta_7[Fs(2)_t] + \beta_8[Fc(2)_t] - 1.00[EE_{t,R} + PV.DG_{t,R}] + \varepsilon_t$$

where

$$\varepsilon_t \sim N(0, \sigma^2). \qquad \text{Eq. 4.2}$$

In Eq. 4.2, y_t represents the RPU monthly residential load (GWh) for the calendar ordered monthly observations and forecasts (*t*=1 → Jan 2003) and the homogeneous residual errors are assumed to be Normally distributed and temporally uncorrelated. Eq. 4.2 was optimized using ordinary least squares estimation, after restricting the avoided load parameter estimate to be equal to -1.00 (which closely corresponds to our system load estimate for this parameter, after removing the impacts of system losses).

All input observations that reference historical time periods were assumed to be fixed (i.e., measured without error) during the estimation process. As with our wholesale models, we treated the forecasted economic indices as fixed variables and the forecasted weather indices as random effects. A first-order Delta method estimate of the forecasting variance was again calculated in the usual manner (where the second variance term is approximated via simulation, once the parameters associated with the weather effects had been estimated).

It should be noted that Eq. 4.2 was initially defined to include both economic drivers. However, the PCPI parameter estimate was found to be clearly non-significant and thus dropped from the final forecasting equation. Likewise, the holiday effect (Xmas) was added to account for an annual residential holiday load increase that is primarily reflected in January billing statements.

4.2 Residential load model statistics and forecasting results

Table 4.1 shows the pertinent model fitting and summary statistics for our residential load forecasting equation. The equation explains 95% of the observed variability associated with the monthly 2003-2016 residential loads and all input parameter estimates are statistically significant below the 0.05 significance level. An analysis of the model residuals confirms that these errors were Normally distributed, devoid of outliers and approximately temporally uncorrelated; implying that our modeling assumptions are reasonable.

The regression parameter estimates shown in the middle of Table 4.1 indicate that monthly residential load increases as either/both weather indices increase (SumCD and SumXHD); an increase in one cooling degree raises the forecasted load about twice as quickly as a one heating degree increase. Note that averages of each current and prior month weather indices are used as input variables in the forecasting equation (to account for the delayed billing effect). RPU residential loads are also expected to increase as the area wide employment levels improve over time. However, the residential load data do not show a statistically significant relationship with the PCPI index. Likewise, our residential load growth would be expected to decrease if future residential specific EE and/or PV-DG trends increase above their current forecasted levels.

Figure 4.1 shows the observed (blue points) versus calibrated (green line) residential loads for the 2003-2016 timeframe. Nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines); the observed versus calibrated load correlation equals 0.97. Figure 4.2 shows the forecasted monthly system loads for 2016 through 2028, along with the corresponding 95% forecasting envelope. This forecasting envelope encompasses both model and weather uncertainty, while treating the projected economic indices as fixed inputs. Our residential loads are forecasted to increase at 0.16% per year for the next 10 years. Or equivalently, our forecasted residential specific EE and/or PV-DG trends are expected to offset nearly all of our future residential load growth over time.

Table 4.2 shows the forecasted monthly RPU residential loads for 2017, along with their forecasted standard deviations. Once again, these standard deviations quantify both model and weather uncertainty. The 2017 forecasts project that our annual residential load should be 693.1 GWh, assuming that the RPU service area experiences typical weather conditions throughout the year.

Table 4.1 Model summary statistics for the monthly residential load forecasting equation.

Residential Demand Model (Jan 2003 - Jun 2016): GWh units
Forecasting Model: includes Weather Covariates, one Economic Covariate,
Fourier Effects, Xmas Effect, and constrained Avoided Load (Solar PV and EE)

Final Forecasting Eqn: assumes constant variance pattern

Dependent Variable: resi Residential (GWh)

Number of Observations Used: 161

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	37606	4700.69665	361.50	<.0001
Error	152	1976.52702	13.00347		
Corrected Total	160	39582			

