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

2022 Annual Report

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

Date: **April 30, 2022**

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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 ratio models are also used in conjunction with the system load forecasts to predict 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 2007. 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) annual per capita personal income (PCPI) and monthly labor employment (Labor_Emp) econometric input variables 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 Light-duty and Medium/Heavy-duty Electric Vehicle (EV) penetration levels and anticipated Building Electrification (fuel switching) 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 currently 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 <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 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

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

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

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.
- Additional future expected load directly attributable to building electrification (fuel switching) 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, 2.7 and 2.8 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, load gain due to vehicle electrification within the RPU service territory, and load gain due to anticipated future building electrification, respectively.

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	Forecasting Eqns. SP
Economic	PCPI	Per Capita Personal Income ($1000 units)	X	X
	Emp_CC	Labor Employment Level (100,000 units)	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
	SqCD	(SumCD/100) squared		X
	SumXHD	Sum of monthly XHD's	X	
	MaxHD1	Maximum 1-day XHD in month		X
	MaxCD3	Maximum concurrent 3-day CD sum in month		X
	Summer2020	SumCD's for 2020	X	
	Summer2021	SumCD's for 2021	X	
Structural (TOU,EE,PV,EV)	EconTOU	Expansion/contraction of New Industrial load	X	X
	Avoided_Load	Cumulative EE+PV-EV-BE load (GWh: calculated)	X	
	Avoided_Peak	Cumulative EE+PV-EV-BE 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 monthly employment (Labor_Emp) statistics have been obtained from the CA Department of Finance (http://www.labormarketinfo.edd.ca.gov). 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); likewise, forecasts of future Labor_Emp levels reflect the current 10-year historical average for the region (e.g., 2.5% employment growth per year). As previously stated, these data correspond to the Riverside-Ontario-San Bernardino metropolitan service area. Note that we have (re) introduced the Labor_Emp economic driver in all our forecasting models because this economic variable closely tracks the temporary load reductions due to the COVID-19 pandemic (observed in 2020 and 2021).

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 January 2022.

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.

Finally, with respect to the load and peak models discussed in section 3, the future impacts from EE savings are forecasted to incrementally offset approximately 1% annual load and peak growth, respectively. These estimates represent a continuation of the average EE savings trends observed over the last 10 years.

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 11 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 March, and HE17 in April 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).

As before, 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.

Additionally, with respect to the load and peak models discussed in section 3, the future installed capacity levels associated with customer solar PV systems are forecasted to grow at 4.2 kW of capacity annually. This estimate coincides with the observed trend over the last four years.

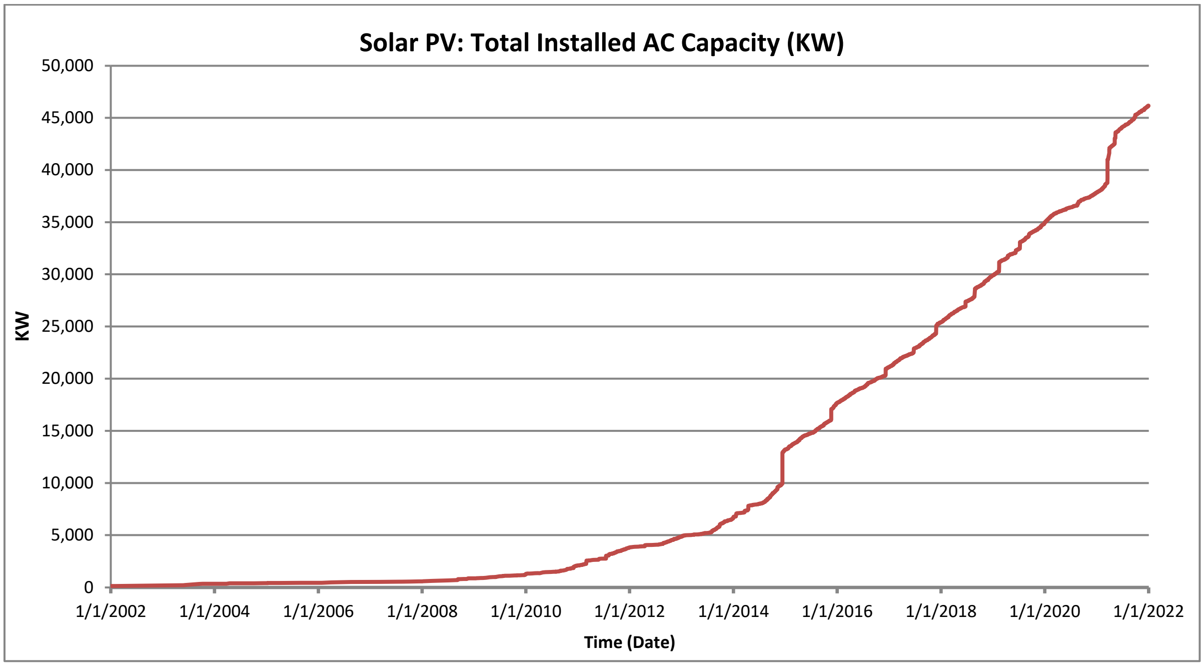

Figure 2.1. Total installed AC capacity of customer owned solar PV in the RPU service territory since 2002.

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
Apr	0.211	0.247
May	0.225	0.285
Jun	0.232	0.294
Jul	0.229	0.269
Aug	0.217	0.219
Sep	0.203	0.156
Oct	0.188	0.098
Nov	0.176	0
Dec	0.170	0

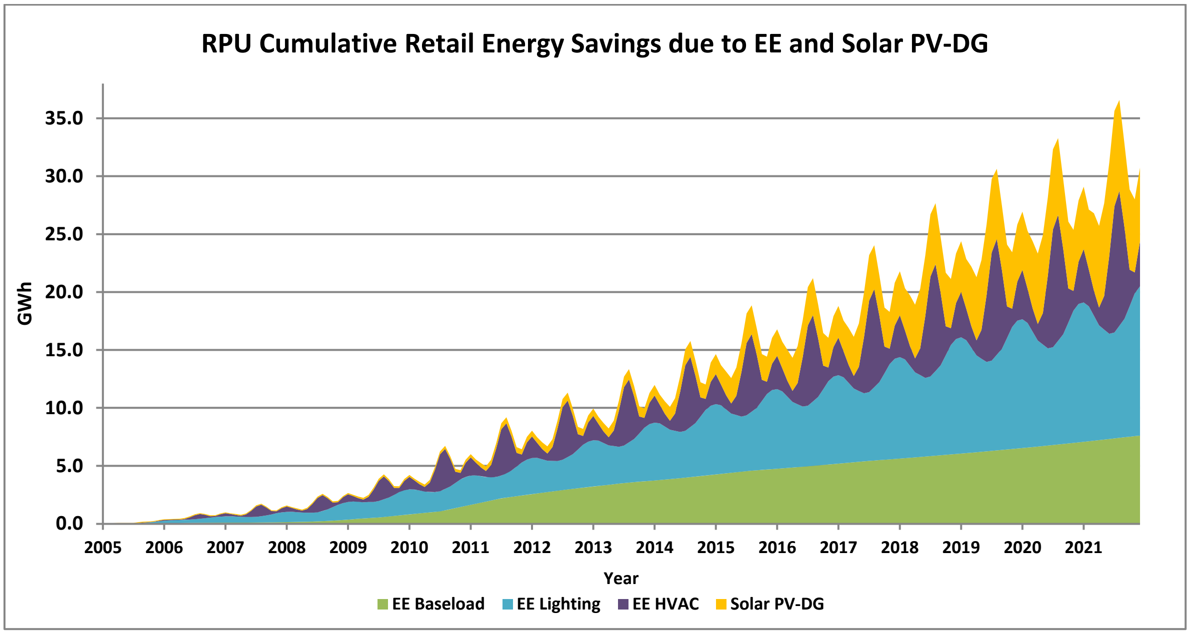

Figure 2.2. Calculated cumulative projected retail energy savings in the RPU service territory due to both EE program and solar PV distributed generation impacts over time.

