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

2020 Annual Report – with recalibrated 2020 COVID-19 Impact Adjustments

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 2005. 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 reports for more detailed information about RPU's various EE/rebate programs, and our prior SB1 reports for more general information about historical 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 ~15 years of historical monthly load data. The parameter estimates for each forecasting equation are normally updated every 12 months; if necessary, the functional form of each equation can also be updated or modified on an annual basis. Please note that this report only 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 in detail, while section 4 provides a high-level overview of how our class-specific, retail load forecasts are derived from our system load forecasts.

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:

- 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.

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. 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, section 2.8 describes how the utility is currently adjusting for temporary load loss due to COVID-19 impacts.

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). 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 system load (SL) and system peak (SP) forecasting equations.

Effect	Variable	Definintion	Forecasting Eqns.	
			SL	SP
Economic	PCPI	Per Capita Personal Income ($1000)	X	X
Calendar	SumMF	# of Mon-Fri (weekdays) in month	X	
	SumSS	# of Saturdays and Sundays in month	X	
Weather	SumCD	Sum of monthly CD's	X	X
	SumXHD	Sum of monthly XHD's	X	
	MaxCD3	Maximum concurrent 3-day CD sum in month	X	X
	CDImpact	Interaction between SumCD and MaxCD3	X	
	MaxHD	Maximum single XHD value in month		X
Structural (TOU,EE,PV,EV)	EconTOU	Expansion/contraction of New Industrial load	X	X
	Avoided_Load	Cumulative EE+PV-EV load (GWh: calculated)	X	
	Avoided_Peak	Cumulative EE+PV-EV peak (MW: calculated)		X
Fourier terms	Fs1	Fourier frequency (Sine: 12 month phase)	X	X
	Fc1	Fourier frequency (Cosine: 12 month phase)	X	X
	Fs2	Fourier frequency (Sine: 6 month phase)	X	X
	Fc2	Fourier frequency (Cosine: 6 month phase)	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

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 recession-adjusted historical average for the region (i.e., approximately 3.25 % 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 our forecasting models because our (previously used) additional set of monthly employment data no longer appears to materially improve the forecasting accuracy.

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 25 year historical averages; these forecasted monthly indices are shown in Table 2.2 below. Note that these average monthly values are used as weather inputs for all future time periods on/after November 2020.

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	2.5	72.6	1.8	9.5
FEB	6.0	60.0	3.5	7.7
MAR	14.4	29.1	8.3	6.5
APR	35.7	14.5	18.4	4.4
MAY	74.2	0.7	28.5	0.5
JUN	173.6	0.6	38.5	0.2
JUL	345.8	0.0	55.0	0.0
AUG	371.8	0.0	57.5	0.0
SEP	266.3	0.0	54.1	0.0
OCT	104.1	0.5	35.3	0.2
NOV	21.0	20.2	14.4	4.1
DEC	2.0	77.4	2.0	9.4

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. 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><th>Year</th><th>Time Period</th><th>EconTOU value</th><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, staff reviewed all EE saving projections going back to fiscal year 2005/06, in order to calculate the cumulative load and peak savings attributable to efficiency improvements and rebate programs. Since that time, staff have continued to track and accumulate this load and peak savings. The steps we perform in this analysis are 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 calculate the cumulative running totals for each component from July 2005 through our most recent EE 1037 filing by performing a linear interpolation on the cumulative fiscal year components.
3. We then convert 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. Note that the monthly HVAC factors reflect an engineering estimated, monthly interpolation of EE savings associated with heating and AC loads in the Riverside service territory.
4. Finally, we sum 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 staff continue to update these projections as new information becomes available. Also, as stated above, 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	Load Scaling Factors			Peak Shaping Factors		
	Baseload	Lighting	HVAC	Baseload	Lighting	HVAC
Jan	0.0833 for all months	0.0970	0.0788	1.0 for all months	1.164	0.411
Feb		0.0933	0.0541		1.119	0.283
Mar		0.0858	0.0367		1.030	0.192
Apr		0.0784	0.0256		0.940	0.134
May		0.0746	0.0486		0.896	0.253
Jun		0.0709	0.1122		0.851	0.586
Jul		0.0709	0.1802		0.851	0.940
Aug		0.0746	0.1916		0.896	1.000
Sep		0.0784	0.1289		0.940	0.673
Oct		0.0858	0.0513		1.030	0.268
Nov		0.0933	0.0294		1.119	0.154
Dec		0.0970	0.0626		1.164	0.327

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 nine years. Historically, RPU had also 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.

Staff estimate the projected net annual energy savings and net coincident peak savings for the RPU distribution system by calculating the cumulative load and peak savings attributable to customer installed PV systems within our service territory. These calculations are 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. These projected monthly components are then summed together to estimate the cumulative projected monthly load and peak reduction estimates, directly attributable to solar PV distributed generation (DG).

Once again, it should be noted that these represent interpolated engineering estimates of solar PV DG impacts. As previously discussed, 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.

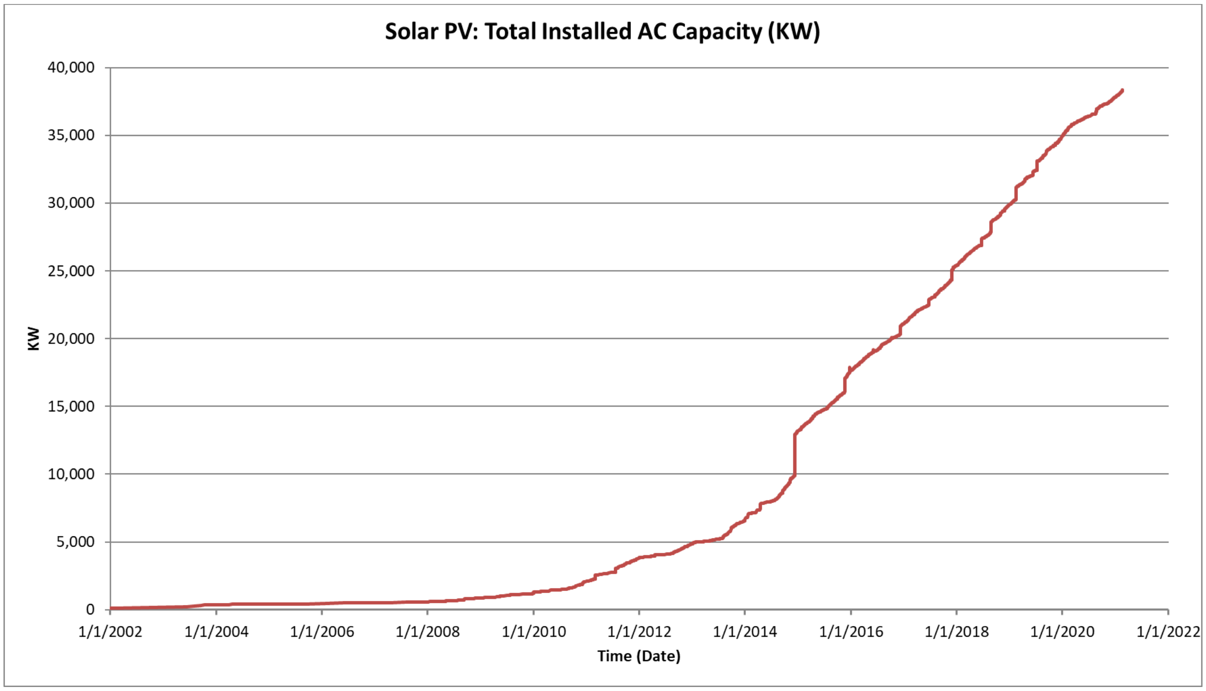

Figure 2.1. Total installed AC capacity of customer owned solar PV in the RPU service territory since 2002.