Root MSE	3.60603	R-Square	0.9501
Dependent Mean	58.58262	Adj R-Sq	0.9474
Coeff Var	6.15546		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	17.71081	5.21724	3.39	0.0009	0
lagEmpCC	1	15.74281	3.17994	4.95	<.0001	1.20155
sum2CD	1	0.11680	0.00842	13.87	<.0001	14.12241
sum2HD	1	0.05842	0.01437	4.07	<.0001	3.20931
xmas	1	8.93846	1.05492	8.47	<.0001	3.05438
s1	1	-2.86130	1.13141	-2.53	0.0125	7.95931
c1	1	-3.12323	1.10134	-2.84	0.0052	7.46798
s2	1	3.14417	0.67529	4.66	<.0001	2.83172
c2	1	-2.30619	0.61327	-3.76	0.0002	2.32093
cust_solar_res	1	-1.00000	0	n/a	n/a	0
ee_res	1	-1.00000	0	n/a	n/a	0

Durbin-Watson D	2.501
Number of Observations	161
1st Order Autocorrelation	-0.253

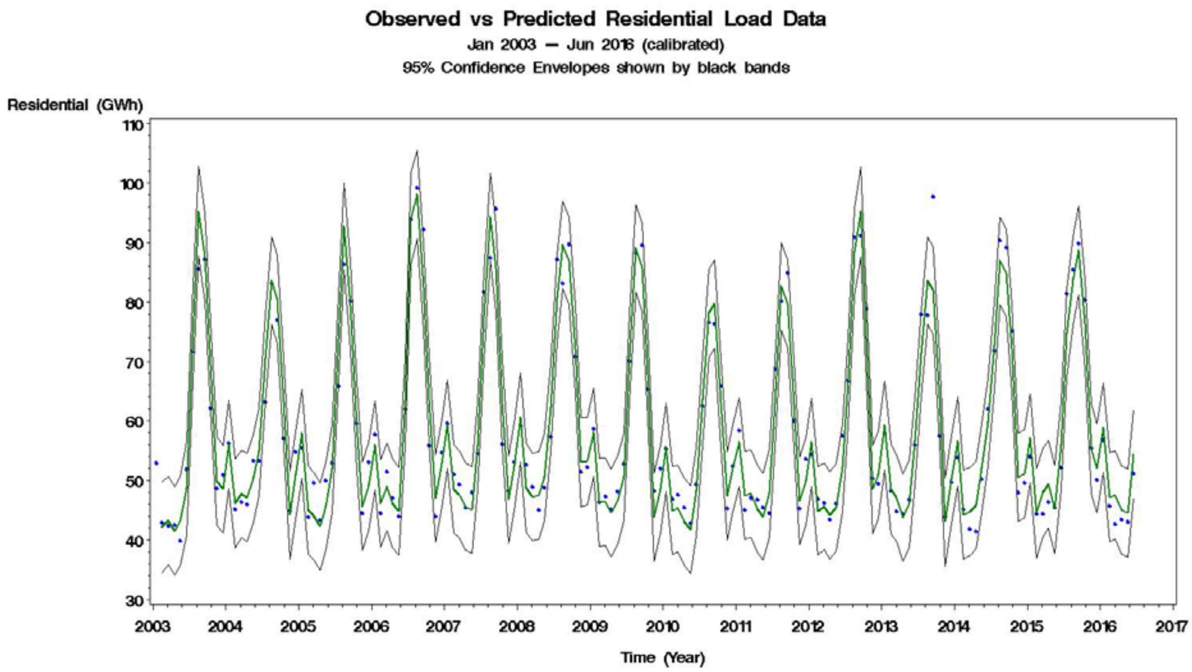

Figure 4.1. Observed and predicted residential load data (2003-06.2016), after adjusting for known weather conditions.