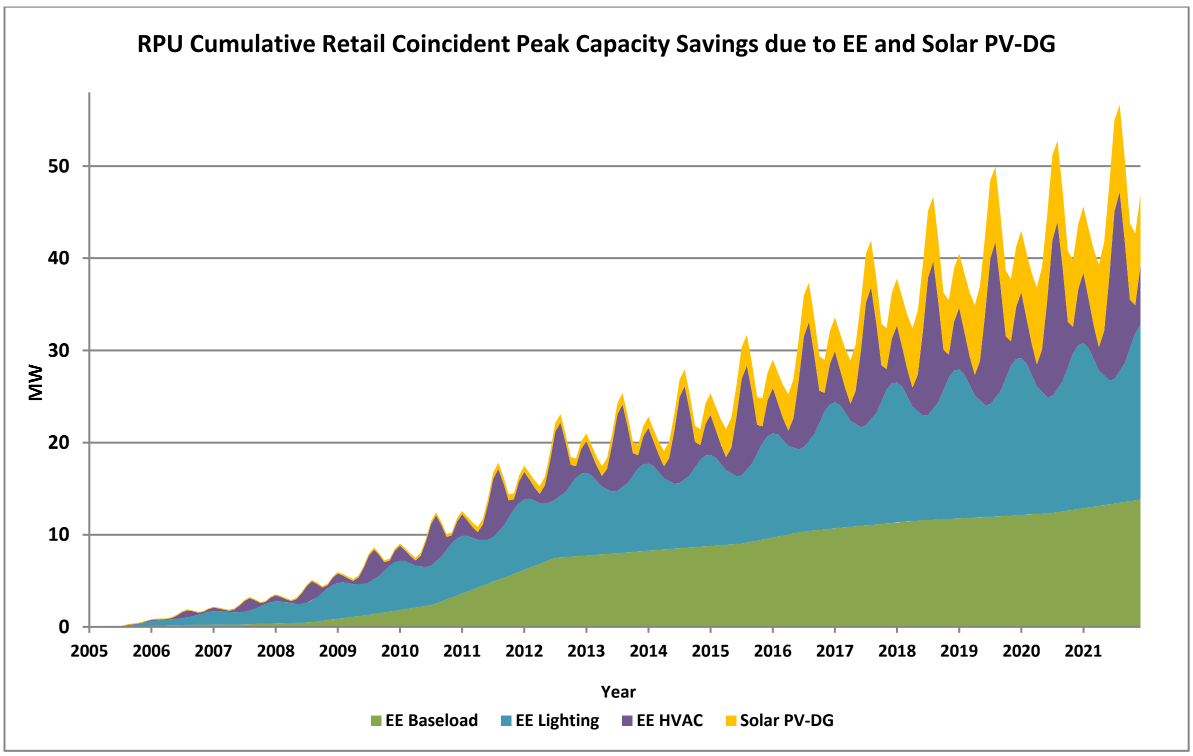

Figure 2.3. Calculated cumulative projected coincident peak capacity savings in the RPU service territory due to both EE program and solar PV distributed generation impacts over time.

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 2022 load forecasting equations to estimate our expected net Light-duty EV load growth. For baseline load forecasting purposes, we assume that Riverside will meet its share of the governors 3,500,000 EV's by 2030 mandate, based on the default 0.61% Riverside estimate that defines our service area PEV population as a percent of the state total. This target has been selected because the forecasted increase in Light-duty EVs for 2020-2021 (2,177 vehicles) closely matches the registered DMV information for our service territory (2,171 vehicles). Note that we also assume 5% distribution losses within our service territory and that 10% of our customers EV charging load is self-supplied.

Currently, Riverside does not have an independent means to estimate Medium/Heavy-duty EV load growth in our service territory. For this metric, we instead have relied on published CEC projections for the SCE service territory. More specifically, we have rescaled the SCE projections published in the 2021 CEC IEPR hourly forecast scenario[1] using a factor of 0.022214 (which represents the ratio of RPU to SCE system loads) to deduce a suitable set of forecasts for RPU.

Based on these input assumptions, Figure 2.4 shows the projected additional utility electrical load from both new Light-duty and Medium/Heavy-duty EVs entering our service territory between 2015 through 2042.[2] 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.

[1] Data obtained from the CED 2021 Hourly Forecast – SCE – Mid Baseline – AAEE Scenario 2 – AAFS Scenario 4 Excel workbook publication (TN241182).

[2] LD-EV forecasts beyond 2030 and MHD-EV forecasts beyond 2035 represent linear extrapolations.

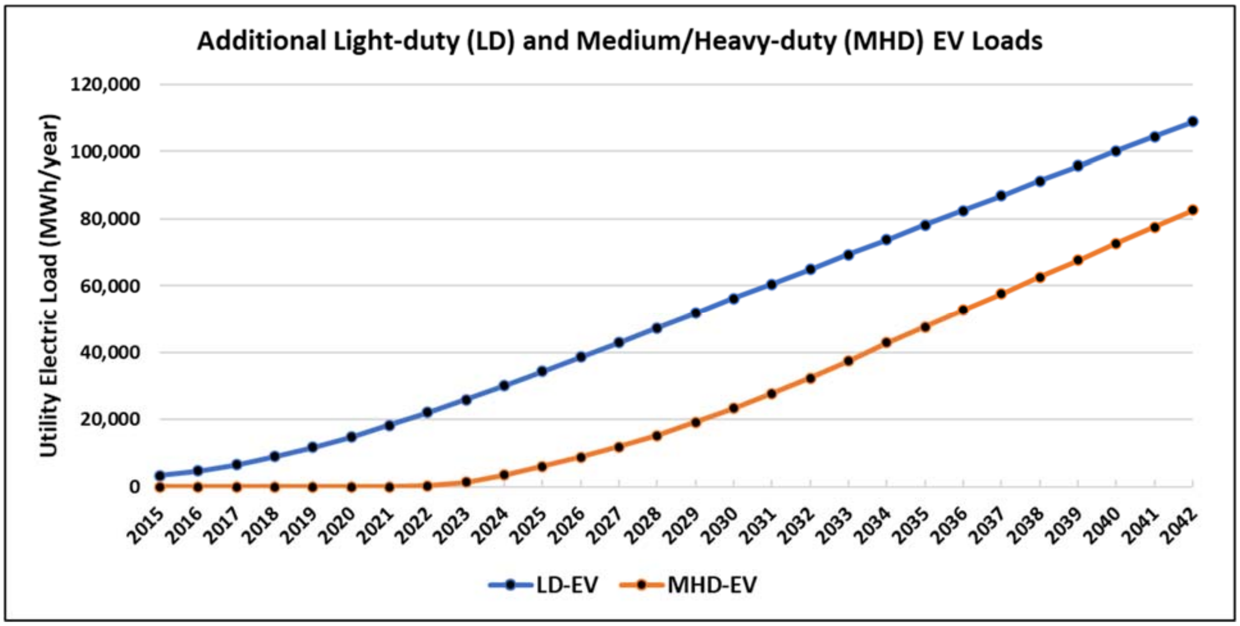

Figure 2.4. Projected 2015-2042 RPU electrical load from both Light-duty and Medium-/Heavy-duty EV penetration within our service territory.

2.8 Incremental Building Electrification (Fuel-Switching) Loads

Like Medium/Heavy-duty EVs, Riverside does not have an independent means to estimate future Building Electrification (BE) load growth in our service territory. For this last load modifier, we once again have relied on published CEC projections for the SCE service territory. As before, we have rescaled the SCE projections published in the 2021 CEC IEPR hourly forecast scenario using a factor of 0.022214 to deduce suitable BE forecasts for RPU.

Figure 2.5 shows the projected additional utility electrical load from building electrification entering our service territory, again from 2015 through 2042.[3] (Loads prior to 2021 are assumed to be 0.) Note that the bulk of the impacts of these anticipated load additions occur beyond 2030 and also appear to be quite similar to the Medium/Heavy-duty EV load forecasts.

[3] BE forecasts beyond 2035 represent linear extrapolations.

