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Subject:	**RPU Wholesale & Retail Load Forecasting Methodologies**
	2017 Annual Report – for use in the 2018 IRP Process
Participant:	**City of Riverside, Riverside Public Utilities (RPU)**
Date:	**November 17, 2017**
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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 and contraction of industrial loads, (d) an annual per capita personal income (PCPI) econometric input variable for the Riverside – San Bernardino – Ontario metropolitan service area, (e) the cumulative load loss effects associated with retail customer solar PV installations and all of our measured Energy Efficiency (EE) programs, and (f) the expected net load gain due to increasing Electric Vehicle (EV) penetration levels within the RPU service territory. 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 EE programs at their current funding and implementation levels, along with the impacts of customer installed solar PV distributed generation and EV penetration within our service territory. This document describes our statistical methodology used to account for these EE, solar PV and EV 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 continues to support 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).

All primary monthly forecasting equations are statistically developed and calibrated to 14 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 <u>only</u> summarizes the methodology and statistical results for 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

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

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

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:

- An indicator variable for 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 this 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 "EconTOU" 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.
- Additional expected load directly attributable to the increasing number of electric vehicles in RPU's service territory.
- An indicator variable for capturing the effects of load migration out of the "Other" retail customer class.

The calculations associated with each of these load and peak impact variables are described in greater detail in subsequent sections. 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, the retail load migration issue is discussed in section 4.3. Additionally, sections 2.5, 2.6 and 2.7 describe how we calculate the cumulative avoided load and peak energy usage associated with RPU energy efficiency programs and rebates, load loss due to customer installed solar PV systems, and load gain due to vehicle electrification 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

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

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

where *m* represents the numerical month number (i.e., 1 = Jan, 2 = Feb, .., 12 = Dec). Note also that a second set of Fourier frequencies are also used in our system load and peak models to account for structural changes to our distribution system that occurred in 2014. These 2014 distribution system upgrades were supposed to reduce our energy losses across all load conditions, but in practice appear to have only reduced energy losses under low load conditions.

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)			
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 (TOU, EE, PV,EV)	EconTOU	Expansion/contraction of New Industrial load	X	X	X
	Avoided_Load	Cumulative EE+PV-EV load (GWh: calculated)	X		
	Avoided_Peak	Cumulative EE+PV-EV peak (MW: calculated)		X	
	Migration	Load migration out of Other retail customer class (GWh)			X
Fourier terms	Fs1	Fourier frequency (Sine: 12 month phase)	X	X	X
	Fc1	Fourier frequency (Cosine: 12 month phase)	X	X	X
	Fs2	Fourier frequency (Sine: 6 month phase)	X	X	X
	Fc2	Fourier frequency (Cosine: 6 month phase)	X	X	X
	Fs3	Fourier frequency (Sine: 4 month phase)		X	
	Fc3	Fourier frequency (Cosine: 4 month phase)		X	
	Fs2014a	Fourier frequency (on/after 2014 effects)	X	X	
	Fc2014a	Fourier frequency (on/after 2014 effects)	X	X	
	Fs2014b	Fourier frequency (on/after 2014 effects)	X	X	
	Fc2014b	Fourier frequency (on/after 2014 effects)	X	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

Annual PCPI data have been obtained from the US Bureau of Economic Analysis (http://www.bea.gov), while forecasts of future PCPI levels reflect the 15-year historical average for the region (i.e., approximately 2.9 % income growth per year). As previously stated, these data correspond to the Riverside-Ontario-San Bernardino metropolitan service area. Note that we now only use the PCPI economic driver in all of our forecasting models because our (previously used) additional set of monthly employment data no longer appears to be statistically significant in any model.

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 future time periods on/after September 2017.

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 Temporary Load/Peak Impacts due to 2011-2012 Economic Incentive Program

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.

In prior iterations of our load forecasting models, staff attempted to directly calculate the approximate GWh energy and MW peak load amounts associated with this economic incentive program. However, since these numbers have proved to be very difficult to accurately determine, in the current forecasting equations staff has instead used indicator variables in the forecasting models that automatically calibrate to the observed load (or peak) gains and losses over the 2011-2014 time period. Table 2.3 shows how the "econTOU" indicator variable is defined, and what the resulting parameter estimate corresponds to in each equation. Note that by definition, this indicator value is set to 0 for all years before 2011 and after 2014.

Table 2.3 Values for econTOU indicator variable used to model RPU's 2011-2014 discounted TOU incentive program. Incentive program was closed in December 2012; nearly all early load gains disappeared by December 2014.

<table>
<tr><td>Year</td><td>Time Period</td><td>EconTOU value</td><td rowspan="7">Load parameter value represents incremental Monthly GWh</td><td rowspan="7">Peak parameter value represents incremental monthly MW peak</td></tr>
<tr><td>2011</td><td>January - June</td><td>0.33</td></tr>
<tr><td>2011</td><td>July-December</td><td>0.67</td></tr>
<tr><td>2012</td><td>All months</td><td>1.00</td></tr>
<tr><td>2013</td><td>All months</td><td>1.00</td></tr>
<tr><td>2014</td><td>January - June</td><td>0.67</td></tr>
<tr><td>2014</td><td>July - December</td><td>0.33</td></tr>
</table>

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.

Since 2014, we have continued to update these projections as new information becomes available. 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 -1.05 (to reflect the anticipated load or peak energy reduction over time, after adjusting for 5% distribution system losses). In practice, this parameter estimate may differ from -1.05 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 seven 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 2017, 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 -1.05 (to reflect the anticipated load or peak energy reduction and distribution system losses over time, etc.). In practice, this parameter estimate may once again differ from -1.05 in a statistically significant manner, due to inaccuracies in the various solar PV-DG savings calculations.

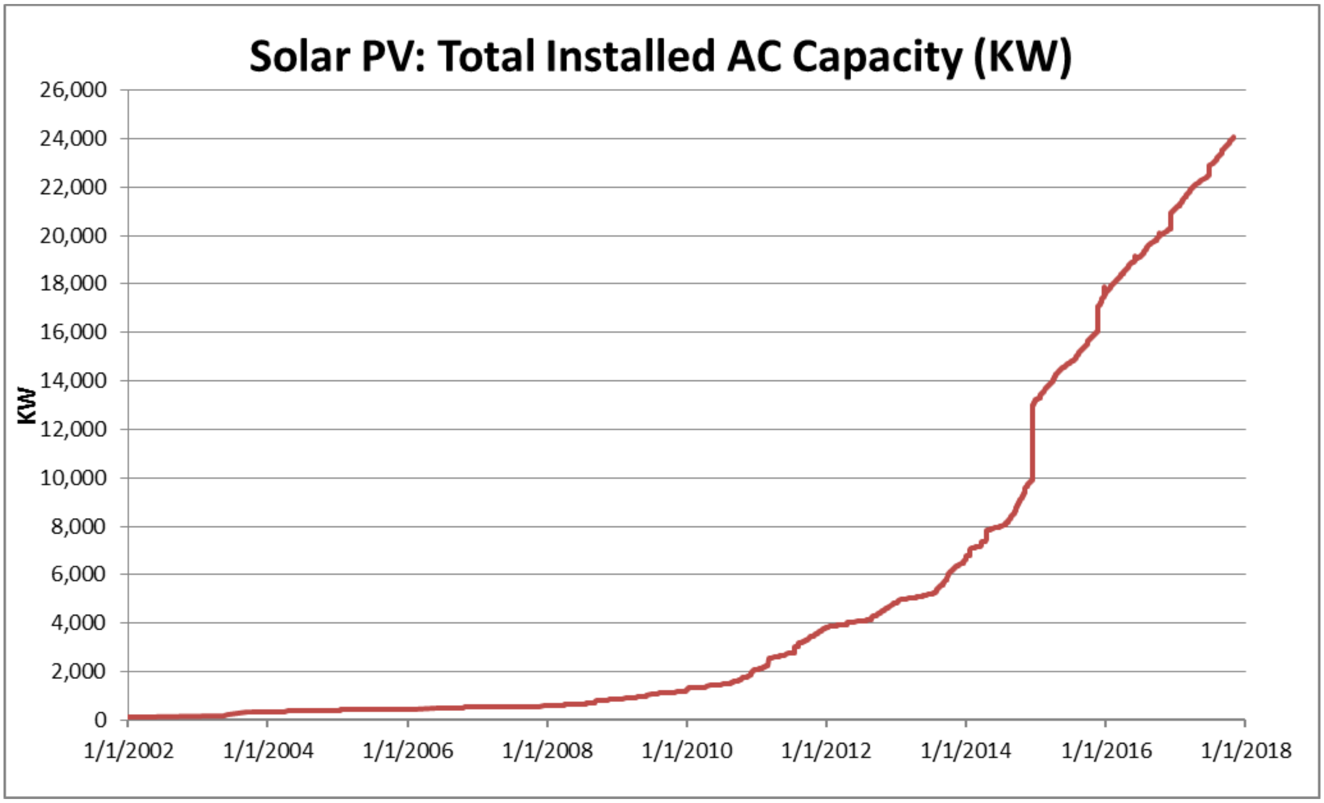

Figure 2.1. Total installed AC capacity of customer owned solar PV in the RPU service territory since 2002.