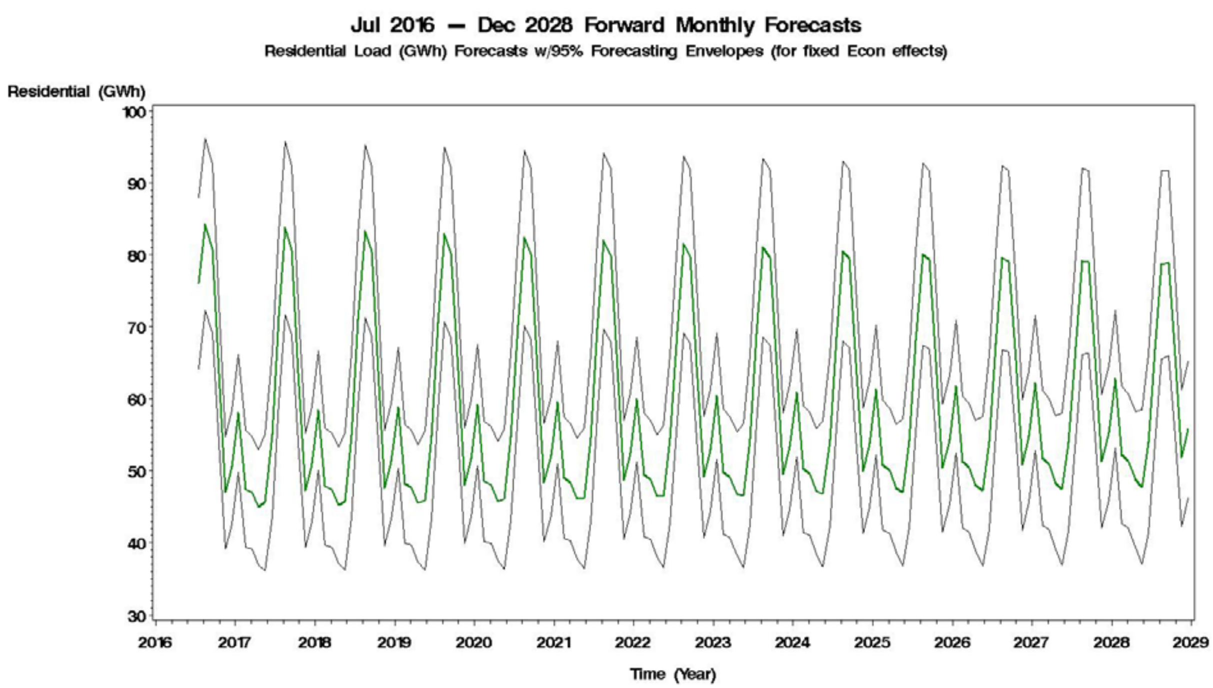

Figure 4.2. Forecasted monthly residential loads for 2016-2027; 95% forecasting envelopes encompass both model and weather uncertainty.

Table 4.2. 2017 monthly residential load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Load (GWh)	Std.Dev (GWh)
JAN	57.80	4.34
FEB	47.32	4.26
MAR	46.81	4.32
APR	44.78	5.32
MAY	45.46	8.34
JUN	54.80	11.26
JUL	71.09	12.58
AUG	83.41	12.54
SEP	80.34	12.02
OCT	63.44	8.67
NOV	47.12	4.68
DEC	50.70	4.25
Annual TOTAL	693.08	

4.3 Monthly commercial + industrial load model (retail sales)

Our composite monthly commercial + industrial load forecasting model is a function of one economic driver (prior month PCPI), two current and prior weather effects that quantify the total monthly cooling and extended heating degrees (SumCD and SumXHD), two low order Fourier frequencies (Fs(1) and Fc(1)), and the a-priori constrained effects that captures both the new Industrial load additions and the combined impacts of avoided load due to commercial/industrial EE and solar PV-DG activities. Mathematically, the model is defined as

$$y_t = \beta_0 + \beta_1[PCPI_{t-1}] + \beta_2[(SumCD_t + SumCD_{t-1})/2] + \beta_3[(SumXHD_t + SumXHD_{t-1})/2] +$$

$$\beta_4[Fs(1)_t] + \beta_5[Fc(1)_t] + 1.00[Load.Indst_t] - 1.00[EE_{t,CI} + PV.DG_{t,CI}] + \varepsilon_t$$

where

$$\varepsilon_t \sim N(0, \sigma^2). \qquad \text{Eq. 4.3}$$

In Eq. 4.3, y_t represents the RPU combined monthly commercial + industrial load (GWh) for the calendar ordered monthly observations and forecasts (t=1 → Jan 2003) and the homogeneous residual errors are assumed to be Normally distributed and temporally uncorrelated. Eq. 4.3 was optimized using ordinary least squares estimation (SAS Reg Procedure).