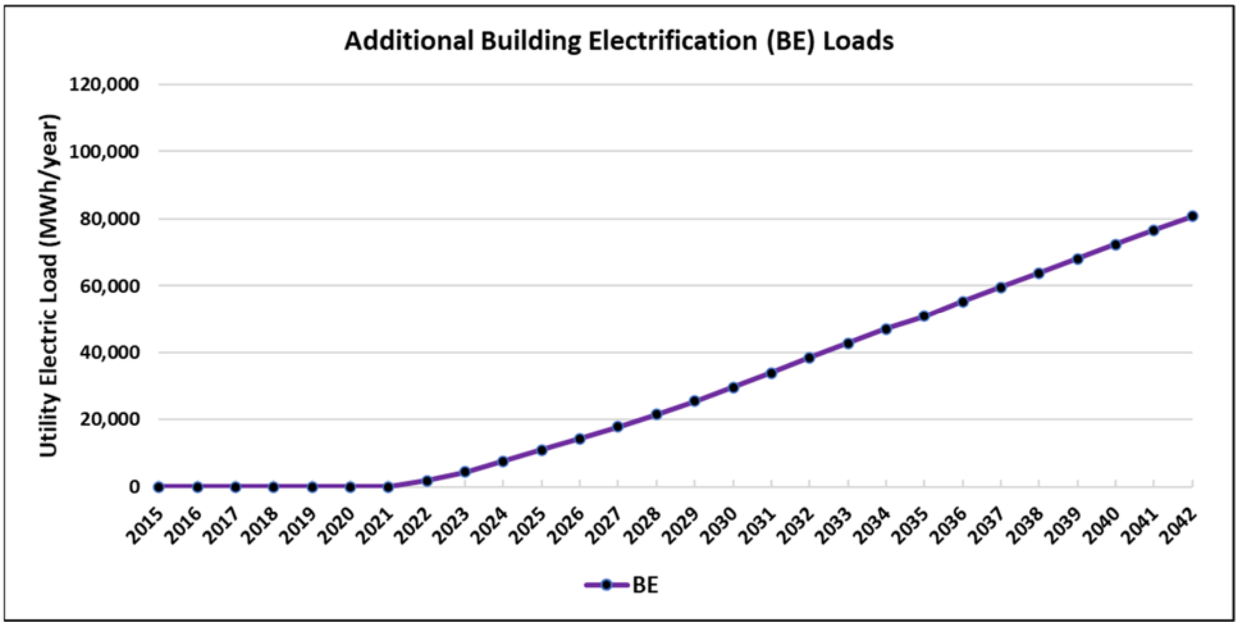

Figure 2.5. Projected 2015-2042 RPU electrical load from new building electrification (fuel-switching) activities our service territory.

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 two primary economic drivers (PCPI and Emp_CC), two calendar effects that quantify the number of weekdays (SumMF) and weekend days (SumSS) in the month, two weather effects that quantify the total monthly cooling and extended heating degrees (SumCD and SumXHD), two additional effects that allow the SumCD impact to be more pronounced in calendar years 2020 and 2021 (summer2020 and summer2021) due to the temporary impacts of more people working from home during the COVID pandemic, 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 and (incremental) EV, BE 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

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

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

$$\beta_{13}[Fs2014b_t] + \beta_{14}[Fc2014b_t] + \beta_{15}[econTOU_t] + \beta_{16}[summer2020_t] +$$

$$\beta_{17}[summer2021_t] + \theta_1[EE_t+PV_t-EV_t-BE_t] + \varepsilon_{jt} \qquad \text{[Eq. 3.1]}$$

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 2007) 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 13.3 and 6.6 GWh^2, suggesting that the variance ratio for the seasonal errors follows a 2:1 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, Emp_CC, econTOU, EE, PV, EV and BE) 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

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

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 can be approximated via an analysis of 25 years of historical weather data, once the parameters associated with the two 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 99.0% of the observed variability associated with the monthly 2007-2021 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 7.15 GWh^2; the corresponding summer component is 2 times this amount (14.30 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 either the area wide PCPI index or Emp_CC level grows over time (i.e., these economic parameter estimates are > 0). However, our load growth will grow more slowly if future EE and/or PV trends increase above their current forecasted levels, or more quickly if future EV or BE penetration levels increase above their baseline levels.

Figure 3.1 shows the observed (blue points) versus calibrated (green line) system loads for the 2007-2021 timeframe. Nearly all back-casts fall within the calculated 95% confidence envelope (thin black lines). Figure 3.2 shows the forecasted monthly system loads for 2022 through 2034, 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.

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

Gross Monthly Demand Model (January 2007 - December 2021): GWh units

Forecasting Model: includes Weather & Economic Covariates, Fourier Effects, pseudo TOU (unconstrained), 2014 Dist.system Adj and Avoided Load (EE+PV-EV-BE). Assumes constrained Avoided load savings and a 2:1 seasonal variance structure.

Dependent Variable: GWhload Load (GWh)

Number of Observations Read	468
Number of Observations Used	180
Number of Observations with Missing Values	288

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	115374	6786.71147	949.22	<.0001
Error	162	1158.26787	7.14980		
Corrected Total	179	116532			

Root MSE	2.67391	R-Square	0.9901
Dependent Mean	179.97801	Adj R-Sq	0.9890
Coeff Var	1.48569		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	Intercept	1	-114.64638	9.22313	-12.43	<.0001
PCPI	PCPI ($1,000)	1	0.28043	0.11202	2.50	0.0133
Emp_CC	Labor (100,000)	1	6.03616	0.37085	16.28	<.0001
SumMF		1	5.84761	0.29673	19.71	<.0001
SumSS		1	5.25615	0.35753	14.70	<.0001
SumCD		1	0.19787	0.00659	30.04	<.0001
SumXHD		1	0.04435	0.01024	4.33	<.0001
Fs1		1	-2.42618	0.83332	-2.91	0.0041
Fc1		1	-3.55067	1.09874	-3.23	0.0015
Fs2		1	1.48735	0.66624	2.23	0.0270
Fc2		1	1.95287	0.54811	3.56	0.0005
Fs2014a		1	-3.35594	0.73686	-4.55	<.0001
Fc2014a		1	-4.24944	0.76999	-5.52	<.0001
Fs2014b		1	3.49973	0.70004	5.00	<.0001
Fc2014b		1	2.09728	0.70474	2.98	0.0034
econTOU		1	6.56760	0.68069	9.65	<.0001
avoided_load	EE+PV-EV-BE	1	-1.05000	0	-Infty	<.0001
summer2020		1	0.01810	0.00641	2.82	0.0054
summer2021		1	0.03960	0.00716	5.53	<.0001

Durbin-Watson D	1.672
Number of Observations	180
1st Order Autocorrelation	0.160

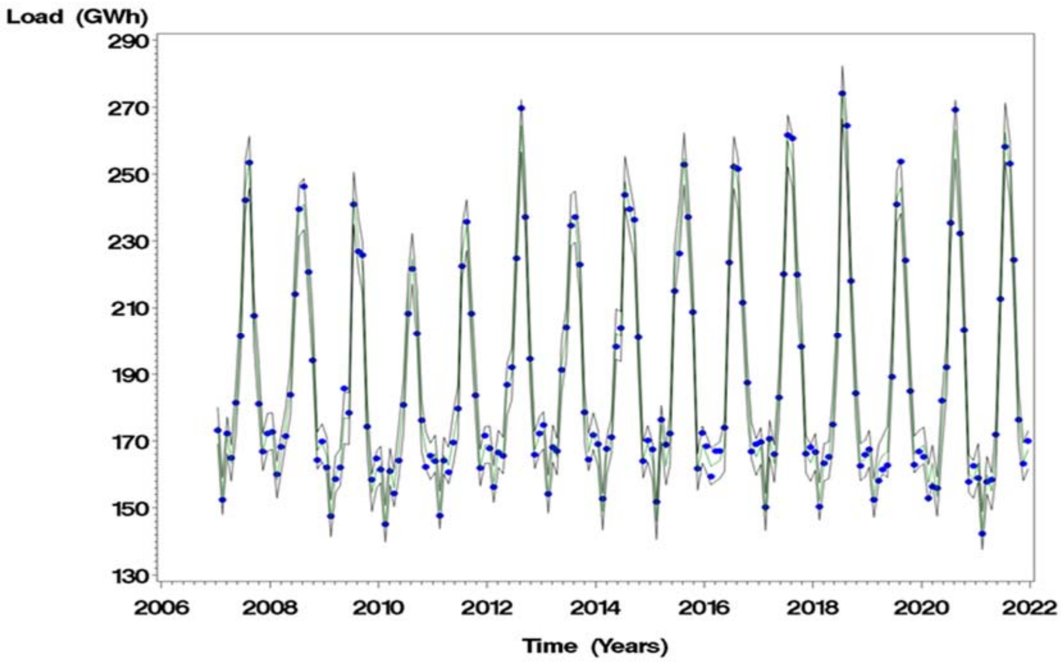

Figure 3.1. Observed and predicted total system load data (2007-2021), after adjusting for known weather conditions.

