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Subject:	**RPU Wholesale & Retail Load Forecasting Methodologies:**
	December 2024 Annual Report for October 2024 Results
Participant:	**City of Riverside, Riverside Public Utilities (RPU)**
Date:	**January 27, 2025**
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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 2008. 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 expansion and contraction of industrial loads, (d) a monthly labor employment (Labor_Emp) 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 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 20+ 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. Additionally, the Power Resources Division does not forecast 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 directly administer any type of long-term, dispatchable Demand Response (DR) program within its service territory. However, RPU continues to support a Power Partners voluntary load curtailment program to call upon up to 5 MW of commercial and industrial load shedding capability during CAISO grid emergencies or extreme heat-storm events. Additionally, the UC Riverside Campus has now enrolled in the CEC DSGS Program and can respond to CEC instructed DR load reductions during similar CAISO Emergency events. Large Commercial and Industrial customers are billed under time-of-use rate structures to encourage and incentivize off-peak energy use. Finally, the Utility has no ESP's in its service territory and does not anticipate either losing any existing load or gaining any new service territory over the next ten years. However, staff do expect to see accelerated load growth over the next 10 years due to increased housing buildouts, an expected 10,000 student enrollment increase at UC Riverside, and a city-sponsored economic expansion program (that began in 2024 and is expected to continue for the next 5-7 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 16+ 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} [Eq. 2.1]

XHD = max{55-ADT, 0} [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 events, programs, and mandates:

- A scaling 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.)
- A second scaling variable for unexplained load reductions in 2023, which now appear to have been transitory in nature.
- Adjustment variables that account for a change in the historical response to maximum and cumulative cooling degrees that began back in 2019. (Note that these variables adjust the SumCD and MaxCD3 weather impact effects in the System Load and Peak forecasting models, as indicated in Table 2.1.)
- 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. Likewise, section 2.5 discusses the amount and timing of the transitory 2023 load reductions, along with some possible explanations for why these reductions occurred. Additionally, sections 2.6 through 2.9 describe how we calculate the cumulative avoided load and peak energy usage associated with RPU energy efficiency programs and rebates (2.6), load loss due to customer installed solar PV systems (2.7), load gain due to vehicle electrification within the RPU service territory (2.8), and load gain due to anticipated future building electrification (2.9), respectively.

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	Defininition	Forecasting Eqns.	
			SL	SP
Economic	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
	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
	SumCD_2019	SumCD x YTIME (interaction variable)	X	
	MaxCD3_2019	MaxCD3 x YTIME (interaction variable)		X
Structural	EconTOU	Expansion/contraction of New Industrial load	X	X
	Econ2023	Transitory load reductions in 2023	X	X
	YTIME[1]	Set to 1 for years > 2018, 0 otherwise – used for weather interactions	X	X
(TOU,EE,PV,EV)	Avoided_Load	Cumulative EE+PV-EV-BE load (GWh: calculated via engineering estimates)	X	
	Avoided_Peak	Cumulative EE+PV-EV-BE peak (MW: calculated via engineering estimates)		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	X
	Fc3	Fourier frequency (Cosine: 4 month phase)	X	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

[1] Used implicitly to create SumCD_2019 and MaxCD3_2019 variables.

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*) = Sine[*n* x 2π x [(*m*-0.5)/12}], [Eq. 2.3]

Fc(*n*) = Cosine[*n* x 2π x [(*m*-0.5)/12}], [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 lower load conditions.

2.3. Historical and forecasted inputs: economic and weather effects

The monthly employment (Labor_Emp) statistics have been obtained from the CA Department of Finance (http://www.labormarketinfo.edd.ca.gov). Note that these data correspond to the Riverside-Ontario-San Bernardino metropolitan service area. Forecasts of future Labor_Emp levels have been set to 4.5% employment growth per year through 2034 to serve as a proxy for the anticipated, accelerated load growth staff expect to see due to the impacts discussed at the end of section 1. Forecasts for Labor_Emp levels beyond 2034 are assumed to be equal to our recent 10-year historical average for the region (e.g., 2.5% employment growth per year).

All SumCD, SumXHD, MaxCD3 and MaxHD weather indices for the Riverside service area have been 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. These average monthly values are used as weather inputs for all future time periods on/after January 2025.

It should be noted that towards the end of the last decade, the residual errors associated with prior load forecasting models began manifesting an apparent "summer bias" effect, e.g., Riverside's observed summer loads began to routinely exceed their forecasts. Initially, this pattern was attributed to random, unexplained variation. However, by the end of 2021 staff correctly hypothesized that a change in customer response to summer temperature conditions had become evident, but mistakenly attributed these effects to the ongoing COVID-19 pandemic.[1] Now, having the benefit of observed load

[1] The working hypothesis at that time was that radically increased levels of telecommuting were significantly impacting (elevating) our summer residential load levels, which in turn more than offset the losses in commercial loads and thus resulted in higher overall summer system loads.

data nearly through the end of 2024, staff believe that this stronger response to summer temperature levels represents a more permanent change in customer behavior that appears to have started before the pandemic.[2] Thus, in order to model this change in customer energy-use behavior, the beta parameter slope estimates associated with the SumCD and MaxCD3 regression variables are now allowed to adjust on/after 2019 in the updated System Load and Peak forecasting equations described in this report (see sections 3.1 and 3.3, respectively).

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 within the city's electric service boundaries over an 18-month period.

[2] Statistical assessments of historical system load data suggest that this change in energy use behavior may have begun occurring as early as 2017. However, because statistical assessments of historical system peak data do not reveal significant deviations occurring until 2019, staff have elected to define 2019 as the starting year for modeling this behavior change.

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 have instead used a scaling variable in the forecasting models that will 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 relative scaling value is set to 0 for all years before 2011 and after 2014.

It is worth noting that a modified version of this historic economic incentive program was re-launched in early 2024. As part of this new program, RPU has reintroduced a two-year, discounted rate structure for businesses that relocate into Riverside. Additionally, the City has directed RPU to continue offering this incentive rate structure for the foreseeable future.

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 Temporary Load/Peak Reductions in 2023

As discussed in section 2.2, Riverside's observed 2023 monthly loads and peaks were uncharacteristically low, even after adjusting for the atypically cooler weather patterns experienced that year. Staff do not have a full understanding of why this low system load pattern materialized, but two possible explanations include (1) a larger than normal number of commercial entities continued downsizing (or went out of business) due to continuing post-COVID-19 impacts, and (2) the atypical reduction in residential load was in response to elevated inflationary pressures and the associated job market stresses experienced in 2023. Nonetheless, regardless of the underlying factor(s), an Econ2023 indicator variable has been introduced to both the system load and peak models to account for these transitory load loss effects. Table 2.4 shows how the "econ2023" indicator variable is defined, and what the resulting parameter estimate corresponds to in each equation. Note that this relative scaling value is set to 0 for all years other than 2023.

Table 2.4. Values for econ2023 indicator variable used to model RPU's 2023 transitory load reductions.

<table>
<tr><th>Year</th><th>Time Period</th><th>EconTOU value</th><td rowspan="4">A negative Load parameter value quantifies the reduction in Monthly GWh</td><td rowspan="4">A negative Peak parameter value quantifies the reduction in monthly MW peak</td></tr>
<tr><td>2023</td><td>January - June</td><td>0.50</td></tr>
<tr><td>2023</td><td>July - September</td><td>1.00</td></tr>
<tr><td>2023</td><td>October - December</td><td>0.50</td></tr>
</table>

2.6 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. Broadly speaking, 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, 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 performed in this analysis are as follows:

1. First compute the sum totals of the 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, calculate the cumulative running totals for each component from July 2005 through the most recent EE 1037 filing by performing a linear interpolation on the cumulative fiscal year components.
3. Third, 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 2.5. 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, 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.

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 2.7). 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 a regression variable containing these observations is introduced 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 decade (prior to the COVID pandemic).

Table 2.5. 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

2.7 Cumulative Solar PV installations since 2001

RPU has been tracking annual projected load and peak savings due to customer solar PV installations for the past three decades. 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 2003.

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 2.6). 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 a regression variable containing these observations is introduced 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 4,200 kW of capacity annually. This estimate coincides with the observed trend over the last five years.

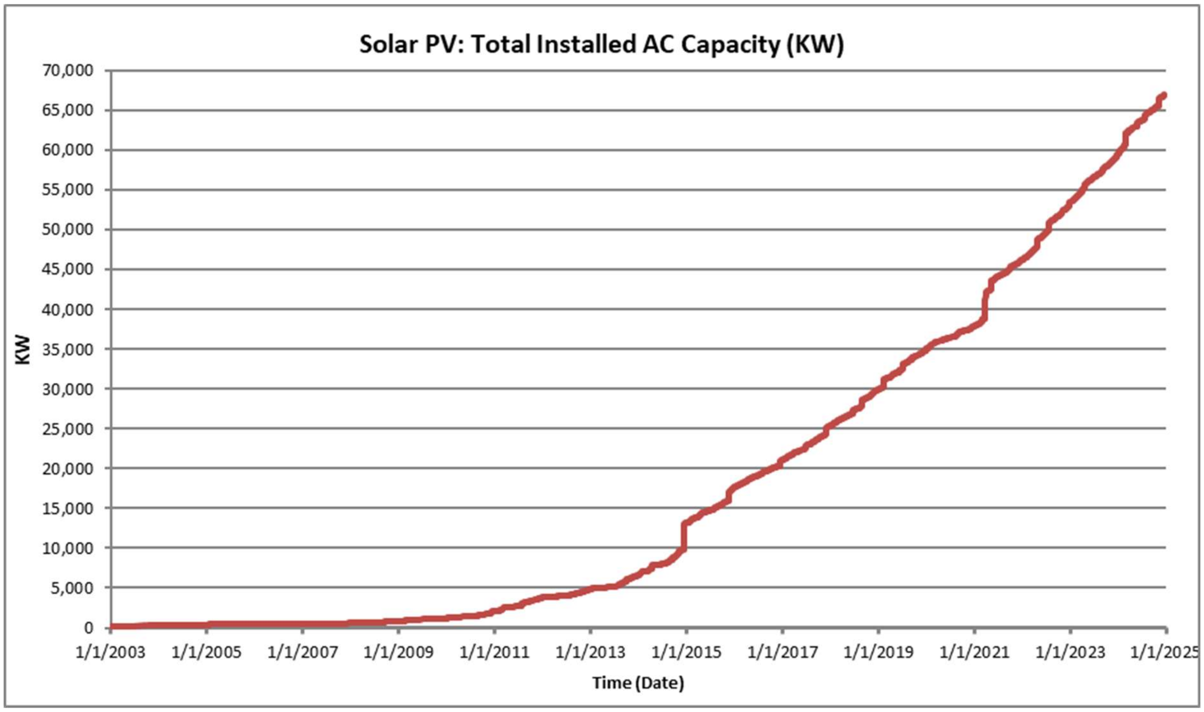

Figure 2.1. Total installed AC capacity of customer owned solar PV in the RPU service territory since 2003.