Once again, all input observations that reference historical time periods were assumed to be fixed during the estimation process. Likewise, the forecasted economic indices are treated as fixed variables and the forecasted weather indices are again treated as random effects. As before, a first-order Delta method estimate of the forecasting variance was calculated in the usual manner. Finally, note that Eq. 4.3 was initially defined to include both economic drivers. However, the employment (EMP) parameter estimate was found to be clearly non-significant and thus dropped from the final forecasting equation.

In order to produce individual commercial and industrial load forecasts, it is necessary to split each monthly load prediction into two components. Table 4.3 shows the monthly C/[C+I] ratios.

4.4 Commercial + Industrial load model statistics and forecasting results

Table 4.4 shows the pertinent model fitting and summary statistics for our commercial (C) + industrial (I) load forecasting equation. The equation explains approximately 88% of the observed variability associated with the monthly 2003-2016 C+I loads. Note that although the heating degree effect is non-significant ($t = 1.83$, $p=0.070$), we’ve elected to retain this weather variable in the equation. (Intuitively, a positive heating degree effect is both reasonable and expected.) Note also that an analysis of the model residuals confirms that these errors are Normally distributed, devoid of outliers and approximately temporally uncorrelated.

Table 4.3. Monthly C/[C+I] ratios.

Month	C/[C+I] ratio
JAN	0.301
FEB	0.300
MAR	0.294
APR	0.287
MAY	0.294
JUN	0.295
JUL	0.307
AUG	0.316
SEP	0.316
OCT	0.300
NOV	0.290
DEC	0.293

The regression parameter estimates shown in the middle of Table 4.4 indicate that monthly residential load increases as either/both weather indices increase (SumCD and SumXHD); once again however, the heating degree effect cannot be judged to be statistically significant. As in the residential model, averages of each current and prior month weather indices are used as input variables in the forecasting equation (to account for the delayed billing effect). RPU C+I loads are also expected to increase as either/both the area wide PCPI and/or employment levels improve over time. Finally, our commercial + industrial load growth will be reduced if future C+I specific EE and/or PV-DG trends increase above their current forecasted levels.

Figure 4.3 shows the observed (blue points) versus calibrated (green line) C+I loads for the 2006-2015 timeframe. Nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines); the observed versus calibrated load correlation is approximately 0.94. Figure 4.4 shows the forecasted monthly C+I loads for 2016 through 2028, along with the corresponding 95% forecasting envelope. This forecasting envelope encompasses both model and weather uncertainty, while treating the projected economic indices as fixed inputs. Note that our C+I loads are forecasted to grow at a 2.06% annual rate, after adjusting for our future C+I EE and solar PV-DG installation trends.

Table 4.5 shows the post-hoc forecasted monthly commercial and industrial loads for 2017, along with their forecasted standard deviations. Once again, these standard deviations quantify both model and weather uncertainty. The 2017 forecasts project that our annual commercial and industrial loads should be 426.9 and 996.0 GWh, respectively, assuming that the RPU service area experiences typical weather conditions throughout the year.

Table 4.4 Model summary statistics for the monthly commercial + industrial load forecasting equation.

Comm+Indst Demand Model (Jan 2003 - Jun 2016): GWh units
Forecasting Model: includes Weather Covariates, Economic Covariates,
Fourier Effects, and constrained extra (new) TOU and Avoided Load (Solar PV and EE)

Final Forecasting Eqn: assumes constant variance pattern

Dependent Variable: cmind Comm+Indst (GWh)

Number of Observations Used: 161

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	25605	4267.54671	183.81	<.0001
Error	154	3575.37434	23.21672		
Corrected Total	160	29181			