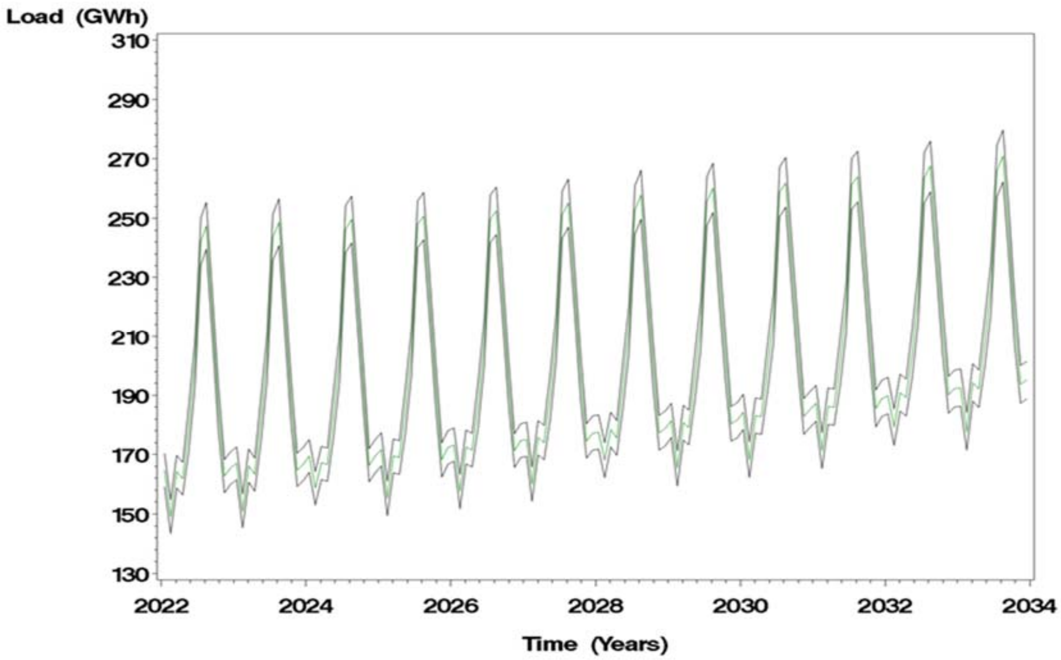

Figure 3.2. Forecasted monthly system loads for 2022-2034; 95% forecasting envelopes encompass model uncertainty only.

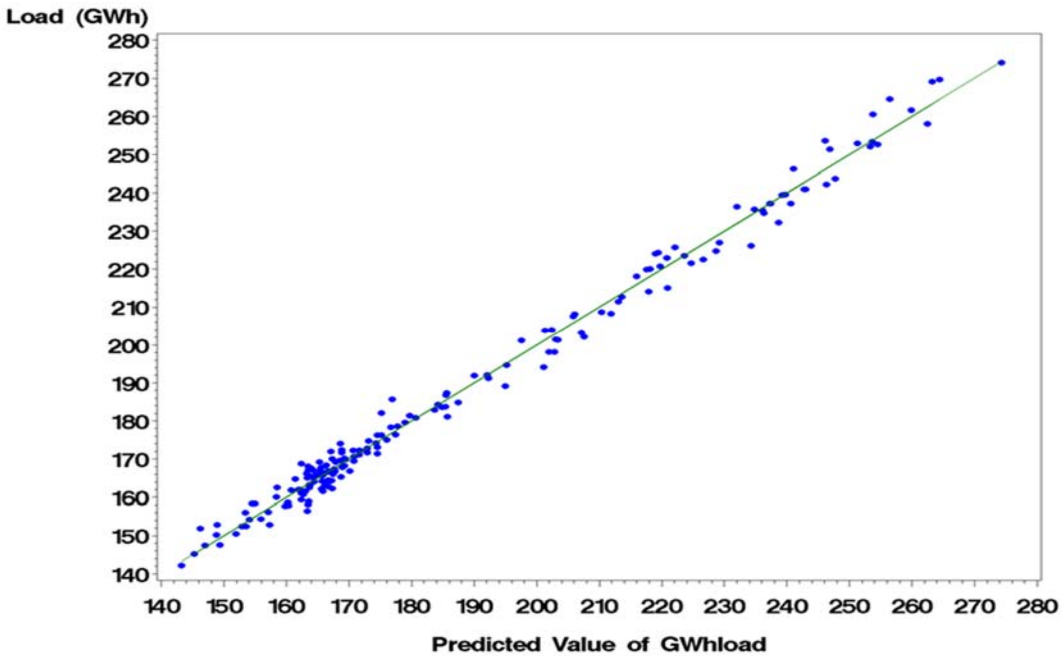

Figure 3.3. Strength of correlation between the observed versus prediction system loads shown in Figure 3.1.

Finally, Figure 3.3 shows the strength of correlation between the observed versus back-cast predicted system loads shown in Figure 3.1. Note that this observed versus calibrated load correlation exceeds 0.995.

It should be noted that these model forecasts assume that our future PV-DG installation rates will continue at 4.2 MW of AC capacity per year, that our future calculated EE savings rate will continue to be approximately equal to 1% of our total annual system loads, and that our EV and BE load additions will materialize as discussed in sections 2.7 and 2.8. Given these assumptions, Table 3.2 shows the forecasted, COVID-19 adjusted monthly RPU system loads for 2022, along with their forecasted standard deviations. In contrast to Figure 3.2, these standard deviations quantify both model and weather uncertainty. The 2022 forecasts project that our annual system load should be 2239.8 GWh, assuming that the RPU service area experiences typical weather conditions throughout the year.

Table 3.2. 2022 monthly total system load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Load (GWh)	Std.Dev (GWh)
JAN	164.60	3.20
FEB	149.16	3.57
MAR	164.22	4.39
APR	161.83	5.19
MAY	178.99	10.36
JUN	200.28	15.04
JUL	242.30	14.82
AUG	247.42	13.16
SEP	217.30	13.02
OCT	185.67	12.28
NOV	162.67	4.43
DEC	165.41	3.31
Annual TOTAL	2239.83	33.86

3.3 Monthly system peak model

The regression component of our monthly system peak forecasting model is a function of our two primary economic drivers (PCPI and Emp_CC), 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, SqCD 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. However, unlike the load forecasting model, the residual variance (mean square prediction error) component was found too not be seasonally dependent. Mathematically, the model is defined as

$$y_t = \beta_0 + \beta_1[PCPI_t] + \beta_2[Emp\_CC_t] + \beta_3[MaxCD3_t] + \beta_4[SumCD_t] + \beta_5[SqCD_t] + \beta_6[MaxHD_t] +$$

$$\beta_7[Fs(1)_t] + \beta_8[Fc(1)_t] + \beta_9[Fs(2)_t] + \beta_{10}[Fc(2)_t] + \beta_{11}[Fs(3)_t] + \beta_{12}[Fc(3)_t] +$$

$$+ \beta_{13}[Fs2014a_t] + \beta_{14}[Fc2014a_t] + \beta_{15}[Fs2014b_t] + \beta_{16}[Fc2014b_t] +$$

$$\beta_{17}[econTOU_t] + \theta_1[EE_t+PV.DG_t-EV_t] + \varepsilon_t \qquad \text{[Eq. 3.4]}$$

where

$$\varepsilon_t \sim N(0, \sigma^2). \qquad \text{[Eq. 3.5]}$$

In Eq. 3.4, y_t represents the RPU monthly system peaks (MW) for the calendar ordered monthly observations and forecasts (t=1 → January 2007) and the seasonally homogeneous 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 329.7 and 283.8 MW^2, confirming that the variance could be treated as homogeneous ($Pr > \chi2 = 0.566$). Based on these results, Eq. 3.4 was refit using ordinary 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

$$Var(\hat{y}_t) = \sigma_m^2 + Var\{ \beta_3[MaxCD3_t] + \beta_4[SumCD_t] + \beta_5[SqCD_t] + \beta_6[MaxHD_t] \} \qquad \text{[Eq. 3.6]}$$

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 97.9% of the observed variability associated with the monthly 2007-2021 system peaks. Note that the avoided peak parameter was constrained to be equal to -1.05 during the ordinary least squares analysis.

As shown in Table 3.3, the estimate for the variance component is 312.5 MW^2. An analysis of the 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, in a linear manner with the MaxCD3 and MaxHD indices and in a curve-linear manner with the SumCD index. RPU system peaks are also expected to increase as either/both the PCPI and/or Emp_CC indices improve over time (e.g., both parameter estimates are > 0). Likewise, our peak loads will grow more slowly if future EE and/or PV trends increase above their current forecasted levels, or more quickly if our EV and/or BE 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 3.4 shows the observed (blue points) versus calibrated (green line) system peaks for the 2007-2021 timeframe. Nearly all the back-casts fall within the calculated 95% confidence envelope (thin black lines). Figure 3.5 shows the forecasted monthly system peaks for 2022 through 2034, 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. Finally, Figure 3.6 shows the strength of correlation between the observed versus back-cast predicted system peaks shown in Figure 3.4. Note that this observed versus calibrated load correlation exceeds 0.985.