Table 2.6. 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

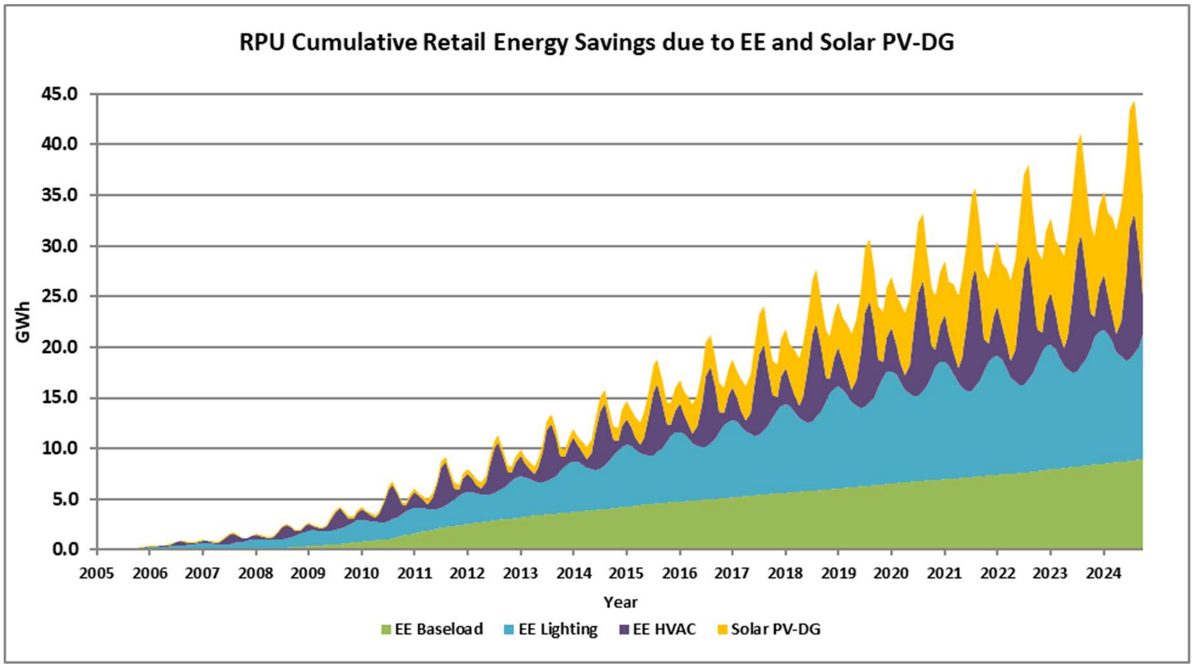

Figure 2.2. Calculated cumulative projected retail energy savings in the RPU service territory due to both EE program and solar PV distributed generation impacts over time.

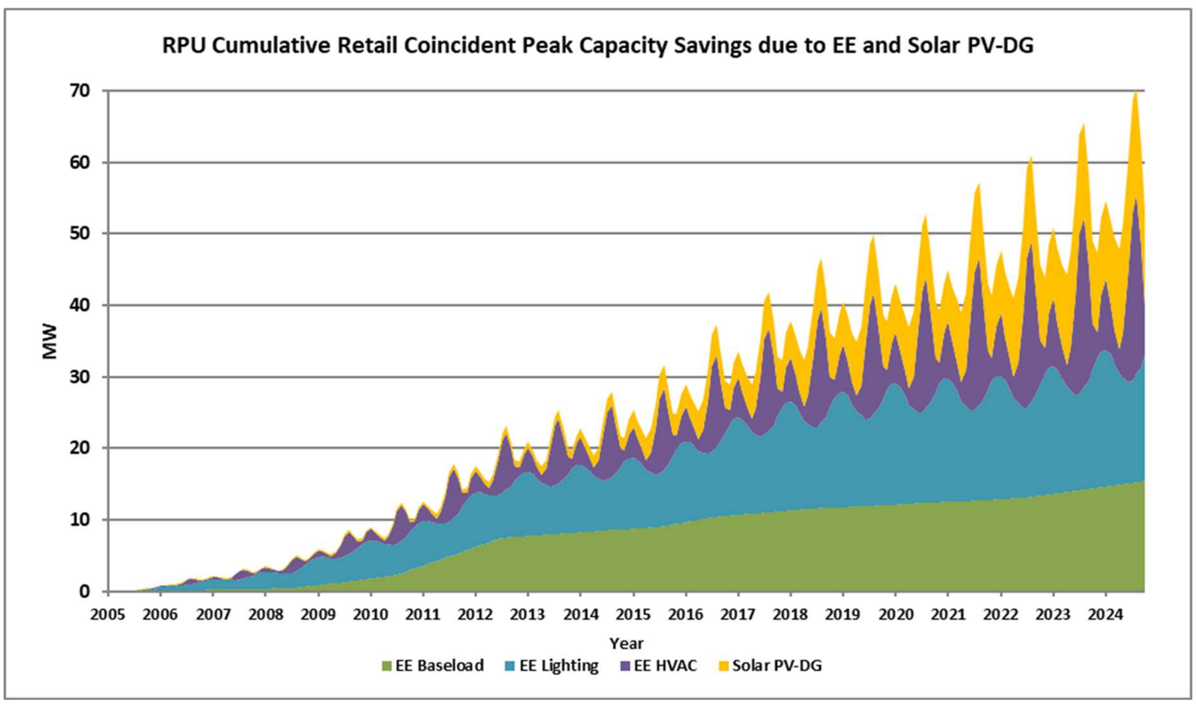

Figure 2.3. Calculated cumulative projected coincident peak capacity savings in the RPU service territory due to both EE program and solar PV distributed generation impacts over time.

2.8 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 2024 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 matched 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, staff instead have relied on published CEC projections for the SCE service territory. More specifically, staff have rescaled the SCE projections published in the 2021 CEC IEPR hourly forecast scenario[3] 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 RPU's service territory between 2015 through 2042.[4] 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.

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

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

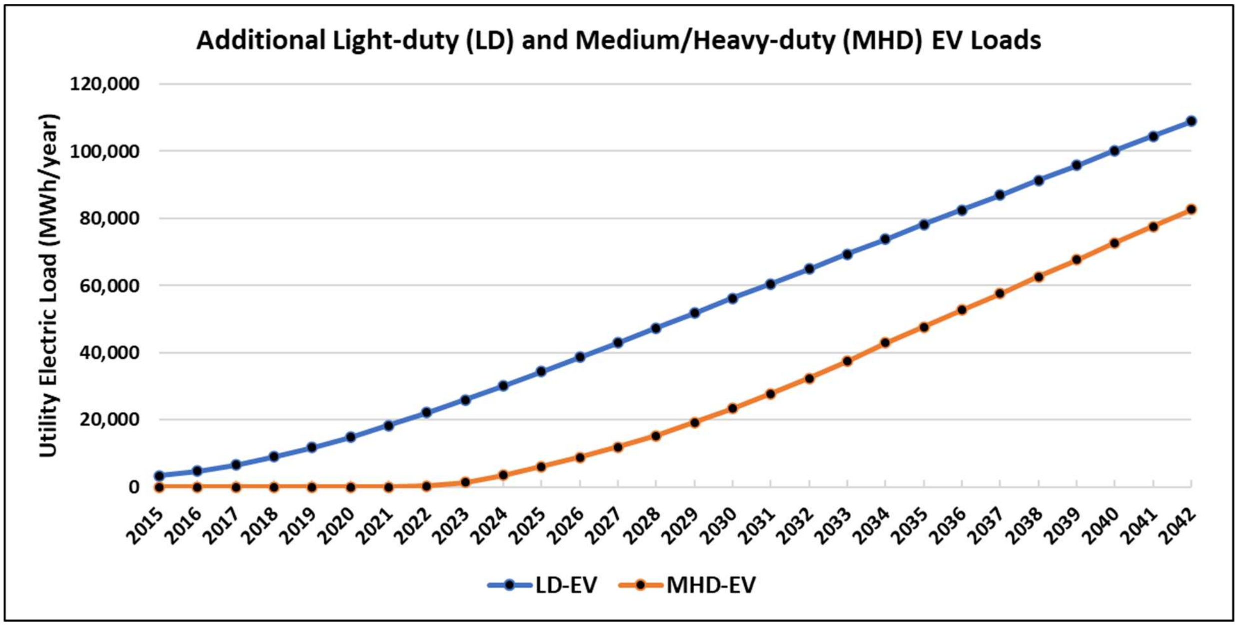

Figure 2.4. Projected 2015-2042 RPU electrical load from both Light-duty and Medium-/Heavy-duty EV penetration within our service territory.

2.9 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, staff once again have relied on published CEC projections for the SCE service territory. As before, staff 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 RPU's service territory, again from 2015 through 2042.[5] (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 appear to be quite similar to the Medium/Heavy-duty EV load forecasts.

[5] BE forecasts beyond 2035 represent linear extrapolations.