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

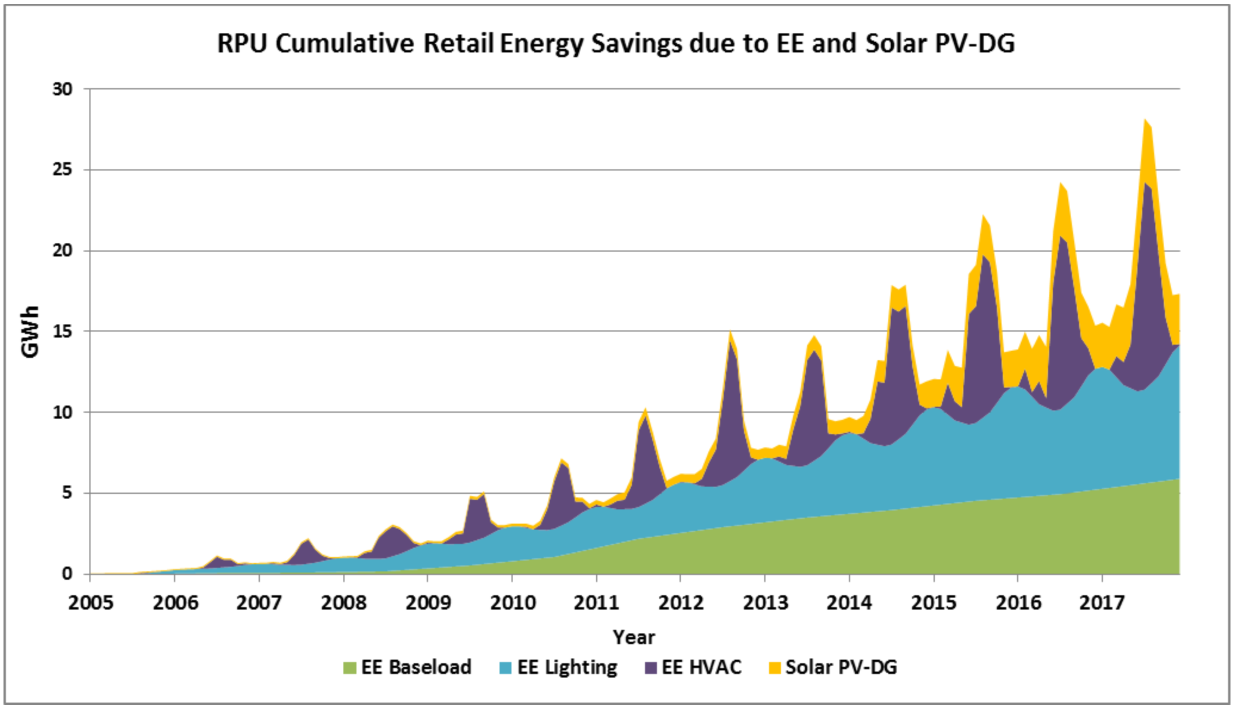

Figure 2.2. Calculated cumulative projected retail energy savings in the RPU service territory due to both EE program and solar PV distributed generation impacts over time.

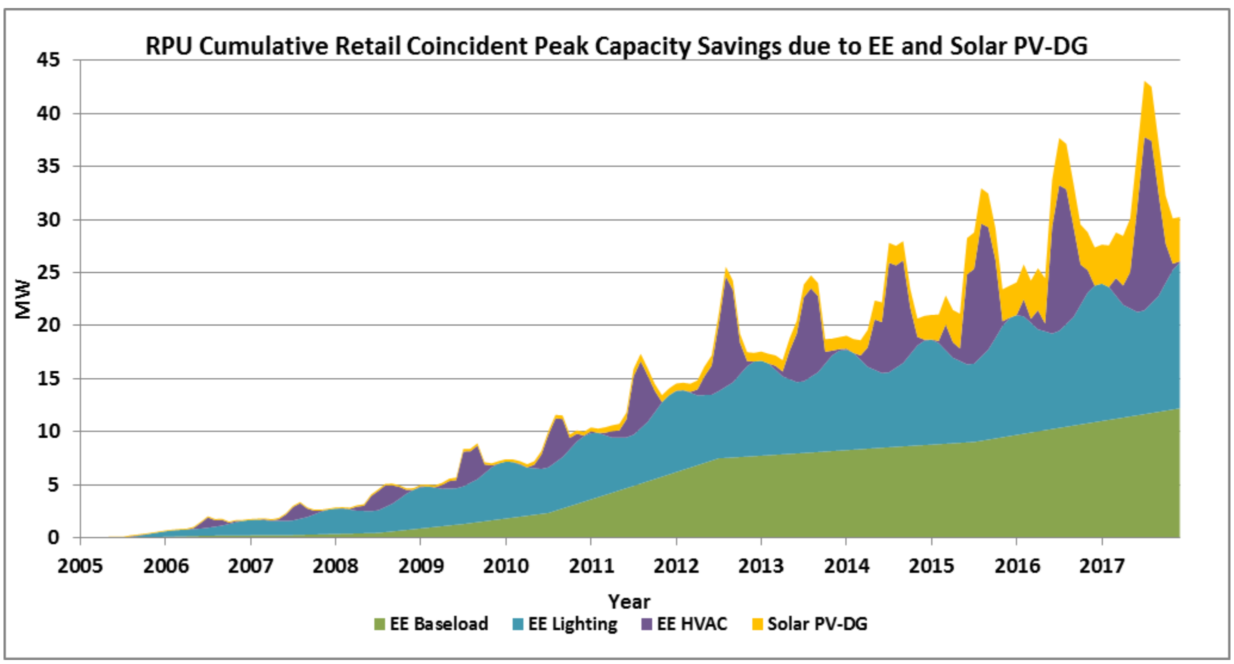

Figure 2.3. Calculated cumulative projected coincident peak capacity savings in the RPU service territory due to both EE program and solar PV distributed generation impacts over time.

2.7 Incremental Electric Vehicle Loads

In early 2017 the CEC released their Transportation Electrification Common Assumptions 3.0 model. This model can be used by CA utilities to forecast EV growth in the utilities service territory through 2030, based on a limited number of objective input assumptions. This model can also be used to forecast a number of emission reduction metrics, in addition to the expected net load growth associated with the forecasted EV penetration level.

Riverside has elected to use this model in our 2017 load forecasting equations and 2018 IRP to estimate our expected net EV load growth. For baseline load forecasting purposes, we have assumed a “business as usual” EV population growth pattern (i.e., 56,100 PEV’s in CA in 2017) and used the default 0.56% Riverside estimate for defining our service area PEV population as a percent of the state total. We also assume 5% distribution losses within our service territory and that 10% of our customers EV charging load is self-supplied. Based on these input assumptions, Figure 2.4 shows the projected additional utility electrical load from new PEVs entering our service territory between 2015 through 2030.

Note that for forecasting purposes, these incremental EV loads (above the 2015 baseline level) are treated as net load additions that effectively offset future EE and DG.PV (solar) load losses. Additionally, we assume that 75% of these net load gains will show up in our Residential customer class, with the remaining 25% spread evenly across our Commercial and Industrial classes.

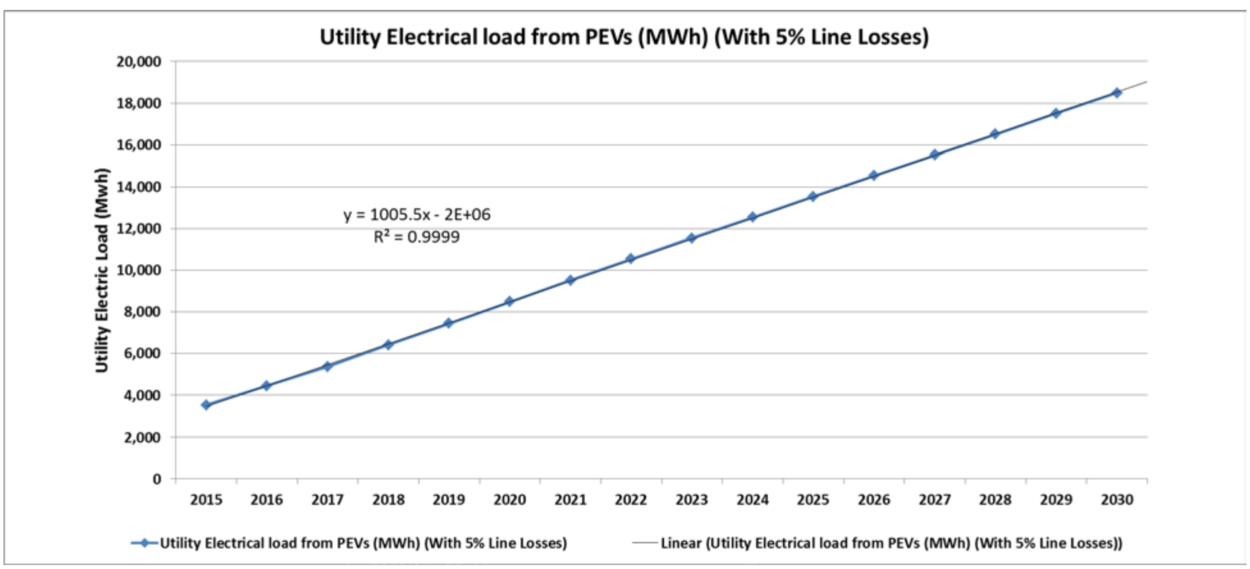

Figure 2.4. Projected 2015-2030 RPU electrical load from EV and PHEV penetration within our service territory.