Table 3.4 shows the forecasted monthly RPU system peaks for 2022, along with their forecasted standard deviations. In contrast to Figure 3.5, these standard deviations quantify both model and weather uncertainty. The 2022 forecasts project that our maximum monthly system peak should be about 594.5 MW and occur in August, assuming that the RPU service area experiences typical weather conditions that month. Note that this represents a 1-in-2 peak forecast, respectively.

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

Gross Monthly Peak Model (January 2007 - December 2021): MW units

Forecasting Model: includes Weather & Economic Covariates, Fourier Effects, pseudo TOU (unconstrained), 2014 Dist.system Adj, and Avoided Peak (PV+EE-EV-FS)
Assumes constrained Avoided peak savings.

Dependent Variable: Peak Peak (MW)

Number of Observations Read	468
Number of Observations Used	180
Number of Observations with Missing Values	288

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	2342965	137821	441.00	<.0001
Error	162	50628	312.51746		
Corrected Total	179	2393592			

Root MSE	17.67816	R-Square	0.9788
Dependent Mean	407.92494	Adj R-Sq	0.9766
Coeff Var	4.33368		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	Intercept	1	151.93512	21.25969	7.15	<.0001
PCPI	PCPI ($1,000)	1	2.27332	0.51922	4.38	<.0001
Emp_CC	Labor (100,000)	1	4.28095	1.87436	2.28	0.0237
MxCD3		1	2.77469	0.20150	13.77	<.0001
SumCD		1	0.47412	0.08853	5.36	<.0001
SqCD		1	-5.55395	1.46659	-3.79	0.0002
MxHD		1	0.76295	0.68943	1.11	0.2701
Fs1		1	-8.64968	4.83337	-1.79	0.0754
Fc1		1	-12.35611	6.79653	-1.82	0.0709
Fs2		1	1.75616	3.79409	0.46	0.6441
Fc2		1	-0.38840	3.06797	-0.13	0.8994
Fs3		1	4.87650	2.21529	2.20	0.0291
Fc3		1	9.84449	2.00155	4.92	<.0001
Fs2014a		1	-8.84831	3.92285	-2.26	0.0254
Fc2014a		1	-26.22864	3.99416	-6.57	<.0001
Fs2014b		1	6.34514	3.87979	1.64	0.1039
Fc2014b		1	8.58756	3.91049	2.20	0.0295
econTOU		1	17.65800	3.91489	4.51	<.0001
avoided_peak	EE+PV-EV-BE	1	-1.05000	0	-Infty	<.0001

Durbin-Watson D	2.060
Number of Observations	180
1st Order Autocorrelation	-0.030

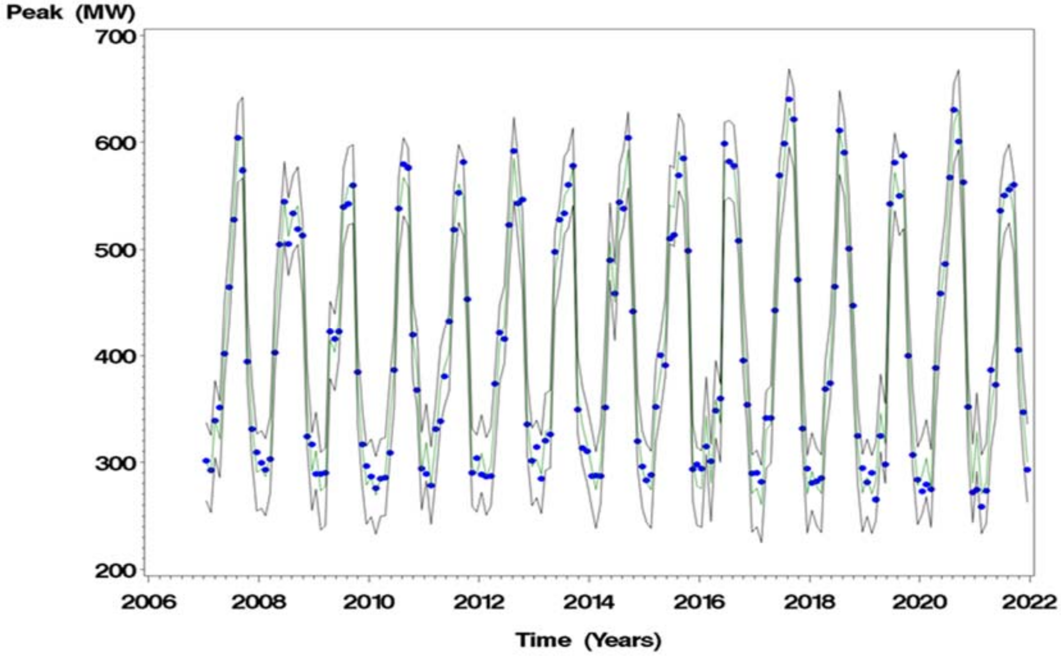

Figure 3.4. Observed and predicted system peak data (2007-2021), after adjusting for known weather conditions.

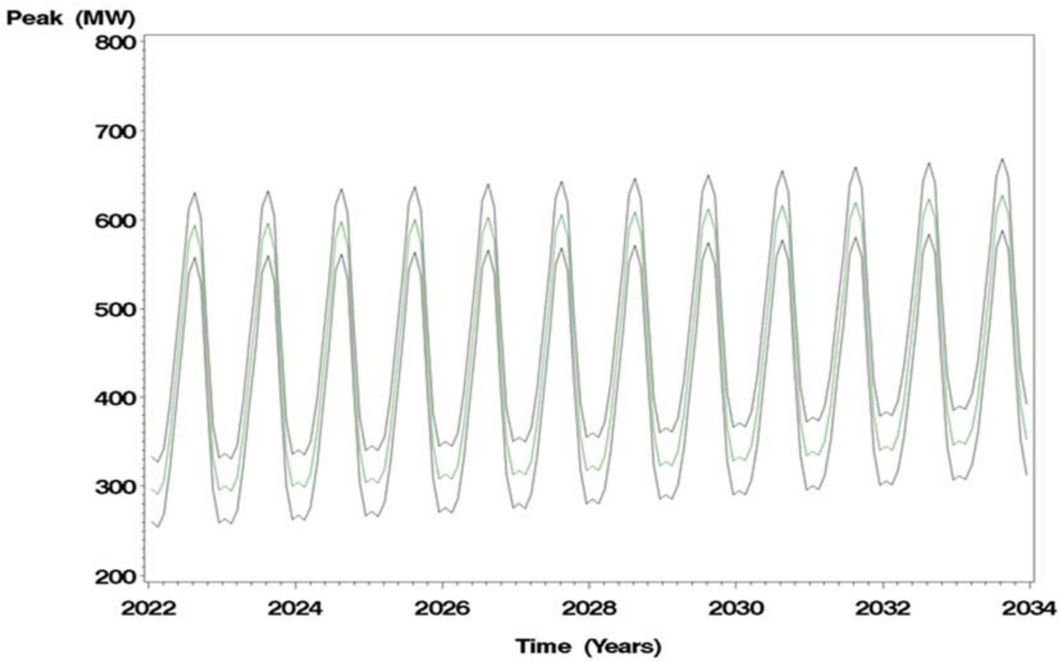

Figure 3.5. Forecasted monthly system peaks for 2022-2034; 95% forecasting envelopes encompass model uncertainty only.

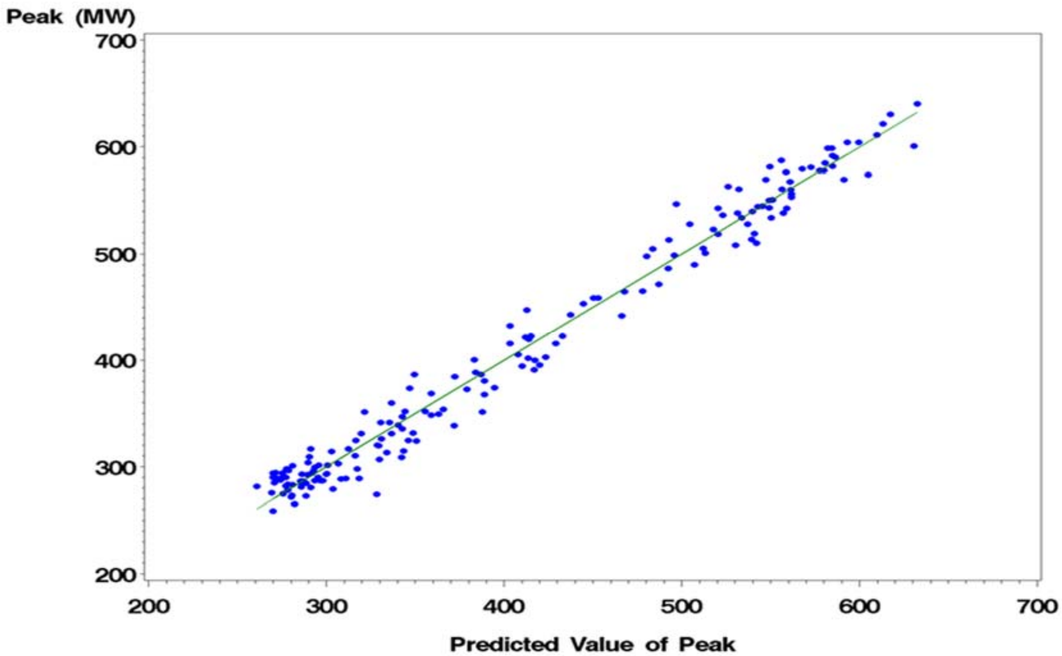

Figure 3.6. Strength of correlation between the observed versus prediction system peaks shown in Figure 3.4.