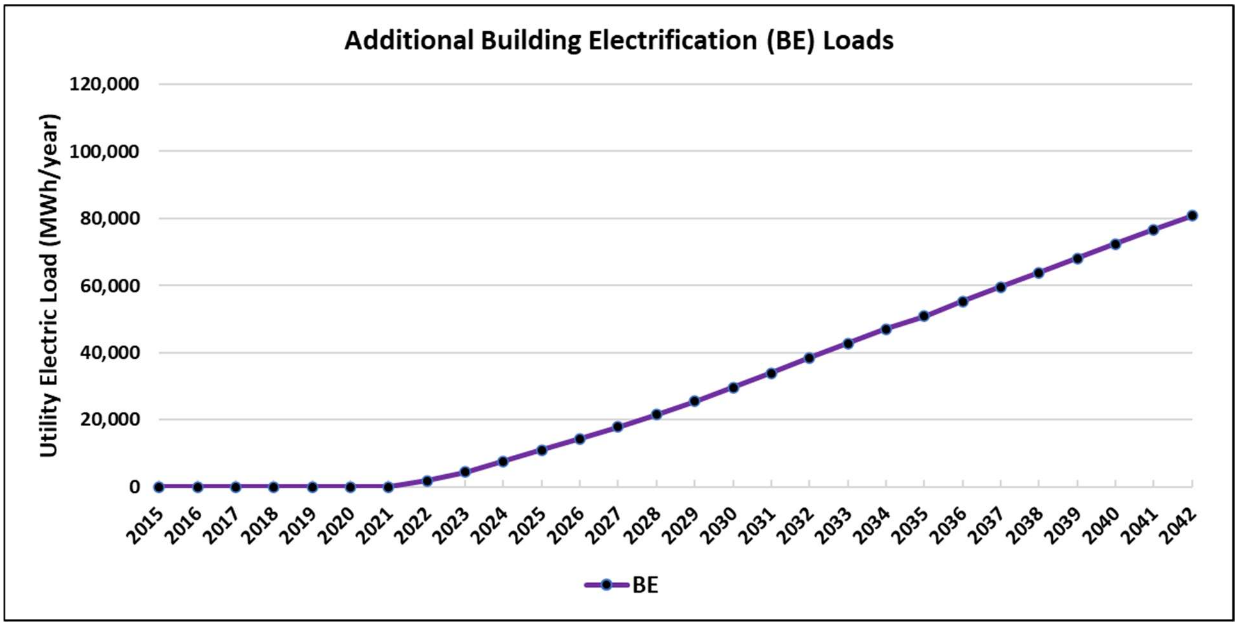

Figure 2.5. Projected 2015-2042 RPU electrical load from new building electrification (fuel-switching) activities our service territory.

3. System Load and Peak Forecast Models

3.1 Monthly system total load model

The regression component of the monthly total system load forecasting model is a function of the primary economic driver (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), an additional adjustment effect that allows the SumCD impact to adjust for increased sensitivity to cooling degrees after 2019 (SumCD_2019), ten low 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 2011-2014 Industrial load indicator variable (econTOU), one unconstrained indicator variable to account for the abnormally low 2023 loads (econ2023), 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

$$y_t = \beta_0 + \beta_1[\text{Emp\_CC}_t] + \beta_2[\text{SumMF}_t] + \beta_3[\text{SumSS}_t] + \beta_4[\text{SumCD}_t] + \beta_5[\text{SumCD\_2019}_t] + \beta_6[\text{SumXHD}_t] +$$

$$\beta_7[\text{Fs1}_t] + \beta_8[\text{Fc1}_t] + \beta_9[\text{Fs2}_t] + \beta_{10}[\text{Fc2}_t] + \beta_{11}[\text{Fs3}_t] + \beta_{12}[\text{Fc3}_t] + \beta_{13}[\text{Fs2014a}_t] + \beta_{14}[\text{Fc2014a}_t] +$$

$$\beta_{15}[\text{Fs2014b}_t] + \beta_{16}[\text{Fc2014b}_t] + \beta_{17}[\text{econTOU}_t] + \beta_{18}[\text{econ2023}_t] +$$

$$\theta_1[\text{EE}_t+\text{PV}_t-\text{EV}_t-\text{BE}_t] + \varepsilon_{jt} \qquad \text{[Eq. 3.1]}$$

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 2008) 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 14.2 and 9.2 GWh^2, suggesting that the variance ratio for the seasonal errors is approximately 1.5 to 1. 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, all forecasted economic indices and structural effects (Emp_CC, econTOU, econ2023, EE, PV, EV and BE) are treated 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 for future predictions becomes

$$\mathrm{Var}(\hat{y}_t) = \sigma_m^2 + \mathrm{Var}\{\ \beta_4[\mathrm{SumCD}_t] + \beta_5[\mathrm{SumCD\_2019}_t] + \beta_6[\mathrm{SumXHD}_t]\ \} \qquad \text{[Eq. 3.3]}$$

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 monthly estimates of the second variance term can be approximated via an analysis of 25 years of historical weather data, once the three 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 the total system load forecasting equation, estimated using weighted least squares. The equation explains 99.0% of the observed variability associated with the monthly 2008-2024 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 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 9.89 GWh^2; the corresponding summer component is 1.5 times this amount (14.84 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). The load response to the sum of the cooling degrees increased after 2019 (SumCD_2019 > 0); the corresponding percent increase can be calculated from the ratio of the two parameter estimates, e.g., 100(0.02460/0.19247) = 12.8%. Additionally, the RPU system load is expected to increase as the Emp_CC level grows over time (i.e., Emp_CC > 0). However, the loads 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 2008-2024 timeframe. Figure 3.2 shows the forecasted monthly system loads for 2025 through 2036, 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 2008 - September 2024): GWh units

Forecasting Model: includes Weather & Economic Covariates, Fourier Effects,
Pseudo TOU & 2023 Load Reductions (unconstrained), 2014 Dist.system Adj,
2019 Weather Adj, and Avoided Loads (EE+PV-EV-FS).

Final Forecasting Equation: assumes constrained Avoided Demand Savings
and 1.5:1 Summer|Winter variance ratio.

Dependent Variable: GWhload Load (GWh)

Number of Observations Read	456
Number of Observations Used	201
Number of Observations with Missing Values	255

Weight: season_wght

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	177453	9858.49493	996.37	<.0001
Error	182	1800.79032	9.89445		
Corrected Total	200	179254			

Root MSE	3.14554	R-Square	0.9900
Dependent Mean	183.04833	Adj R-Sq	0.9890
Coeff Var	1.71842		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	Intercept	1	-97.16541	10.85223	-8.95	<.0001
Emp_CC	Labor (100,000)	1	6.43967	0.18332	35.13	<.0001
SumMF		1	5.38800	0.35338	15.25	<.0001
SumSS		1	4.79856	0.40851	11.75	<.0001
SumCD		1	0.19247	0.00651	29.58	<.0001
SumCD_2019		1	0.02460	0.00368	6.68	<.0001
SumXHD		1	0.02874	0.01161	2.48	0.0142
Fs1		1	-3.00779	0.88744	-3.39	0.0009
Fc1		1	-3.71724	1.12307	-3.31	0.0011
Fs2		1	2.11633	0.74213	2.85	0.0049
Fc2		1	2.33368	0.62523	3.73	0.0003
Fs3		1	-0.27324	0.38590	-0.71	0.4798
Fc3		1	1.90297	0.38067	5.00	<.0001
Fs1_2014		1	-3.67728	0.77722	-4.73	<.0001
Fc1_2014		1	-4.39653	0.83460	-5.27	<.0001
Fs2_2014		1	3.96539	0.75478	5.25	<.0001
Fc2_2014		1	2.06357	0.74437	2.77	0.0061
econTOU		1	6.42796	0.77930	8.25	<.0001
econ2023		1	-14.44990	1.75025	-8.26	<.0001
avoided_load	EE+PV-EV-FS	1	-1.05000	0	n/a	n/a

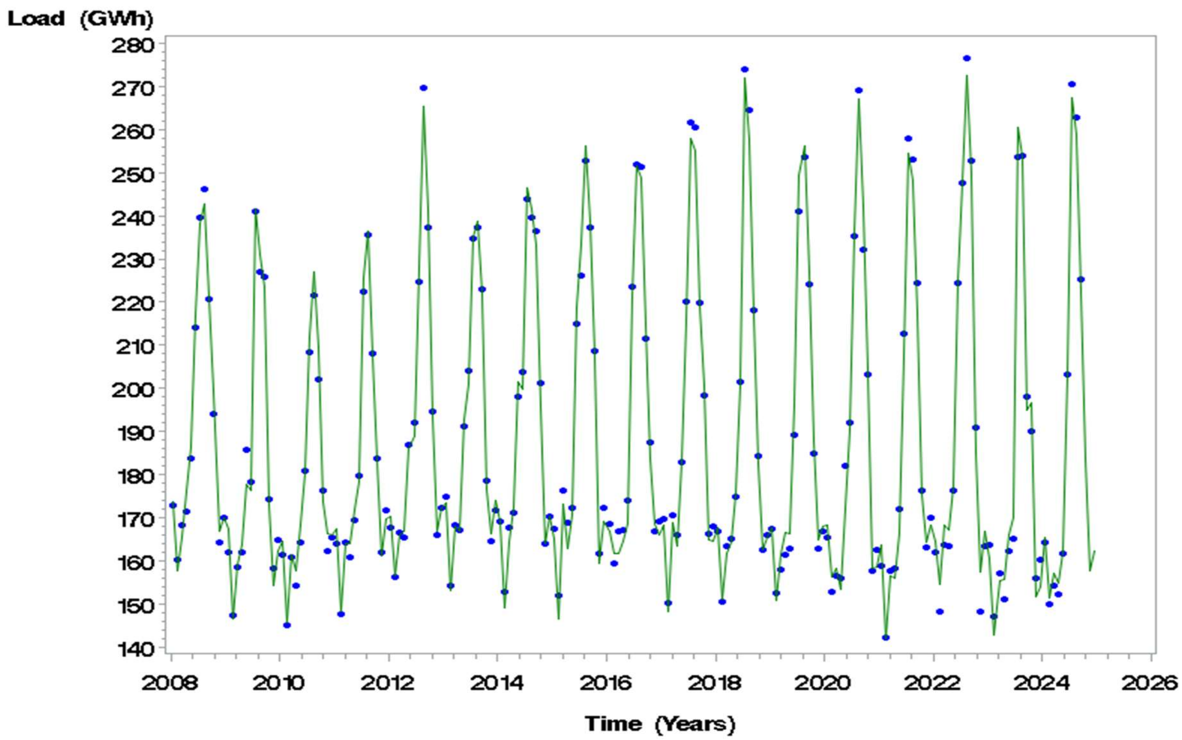

Figure 3.1. Observed and predicted total system load data (2008-2024), after adjusting for known weather conditions.