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 primary economic driver (PCPI), 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), eight low order Fourier frequencies that quantify seasonal impacts both before and after our distribution system upgrades (Fs1, Fc1, Fs2, Fc2, Fs2014a, Fc2014a, Fs2014b, and Fc2014b), one unconstrained Industrial load indicator variable (econTOU), and one initially unconstrained effect that captures the combined impacts of (avoided) EE, PV-DG and (incremental) EV loads. 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

$$y_t = \beta_0 + \beta_1[PCPI_t] + \beta_2[SumMF_t] + \beta_3[SumSS_t] + \beta_4[SumCD_t] + \beta_5[SumXHD_t] + \beta_6[SumCD_t][MaxCD3_t]/100$$

$$+ \beta_7[Fs1_t] + \beta_8[Fc1_t] + \beta_9[Fs2_t] + \beta_{10}[Fc2_t] + \beta_{11}[Fs2014a_t] + \beta_{12}[Fc2014a_t]$$

$$+ \beta_{13}[Fs2014b_t] + \beta_{14}[Fc2014b_t] + \beta_{15}[econTOU_t] + \theta_1[EE_t+PV.DG_t-EV_t] + \varepsilon_{jt} \qquad \text{[Eq. 3.1]}$$

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 (REML) estimation (SAS MIXED Procedure). These REML results yielded summer and winter variance component estimates of 16.7 and 8.0 GWh^2, suggesting that the variance ratio for the seasonal errors can be assumed to be 2:1. Additionally, the θ_1 parameter estimate was estimated to be -1.303 (0.101), which is reasonably close to the -1.05 avoided/incremental load impact assumption discussed in sections 2.5 through 2.7. Based on these results, Eq. 3.1 was refit using weighted least squares (SAS REG Procedure), where the θ_1 parameter estimate was constrained to be equal to -1.05.

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 all forecasted economic indices and structural effects (PCPI, econTOU, EE, PV.DG and EV) 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

$$\mathrm{Var}(\hat{y}_t) = \sigma_m^2 + \mathrm{Var}\{\ \beta_4[\mathrm{SumCD}_t] + \beta_5[\mathrm{SumXHD}_t] + \beta_6[\mathrm{SumCD}_t][\mathrm{MaxCD3}_t]/100\ \} \qquad \text{[Eq. 3.3]}$$

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 the analysis of historical weather data, 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 98.8% of the observed variability associated with the monthly 2003-2017 system loads and nearly all input parameter estimates are statistically significant below the 0.01 significance level. Note that the summer and winter variance components were restricted to a 2:1 variance ratio during the weighted least squares analysis; likewise, the avoided_load parameter was constrained to be equal to -1.05.

As shown in Table 3.1, the estimate for the winter seasonal variance component is 8.01 GWh^2; the corresponding summer component is twice this amount (16.02 GWh^2). 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. By definition, all of the engineering calculated avoided (and incremental) load effect is accounted for in this econometric model via use of the avoided_load input variable.

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 the area wide PCPI index grows over time (i.e., this economic parameter estimate is > 0). However, our load growth will grow more slowly if future EE and/or PV-DG trends increase above their current forecasted levels, or more quickly if future EV penetration levels increase above their baseline levels.

Figure 3.1 shows the observed (blue points) versus calibrated (green line) system loads for the 2003-2017 timeframe. Nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines) and the observed versus calibrated load correlation exceeds 0.99. Figure 3.2 shows the forecasted monthly system loads for 2018 through 2030, along with the corresponding 95% forecasting envelope. This forecasting envelope encompasses model uncertainty only, while treating both the weather and projected economic indices as fixed inputs. Note also that these forecasts assume that our future PV-DG installation rates will stabilize at approximately 2 MW of AC capacity per year (once we reach our NEM 1.0 cap), 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 - Aug 2017): GWh units
Forecasting Model: includes Weather & Economic Covariates, Fourier Effects
pseudo TOU (unconstrained), 2014 Dist.system Adj and Avoided Load (PV + EE - EV)

Final Forecasting Equation: assumes constrained Avoided Demand Savings

Dependent Variable: GWhload Load (GWh)
Number of Observation Used: 176
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	104340	6955.99373	868.06	<.0001
Error	160	1282.12160	8.01326		
Corrected Total	175	105622			

Root MSE	2.83077	R-Square	0.9879
Dependent Mean	176.83540	Adj R-Sq	0.9867
Coeff Var	1.60079		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	-110.31151	9.54998	-11.55	<.0001	0
PCPI	PCPI ($1,000)	1	3.59642	0.09650	37.27	<.0001	1.24443
SumMF		1	5.65973	0.31770	17.81	<.0001	1.60298
SumSS		1	4.84532	0.37928	12.78	<.0001	1.49294
SumCD		1	0.14824	0.01477	10.04	<.0001	55.78514
CDimpact		1	0.06160	0.01993	3.09	0.0024	35.39460
SumXHD		1	0.05040	0.00972	5.18	<.0001	2.63186
Fs1		1	-4.42577	0.75950	-5.83	<.0001	4.60403
Fc1		1	-5.70859	1.01770	-5.61	<.0001	7.99335
Fs2		1	1.09362	0.61457	1.78	0.0771	3.11007
Fc2		1	1.70306	0.48170	3.54	0.0005	1.91111
Fs2014a		1	-4.53164	0.96929	-4.68	<.0001	1.51380
Fc2014a		1	-2.95335	0.94062	-3.14	0.0020	1.43455
Fs2014b		1	4.15689	0.91896	4.52	<.0001	1.38141
Fc2014b		1	-0.04606	0.94319	-0.05	0.9611	1.45711
econTOU		1	6.38842	0.69456	9.20	<.0001	1.05338
avoided_load	EE+PV.DG-EV	1	-1.05000	0	n/a	n/a	0.0

Durbin-Watson D	1.277
Number of Observations	176
1st Order Autocorrelation	0.341

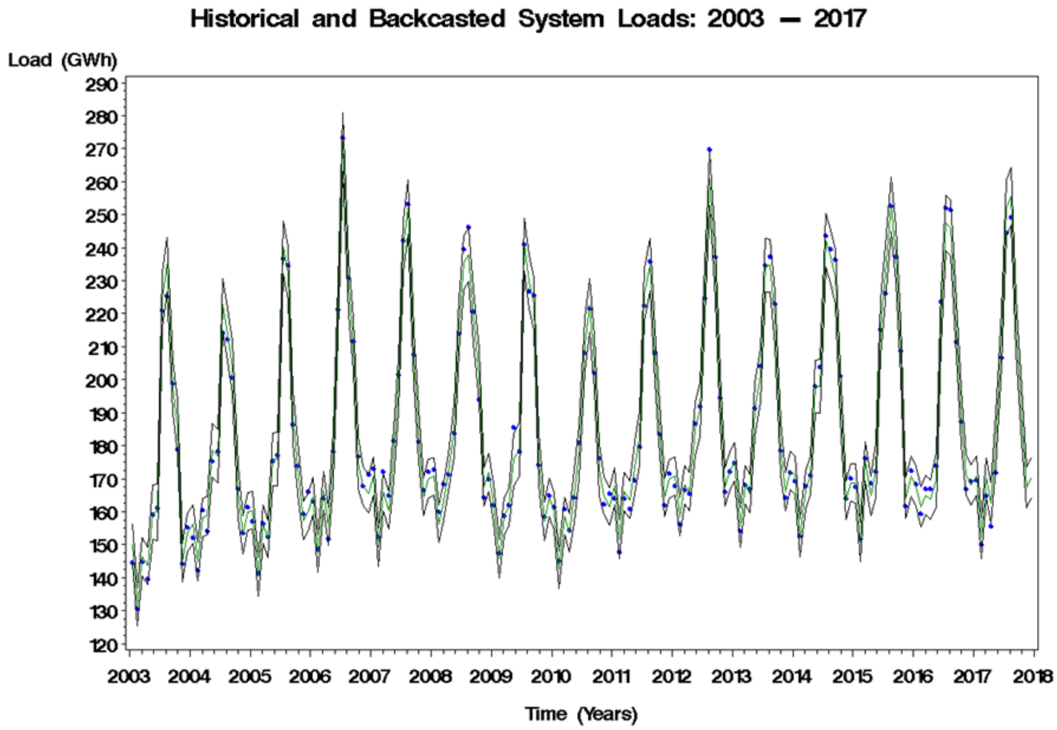

Figure 3.1. Observed and predicted total system load data (2003-2017), after adjusting for known weather conditions.