Table 3.4. 2022 monthly system peak forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Peak (MW)	Std.Dev (MW)
JAN	296.7	22.3
FEB	290.5	25.9
MAR	305.3	33.1
APR	356.2	43.9
MAY	425.2	56.9
JUN	494.4	57.7
JUL	576.1	30.5
AUG	594.5	30.6
SEP	565.5	39.3
OCT	438.8	54.2
NOV	331.7	38.8
DEC	295.4	23.6

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 2022, our forecasted, COVID-19 adjusted 1-in-5, 1-in-10, 1-in-20 and 1-in-40 peaks are 620.3, 633.7, 644.8 and 654.5 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 February 2022 (e.g., California Energy Demand 2022-2035 Managed Forecasts).

Figure 3.7 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 - AAEE Scenario 2 – AAFS Scenario 4 workbook (CEC Publication TN241384). As shown in Figure 3.7, the two forecasts align quite closely up through 2030. After 2030, the RPU forecasts begin project more load growth within the City of Riverside; staff believe that these differences are most likely due to differences in assumptions about longer-term customer solar PV load growth within the RPU service territory.

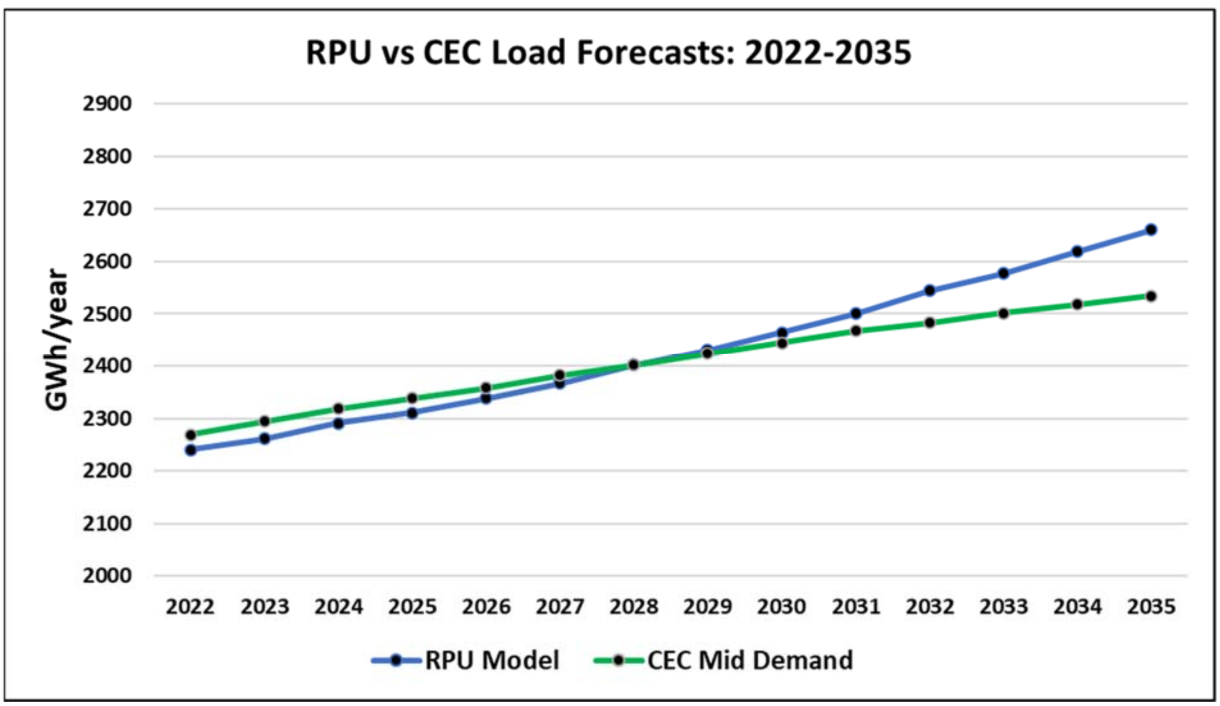

Figure 3.7. A comparison of RPU system load forecasts produced by RPU staff versus the most recent CEC CEDU demand forecasts for the City of Riverside (Mid-Demand - AAEE Scenario 2 – AAFS Scenario 4).

Likewise, Figure 3.8 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 - AAEE Scenario 2 – AAFS Scenario 4 workbook. 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 3.8, both the growth rate and absolute levels for our peak forecasts corresponds very closely to the CEC forecasts up through 2030. After 2030, the RPU forecasts tend to be 7-10 MW lower, but again exhibit similar growth rates. Therefore, staff believe that our peak forecasts exhibit close consistency with these latest CEC Mid-Demand - AAEE Scenario 2 – AAFS Scenario 4 peak forecasts.

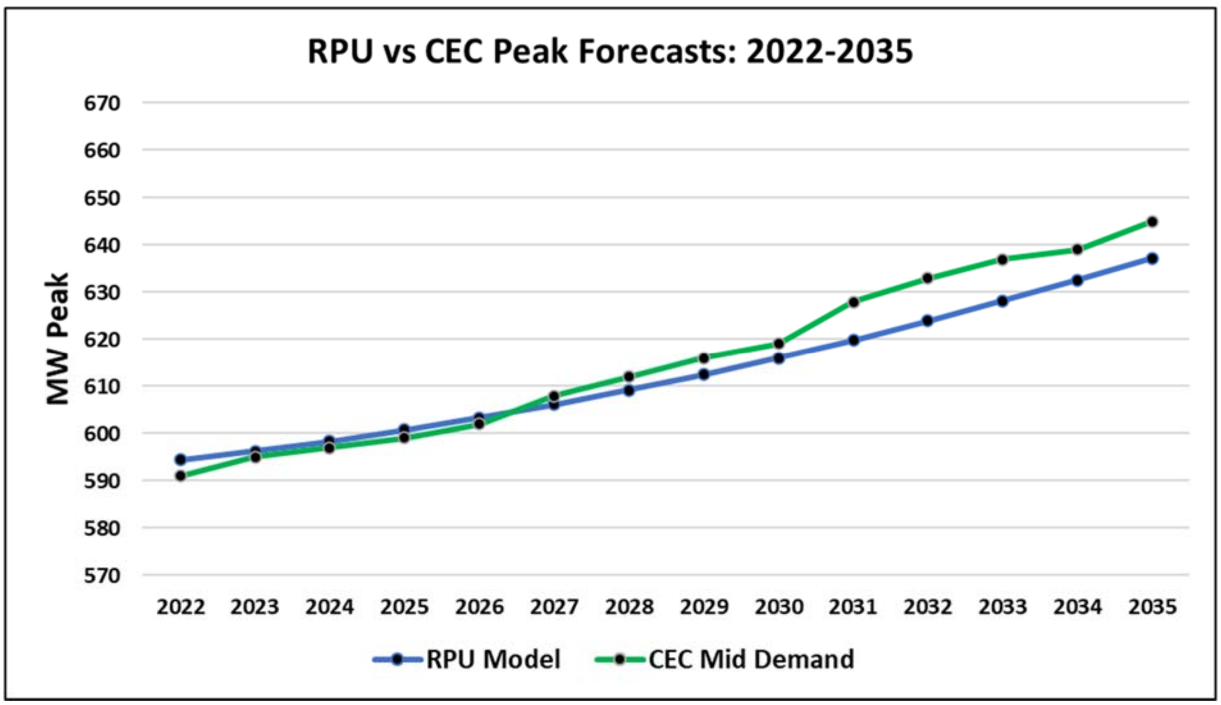

Figure 3.8. A comparison of RPU system 1-in-2 peak forecasts produced by RPU staff versus the most recent CEC CEDU 1-in-2 peak forecasts for the City of Riverside (CEC Mid-Demand - AAEE Scenario 2 – AAFS Scenario 4).