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

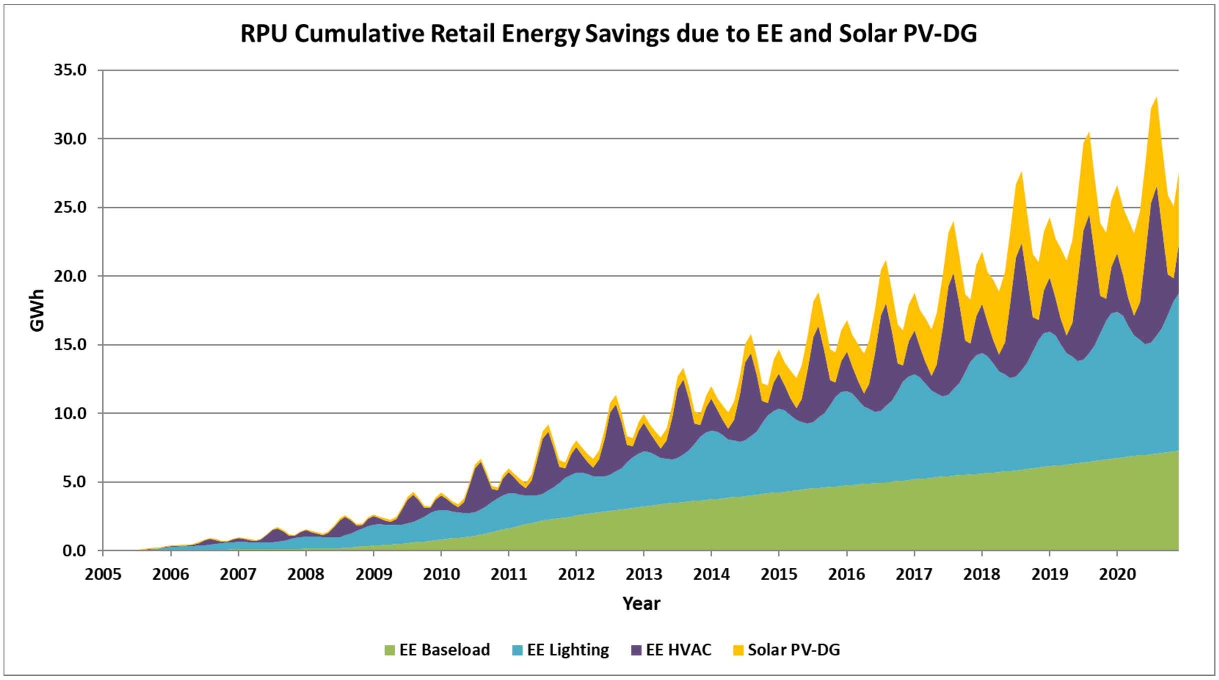

Figure 2.2. Calculated cumulative projected retail energy savings in the RPU service territory due to both EE program and solar PV distributed generation impacts over time.

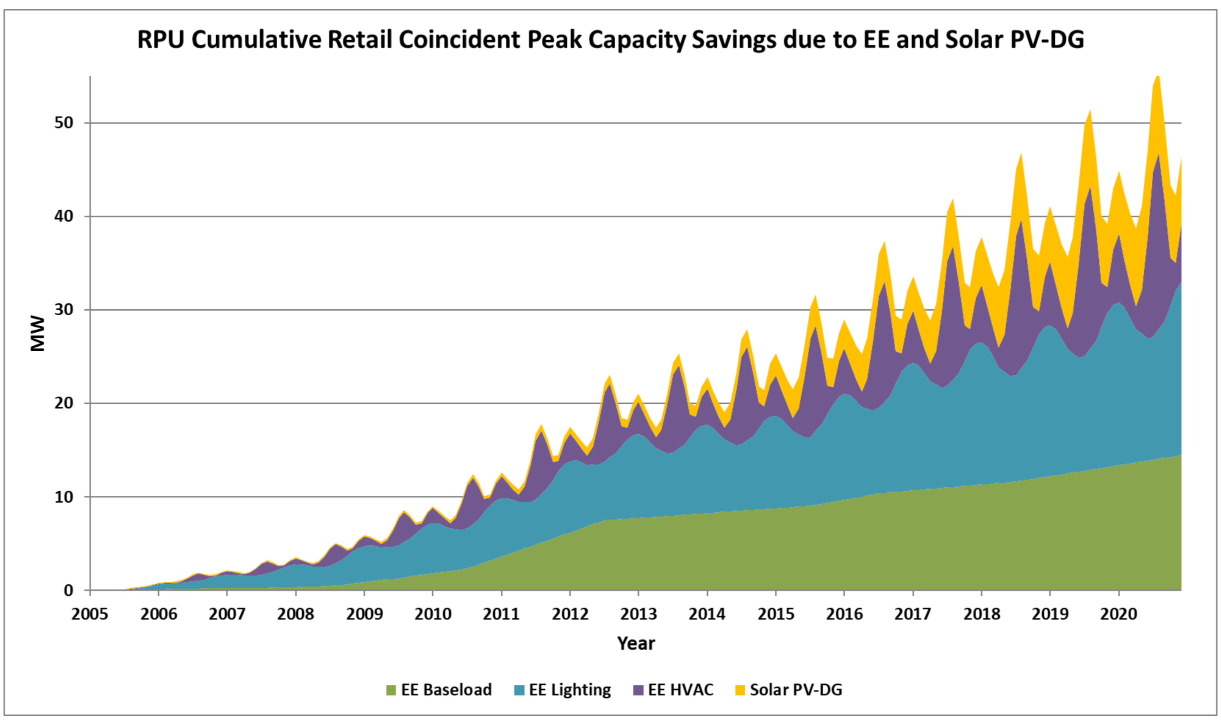

Figure 2.3. Calculated cumulative projected coincident peak capacity savings in the RPU service territory due to both EE program and solar PV distributed generation impacts over time.

2.7 Incremental Electric Vehicle Loads

In early 2017 the CEC released their Transportation Electrification Common Assumptions 3.0 model. Since that time, this model has been periodically updated. (RPU staff are currently using version 3.5-3). 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 several emission reduction metrics, in addition to the expected net load growth associated with the forecasted EV penetration level.

Riverside has elected to continue using this model in our 2020 load forecasting equations to estimate our expected net EV load growth. For baseline load forecasting purposes, we assume that Riverside will meet its share of the "Governors 2025 Goal" of 1,500,000 EV's by 2025 and use 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 some of our future EE and DG.PV (solar) load losses.

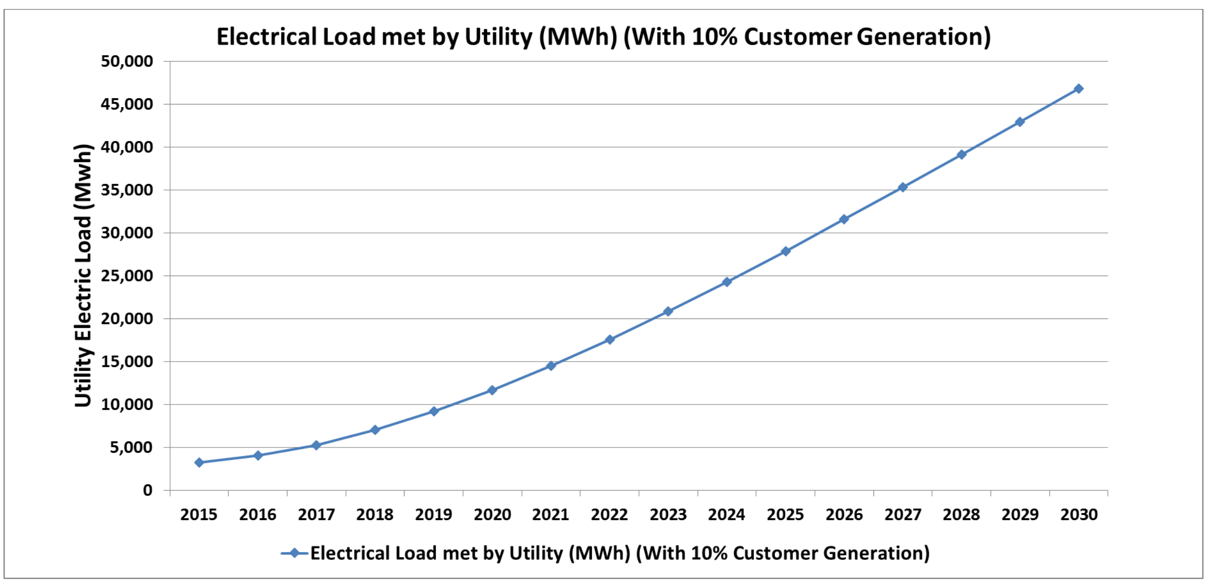

Figure 2.4. Projected 2015-2030 RPU electrical load from EV and PHEV penetration within our service territory.

2.8 Accounting for COVID-19 Pandemic Impacts on Load and Peak Forecasts

Historical and projected values of per capita personal income (PCPI) are used in both the system load and peak forecasting models. Specifically, PCPI data is input as a calibrated regression variable in each equation. This process ties each model to historical economic information (about our regional area), and simultaneously allows the calibrated equations to forecast various future economic scenarios (by changing the projections of future PCPI data).