Root MSE	4.81837	R-Square	0.8775
Dependent Mean	111.91634	Adj R-Sq	0.8727
Coeff Var	4.30533		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	0.65991	6.81624	0.10	0.9230	0
lagPCPI	lag(PCPI)	1	4.18626	0.48393	8.65	<.0001	6.95085
sum2CD	SumCD+lag(SumCD)	1	0.05323	0.00684	7.78	<.0001	5.22199
sum2HD	SumXHD+lag(SumXHD)	1	0.02603	0.01530	1.70	0.0909	2.03753
s1		1	-5.79658	1.06817	-5.43	<.0001	3.97348
c1		1	-4.45444	1.00210	-4.45	<.0001	3.46294
cust_solar_ci	Solar_ci(GWh)	1	-1.00000	0	n/a	n/a	0
ee_ci	ee_ci(GWh)	1	-1.00000	0	n/a	n/a	0
extra_tou	extra_tou(GWh)	1	1.00000	0	n/a	n/a	0

Durbin-Watson D	2.387
Number of Observations	161
1st Order Autocorrelation	-0.197

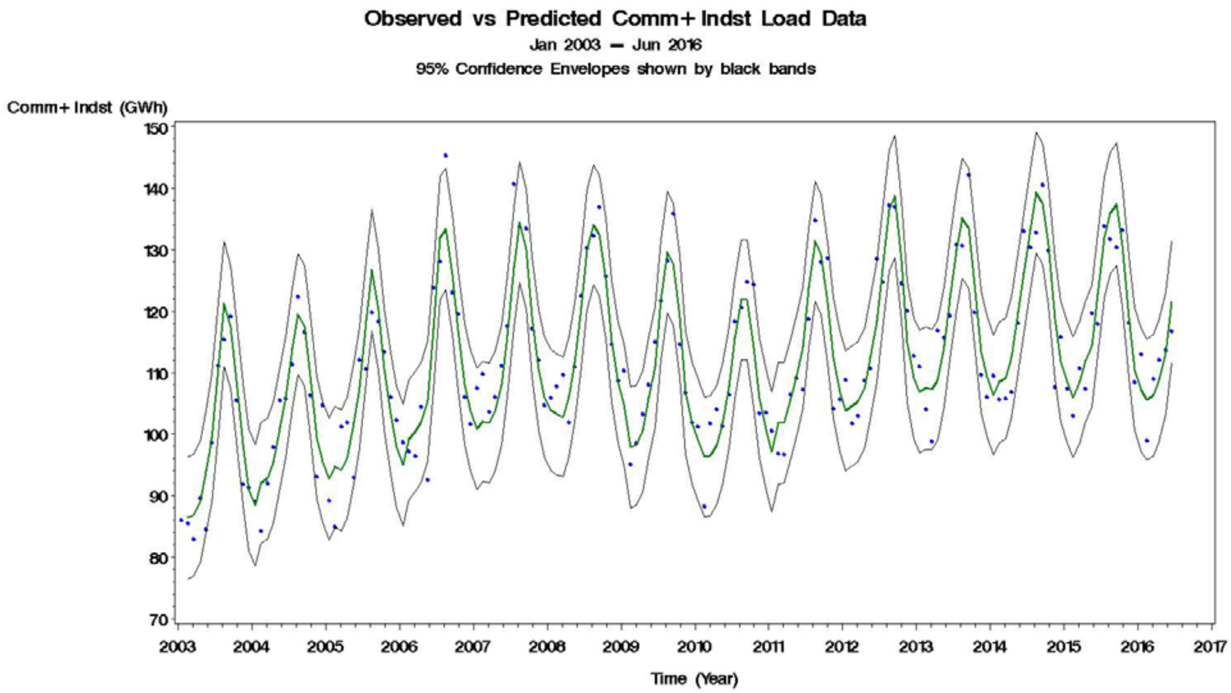

Figure 4.3. Observed and predicted C+I load data (2003-06.2016), after adjusting for known weather conditions.