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 α+β = 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

Est.Retail[m] = 0.398(Est.System[m]) + 0.548(Est.System[m-1]) [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.

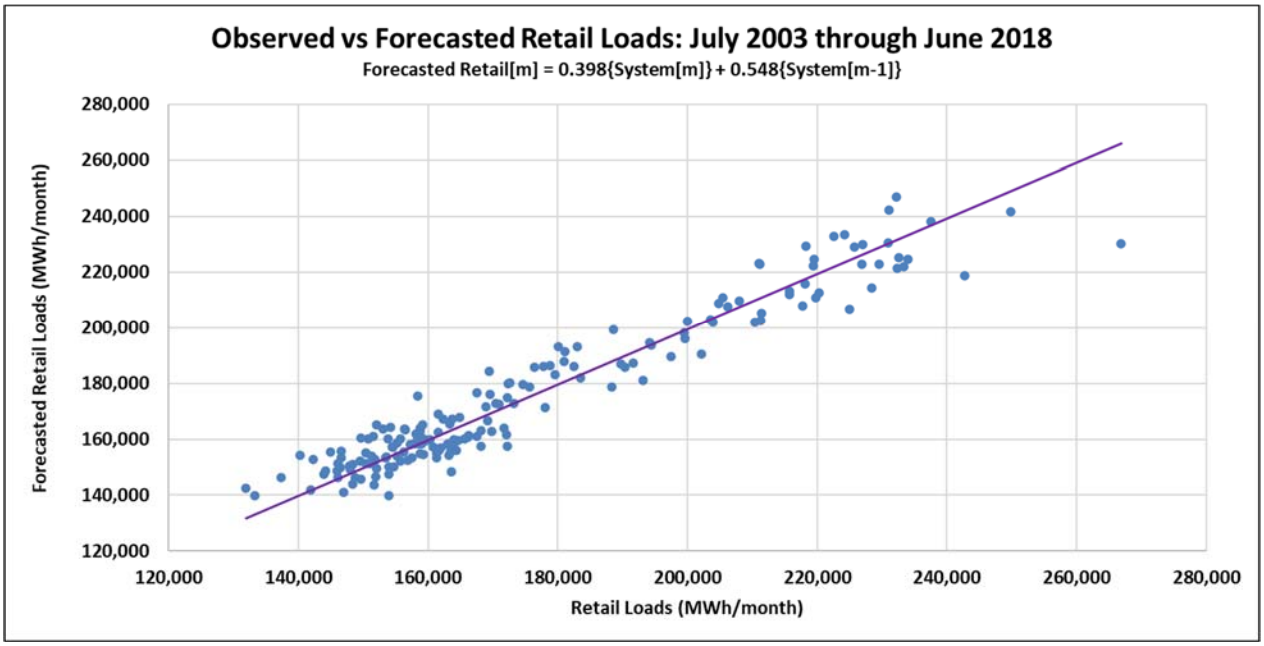

Figure 4.1. Observed versus forecasted retail load relationship: July 2003 through June 2018.

4.3 Load Forecasts for the Other Customer Class

The loads associated with the Other customer class currently account for less than 1% 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. Additionally, in January 2018 the Finance Division migrated additional accounts out of the Other class, resulting in further load reductions to this class. Again, this effect can be modeled using a second "migration-2" indicator variable (defined to be 1 on/after January 2018).

Based on the above information, the simplified seasonal load forecasting model for this customer class was defined to be a function of six low order Fourier frequencies and two indicator variables to account for this load migration effect. The corresponding equation (derived using ordinary least squares) describes about 93% of the observed load variation associated with the monthly data from January 2012 through December 2021; a plot of the forecasted versus observed loads for the Other customer class is shown in Figure 4.2 below.

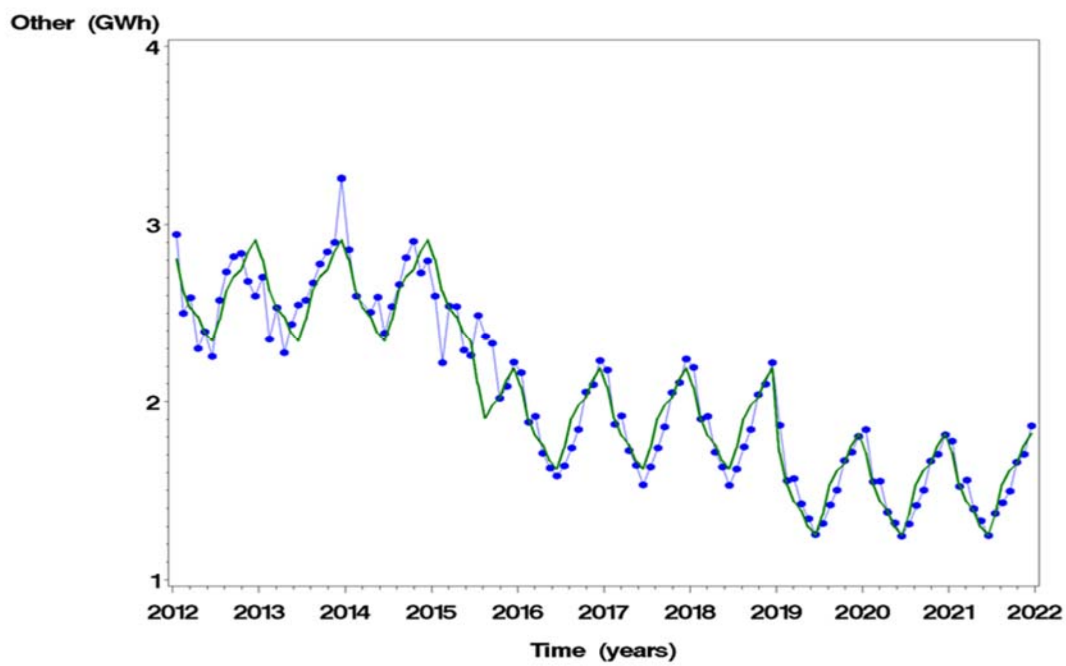

Figure 4.2. Predicted versus observed loads: Other customer class, January 2012 through December 2021.

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 one adjustment variable for modeling increased residential loads due to the COVID-19 pandemic.[4] 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 2012 through December 2021 calibration data.

The Residential ratio model describes about 94% of the observed load variation associated with the monthly data from January 2012 through December 2021; 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 66% of the observed load variation associated with the monthly data from January 2012 through December 2021; a plot of the forecasted versus observed loads for the Commercial customer class is shown in Figure 4.4.

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] This COVID indicator variable is defined to be equal to 1 from March 2020 through December 2021, equal to 0.5 from January 2022 through December 2022, and equal to 0 otherwise.

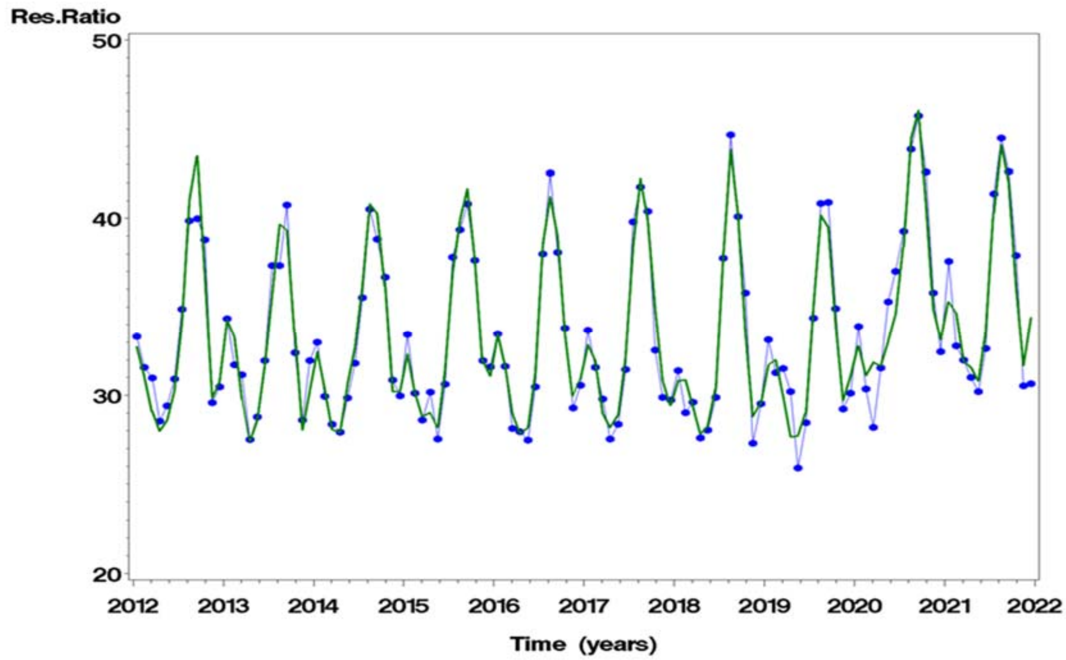

Figure 4.3. Predicted versus observed load ratios: Residential customer class, January 2012 through December 2021.