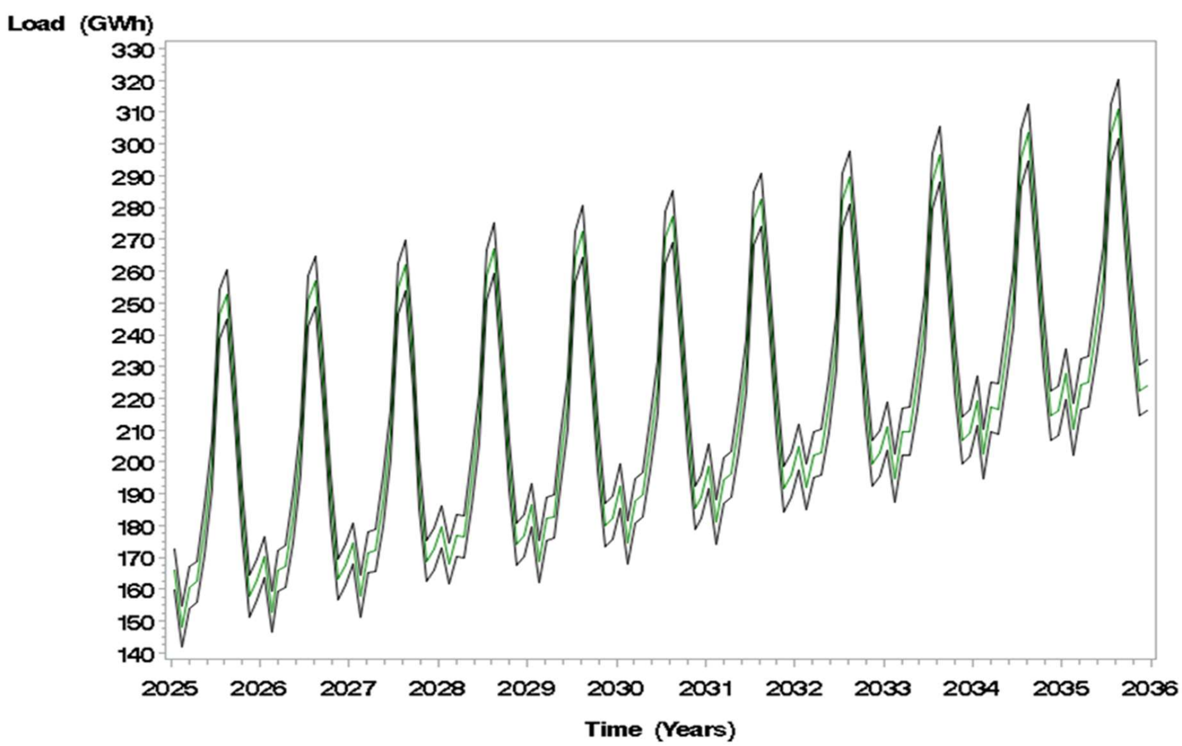

Figure 3.2. Forecasted monthly system loads for 2025-2036; 95% forecasting envelopes encompass model uncertainty only.

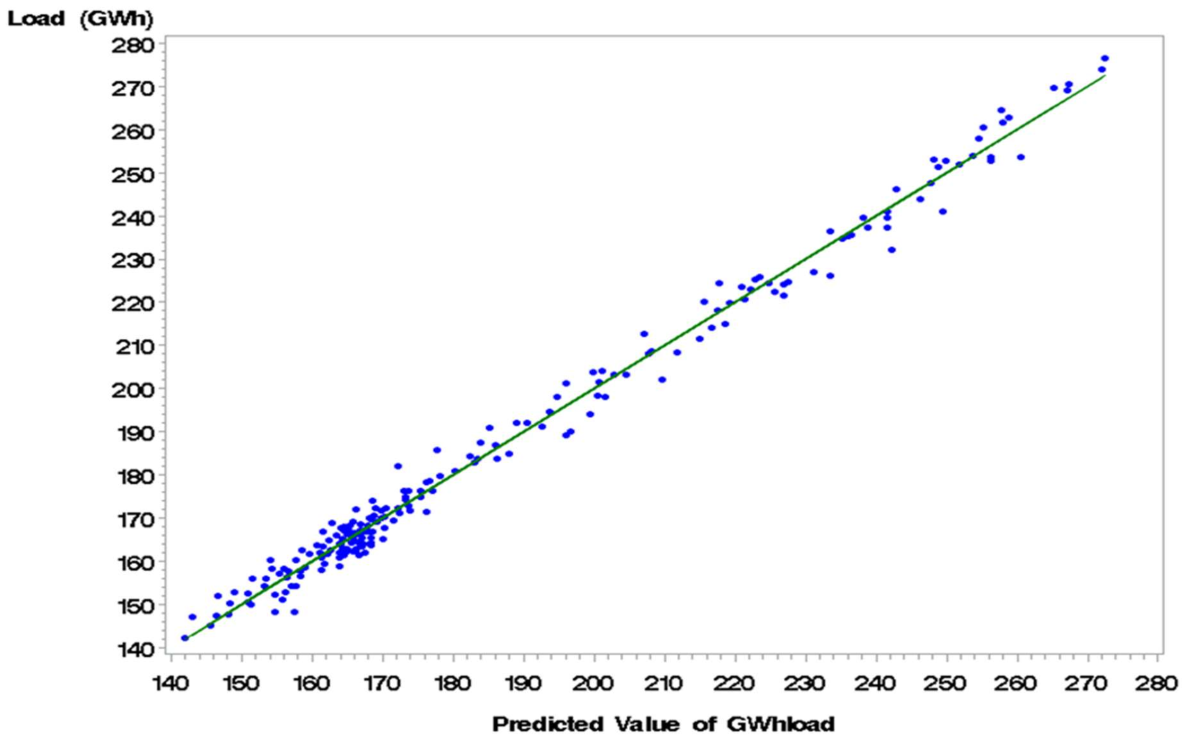

Figure 3.3. Strength of correlation between the observed versus prediction system loads shown in Figure 3.1.

Finally, Figure 3.3 above 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 is equal to 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, that our EV and BE load additions will materialize as discussed in sections 2.8 and 2.9, and that the anticipated accelerated load growth over the next 10 years can be well approximated by using a 4.5% annual labor growth rate. Given these assumptions, Table 3.2 shows the forecasted monthly RPU system loads for 2025, along with their forecasted standard deviations. In contrast to Figure 3.2, these standard deviations quantify both model and weather uncertainty. The 2025 forecasts project that our annual system load should be about 2,240 GWh, assuming that the RPU service area experiences typical weather conditions throughout the year.

Table 3.2. 2025 monthly total system load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Load (GWh)	Std.Dev (GWh)
JAN	166.08	3.43
FEB	148.20	3.82
MAR	160.52	4.70
APR	162.34	5.35
MAY	178.31	8.96
JUN	198.87	15.51
JUL	246.35	14.02
AUG	252.61	11.34
SEP	221.71	13.04
OCT	184.64	11.93
NOV	157.75	4.72
DEC	162.98	3.44
Annual TOTAL	2240.37	32.70

3.3 Monthly system peak model

The regression component of the monthly system peak forecasting model is a function of the primary economic driver (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, and MaxHD, respectively), an additional interaction effect that allows the MaxCD3 impact to adjust for increased sensitivity to maximum cooling degrees after 2019 (MaxCD3_2019), eight lower order Fourier frequencies that quantify seasonal impacts both before and after our distribution system upgrades (Fs1, Fc1, Fs2, Fc2, Fs3, Fc3, Fs2014a, and Fc2014a), one unconstrained 2011-2014 Industrial peak indicator variable (econTOU), one unconstrained indicator variable to account for the abnormally low 2023 peaks (econ2023), and one constrained effect that captures the combined impacts of (avoided) EE, PV-DG and (incremental) EV peaks. 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

$y_t = \beta_0 + \beta_1[Emp\_CC_t] + \beta_2[MaxCD3_t] + \beta_3[MaxCD3\_2019_t] + \beta_4[SumCD_t] + \beta_5[MaxHD_t] +$

$\beta_6[Fs(1)_t] + \beta_7[Fc(1)_t] + \beta_8[Fs(2)_t] + \beta_9[Fc(2)_t] + \beta_{10}[Fs(3)_t] + \beta_{11}[Fc(3)_t] +$

$+ \beta_{12}[Fs2014a_t] + \beta_{13}[Fc2014a_t] + \beta_{14}[econTOU_t] + \beta_{15}[econ2023_t] +$

$\theta_1[EE_t+PV.DG_t-EV_t] + \varepsilon_{jt}$ [Eq. 3.4]

where

$\varepsilon_{jt \text{ for } j=1(\text{summer}), 2(\text{winter})} \sim N(0, \sigma_j^2)$. [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 2008) 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 391.3 and 280.3 MW^2, suggesting that the variance ratio was again approximately 1.5 to 1. Based on these results, Eq. 3.4 was refit using weighted least squares (SAS REG Procedure), with the θ_1 parameter estimate also 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, the forecasted economic indices are treated 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 for future predictions becomes

$Var(\hat{y}_t) = \sigma_m^2 + Var\{ \beta_2[MaxCD3_t] + \beta_3[MaxCD3\_2019_t] +$

$\beta_4[SumCD_t] + \beta_5[MaxHD_t] \}$ [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 the system peak forecasting equation. This equation explains approximately 97.7% of the observed variability associated with the monthly 2008-2024 system peaks. Note that the avoided peak parameter was constrained to be equal to -1.05 during the weighted least squares analysis.