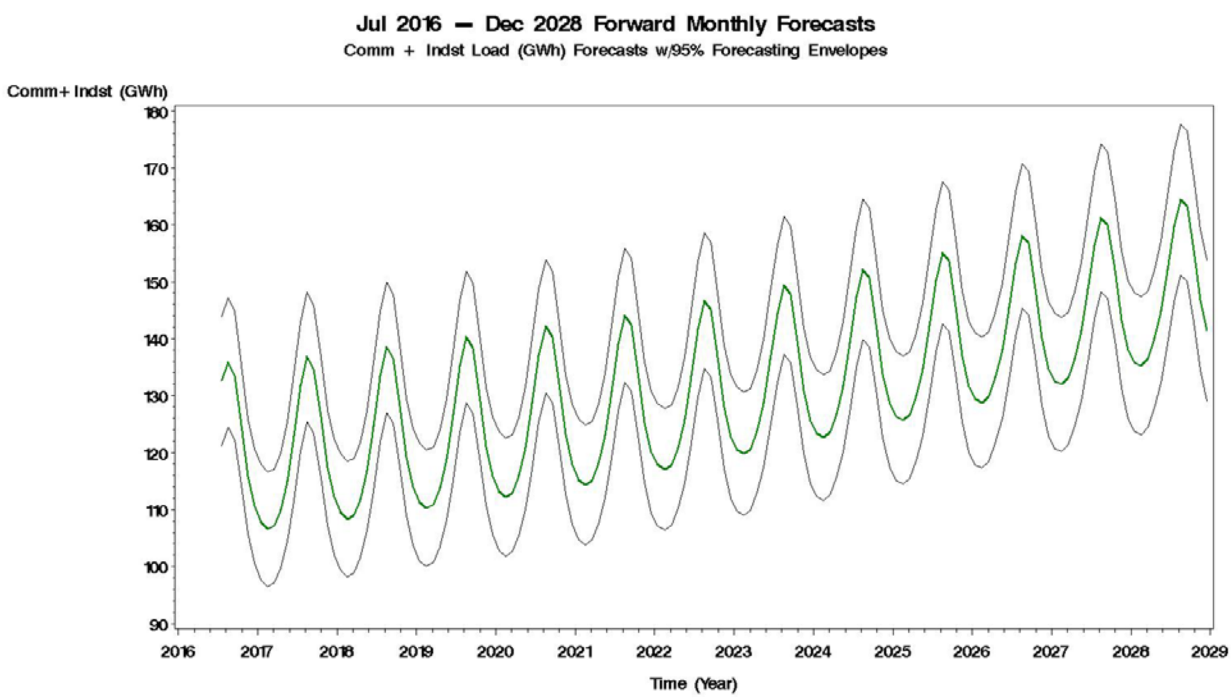

Figure 4.4. Forecasted monthly C+I loads for 07.2016-12.2028; 95% forecasting envelopes encompass both model and weather uncertainty.

Table 4.5. 2017 monthly commercial and industrial load forecasts for RPU; forecast standard deviations.

Month	Comm Load (GWh)	Std. Dev (GWh)	Indst Load (GWh)	Std. Dev (GWh)
JAN	32.33	1.53	75.07	3.55
FEB	31.84	1.51	74.29	3.53
MAR	31.38	1.47	75.35	3.52
APR	31.42	1.44	78.05	3.58
MAY	33.67	1.55	80.84	3.71
JUN	36.09	1.65	86.26	3.93
JUL	40.26	1.74	90.87	3.93
AUG	43.08	1.80	93.25	3.91
SEP	42.42	1.78	91.81	3.86
OCT	37.75	1.59	88.09	3.71
NOV	33.92	1.47	83.05	3.60
DEC	32.78	1.49	79.09	3.59
Annual Total	426.92		996.02	

4.5 Modeling and forecasting results for the Other customer class

All remaining RPU customers not classified into one of our three primary customer classes (Residential, Commercial and Industrial) have historically been grouped into an “Other” class. The loads associated with this class currently account for about 1.5% of our total retail load; note that this class is primary comprised of city accounts, street lighting and miscellaneous agricultural customers.

Since January 2008, the monthly loads associated with the Other customer class have exhibited a fairly stable, seasonal pattern that is independent of changing economic conditions (and is expected to remain so for the foreseeable future). Additionally, this pattern does not exhibit any statistically significant relationship with the observed weather variables, after accounting for three obvious outlier months (January 2009, May 2011, March 2014). As such, our load forecasting model for this customer class is defined to just be a function of two low order Fourier frequencies (Fs(1) and Fc(1)) and three indicator variables to account for the monthly outliers. The corresponding model estimation results (derived using ordinary least squares) are shown in Table 4.6; note that this equation describes about 59% of the observed load variation.