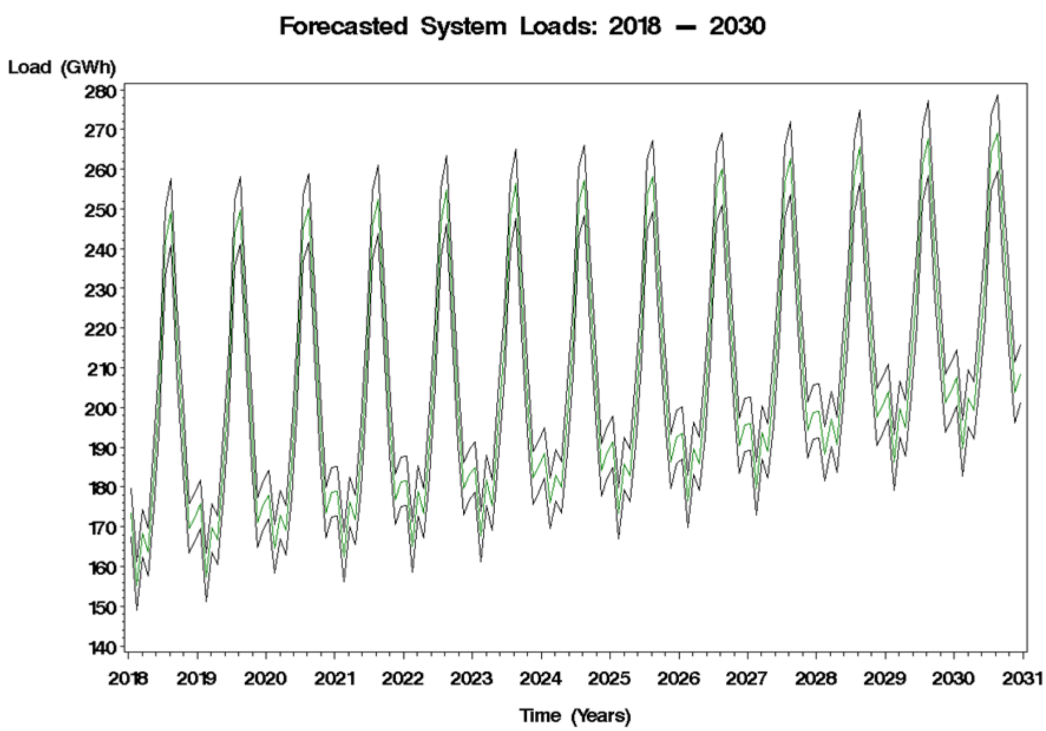

Figure 3.2. Forecasted monthly system loads for 2017-2030; 95% forecasting envelopes encompass model uncertainty only.

Table 3.2 shows the forecasted monthly RPU system loads for 2018, along with their forecasted standard deviations. In contrast to figure 3.2, these standard deviations quantify both model and weather uncertainty. The 2018 forecasts project that our annual system load should be 2291.2 GWh, assuming that the RPU service area experiences typical weather conditions throughout the year.

Table 3.2. 2018 monthly total system load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Load (GWh)	Std.Dev (GWh)
JAN	173.5	3.17
FEB	155.1	3.69
MAR	168.4	4.69
APR	163.7	5.36
MAY	183.0	8.86
JUN	205.6	17.41
JUL	241.7	14.21
AUG	249.3	11.36
SEP	217.4	12.77
OCT	192.0	11.41
NOV	169.5	4.58
DEC	172.3	3.15
Annual TOTAL	2291.2	

3.3 Monthly system peak model

The regression component of our monthly system peak forecasting model is a function of our primary economic driver (PCPI), 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), ten lower order Fourier frequencies that quantify seasonal impacts both before and after our distribution system upgrades (Fs1, Fc1, Fs2, Fc2, Fs3, Fc3, Fs2014a, Fc2014a, Fs2014b and Fc2014b), one unconstrained Industrial peak indicator variable (econTOU), and one initially unconstrained effect that captures the combined impacts of (avoided) EE, PV-DG and (incremental) EV peaks. 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

$$y_t = \beta_0 + \beta_1[\mathrm{PCPI}_t] + \beta_2[\mathrm{MaxCD3}_t] + \beta_3[\mathrm{SumCD}_t][\mathrm{MaxCD3}_t]/100 + \beta_4[\mathrm{MaxHD}_t] +$$

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

$$+ \beta_{11}[\mathrm{Fs2014a}_t] + \beta_{12}[\mathrm{Fc2014a}_t] + \beta_{13}[\mathrm{Fs2014b}_t] + \beta_{14}[\mathrm{Fc2014b}_t] +$$

$$\beta_{15}[\mathrm{econTOU}_t] + \theta_1[\mathrm{EE}_t\mathrm{+PV.DG}_t\mathrm{-EV}_t] + \varepsilon_{jt} \qquad \text{[Eq. 3.4]}$$

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 REML estimation (SAS MIXED Procedure). These REML results yielded summer and winter variance component estimates of 492.1 and 197.9 MW^2, suggesting that the variance ratio for the seasonal errors is reasonably close to a 2:1 ratio. Additionally, the θ_1 parameter estimate was estimated to be -1.055 (0.322), which almost exactly matches the -1.05 avoided/incremental peak impact assumption discussed in sections 2.5 through 2.7. Based on these results, Eq. 3.4 was refit using weighted least squares (SAS REG Procedure), where the θ_1 parameter estimate was constrained to be equal to -1.05.

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

$$\mathrm{Var}(\hat{y}_t) = \sigma_m^2 + \mathrm{Var}\{\, \beta_2[\mathrm{MaxCD3}_t] + \beta_3[\mathrm{SumCD}_t][\mathrm{MaxCD3}_t]/100 + \beta_4[\mathrm{MaxHD}_t] \,\} \qquad \text{[Eq. 3.6]}$$

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 the analysis of historical weather data 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 97.4% of the observed variability associated with the monthly 2003-2017 system peaks. Note that the summer and winter variance components were restricted to a 2:1 variance ratio during the weighted least squares analysis; likewise, the avoided_peak parameter was constrained to be equal to -1.05.

As shown in Table 3.3, the estimate for the winter seasonal variance component is 218.8 MW^2; the corresponding summer component is twice this amount (437.6 MW^2). An analysis of the variance adjusted model residuals suggests that the model errors are again Normally distributed, devoid of outliers and approximately temporally uncorrelated; implying that our modeling assumptions are reasonable. By definition, all of the engineering calculated avoided (and incremental) peak effect is accounted for in this econometric model via use of the avoided_peak input variable.

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 loads will grow more slowly if future EE and/or PV-DG trends increase above their current forecasted levels, or more quickly if our EV penetration levels increase. 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 2003-2017 timeframe. Nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines) and the observed versus calibrated load correlation exceeds 0.98. Figure 3.4 shows the forecasted monthly system peaks for 2018 through 2030, along with the corresponding 95% forecasting envelope. This forecasting envelope again encompasses just the model uncertainty, while treating the weather variables and projected economic and structural indices as fixed inputs. Note that our system peaks are forecasted to grow at just 0.4% 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 - Aug 2017): MW units
Forecasting Model: includes Weather & Economic Covariates, Fourier Effects
pseudo TOU (unconstrained), 2014 Dist.system Adj, and Avoided Peak (PV + EE - EV)

Final Forecasting Equation: using optimized Forier coefs and constrained Avoided Peak Load Effect

Dependent Variable: peak Peak (MW)
Number of Observations Used: 176

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	1329764	88651	405.16	<.0001
Error	160	35009	218.80601		
Corrected Total	175	1364773			