As shown in Table 3.3, the estimate for the winter variance component is 276.8 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 increase as each of the weather indices increase. Furthermore, the peak response to 3-day heatwaves became stronger on/after 2019 (MaxCD3_2019 > 0); the percent increase for this response calculates out to 100(0.49424/2.98855) = 16.5%. RPU system peaks are also expected to increase as the Emp_CC index increases (i.e., Emp_CC > 0). These 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. Finally, 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 2008-2024 timeframe. Figure 3.5 shows the forecasted monthly system peaks for 2025 through 2036, 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 0.988.

Table 3.4 shows the forecasted monthly RPU system peaks for 2025, along with their forecasted standard deviations. In contrast to Figure 3.5, these standard deviations quantify both model and weather uncertainty. The 2025 forecasts project that our maximum monthly system peak should be about 592 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 2008 - September 2024): MW units

Forecasting Model: includes Weather & Economic Covariates,
Fourier Effects,
Pseudo TOU & 2023 Peak Reductions (unconstrained), 2014 Dist.system Adj,
2019 Weather Adj, and Avoided Peaks (EE+PV-EV-FS).

Final Forecasting Equation: assumes constrained Avoided Peak Savings
and 1.5:1 Summer|Winter variance ratio.

Dependent Variable: Peak Peak (MW)

Number of Observations Read	456
Number of Observations Used	201
Number of Observations with Missing Values	255

Weight: season_wght

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	2195645	146376	528.81	<.0001
Error	185	51209	276.80413		
Corrected Total	200	2246853			

Root MSE	16.63743	R-Square	0.9772
Dependent Mean	387.43706	Adj R-Sq	0.9754
Coeff Var	4.29423		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	Intercept	1	168.35458	19.65831	8.56	<.0001
Emp_CC	Labor (100,000)	1	8.47812	1.02325	8.29	<.0001
MxCD3		1	2.98855	0.19260	15.52	<.0001
MxCD3_2019		1	0.49424	0.10762	4.59	<.0001
SumCD		1	0.18345	0.04377	4.19	<.0001
MxHD1		1	0.42575	0.60509	0.70	0.4826
Fs1		1	-15.92847	4.76605	-3.34	0.0010
Fc1		1	-23.64181	6.21740	-3.80	0.0002
Fs2		1	6.20904	3.43165	1.81	0.0720
Fc2		1	3.99940	2.30480	1.74	0.0844
Fs3		1	7.69214	2.12888	3.61	0.0004
Fc3		1	9.69644	1.89563	5.12	<.0001
Fs1_2014		1	-4.29654	4.00299	-1.07	0.2845
Fc1_2014		1	-19.50794	4.33276	-4.50	<.0001
econTOU		1	15.52169	4.14113	3.75	0.0002
econ2023		1	-28.20939	9.20385	-3.06	0.0025
avoided_peak	EE+PV-EV-FS	1	-1.05000	0	n/a	n/a

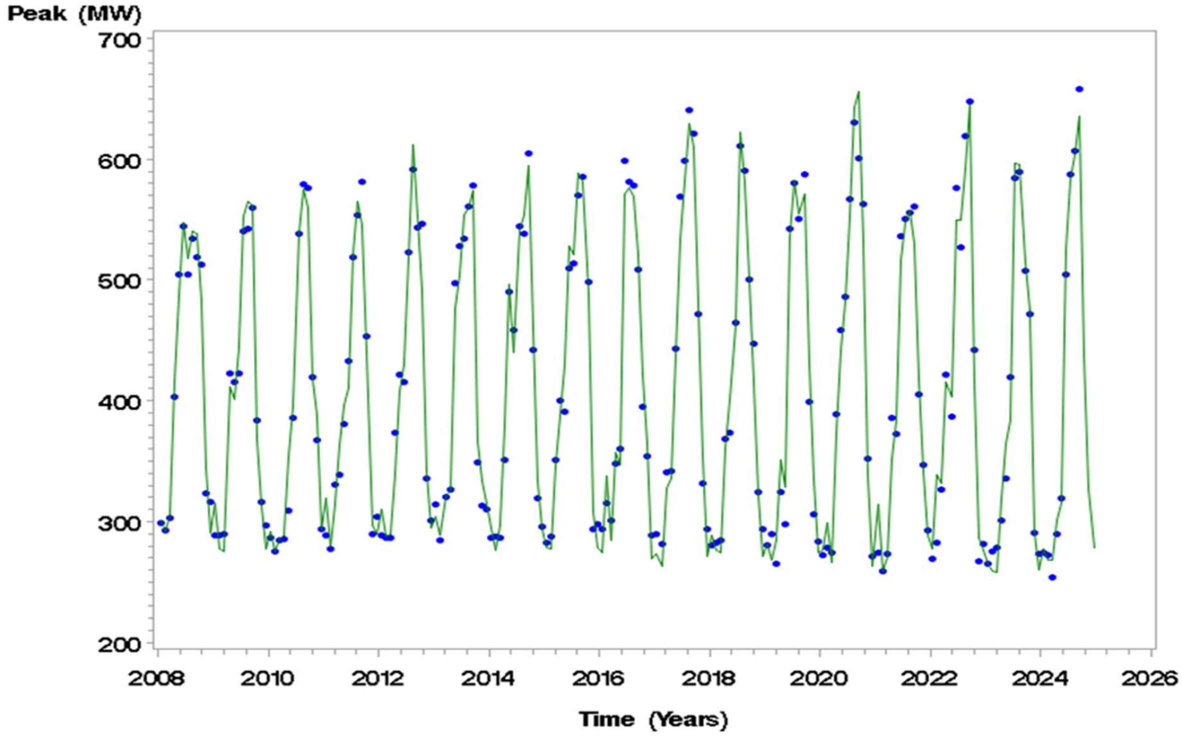

Figure 3.4. Observed and predicted system peak data (2008-2024), after adjusting for known weather conditions.

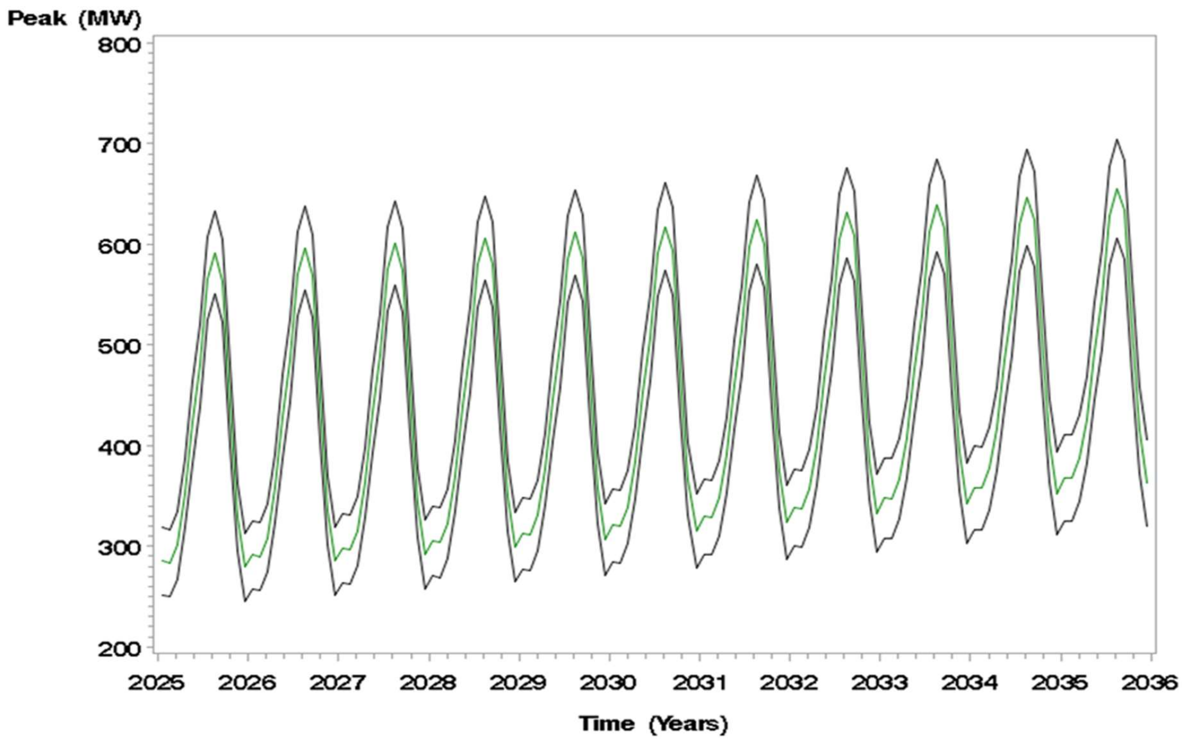

Figure 3.5. Forecasted monthly system peaks for 2025-2036; 95% forecasting envelopes encompass model uncertainty only.