In order to calibrate observed 2020 load reductions from the COVID-19 pandemic to this PCPI variable, staff has applied "shock-recovery impacts" to the 2020-2021 monthly PCPI projections. These impacts have been specified as specific percent reductions to the quarterly PCPI data across 24 months (i.e., from Q1-2020 through Q4-2021), as shown in Table 2.6 below. Note that the "shocks" applied to the quarterly 2020 data reduces the projected Q1-Q4 PCPI levels by 2%, 12%, 8% and 7%, respectively. Likewise, the "recovery" impacts projected in 2021 are assumed to be moderate and linear.

Table 2.6. COVID-19 "shock-recovery impacts" applied to projected PCPI data.

Quarter	% Reduction to PCPI levels	Quarter	% Reduction to PCPI levels
Q1-2020	2%	Q1-2021	7%
Q2-2020	12%	Q2-2021	5%
Q3-2020	8%	Q3-2021	3%
Q4-2020	7%	Q4-2021	1%

These shock-recovery impacts produce a reasonably material reduction in both the load and peak forecasts, particularly in 2020. However, these PCPI shock-recovery impacts (i.e., modified 2020-2021 PCPI input levels) result in COVID-19 adjusted load and peak forecasts that align well with our observed March through November data. Additionally, the assumption of a full recovery by the end of 2021 appears to be reasonable, given the rapid distribution of COVID-19 vaccines now occurring across the United States.

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 constrained 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

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

$$\beta_{46}[SumCD_t][MaxCD3_t]/100 + \beta_7[Fs1_t] + \beta_8[Fc1_t] + \beta_9[Fs2_t] + \beta_{10}[Fc2_t] + \beta_{11}[Fs2014a_t] +$$

$$\beta_{12}[Fc2014a_t] + \beta_{13}[Fs2014b_t] + \beta_{14}[Fc2014b_t] + \beta_{15}[econTOU_t] +$$

$$\theta_1[EE_t+PV.DG_t-EV_t] + \varepsilon_{jt} \qquad \text{[Eq. 3.1]}$$

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 → January 2005) 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 12.0 and 8.8 GWh^2, suggesting that the variance ratio for the seasonal errors follows an approximate 1.5:1 ratio. Based on these results, 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 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

$$\mathrm{Var}(\hat{y}_t) = \sigma_m^2 +$$

$$\mathrm{Var}\{\ \beta_4[\mathrm{SumCD}_t] + \beta_5[\mathrm{SumXHD}_t] + \beta_6[\mathrm{MaxCD3}_t] + \beta_{46}[\mathrm{SumCD}_t][\mathrm{MaxCD3}_t]/100\ \} \qquad \text{[Eq. 3.3]}$$

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 an analysis of 25 years of historical weather data, once the parameters associated with the four 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 99.0% of the observed variability associated with the monthly 2005-2020 system loads and most input parameter estimates are statistically significant below the 0.01 significance level. Note that the summer and winter variance components were restricted to a 1.5:1 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 8.35 GWh^2; the corresponding summer component is 1.5 times this amount (12.53 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 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 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). Also, 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 2005-2020 timeframe. Nearly all back-casts 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 2021 through 2031, 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. These forecasts assume that our future PV-DG

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

Gross Monthly Demand Model (Jan 2005 - Nov 2020): GWh units
Forecasting Model: includes Weather & Economic Covariates, Fourier Effects pseudo TOU (unconstrained), 2014 Dist.system Adj, Avoided Load (PV + EE - EV) and COVID-19 Effects

Final Forecasting Equation: assumes constrained Avoided Demand Savings

Dependent Variable: GWhload Load (GWh)
Number of Observation Used: 191
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	149698	9356.12867	1120.33	<.0001
Error	174	1453.11000	8.35121		
Corrected Total	190	151151			

Root MSE	2.88985	R-Square	0.9904
Dependent Mean	182.81601	Adj R-Sq	0.9895
Coeff Var	1.58074		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	-82.95227	9.02258	-9.19	<.0001	0
PCPI	PCPI ($1,000)	1	2.51572	0.05870	42.86	<.0001	1.12041
SumMF		1	5.77616	0.30140	19.16	<.0001	1.62048
SumSS		1	5.21845	0.36482	14.30	<.0001	1.57086
SumCD		1	0.18096	0.01253	14.44	<.0001	54.29896
CDimpact		1	0.03731	0.01639	2.28	0.0240	34.69456
MxCD3		1	-0.06357	0.03342	-1.90	0.0588	10.84442
SumXHD		1	0.04167	0.01103	3.78	0.0002	3.33116
Fs1		1	-3.09779	0.75702	-4.09	<.0001	5.43711
Fc1		1	-3.78338	1.05950	-3.57	0.0005	10.38729
Fs2		1	0.55897	0.60365	0.93	0.3557	3.47975
Fc2		1	1.73013	0.50357	3.44	0.0007	2.40630
Fs2014a		1	-3.91514	0.70005	-5.59	<.0001	1.82264
Fc2014a		1	-3.96485	0.71747	-5.53	<.0001	1.85343
Fs2014b		1	4.28184	0.68974	6.21	<.0001	1.76593
Fc2014b		1	2.00946	0.70245	2.86	0.0047	1.80184
econTOU		1	6.33426	0.65973	9.60	<.0001	1.03809
avoided_load	EE+PV.DG-newEV	1	-1.05000	0			

Durbin-Watson D	1.407
Number of Observations	191
1st Order Autocorrelation	0.274

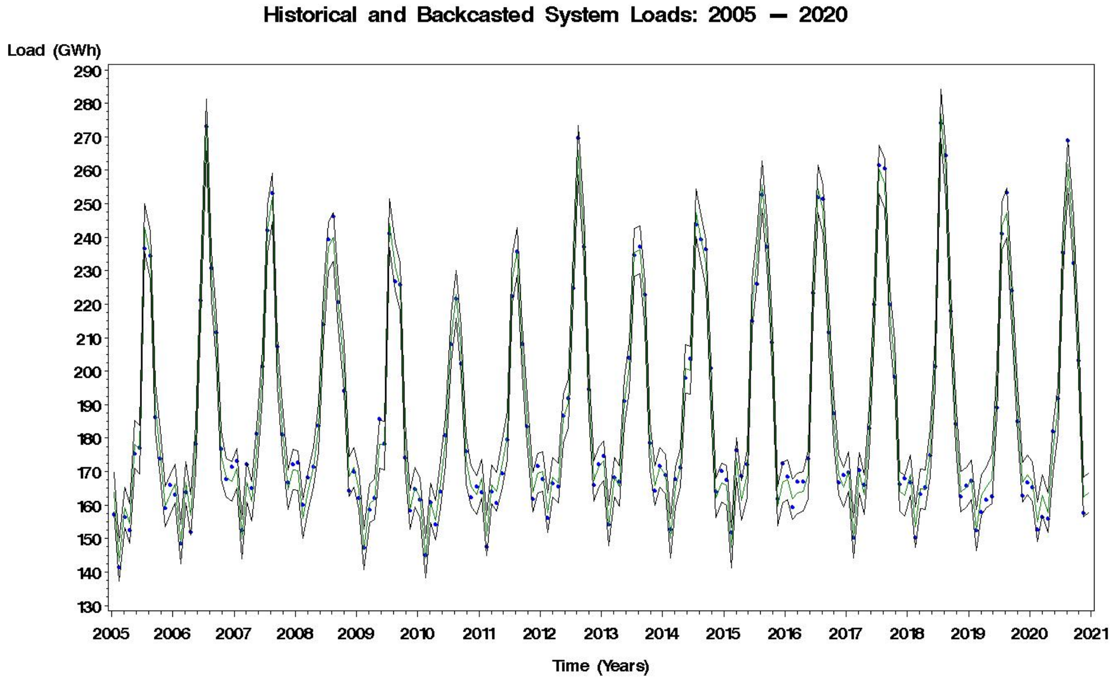

Figure 3.1. Observed and predicted total system load data (2005-2020), after adjusting for known weather conditions.