Root MSE	14.79209	R-Square	0.9743
Dependent Mean	368.89432	Adj R-Sq	0.9719
Coeff Var	4.00985		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	135.37471	15.57677	8.69	<.0001	0
PCPI	PCPI ($1,000)	1	5.59794	0.50176	11.16	<.0001	1.23228
MxCD3		1	2.83380	0.18781	15.09	<.0001	9.72788
CDimpact		1	0.23740	0.06190	3.84	0.0002	12.50081
MxHD1		1	1.84252	0.34492	5.34	<.0001	2.04283
Fs1		1	-22.84073	3.59551	-6.35	<.0001	3.77879
Fc1		1	-39.10284	4.43850	-8.81	<.0001	5.56814
Fs2		1	2.14027	3.28954	0.65	0.5162	3.26320
Fc2		1	-2.05045	2.47581	-0.83	0.4088	1.84892
Fs3		1	8.22466	2.12678	3.87	0.0002	1.34902
Fc3		1	8.10454	1.90719	4.25	<.0001	1.09717
Fs2014a		1	-4.16401	5.05280	-0.82	0.4111	1.50651
Fc2014a		1	-20.00732	4.93997	-4.05	<.0001	1.44904
Fs2014b		1	11.53635	4.76977	2.42	0.0167	1.36292
Fc2014b		1	4.59643	4.91722	0.93	0.3513	1.45037
econTOU		1	14.78063	3.63449	4.07	<.0001	1.05634
avoided_peak	EE+PV-EV	1	-1.05000	0	n/a	n/a	0.0

Durbin-Watson D	2.138
Number of Observations	176
1st Order Autocorrelation	-0.078

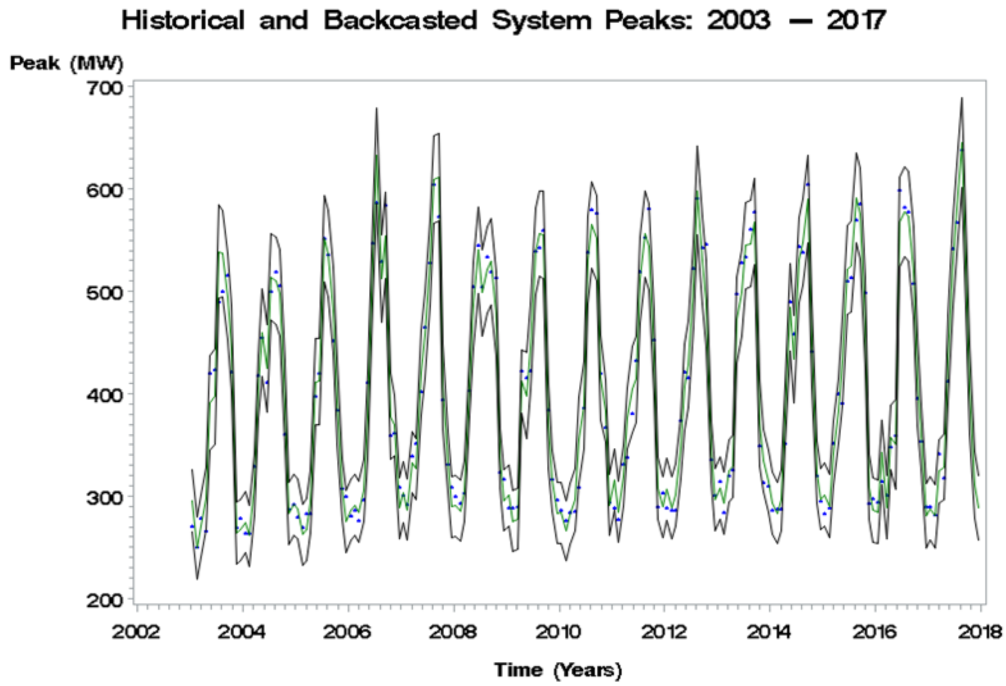

Figure 3.3. Observed and predicted system peak data (2003-2017), after adjusting for known weather conditions.

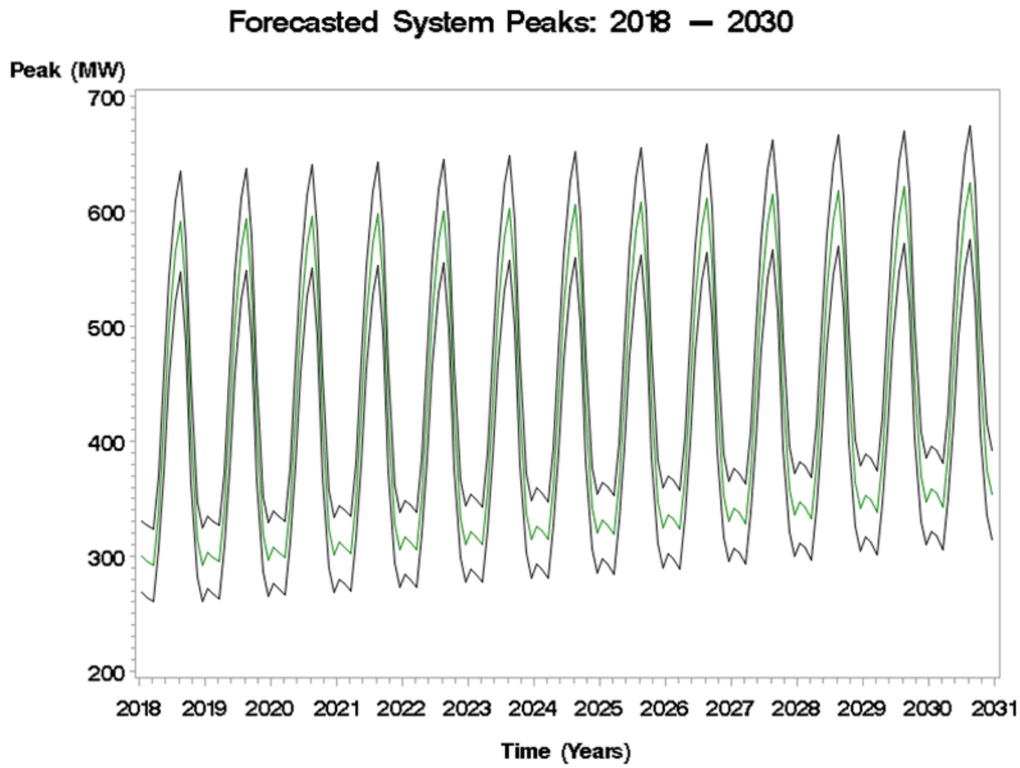

Figure 3.4. Forecasted monthly system peaks for 2018-2030; 95% forecasting envelopes encompass model uncertainty only.

Table 3.4 shows the forecasted monthly RPU system peaks for 2018, along with their forecasted standard deviations. In contrast to figure 3.4, these standard deviations quantify both model and weather uncertainty. The 2018 forecasts project that our maximum monthly system peak should be about 591.5 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. 2018 monthly system peak forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Peak (MW)	Std.Dev (MW)
JAN	299.3	19.05
FEB	295.1	23.24
MAR	291.7	26.43
APR	338.3	44.95
MAY	415.1	46.67
JUN	499.3	57.63
JUL	565.8	41.40
AUG	591.5	39.70
SEP	531.2	40.76
OCT	408.2	46.63
NOV	314.9	34.21
DEC	292.5	17.89

3.5 Peak demand weather scenario forecasts

After calculating all of the 2018-2030 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 2018, our forecasted 1-in-5, 1-in-10, 1-in-20 and 1-in-40 peaks are 624.9, 642.4, 656.8 and 669.3, 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 and incremental EV structural term in our retail models cannot be reliably estimated with reasonable precision. Instead, we have chosen to restrict the parameter estimates for these pooled terms 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 PCPI), 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 (Fs1, Fc1, Fs2 and Fc2), and an a-priori constrained effect that captures the combined impacts of avoided load due to residential EE and solar PV-DG activities and the incremental load due to additional EV penetration. Mathematically, the model is defined as

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

$$\beta_5[Fs1_t] + \beta_6[Fc1_t] + \beta_7[Fs2_t] + \beta_8[Fc2_t] - 1.00[EE_{t,R} + PV.DG_{t,R} - Ev_{t,R}] + \varepsilon_t \qquad \text{[Eq. 4.2]}$$

where

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

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 corresponds to our system load estimate for this parameter, after removing the impacts of system losses). Additionally, the holiday effect (Xmas) was added to account for an annual residential holiday load increase that is primarily reflected in January billing statements.

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 index as fixed 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 the analysis of historical weather data, once the parameters associated with the weather effects had been estimated).

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 94.5% of the observed variability associated with the monthly 2003-2017 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 PCPI level improves over time. 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, or increase if a higher level of EV penetration occurs.

Figure 4.1 shows the observed (blue points) versus calibrated (green line) residential loads for the 2003-2017 timeframe. Nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines); the observed versus calibrated load correlation is approximately 0.97. Figure 4.2 shows the forecasted monthly system loads for 2018 through 2030, along with the corresponding 95% forecasting envelope. This forecasting envelope encompasses model uncertainty only, while treating the projected economic index and weather variables as fixed inputs. Our residential loads are forecasted to increase at just 0.3% 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 2018, along with their forecasted standard deviations. Note that these standard deviations quantify both model and weather uncertainty. The 2018 forecasts project that our annual residential load should be 706.3 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.