Table 4.7 shows the monthly load forecasts for 2016 along with their forecasted standard deviations. These forecasts do not grow over time, since the forecasting equation for this latter customer class includes no economic driver variables.

Table 4.6 Model summary statistics for our monthly "other" load forecasting equation.

```
              Other (Non-RCI) Sales Forecasts (Jan 2008 – Jun 2016)
                 Forecasting Model: includes two Fourier Effects
                          and three outlier adjustments

  Final Forecasting Eqn: assumes constant variance pattern no growth in forecasts

                      Dependent Variable: other Other (GWh)

                        Number of Observations Used: 102
```

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	9.22475	1.84495	27.58	<.0001
Error	96	6.42291	0.06691		
Corrected Total	101	15.64766			

Root MSE	0.25866	R-Square	0.5895
Dependent Mean	2.54240	Adj R-Sq	0.5682
Coeff Var	10.17387		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Inflation
Intercept	Intercept	1	2.57056	0.02601	98.84	<.0001	0
s1		1	-0.22397	0.03678	-6.09	<.0001	1.02813
c1		1	0.09521	0.03677	2.59	0.0111	1.03036
outlier1		1	0.67158	0.26255	2.56	0.0121	1.02021
outlier2		1	-0.58638	0.26246	-2.23	0.0278	1.01952
outlier3		1	-2.09229	0.26246	-7.97	<.0001	1.01952

Durbin-Watson D	0.491
Number of Observations	102
1st Order Autocorrelation	0.691

Table 4.7. 2017 monthly load forecasts for the "Other" customer class.

Month	Load (GWh)	Std.Dev (GWh)
JAN	2.65	0.25
FEB	2.55	0.25
MAR	2.47	0.25
APR	2.42	0.25
MAY	2.43	0.25
JUN	2.48	0.25
JUL	2.57	0.25
AUG	2.67	0.25
SEP	2.76	0.25
OCT	2.80	0.25
NOV	2.79	0.25
DEC	2.74	0.25
Annual TOTAL	31.33	

4.6 Final post-hoc forecasting alignment

As described earlier at the beginning of section 4, a post-hoc correction factor was applied to the Residential, Commercial, and Industrial retail forecasts. This correction factor (calculated via Eq. 4.1.) was used to constrain the annual sums of our retail load forecasts to equal our (loss adjusted) system load forecasts. These annual adjustment factors shifted our retail forecasts from 1% to 3%, respectively.

The monthly 2016-2028 forecasts for all of our retail customer classes are shown in Figure 4.5, along with our total system and retail load forecasts. Our final annual, class-specific adjusted retail forecasts are reported in Table 4.8, along with our system load and peak forecasts. Two general features are apparent. First, our forecasted residential loads exhibit a much more pronounced reaction to summer temperature effects. This pattern reflects the increased load associated with running residential air conditioning units during the June-September summer season in the RPU service territory. Second, we no longer expect to see any significant load growth in our residential customer class. As discussed previously in section 4.2, our forecasted residential specific EE and/or PV-DG trends are expected to mostly offset any increases in residential load growth over time (i.e., our residential growth rate is ~0.2% per year). In contrast, the forecasted 10-year load growths associated with our commercial and industrial classes are expected to be ≥ 2.0% per year. In the Riverside service territory, there is a greater potential for increased commercial and industrial growth. The potential for new residential development is far more restricted, given current Riverside City zoning regulations, City Council adopted slow-growth initiatives, and the expected avoided load effects attributable to our residential EE programs and solar PV-DG trends.