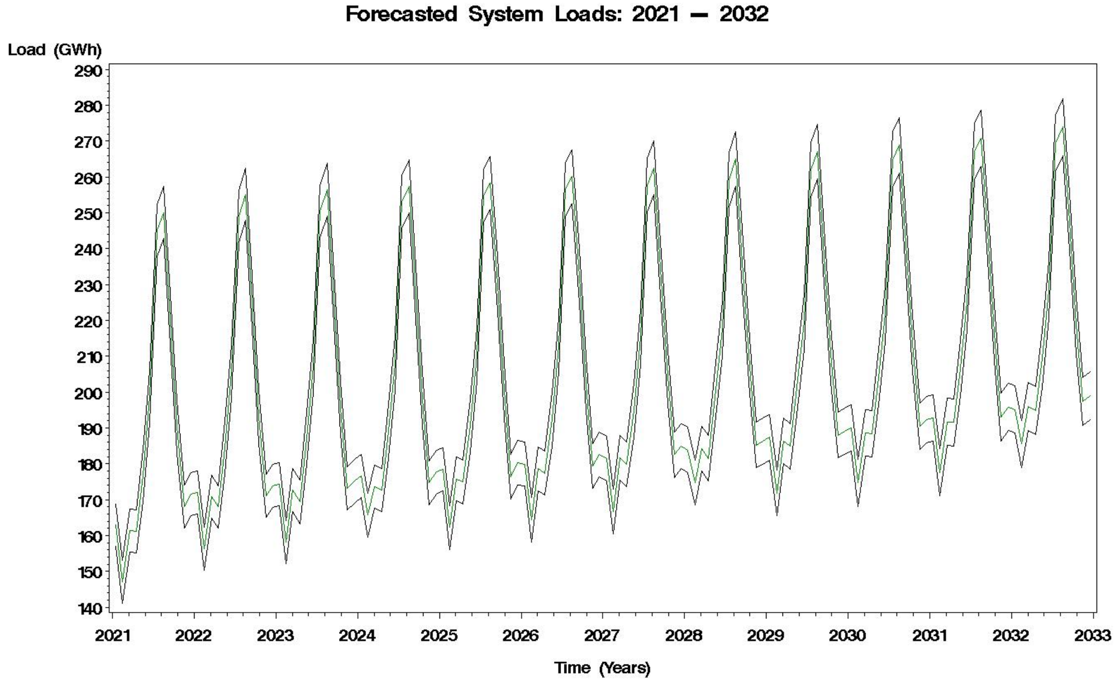

Figure 3.2. Forecasted monthly system loads for 2021-2032; 95% forecasting envelopes encompass model uncertainty only.

installation rates will stabilize at approximately 3 MW of AC capacity per year (once we pass our NEM 1.0 cap), that our future calculated EE savings rate will continue to be approximately equal to 1% of our total annual system loads, and that our near-term loads will be depressed from the COVID-19 pandemic.

Table 3.2 shows the forecasted, COVID-19 adjusted monthly RPU system loads for 2021, along with their forecasted standard deviations. In contrast to Figure 3.2, these standard deviations quantify both model and weather uncertainty. The 2021 forecasts project that our annual system load should be 2253.2 GWh, after adjusting for COVID-19 impacts and assuming that the RPU service area experiences typical weather conditions throughout the year.

Table 3.2. 2021 monthly total system load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Load (GWh)	Std.Dev (GWh)
JAN	162.9	3.25
FEB	147.0	3.57
MAR	161.4	4.21
APR	161.1	4.95
MAY	176.7	9.64
JUN	198.7	14.84
JUL	245.0	15.55
AUG	250.1	13.56
SEP	220.2	12.72
OCT	190.3	10.98
NOV	168.2	4.12
DEC	171.6	3.38
Annual TOTAL	2253.2	

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 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 constrained 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 with the same summer period (May through October). Mathematically, the model is defined as

$$y_t = \beta_0 + \beta_1[PCPI_t] + \beta_2[MaxCD3_t] + \beta_3[SumCD_t] + \beta_4[MaxHD_t] +$$

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

$$+ \beta_{11}[Fs2014a_t] + \beta_{12}[Fc2014a_t] + \beta_{13}[Fs2014b_t] + \beta_{14}[Fc2014b_t] +$$

$$\beta_{15}[econTOU_t] + \theta_1[EE_t+PV.DG_t-EV_t] + \varepsilon_{jt} \qquad \text{[Eq. 3.4]}$$

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 → January 2005) 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 425.5 and 212.7 MW^2, suggesting that the variance ratio for the seasonal errors follow a 2:1 ratio. 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

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

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 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 97.6% of the observed variability associated with the monthly 2005-2020 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 225.0 MW^2; the corresponding summer component is twice this amount (450.0 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 2005-2020 timeframe. Nearly all the back-casts 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 2021 through 2032, 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.

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

Gross Monthly Peak Model (Jan 2005 - Nov 2020): 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: 191

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	1570291	104686	465.15	<.0001
Error	175	39385	225.05919		
Corrected Total	190	1609677			

Root MSE	15.00197	R-Square	0.9755
Dependent Mean	374.03731	Adj R-Sq	0.9734
Coeff Var	4.01082		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	166.31910	11.84751	14.04	<.0001	0
PCPI	PCPI ($1,000)	1	4.37108	0.32920	13.28	<.0001	1.17885
MxCD3		1	2.98118	0.18967	15.72	<.0001	10.84037
SumCD		1	0.17405	0.04466	3.90	0.0001	20.61478
MxHD1		1	1.33265	0.56686	2.35	0.0198	4.20399
Fs1		1	-16.26615	4.40805	-3.69	0.0003	6.06140
Fc1		1	-27.12852	6.06109	-4.48	<.0001	10.84040
Fs2		1	2.55860	3.66934	0.70	0.4865	4.29232
Fc2		1	-0.06537	2.81182	-0.02	0.9815	2.50282
Fs3		1	6.91602	2.13111	3.25	0.0014	1.42698
Fc3		1	9.49408	1.86518	5.09	<.0001	1.10517
Fs2014a		1	-7.01567	3.94763	-1.78	0.0773	1.92213
Fc2014a		1	-24.36998	4.01981	-6.06	<.0001	1.90304
Fs2014b		1	7.02367	3.81688	1.84	0.0674	1.80430
Fc2014b		1	5.23356	3.89486	1.34	0.1808	1.84484
econTOU		1	13.80725	3.61382	3.82	0.0002	1.03999
avoided_peak	EE+PV-EV	1	-1.05000	0			

Durbin-Watson D	2.061
Number of Observations	191
1st Order Autocorrelation	-0.035

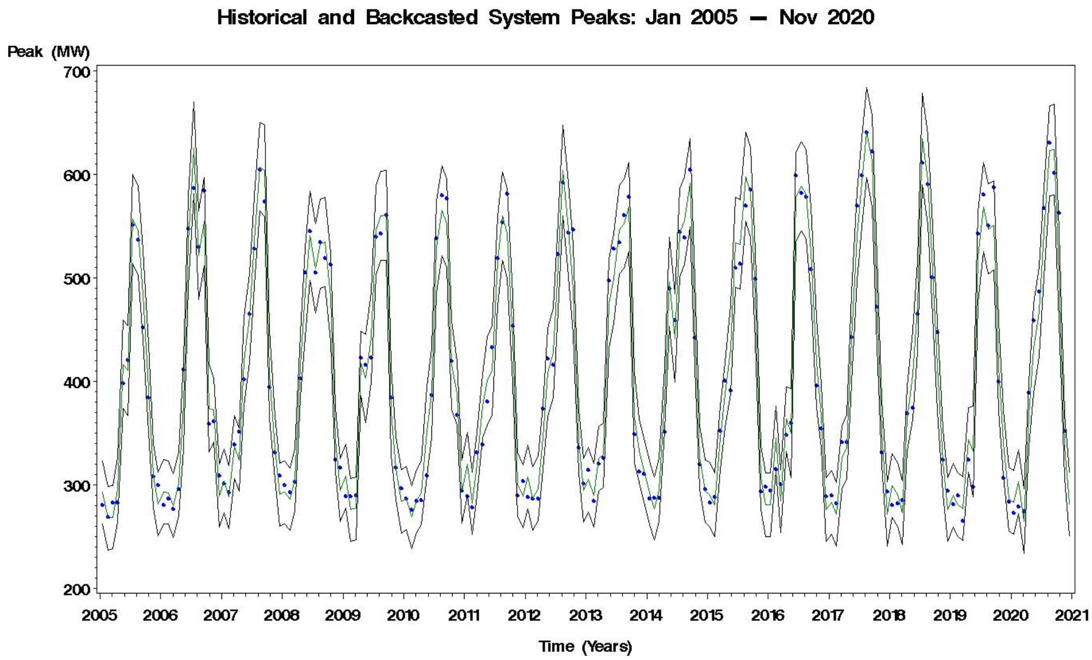

Figure 3.3. Observed and predicted system peak data (2005-2020), after adjusting for known weather conditions.