The REG Procedure
Model: MODEL1
Dependent Variable: resi Residential (GWh)

NOTE: Restrictions have been applied to parameter estimates.

Number of Observations Read	456
Number of Observations Used	175
Number of Observations with Missing Values	281

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	43942	5492.80692	359.23	<.0001
Error	166	2538.18832	15.29029		
Corrected Total	174	46481			

Root MSE	3.91028	R-Square	0.9454
Dependent Mean	59.14618	Adj R-Sq	0.9428
Coeff Var	6.61121		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	19.43233	3.57086	5.44	<.0001	0
lagPCPI	lag(PCPI)	1	0.77046	0.11521	6.69	<.0001	1.21801
sum2CD	SumCD+lag(SumCD)	1	0.12153	0.00885	13.72	<.0001	15.00539
sum2HD	SumXHD+lag(SumXHD)	1	0.06305	0.01537	4.10	<.0001	3.31075
xmas	XMas Effect	1	8.84804	1.09830	8.06	<.0001	3.03732
Fs1		1	-2.73398	1.18323	-2.31	0.0221	8.00814
Fc1		1	-3.04760	1.16297	-2.62	0.0096	7.73631
Fs2		1	3.17479	0.71471	4.44	<.0001	2.93965
Fc2		1	-2.02375	0.62785	-3.22	0.0015	2.24290
Avoided_load	EE+PV-EV	1	-1.00000	0	n/a	n/a	0.0

Durbin-Watson D	2.176
Number of Observations	175
1st Order Autocorrelation	-0.094

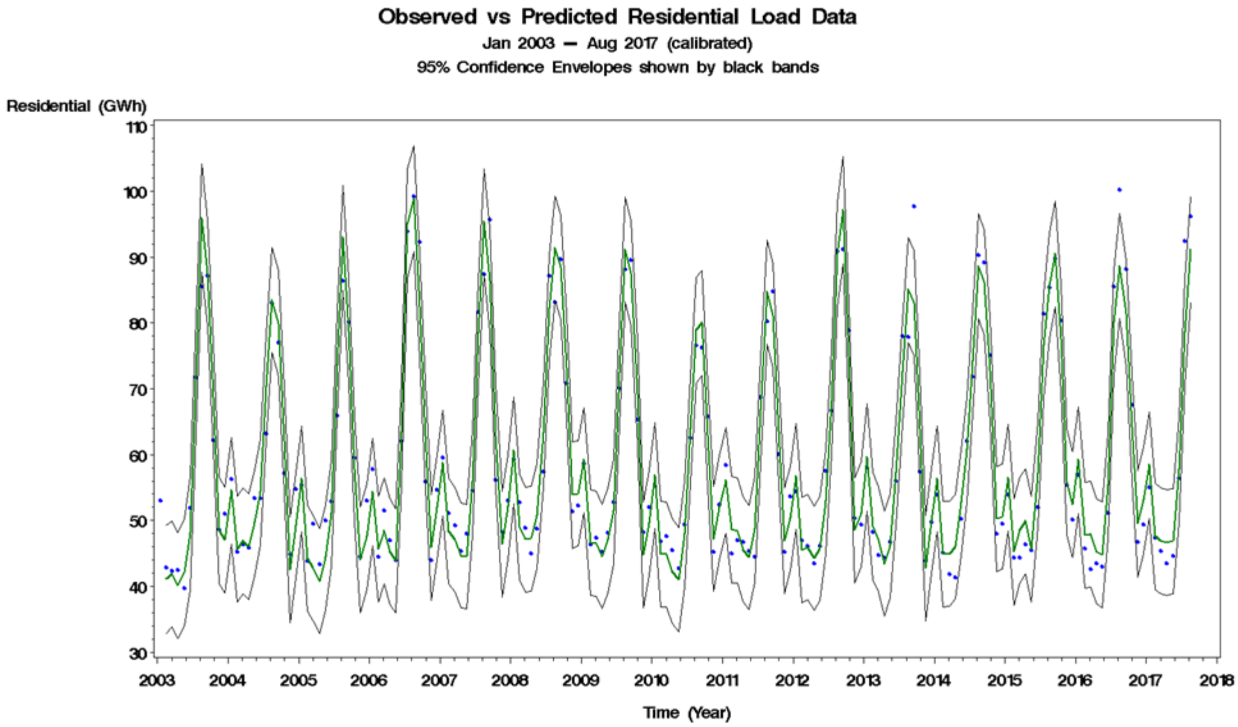

Figure 4.1. Observed and predicted residential load data (2003-2017), after adjusting for known weather conditions.

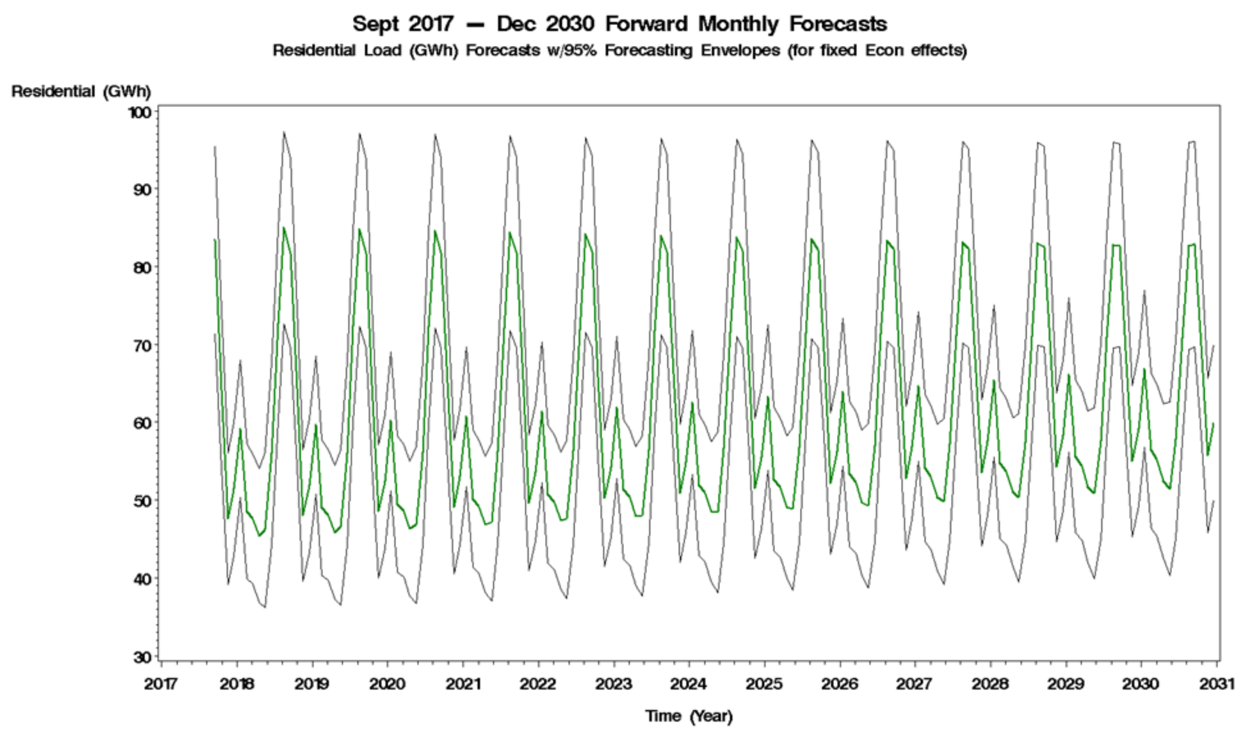

Figure 4.2. Forecasted monthly residential loads for 2018-2030; 95% forecasting envelopes encompass model uncertainty only.

Table 4.2. 2018 monthly residential load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Load (GWh)	Std.Dev (GWh)
JAN	59.11	4.85
FEB	48.54	5.34
MAR	47.60	5.06
APR	45.40	5.94
MAY	46.20	7.86
JUN	55.93	11.24
JUL	72.57	15.73
AUG	85.00	10.73
SEP	81.70	12.79
OCT	64.41	13.48
NOV	48.02	8.17
DEC	51.84	4.80
Annual TOTAL	706.31	

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 (Fs1 and Fc1), one unconstrained Industrial load indicator variable (econTOU), and the combined impacts of avoided load due to commercial/industrial EE and solar PV-DG activities and incremental load due to additional EV penetration. Mathematically, the model is defined as

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

$$\beta_4[Fs1_t] + \beta_5[Fc1_t] + \beta_6[econTOU_t] - 1.00[EE_{t,CI} + PV.DG_{t,CI} - Ev_{t,CI}] + \varepsilon_t \qquad \text{Eq. 4.4}$$

where

$$\varepsilon_t \sim N(0, \sigma^2). \qquad \text{Eq. 4.5}$$

In Eq. 4.4, 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. 4.4 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 index is treated as fixed 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.