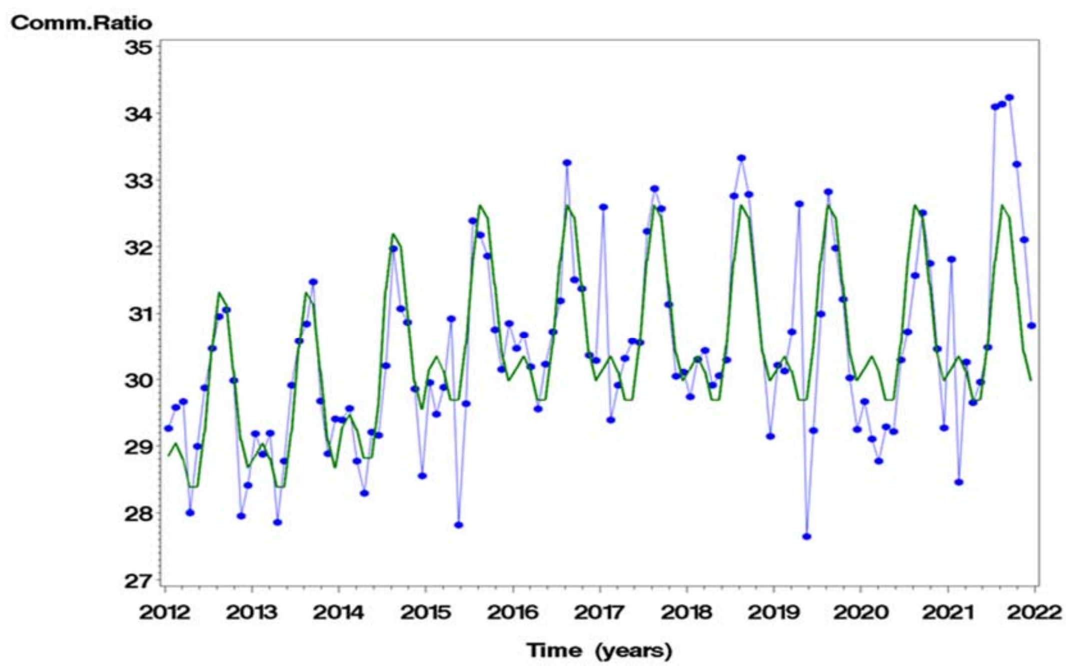

Figure 4.4. Predicted versus observed load ratios: Commercial customer class, January 2012 through December 2021.

4.5 Final Retail Forecasts

The computed monthly 2022-2042 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 2042). 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.

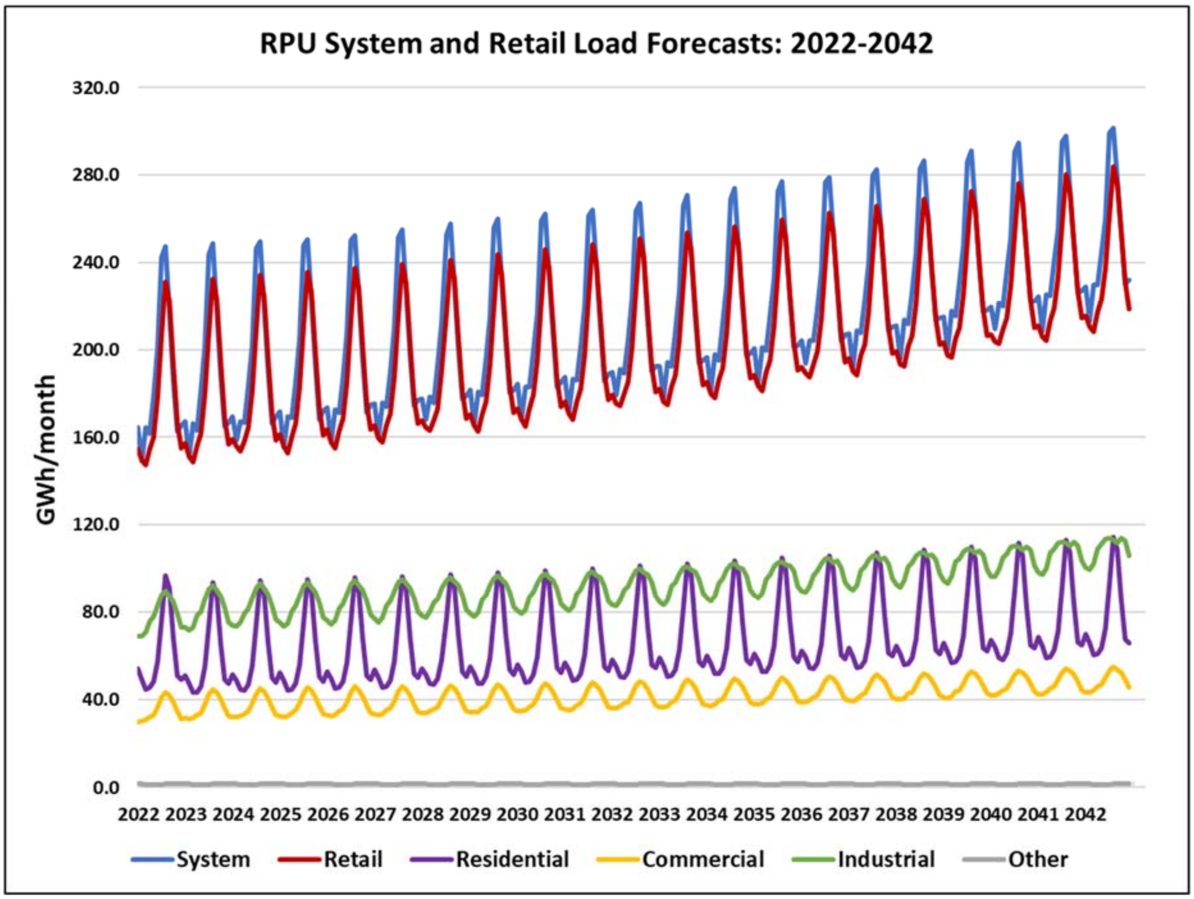

Figure 4.5. RPU monthly retail load forecasts (2022-2042) for the system load, total retail load, and the residential, commercial, industrial, and other customer classes.

Table 4.1. 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
2022	2,239,834	594.5	729,929	422,423	946,491	18,363	2,117,206
2023	2,260,840	596.3	702,518	437,276	979,884	18,363	2,138,041
2024	2,290,731	598.4	711,262	443,003	992,912	18,363	2,165,539
2025	2,310,753	600.7	717,437	446,901	1,001,689	18,363	2,184,390
2026	2,337,889	603.3	725,795	452,287	1,013,887	18,363	2,210,333
2027	2,366,730	606.2	734,553	457,937	1,026,688	18,363	2,237,541
2028	2,401,617	609.2	745,287	464,926	1,042,545	18,363	2,271,120
2029	2,429,972	612.5	753,803	470,317	1,054,698	18,363	2,297,181
2030	2,464,225	616.0	764,156	476,955	1,069,710	18,363	2,329,185
2031	2,500,416	619.8	775,199	484,036	1,085,720	18,363	2,363,318
2032	2,543,729	623.9	788,413	492,610	1,105,179	18,363	2,404,565
2033	2,577,244	628.1	798,869	499,224	1,120,072	18,363	2,436,528
2034	2,618,512	632.6	811,454	507,310	1,138,359	18,363	2,475,486
2035	2,660,749	637.3	824,262	515,522	1,156,932	18,363	2,515,078
2036	2,710,128	642.3	839,057	525,073	1,178,564	18,363	2,561,056
2037	2,750,094	647.5	851,589	533,017	1,196,477	18,363	2,599,445
2038	2,796,977	652.9	865,907	542,202	1,217,253	18,363	2,643,724
2039	2,844,879	658.6	880,684	551,649	1,238,594	18,363	2,689,290
2040	2,900,298	664.6	897,512	562,527	1,263,238	18,363	2,741,639
2041	2,947,464	670.9	911,853	571,608	1,283,708	18,363	2,785,532
2042	3,001,051	677.5	928,262	582,102	1,307,417	18,363	2,836,144