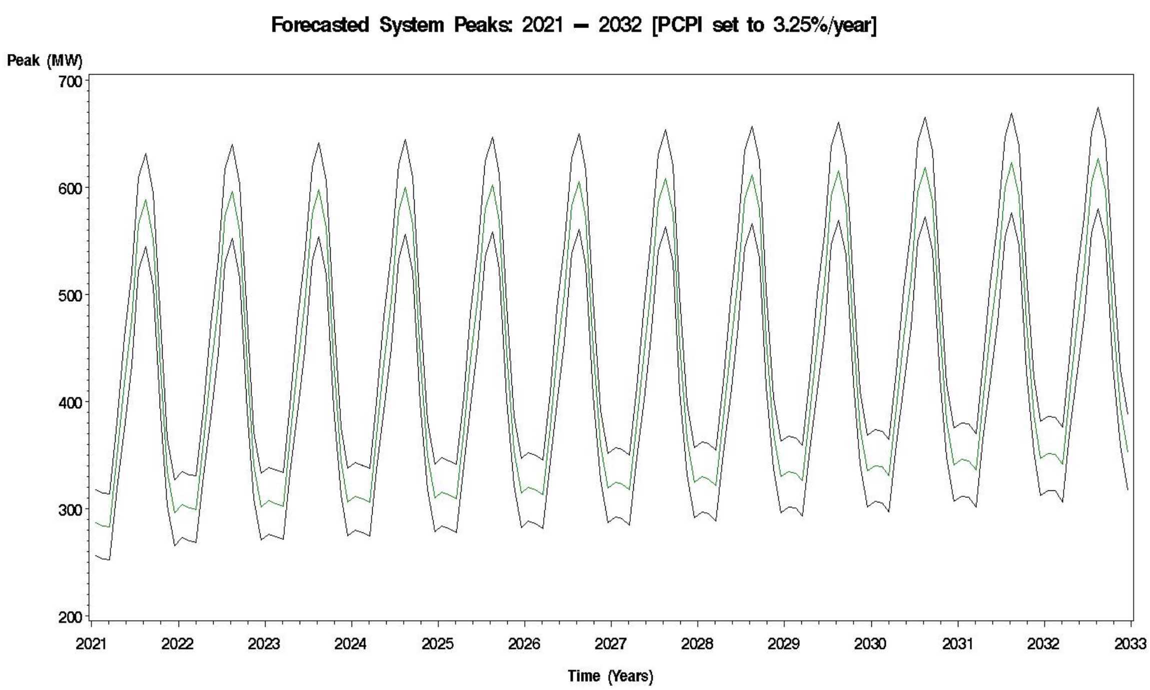

Figure 3.4. Forecasted monthly system peaks for 2021-2032; 95% forecasting envelopes encompass model uncertainty only.

Table 3.4 shows the forecasted, COVID-19 adjusted monthly RPU system peaks for 2021, along with their forecasted standard deviations. In contrast to figure 3.4, these standard deviations quantify both model and weather uncertainty. The 2021 forecasts project that our maximum monthly system peak should be about 587.9 MW and occur in August, after adjusting for the expected COVID-19 impacts and 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. 2021 monthly system peak forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Peak (MW)	Std.Dev (MW)
JAN	286.8	18.38
FEB	283.3	24.50
MAR	283.0	28.70
APR	349.1	41.14
MAY	416.5	52.32
JUN	476.8	54.12
JUL	565.3	40.00
AUG	587.9	37.37
SEP	550.9	40.80
OCT	430.0	46.68
NOV	334.1	35.89
DEC	295.8	21.57

3.5 Peak demand weather scenario forecasts

After calculating the 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 2021, our forecasted, COVID-19 adjusted 1-in-5, 1-in-10, 1-in-20 and 1-in-40 peaks are 619.4, 635.8, 649.4 and 661.1 MW, respectively.

3.6 CEC Load and Peak Forecasts for RPU versus RPU Staff Forecasts

RPU staff are aware that the CEC produces their own set of system load and peak forecasts for the City of Riverside during each annual IEPR reporting process. Historically, these CEC forecasts have been presented on the California Energy Demand Managed Forecast tables for various Demand and AAEE scenarios. Note that the most recent set of tables were published by the CEC in January 2021 (i.e., California Energy Demand 2020-2030 Managed Forecasts).

Figure 3.5 compares RPU's staff annual system load forecasts (produced by the load model discussed in section 3.2) to the most recent CEC Demand forecasts from the Mid-Demand / Low AAEE and High-Demand / Low AAEE scenarios. RPU's most recent observed annual system loads (2018-2020) are also shown in Figure 3.5 for reference purposes. As shown in Figure 3.5, the growth rate in our forecasts corresponds very closely to the forecasted CEC High-Demand / Low AAEE growth rate for the City of Riverside, although our forecasts appear to consistently be about 80 to 120 GWh/year higher than the CEC forecasts throughout the 2021-2031 forecast period. Notwithstanding this issue, staff believe that our forecasts show better alignment with RPU's most recent observed annual system loads.

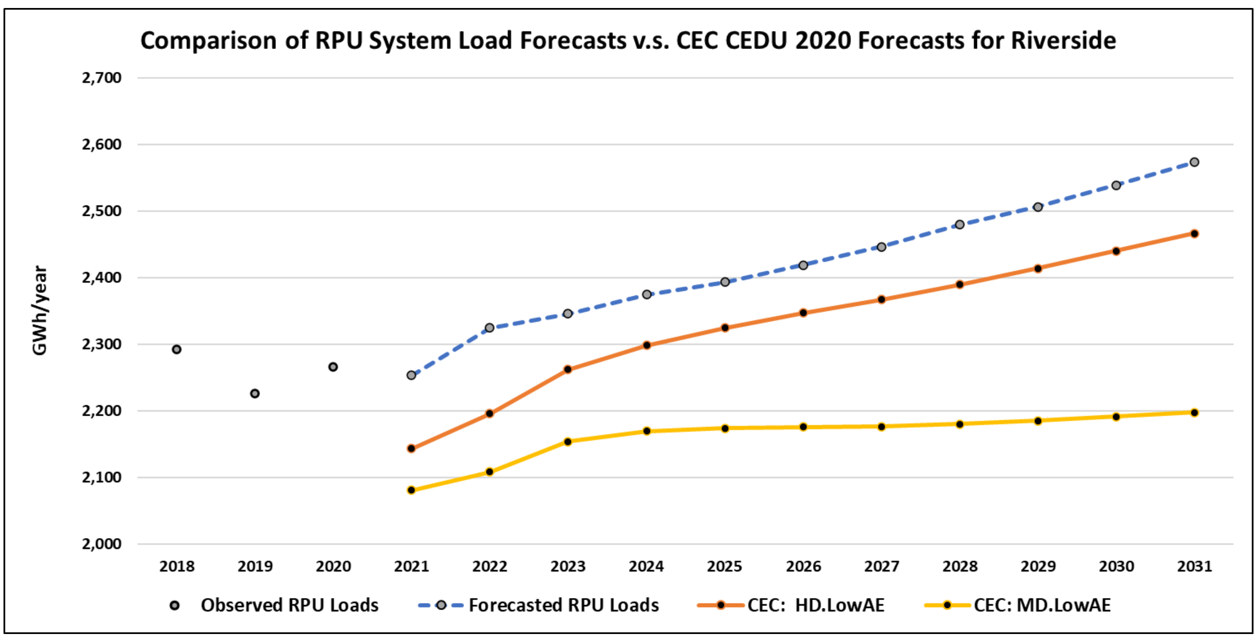

Figure 3.5. A comparison of RPU system load forecasts produced by RPU staff versus the most recent CEC CEDU demand forecasts for the City of Riverside (High-Demand / Low AAEE and Mid-Demand / Low AAEE scenarios). Observed RPU system loads for 2018-2020 also shown for reference.