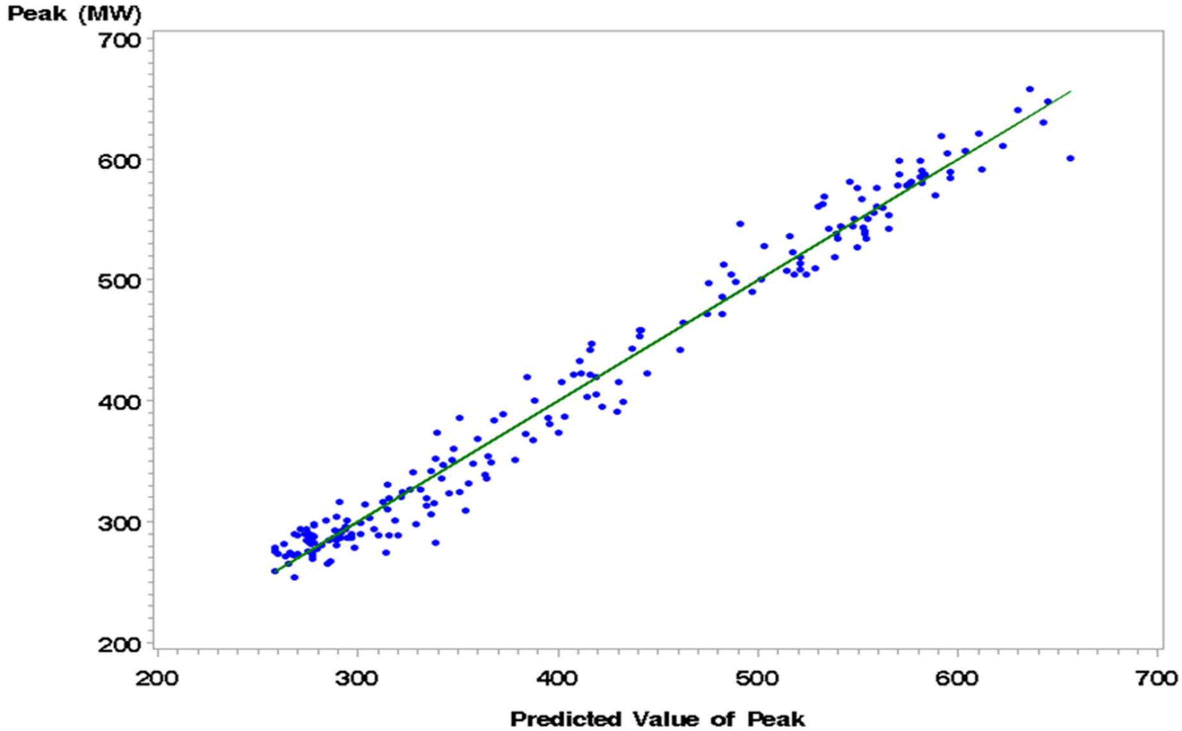

Figure 3.6. Strength of correlation between the observed versus prediction system peaks shown in Figure 3.4.

Table 3.4. 2025 monthly system peak forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Peak (MW)	Std.Dev (MW)
JAN	285.3	20.7
FEB	283.1	25.8
MAR	301.3	29.5
APR	352.3	42.4
MAY	422.9	50.4
JUN	479.4	56.8
JUL	565.9	37.6
AUG	591.6	35.9
SEP	563.6	43.4
OCT	440.4	49.7
NOV	329.3	35.4
DEC	278.9	22.2

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: $\hat{y}_t + 0.842[\ Std(\hat{y}_t)\ ]$ [Eq. 3.7]

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

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

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

In Eqs. 3.7 through 3.10, the 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, the maximum weather scenario peaks are always forecasted to occur in the month of August. Thus, for 2025, the forecasted 1-in-5, 1-in-10, 1-in-20 and 1-in-40 peaks are 621.8, 637.6, 650.7 and 662.0 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 June 2024 (e.g., California Energy Demand 2023 Planning Forecast LSE and BAA Tables – corrected).

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 Planning Forecast Tables workbook (CEC Publication TN257110). As shown in Figure 3.7, the two forecasts align quite well; both sets of forecasts show very similar load growth patterns through 2040.

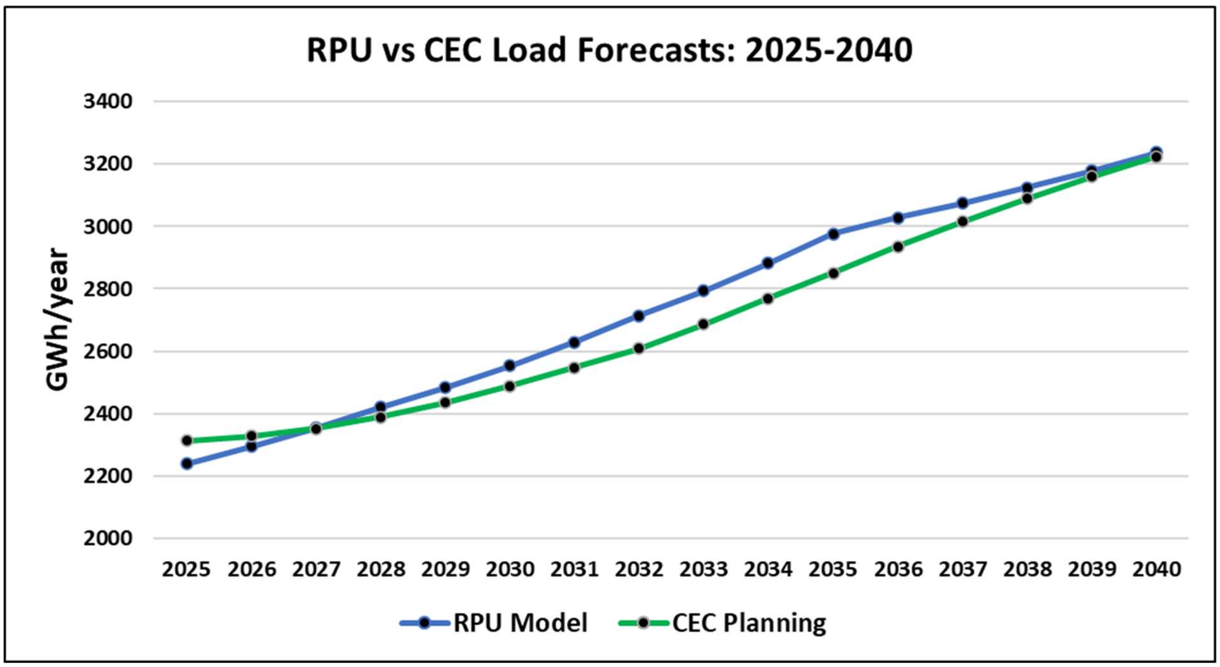

Figure 3.7. A comparison of RPU system load forecasts produced by RPU staff versus the most recent CEC Planning forecasts for the City of Riverside (2023 Planning Forecast LSE and BA Tables).

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 2023 LSE and BA Planning Forecast Tables. 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 differ materially from the CEC forecasts through 2040. The CEC forecasts start out about 10% lower and exhibit a more delayed growth rate than the RPU forecasts. Staff believe that these differences are most likely reflect two issues: (1) different assumptions about longer-term customer solar PV load growth and EV adoption rates within the RPU service territory, and (2) methodology differences for how these peak forecasts are constructed. The second issue is probably more relevant; CEC forecasting models have been consistently underestimating RPU peak loads since 2017 (and the last time that RPU experienced an annual peak load < 550 MW was back in 2008).

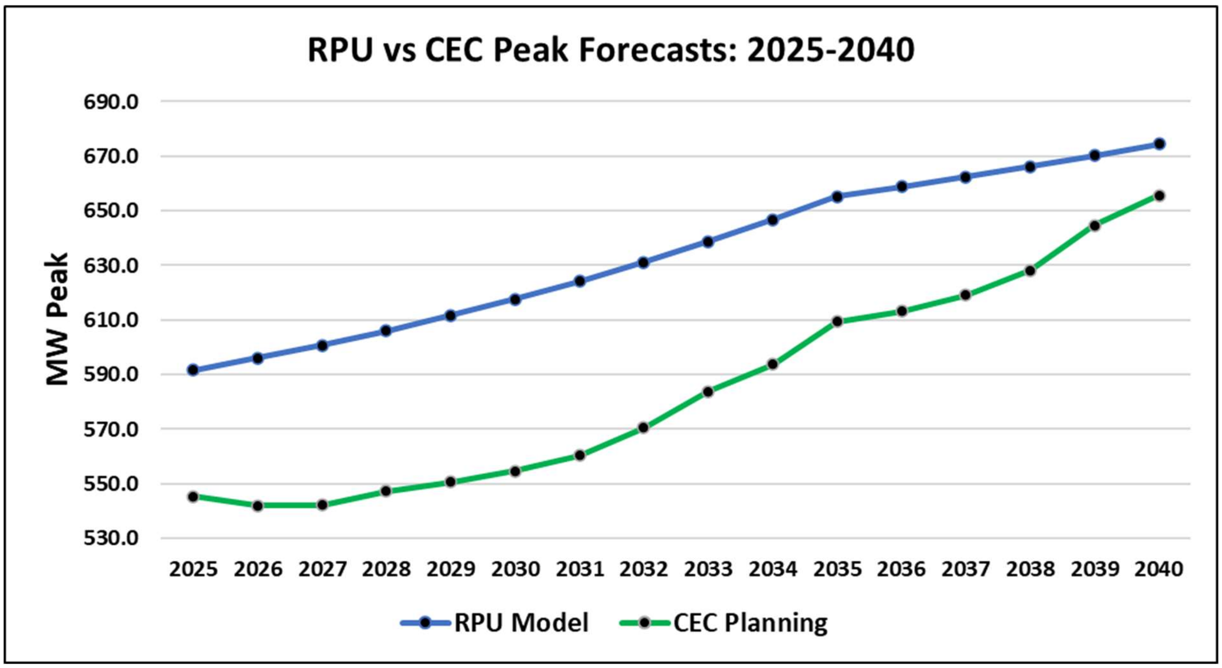

Figure 3.8. A comparison of RPU system 1-in-2 peak forecasts produced by RPU staff versus the most recent CEC Planning forecasts for the City of Riverside (2023 Planning Forecast LSE and BA Tables).

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 two 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, when using a direct load forecasting approach, there is not a convenient way to simultaneously constrain the annual sum of the 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 been 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 the forecasted annual Residential, Commercial, Industrial and Other retail loads, and *W* represented the forecasted annual wholesale system load. Historically, this process was done to force the (less accurate) retail load forecasts to align with the loss-adjusted system load forecasts, after accounting for the fact that staff expect 0% growth in the Other retail load class for the foreseeable future.

Due to 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 the 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] {i.e., the sum of 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 the four customer classes which (after adjusting for expected system losses) automatically align with the system load forecasts (to within 0.1% of the 94.6% target).

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], and 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 the current month's MWh retail sales and the 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 for 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; note that this simple regression relationship explains approximately 92% of the observed variation in the observed 2003-2018 monthly retail load data.