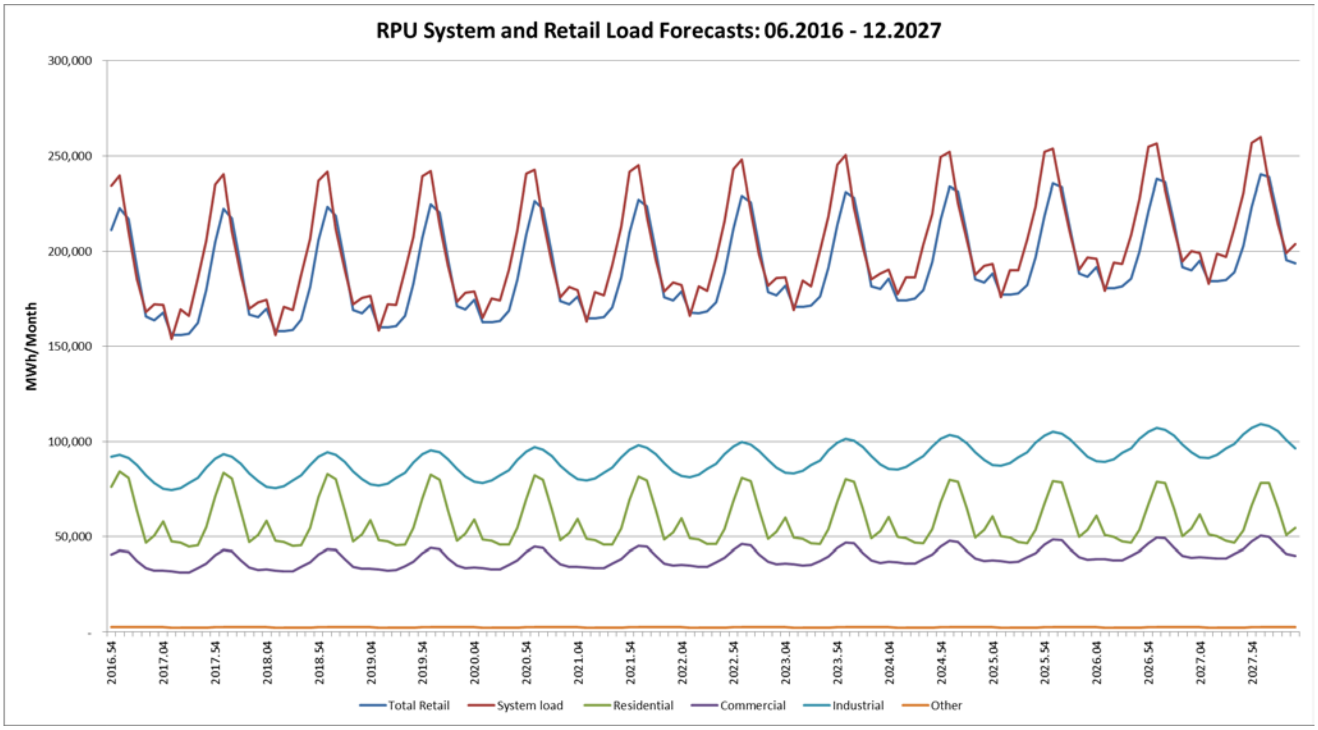

Figure 4.5. RPU monthly retail load forecasts (Jun 2016 - Dec 2027) for the residential, commercial and industrial customer classes.

Table 4.8. Final Retail and System (wholesale) load and peak forecasts: 2017-2028.

year	System Load	System Peak	Residential	Commercial	Industrial	Other	Total Retail	Ratio R/S
2017	2,269,421	578	693,078	426,923	996,024	30,847	2,146,872	94.6%
2018	2,292,411	581	693,888	433,187	1,010,699	30,847	2,168,621	94.6%
2019	2,315,828	584	694,557	439,613	1,025,756	30,847	2,190,773	94.6%
2020	2,345,778	587	696,891	447,394	1,043,975	30,847	2,219,106	94.6%
2021	2,366,412	590	696,199	453,437	1,058,143	30,847	2,238,626	94.6%
2022	2,399,331	595	696,954	462,529	1,079,438	30,847	2,269,767	94.6%
2023	2,434,390	599	698,054	472,124	1,101,909	30,847	2,302,933	94.6%
2024	2,476,881	604	700,965	483,283	1,128,035	30,847	2,343,129	94.6%
2025	2,509,571	608	700,834	492,573	1,149,800	30,847	2,374,054	94.6%
2026	2,549,011	613	702,300	503,299	1,174,919	30,847	2,411,364	94.6%
2027	2,590,010	618	703,896	514,428	1,200,980	30,847	2,450,150	94.6%
2028	2,636,279	624	706,576	526,725	1,229,773	30,847	2,493,920	94.6%