Likewise, Figure 3.6 compares RPU's staff annual 1-in-2 system peak forecasts (produced by the peak model discussed in section 3.3) to the most recent CEC 1-in-2 Peak forecasts from the Mid-Demand / Low AAEE and High-Demand / Low AAEE scenarios. RPU's most recent observed annual system peaks (2018-2020) are also shown in Figure 3.6 for reference purposes. It should be noted that the CEC peak forecasts for individual cities in past CEDU publications have historically represented coincident peak forecasts, but now appear to instead represent non-coincident peak forecasts. Assuming that this is indeed the case, these RPU versus CEC forecasts should be directly comparable.

As shown in Figure 3.6, both the growth rate and absolute levels for our peak forecasts corresponds very closely to the forecasted CEC Mid-Demand / Low AAEE forecasts for the City of Riverside, throughout the 2021-2031 forecast period. Therefore, staff believe that our peak forecasts exhibit very close consistency with these latest CEC Mid-Demand / Low AAEE peak forecasts.

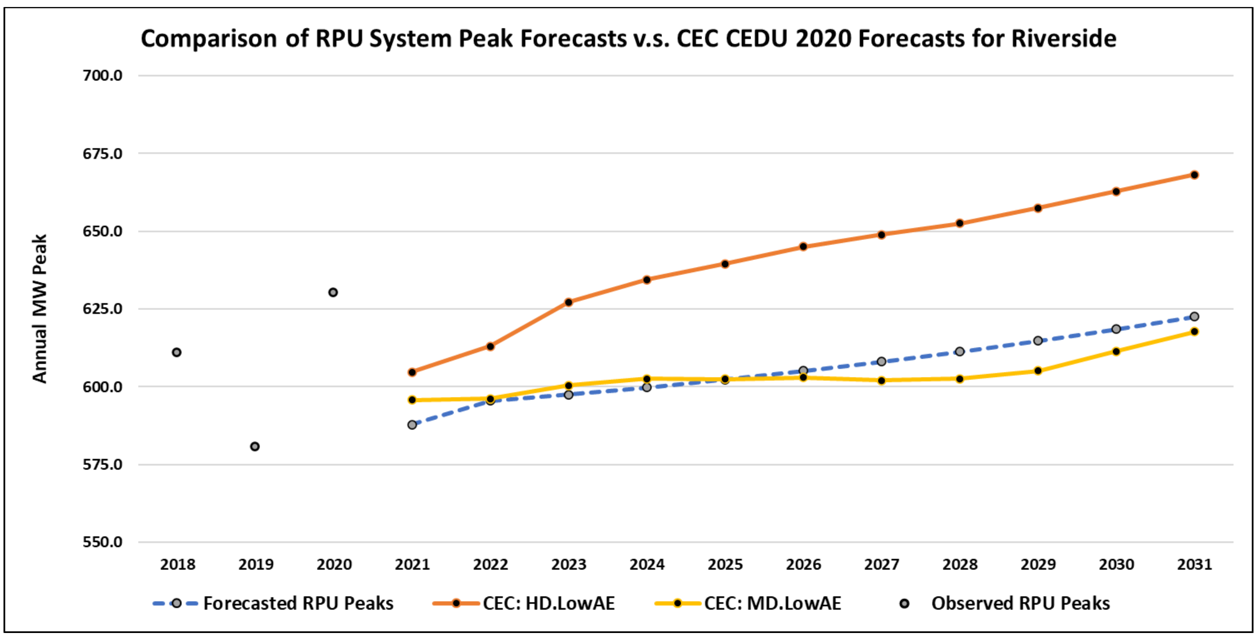

Figure 3.6. A comparison of RPU system 1-in-2 peak forecasts produced by RPU staff versus the most recent CEC CEDU 1-in-2 peak forecasts for the City of Riverside (High-Demand / Low AAEE and Mid-Demand / Low AAEE scenarios). Observed RPU system peaks for 2018-2020 also shown for reference.

4. Class-specific Retail Load Forecasts

A simplified methodology for partitioning out our system load forecasts into class specific retail load forecasts is described in this section. This new methodology was adopted in 2020 to simplify the generation of these retail forecasts, given that its accuracy is virtually equivalent to our prior, more complicated forecasting approach.

The following issues have traditionally complicated any attempts to produce a robust and statistically rigorous set of retail load forecasts. First, our retail sales data span overlapping monthly billing cycles and are subject to post-billing invoice corrections. Likewise, customers' monthly cycles can (and do) vary from 27 to 33 days per cycle, depending on when specific meter reading cycles are completed. As such, our retail load models tend to be inherently less precise and thus subject to significantly more forecasting uncertainty.

Second, RPU cannot effectively 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. Historically, we would estimate 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 (where these ratio metrics were also estimated from 10-12 years of prior retail load data).

Third, when using a direct load forecasting approach, there was not a convenient way to simultaneously constrain the annual sum of our class specific, retail forecasts to be equal to 94.6% of the forecasted annual wholesale loads. (RPU internal distribution losses have averaged 5.4% over the last 15 years.) Instead, this constraint had to be applied after-the-fact by determining a post-hoc, annual adjustment factor (f_R) computed as

$$f_R = [\, 0.946(W) - O \,] \,/\, [\, R + C + I \,]$$

where R, C, I and O represented our forecasted annual Residential, Commercial, Industrial and Other retail loads, and W represented our forecasted annual wholesale system load. Historically, this process was 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.

Due to all these issues, in 2020 staff changed to a simpler retail forecasting approach based on modeling simpler retail load ratio metrics. These load ratio metrics are then used in conjunction with a simplified (yet reasonably accurate) relationship for estimating the total monthly retail load from the current and prior month's wholesale loads to produce class specific retail forecasts. This simplified forecasting approach is described in more detail in the next section.

4.1 Calculating Retail Sales from System Load Forecasts

The following simplified methodology is currently employed to partition out our system load forecasts into class specific retail load forecasts. Let

Est.System[m] = system load forecast for month m

Res[m] = residential retail load billed during month m

Comm[m] = commercial retail load billed during month m

Indst[m] = industrial retail load billed during month m

Other[m] = all other retail load billed during month m

Retail[m] = total retail sales billed during month m = Res[m] + Comm[m] + Indst[m] + Other[m] {our four customer classes}

Res.Ratio[m] = Res[m] / [Res[m] + Comm[m] + Indst[m]]

Comm.Ratio[m] = Comm[m] / [Comm[m] + Indst[m]]

Then the following five step process can be used to produce forecasted estimates of our four customer classes which (after adjusting for expected system losses) automatically align with our system load forecasts.

Steps / Methodology:

1. Forecast Est.Retail[m] = α(Est.System[m]) + β(Est.System[m-1])
   {weighted two month average, where $\alpha+\beta = 0.946$}

2. Forecast Est.Other[m], Est.Res.Ratio[m], Est.Comm.Ratio[m] using simple seasonal regression models

3. Compute Est.Res[m] = Est.Res.Ratio[m] x (Est.Retail[m] – Est.Other[m])

4. Compute Est.Comm[m] = Est.Comm.Ratio[m] x (Est.Retail[m] – Est.Other[m] – Est.Res[m])

5. Compute Est.Indst[m] = (1 - Est.Comm.Ratio[m]) x (Est.Retail[m] – Est.Other[m] – Est.Res[m])

High-level descriptions of steps 1 and 2 are presented below.

4.2 The System Load / Retail Load Relationship

A simple relationship can be established between our current month's MWh retail sales and our current and prior month's MWh system loads. Specifically, based on observed load and sales data from

July 2003 through June 2018, staff have determined that a reasonable forecast of the current month's retail sales can be calculated as

$$\text{Est.Retail}[m] = 0.398(\text{Est.System}[m]) + 0.548(\text{Est.System}[m-1]) \qquad \text{[Eq. 4.1]}$$

A plot of this relationship is shown in Figure 4.1 below; note that this simple regression relationship explains approximately 92% of the observed variation in the observed monthly retail load data.