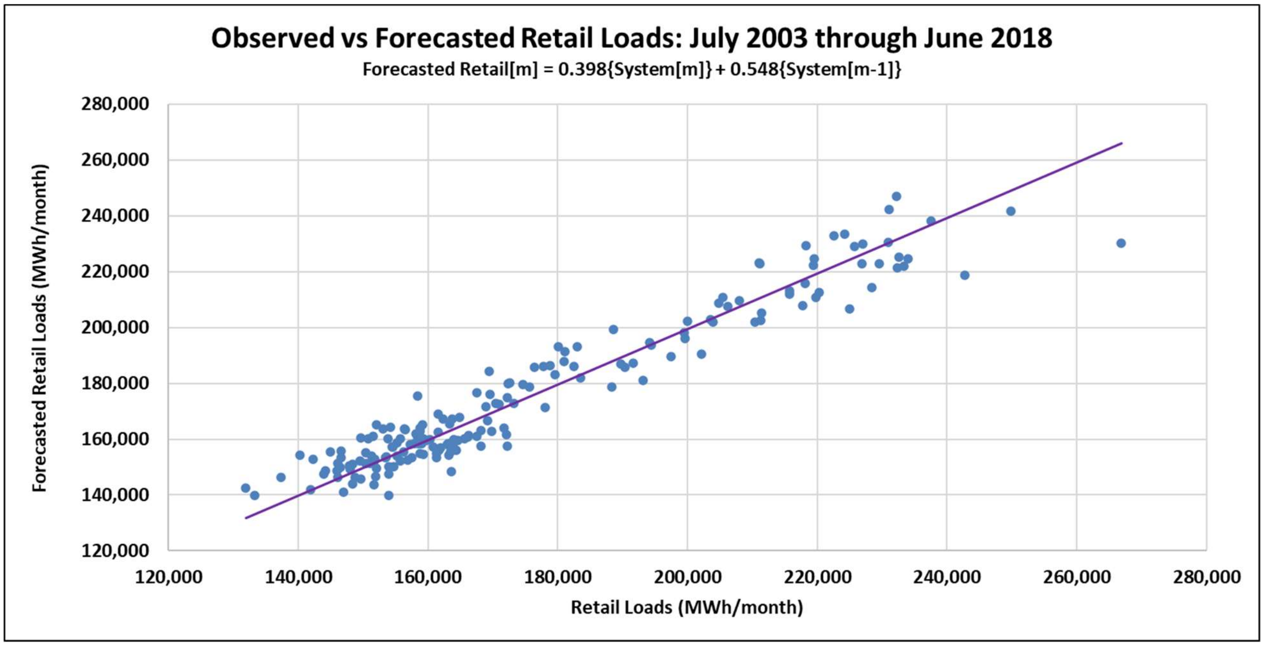

Figure 4.1. Observed versus forecasted retail load relationship: July 2003 through June 2018.

4.3 Load Forecasts for the Other Customer Class

The loads associated with the "Other" customer class currently account for less than 1% of the 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 Commercial (Comm) and Industrial (Indst) classes. Although this load migration barely impacted the Comm or Indst classes, 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 December 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 2019). Finally, in June 2022 the Finance Division made further adjustments to the street lighting component of the Other class, which again resulted in further load reductions to this class. This latter effect can be modeled using a third "migration-3" indicator variable (defined to be 1 on/after July 2022).

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 three indicator variables to account for the three load migration effects. The corresponding equation (derived using ordinary least squares) describes about 95% of the observed load variation associated with the monthly data from January 2012 through September 2024; a plot of the forecasted versus observed loads for the Other customer class is shown in Figure 4.2 below.

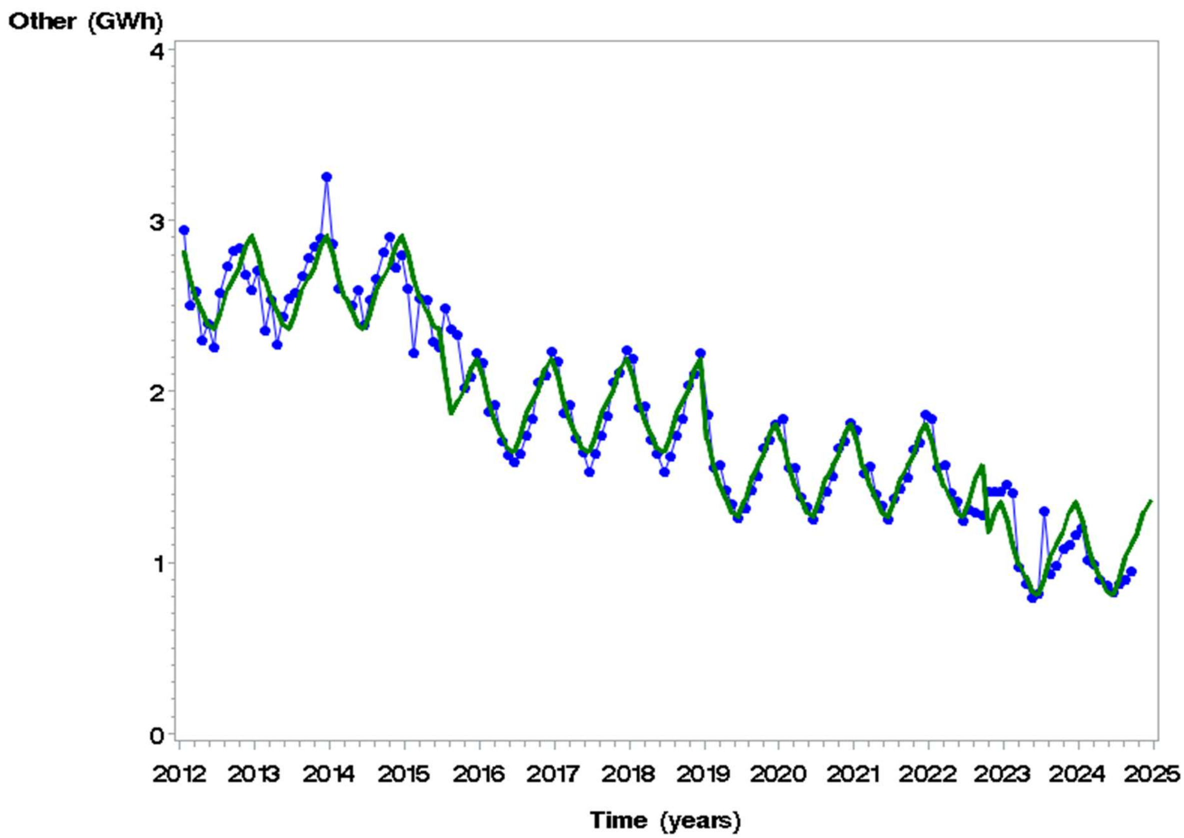

Figure 4.2. Predicted versus observed loads: Other customer class, January 2012 through September 2024.

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), one adjustment variable for modeling increased residential loads during to the primary COVID-19 pandemic,[6] and one additional shift indicator variable defined to be equal to 1 on/after July 2021. (This latter shift indicator variable adjusts for the permanent loss of a few very large Industrial customers during the latter part of the COVID pandemic, which in turn has systematically increased both the Residential and Commercial ratios.) Likewise, a simplified seasonal load ratio forecasting model for the Commercial customer class was defined as a function of six low order Fourier frequencies, the EconTOU variable (which accounts for the expansion and contraction of new Industrial load during the 2011-2014 time-period), and the previously mentioned, additional shift indicator variable defined to be equal to 1 on/after July 2021. Both load ratio equations were again derived via ordinary least squares using January 2012 through September 2024 calibration data.

The Residential ratio model describes about 94% of the observed load variation associated with the monthly data from January 2012 through September 2024; 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 78% of the observed load variation associated with the monthly data from January 2012 through September 2024; 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.

[6] This COVID indicator variable is defined to be equal to 1 from March 2020 through June 2021, and 0 otherwise.

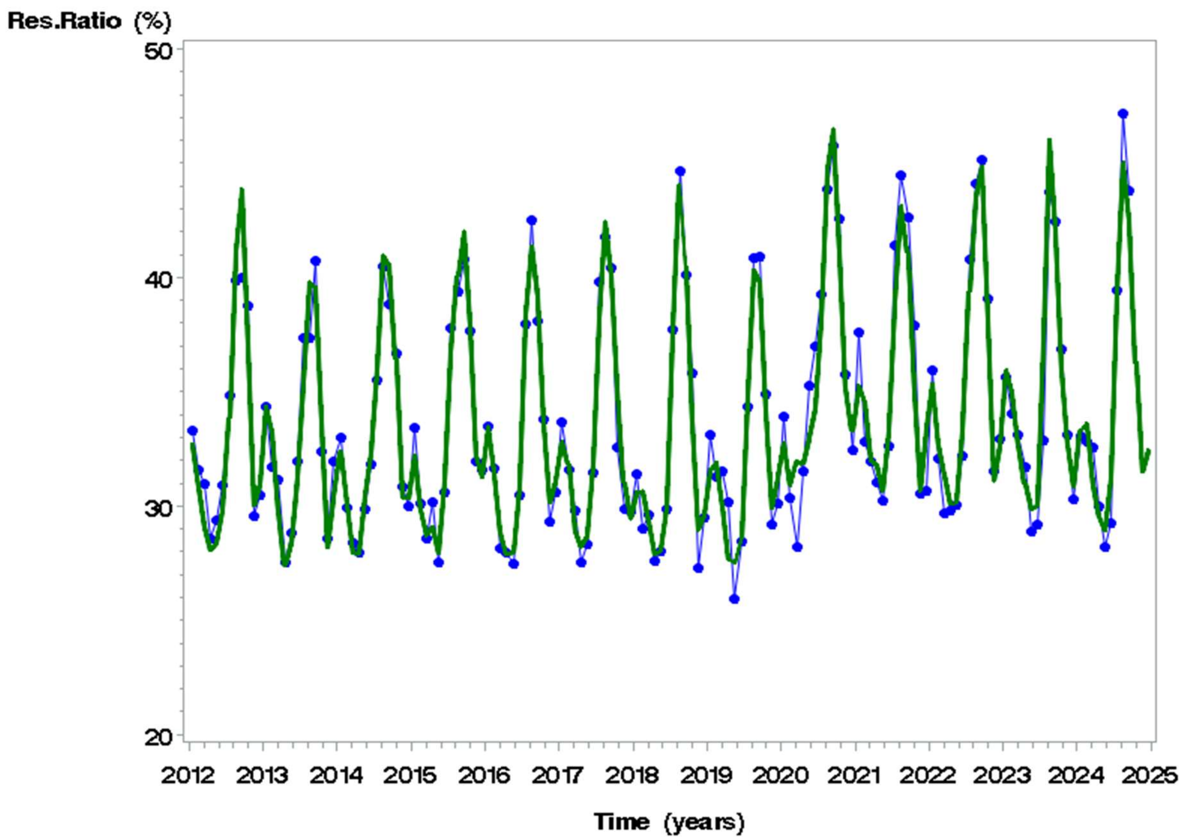

Figure 4.3. Predicted versus observed load ratios: Residential customer class, January 2012 through September 2024.