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 2003-2017 C+I loads. Note that although the heating degree effect is non-significant ($t = 1.57$, $p=0.119$), 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.

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,

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

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 the area wide PCPI level improves over time. Finally, our C+I load growth will be reduced if future C+I specific EE and/or PV-DG trends increase above their current forecasted levels. Likewise, our C+I load growth will increase if future C+I specific EV trends increase above their current forecasted levels.

Figure 4.3 shows the observed (blue points) versus calibrated (green line) C+I loads for the 2003-2017 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 2018 through 2030, along with the corresponding 95% forecasting envelope. This forecasting envelope encompasses model uncertainty only, while treating the projected economic indices and weather variables as fixed inputs. Note that our C+I loads are forecasted to grow at a 1.8% annual rate, after adjusting for our future C+I EE, solar PV-DG and EV installation trends.

Table 4.5 shows the post-hoc forecasted monthly commercial and industrial loads for 2018, along with their forecasted standard deviations. Note that these standard deviations quantify both model and weather uncertainty. The 2018 forecasts project that our annual commercial and industrial loads should be 457.5 and 1016.5 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.

The REG Procedure
Model: MODEL1
Dependent Variable: cmind Comm+Indst (GWh)

NOTE: Restrictions have been applied to parameter estimates.

Number of Observations Read	456
Number of Observations Used	175
Number of Observations with Missing Values	281

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	29393	4898.79338	209.37	<.0001
Error	168	3930.89355	23.39818		
Corrected Total	174	33324			

Root MSE	4.83717	R-Square	0.8820
Dependent Mean	112.78112	Adj R-Sq	0.8778
Coeff Var	4.28899		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	9.21888	4.34312	2.12	0.0352	0
lagPCPI	lag(PCPI)	1	3.18696	0.14013	22.74	<.0001	1.17742
sum2CD	SumCD+lag(SumCD)	1	0.05495	0.00658	8.35	<.0001	5.40936
sum2HD	SumXHD+lag(SumXHD)	1	0.02359	0.01506	1.57	0.1191	2.07635
s1		1	-5.89334	1.04100	-5.66	<.0001	4.05070
c1		1	-4.39702	0.98993	-4.44	<.0001	3.66297
econTOU		1	5.37892	1.01996	5.27	<.0001	1.03541
avoided_load	EE+PV-EV	1	-1.00000	0	n/a	n/a	0.0

Durbin-Watson D	2.368
Number of Observations	175
1st Order Autocorrelation	-0.191

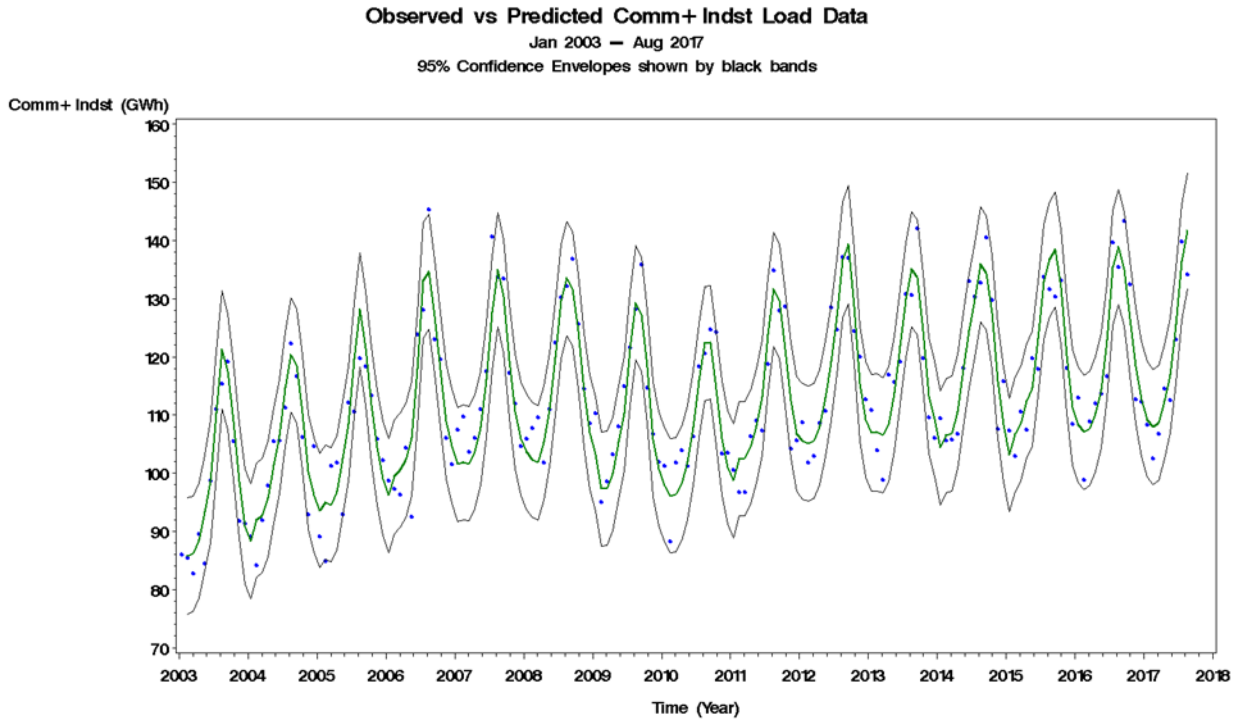

Figure 4.3. Observed and predicted C+I load data (2003-2017), after adjusting for known weather conditions.

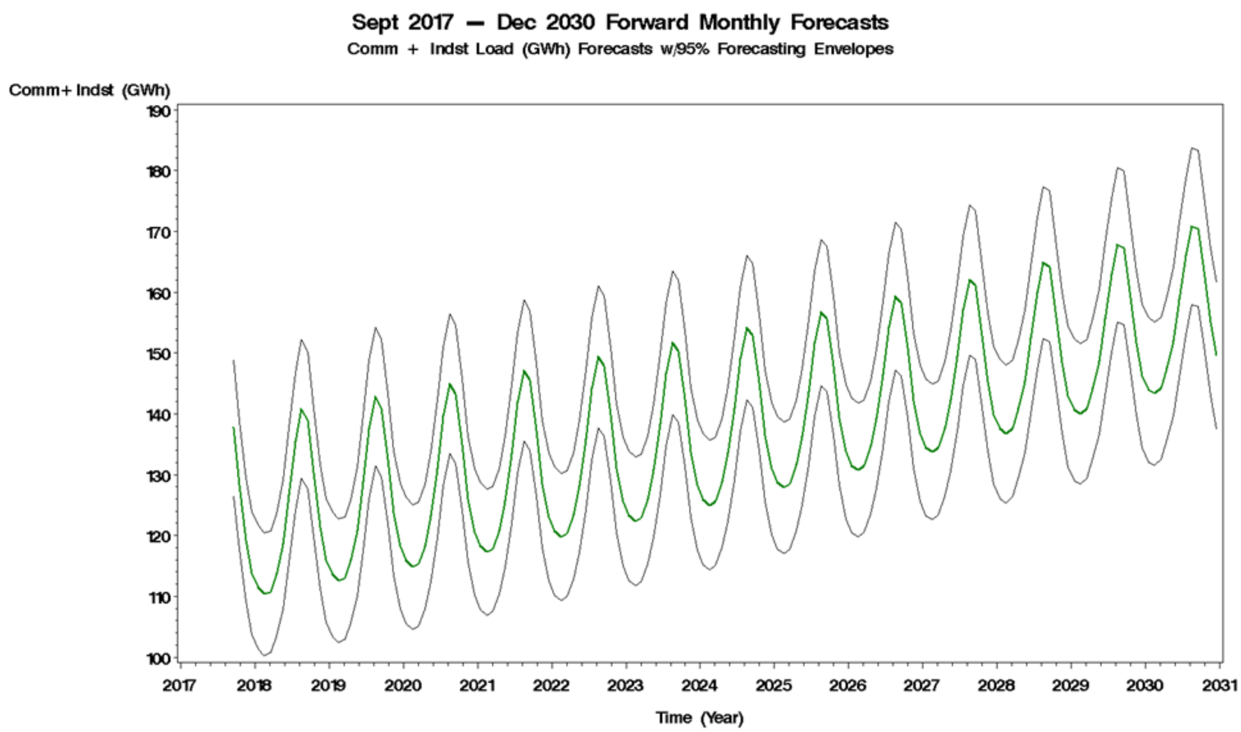

Figure 4.4. Forecasted monthly C+I loads for 2018-2030; 95% forecasting envelopes encompass model uncertainty only.