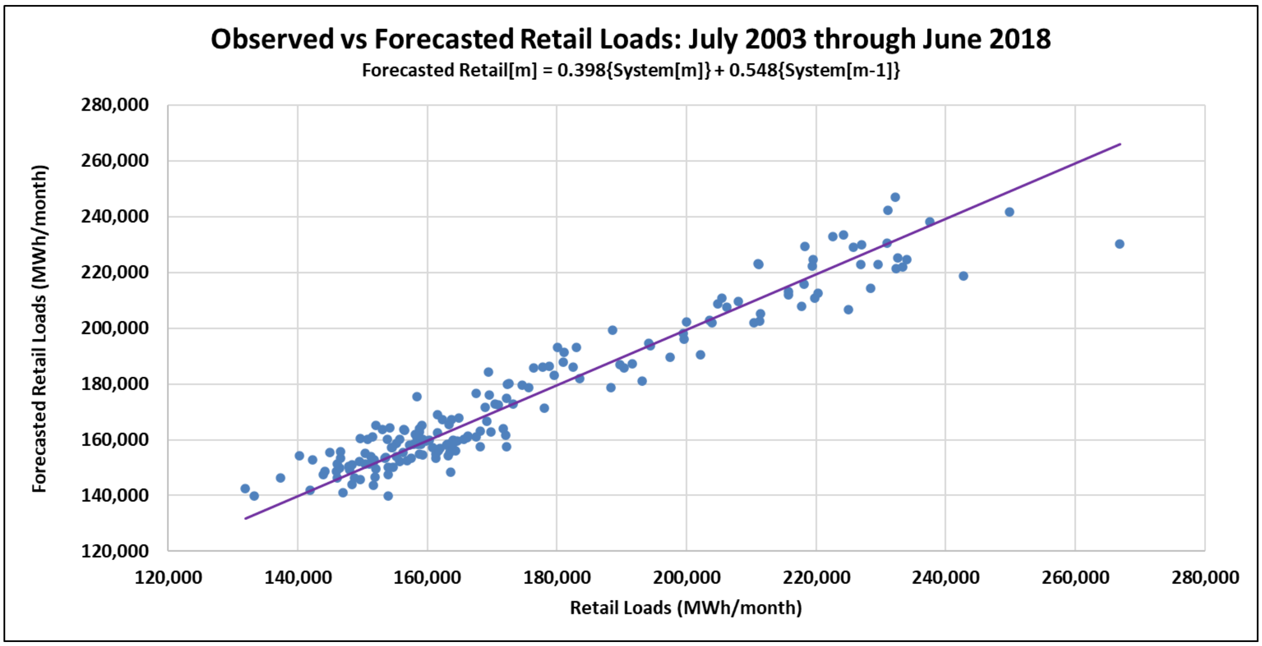

Figure 4.1. Observed versus forecasted retail load relationship: July 2003 through June 2018.

4.3 Load Forecasts for the Other Customer Class

The loads associated with the Other customer 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 2010 through June 2015, the monthly loads associated with this class exhibited a 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 removing two obvious outlier months (May 2011 and 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 was incorporated into the model. Hence, the simplified seasonal load forecasting model for this customer class was defined to be a function of six low order Fourier frequencies and one indicator variable to account for this load migration effect. The corresponding equation (derived using ordinary least squares) describes about 85% of the observed load variation associated with the monthly data from January 2010 through November 2020; a plot of the forecasted versus observed loads for the Other customer class is shown in Figure 4.2 below.

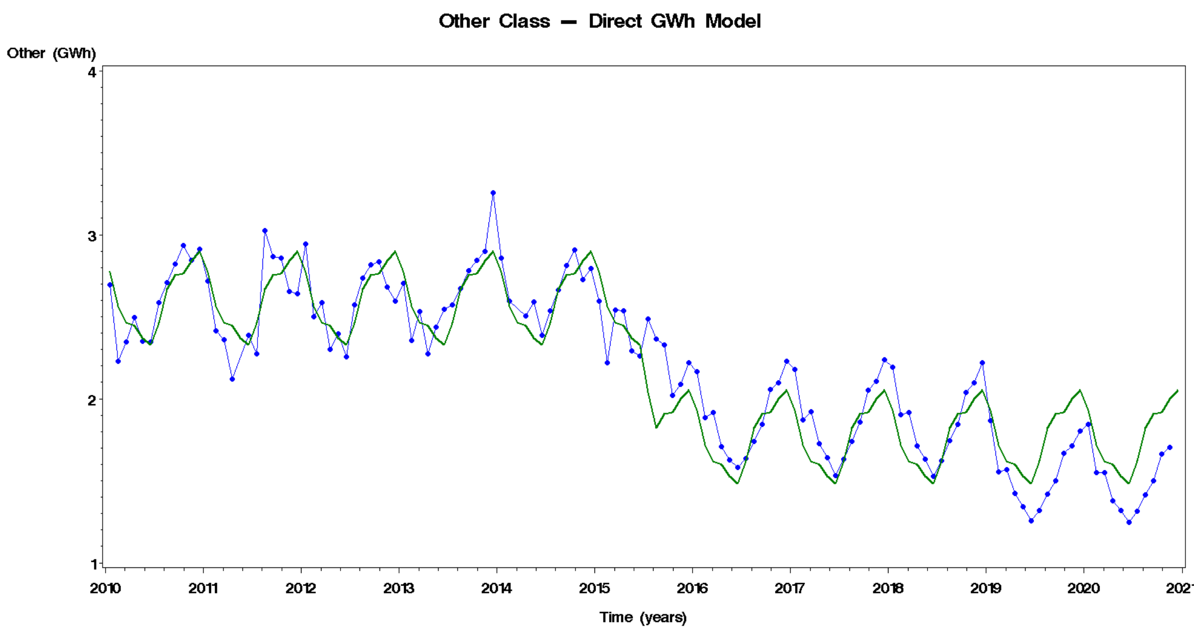

Figure 4.2. Predicted versus observed loads: Other customer class, January 2010 through November 2020.

4.4 Residential and Commercial Load Ratio Models

In addition to the guaranteed alignment of all retail load forecasts with the forecasted system load, the modeling of load ratios is also advantageous because the models themselves are quite simple. A simplified seasonal load ratio forecasting model for the Residential customer class was defined to be a function of six low order Fourier frequencies, weighted functions of the current and prior month's cooling degrees (SumCD) and heating degrees (SumXHD), and a simple linear trend variable. Likewise, a simplified seasonal load ratio forecasting model for the Commercial customer class was defined to be a function of six low order Fourier frequencies and the EconTOU variable (which accounts for the expansion and contraction of new Industrial load during the 2011-2014 time period). Both load ratio equations were again derived via ordinary least squares using January 2010 through November 2020 calibration data.

The Residential ratio model describes about 88% of the observed load variation associated with the monthly data from January 2010 through November 2020; a plot of the forecasted versus observed loads for the Residential customer class is shown in Figure 4.3. Likewise, the Commercial ratio model describes about 70% of the observed load variation associated with the monthly data from January 2010 through November 2020; a plot of the forecasted versus observed loads for the Commercial customer class is shown in Figure 4.4.

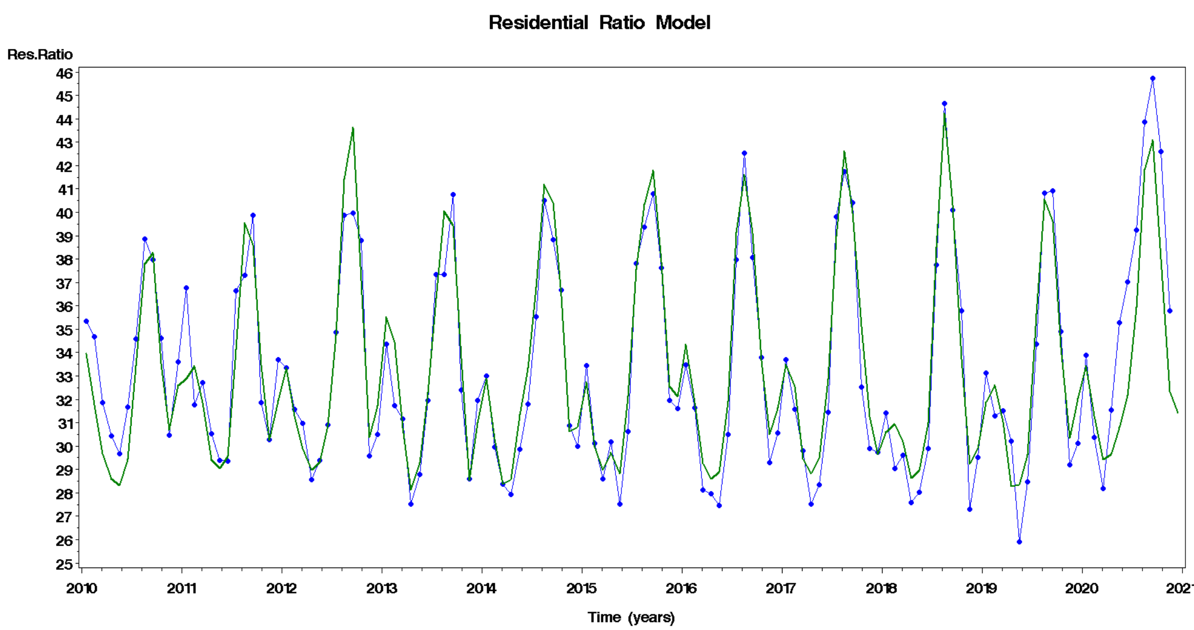

Figure 4.3. Predicted versus observed load ratios: Residential customer class, January 2010 through November 2020.