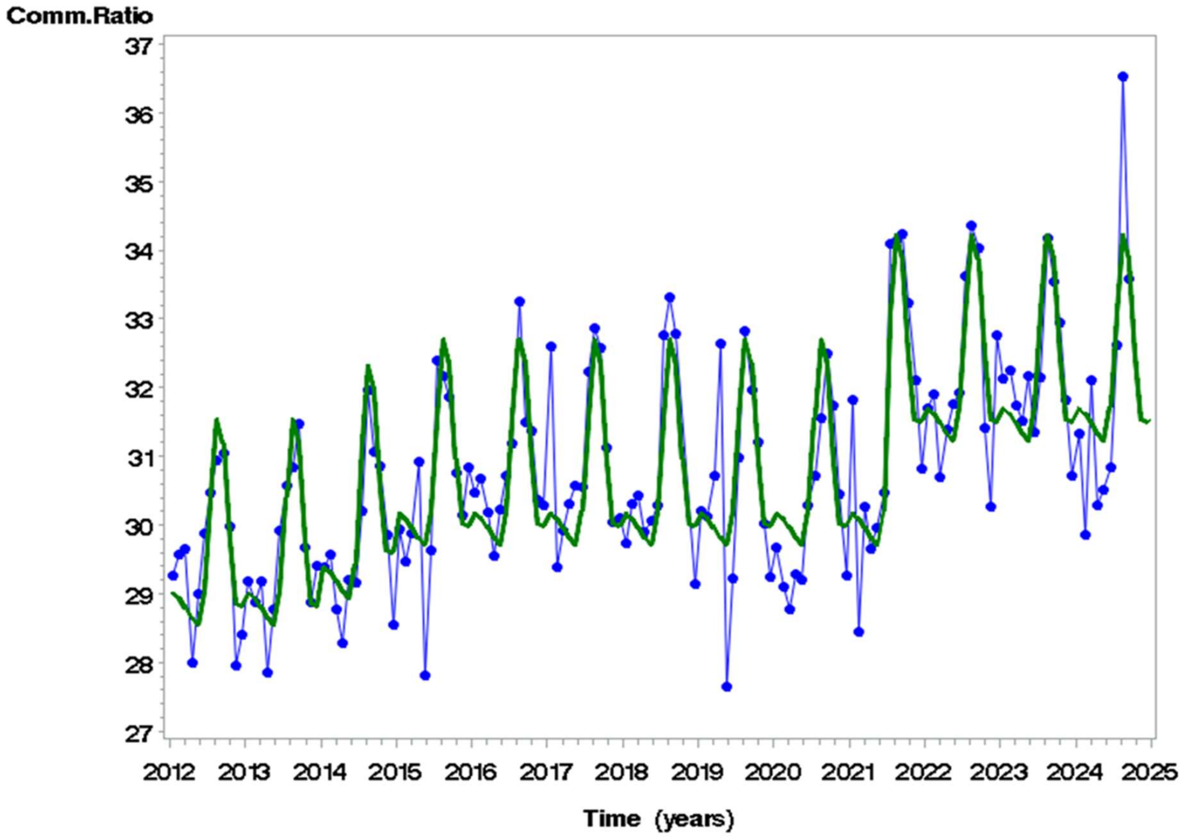

Figure 4.4. Predicted versus observed load ratios: Commercial customer class, January 2012 through September 2024.

4.5 Final Retail Forecasts

The computed monthly 2025-2034 forecasts for all the retail customer classes are shown in Figure 4.5, along with the total system and total retail load forecasts. The final annual, class-specific adjusted retail forecasts are reported in Table 4.1, along with the system load and peak forecasts (through 2045). It should be noted that the 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.

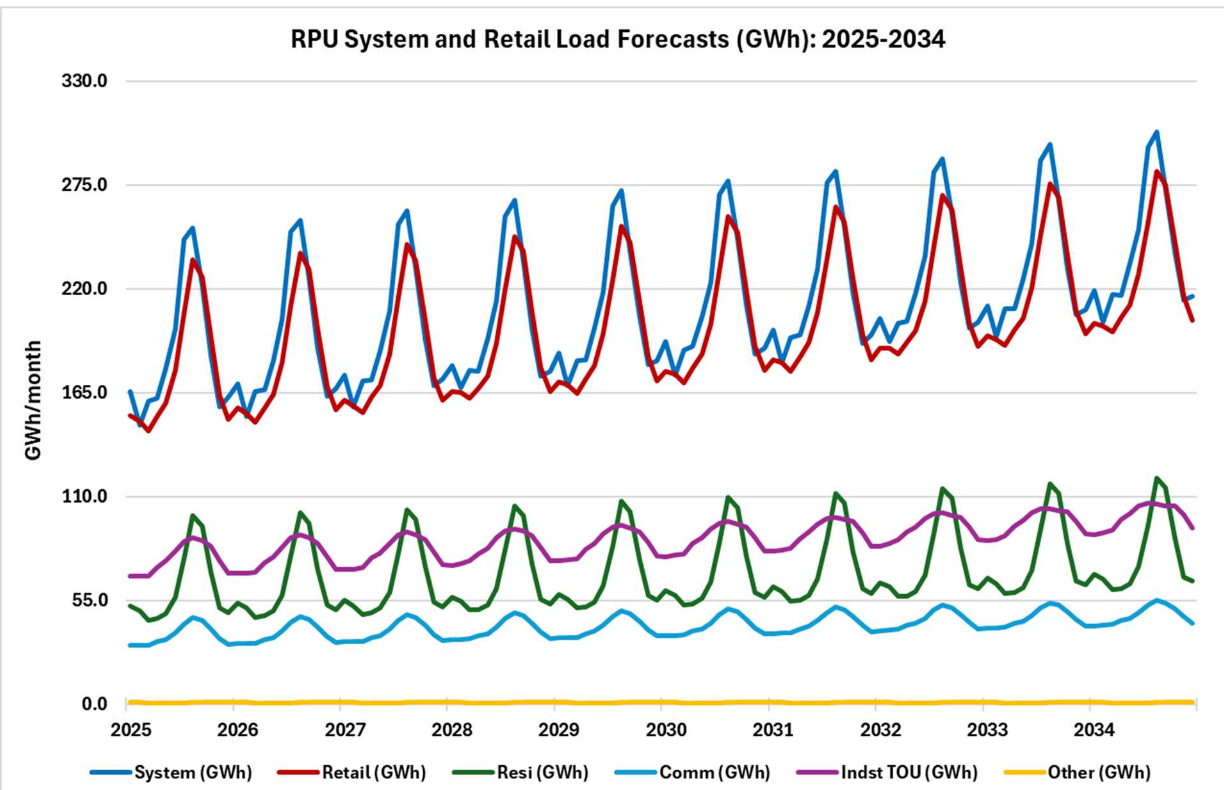

Figure 4.5. RPU monthly retail load forecasts (January 2025 through December 2034) for the system load, total retail load, and the residential, commercial, industrial, and other customer classes.

Table 4.1. Annual system load (MWh), system peak (MW) and retail load (MWh) forecasts: 2025-2045.

Year	System Load	System Peak	Residential	Commercial	Industrial	Other	Total Retail
2025	2,240,370	591.6	738,650	440,340	925,110	12,800	2,116,900
2026	2,295,050	596.0	756,360	451,220	948,190	12,800	2,168,570
2027	2,353,540	600.8	775,260	462,850	972,820	12,800	2,223,730
2028	2,419,810	605.9	796,820	476,170	1,001,100	12,800	2,286,890
2029	2,482,880	611.6	817,100	488,530	1,027,260	12,800	2,345,690
2030	2,553,830	617.6	839,980	502,560	1,056,960	12,800	2,412,300
2031	2,629,330	624.2	864,430	517,550	1,088,720	12,800	2,483,500
2032	2,714,210	631.2	891,940	534,510	1,124,700	12,800	2,563,950
2033	2,793,180	638.7	917,760	550,240	1,157,970	12,800	2,638,770
2034	2,882,470	646.7	946,680	567,980	1,195,560	12,800	2,723,020
2035	2,975,960	655.1	976,890	586,500	1,234,770	12,800	2,810,960
2036	3,029,060	658.7	994,510	597,380	1,257,910	12,800	2,862,600
2037	3,073,780	662.3	1,009,300	606,400	1,276,980	12,800	2,905,480
2038	3,124,960	666.2	1,025,860	616,590	1,298,580	12,800	2,953,830
2039	3,177,220	670.2	1,042,910	627,050	1,320,750	12,800	3,003,510
2040	3,236,530	674.4	1,062,000	638,880	1,345,870	12,800	3,059,550
2041	3,288,620	678.8	1,078,760	649,080	1,367,450	12,800	3,108,090
2042	3,346,690	683.4	1,097,580	660,630	1,391,930	12,800	3,162,940
2043	3,406,570	688.2	1,117,090	672,620	1,417,330	12,800	3,219,840
2044	3,472,450	693.2	1,138,460	685,810	1,445,330	12,800	3,282,400
2045	3,531,430	698.4	1,157,650	697,530	1,470,120	12,800	3,338,100