Table 4.5. 2018 monthly commercial and industrial load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Comm Load (GWh)	Std. Dev (GWh)	Indst Load (GWh)	Std. Dev (GWh)
JAN	34.49	1.57	76.98	3.64
FEB	33.63	1.57	76.71	3.66
MAR	33.87	1.52	76.84	3.65
APR	34.04	1.54	79.49	3.82
MAY	35.76	1.80	82.77	4.31
JUN	38.90	2.18	87.65	5.21
JUL	43.43	2.75	92.00	6.20
AUG	45.87	2.28	94.96	4.94
SEP	44.83	2.48	94.05	5.37
OCT	40.75	2.36	89.60	5.51
NOV	36.51	1.74	84.86	4.27
DEC	35.41	1.53	80.58	3.69
Annual Total	457.48		1016.49	

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.

From January 2008 through June 2015, the monthly loads associated with the Other customer class exhibited a fairly stable, seasonal pattern that was 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).

In July 2015, the RPU Finance Division migrated all Agricultural Pumping customers from their miscellaneous contracts over to Industrial TOU accounts (i.e., out of the "Other" class and into the C&I class). Although this load migration barely impacted the C&I class, the apparent load loss in the Other class was significant and must therefore be accounted for in the forecasting model. To account for this migration, a "migration" indicator variable defined as 0 for all time periods before July 2015 and 1 for all periods after July 2015 should be introduced to the model.

Based on the above discussed trends and patterns, our load forecasting model for this customer class is defined to be a function of two low order Fourier frequencies (Fs1 and Fc1), three indicator variables to account for the monthly outliers, and one indicator variable to account for the load migration effect. The corresponding model estimation results (derived using ordinary least squares) are shown in Table 4.6; note that this equation describes about 87% of the observed load variation.

Table 4.7 shows the monthly load forecasts for 2018 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. Additionally, the forecasted standard errors do not reflect any weather uncertainty, since the model is devoid of any weather inputs.

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

The REG Procedure
Model: MODEL1
Dependent Variable: other Other (GWh)

Number of Observations Read	396
Number of Observations Used	116
Number of Observations with Missing Values	280

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	19.32869	3.22145	119.50	<.0001
Error	109	2.93839	0.02696		
Corrected Total	115	22.26708			

Root MSE	0.16419	R-Square	0.8680
Dependent Mean	2.45829	Adj R-Sq	0.8608
Coeff Var	6.67896		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	2.64568	0.01761	150.27	<.0001	0
s1		1	-0.20683	0.02194	-9.43	<.0001	1.02697
c1		1	0.12608	0.02178	5.79	<.0001	1.02773
migration		1	-0.72269	0.03698	-19.54	<.0001	1.00972
outlier1		1	0.56222	0.16656	3.38	0.0010	1.02021
outlier2		1	-0.65178	0.16653	-3.91	0.0002	1.01983
outlier3		1	-2.19194	0.16652	-13.16	<.0001	1.01969

Durbin-Watson D	1.299
Number of Observations	116
1st Order Autocorrelation	0.332

Table 4.7. 2018 monthly load forecasts for the "Other" customer class.

Month	Load (GWh)	Std.Dev (GWh)
JAN	1.99	0.17
FEB	1.87	0.17
MAR	1.76	0.17
APR	1.69	0.17
MAY	1.69	0.17
JUN	1.75	0.17
JUL	1.85	0.17
AUG	1.98	0.17
SEP	2.09	0.17
OCT	2.16	0.17
NOV	2.16	0.17
DEC	2.10	0.17
Annual TOTAL	23.08	

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 (i.e., reduced) our retail forecasts from 2% to 5%, respectively.

The monthly 2018-2030 forecasts for all of our retail customer classes are shown in Figure 4.5, along with our total system and total 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 do not expect to see significant future 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 ~0.3% per year). In contrast, the forecasted 10-year load growths associated with our commercial and industrial classes are expected to be 1.8% 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. Additionally, the current low EV penetration levels in our service territory are not resulting in enough new load growth to significantly impact this anemic residential trend.

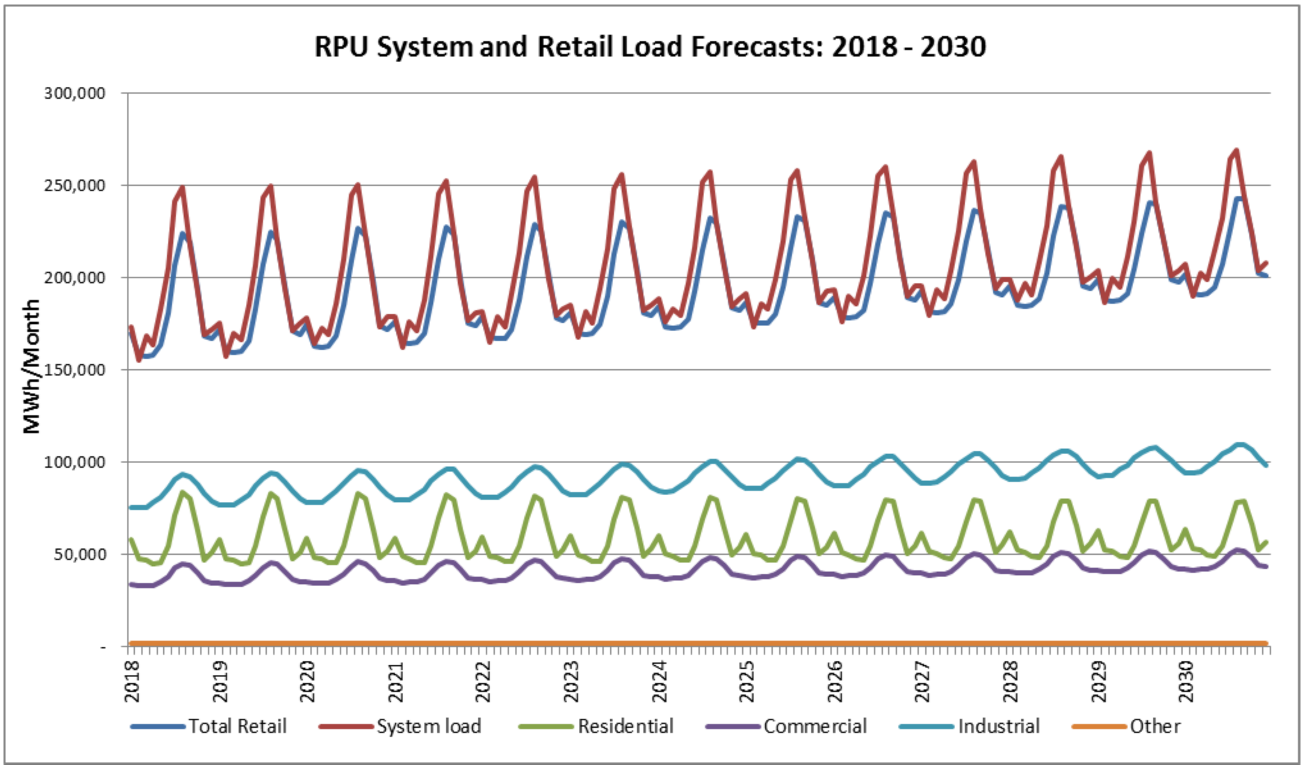

Figure 4.5. RPU monthly retail load forecasts (2018-2030) for the system load, total retail load, and the residential, commercial, industrial and other customer classes.

Table 4.8. Final Retail and System (wholesale) load and peak forecasts: 2018-2030.

Year	**System Load**	System Peak	**Residential**	**Commercial**	**Industrial**	**Other**	**Total Retail**	**Ratio R/S**
2018	2,291,248	591	694,702	449,961	999,782	23,076	2,167,521	94.6%
2019	2,314,846	593	695,666	456,566	1,014,536	23,076	2,189,844	94.6%
2020	2,345,843	596	698,825	464,661	1,032,605	23,076	2,219,167	94.6%
2021	2,366,858	598	698,889	470,785	1,046,297	23,076	2,239,048	94.6%
2022	2,393,687	600	700,525	478,128	1,062,699	23,076	2,264,428	94.6%
2023	2,422,473	603	702,591	485,911	1,080,082	23,076	2,291,659	94.6%
2024	2,458,739	606	706,642	495,273	1,100,976	23,076	2,325,967	94.6%
2025	2,484,437	608	707,544	502,509	1,117,148	23,076	2,350,277	94.6%
2026	2,516,886	611	710,212	511,179	1,136,507	23,076	2,380,974	94.6%
2027	2,550,641	615	713,097	520,164	1,156,569	23,076	2,412,906	94.6%
2028	2,589,567	618	717,230	530,279	1,179,145	23,076	2,449,730	94.6%
2029	2,622,242	621	719,551	539,121	1,198,894	23,076	2,480,641	94.6%
2030	2,660,182	625	723,137	549,114	1,221,205	23,076	2,516,532	94.6%