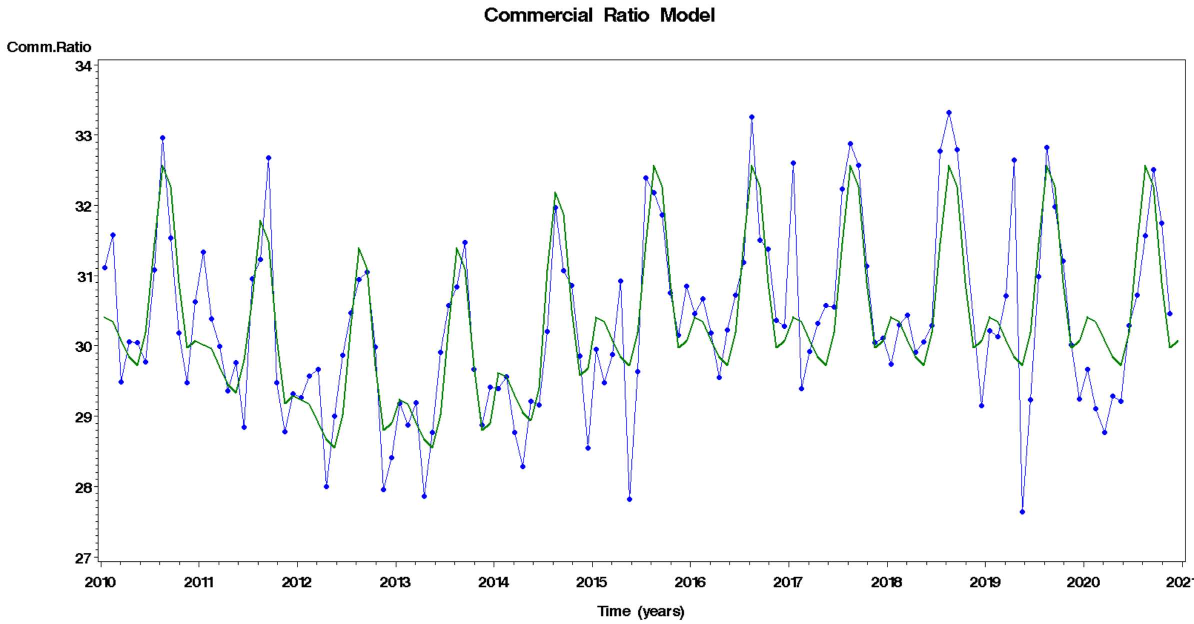

Figure 4.4. Predicted versus observed load ratios: Commercial customer class, January 2010 through November 2020.

Once the models for the Residential load ratios, Commercial load ratios and Other direct loads were established, steps 3, 4 and 5 were performed to produce the final set of retail load forecasts. A summary of these final forecasts is presented in section 4.5.

4.5 Final Retail Forecasts

The computed monthly 2021-2030 forecasts for all 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 4.1, along with our system load and peak forecasts (through 2040). It should be noted that 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.

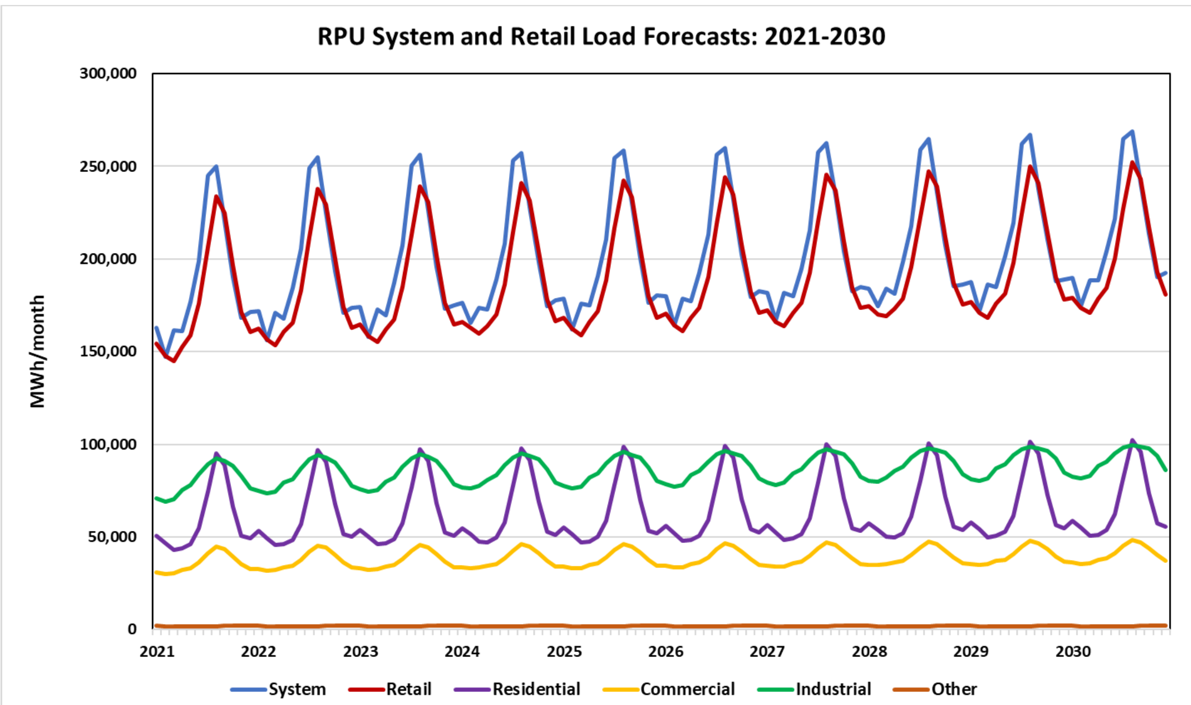

Figure 4.5. RPU monthly retail load forecasts (2021-2030) for the system load, total retail load, and the residential, commercial, industrial and other customer classes.

Table 4.8. Final system load (MWh), system peak (MW) and retail load (MWh) forecasts: 2021-2040.

Year	System Load	System Peak	Residential	Commercial	Industrial	Other	Total Retail
2021	2,253,177	587.9	709,148	429,245	967,528	21,188	2,127,109
2022	2,324,657	595.5	732,169	443,809	1,000,729	21,188	2,197,895
2023	2,345,554	597.5	738,732	447,999	1,010,283	21,188	2,218,202
2024	2,374,184	599.8	747,215	453,453	1,022,743	21,188	2,244,599
2025	2,392,801	602.3	753,007	457,050	1,030,890	21,188	2,262,136
2026	2,418,609	605.1	761,017	462,127	1,042,447	21,188	2,286,780
2027	2,446,080	608.1	769,432	467,466	1,054,604	21,188	2,312,690
2028	2,479,611	611.3	779,844	474,123	1,069,789	21,188	2,344,943
2029	2,506,117	614.8	787,879	479,126	1,081,135	21,188	2,369,327
2030	2,538,757	618.5	797,834	485,398	1,095,397	21,188	2,399,817
2031	2,573,214	622.5	808,451	492,086	1,110,604	21,188	2,432,330
2032	2,614,973	626.8	821,315	500,276	1,129,273	21,188	2,472,053
2033	2,647,235	631.3	831,461	506,580	1,143,559	21,188	2,502,789
2034	2,687,479	636.2	843,856	514,394	1,161,330	21,188	2,540,768
2035	2,730,338	641.3	856,977	522,649	1,180,097	21,188	2,580,911
2036	2,780,140	646.7	872,074	532,204	1,201,848	21,188	2,627,314
2037	2,821,376	652.5	885,104	540,311	1,220,229	21,188	2,666,833
2038	2,870,253	658.6	900,189	549,797	1,241,792	21,188	2,712,966
2039	2,920,910	665.0	915,960	559,685	1,264,252	21,188	2,761,085
2040	2,980,313	671.8	934,200	571,233	1,290,547	21,188	2,817,168