City of Riverside, Riverside Public Utilities

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Subject:	**RPU Wholesale & Retail Load Forecasting Methodologies**
	CEC 2013 IEPR Form 4 Report
Participant:	**City of Riverside, Riverside Public Utilities (RPU)**
Date:	**April 5, 2013**
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1. Overview & Introduction

RPU uses regression based econometric models to forecast both its total expected GWh system load and system MW peak on a monthly basis. Regression based econometric models are also used to forecast expected monthly retail loads (GWh) for our four primary customer classes. These models are calibrated to historical load and/or sales data extending back to January 2003. The input variables to these econometric models include various monthly weather summary statistics, specific calendar effects and two econometric input variables for the Riverside – San Bernardino – Ontario metropolitan service area; annual per capita personal income (PCPI) and monthly non-farm employment (EMP) estimates. The monthly forecasts produced by these models are used to project RPU wholesale gross and peak loads and retail sales 10 to 20 years forward.

RPU does not currently produce forecasts of the following variables; customer counts associated with any specific customer class, peak loads associated with any specific customer class, or future electrical rates for any customer class and/or tier rate structure. Since both our wholesale and retail forecast models are calibrated to historical load data, the corresponding forecasts implicitly capture the effects of all active RPU Energy efficiency programs at their current funding and implementation levels. Please see the SB1037/AB2021 report submitted with this filing for more detailed information about RPU's various EE / rebate programs.

RPU does not currently administer any type of long-term Demand Response program in its service territory. In response to the SONGS outage, RPU did implement a Power Partners voluntary load curtailment program in 2012 to call upon up to 14 MW of load shedding capability (during any stage 3 emergency situation). We currently expect this program to continue into 2013, if both SONGS units remain off-line. 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 10 years.

2. Forecasting Approach

2.1. General modeling methodology

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

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

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

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

These daily weather data simulations are used in our hourly system load equations (to produce prospective, simulated hourly system loads). These daily temperature simulations are also summarized into monthly cumulative cooling and heating degree indexes; the average value of these indexes are in turn used as prospective weather input values for our monthly load forecasting equations, respectively.

All primary monthly forecasting equations are statistically developed and calibrated to 8-9 years of historical monthly load data. The parameter estimates for each forecasting equation are updated every 6 to 12 months; if necessary, the functional form of each equation can be updated or modified on an annual basis. Please note that this report <u>only</u> summarizes the methodology and statistical results pertaining to our monthly forecasting equations. (Section 3 of this report describes our monthly system load and system peak equations, while section 4 discusses our class-specific, retail load models.)

2.2. Input variables

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

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

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

Thus, two days with average temperatures of 73.3° and 51.5° would have corresponding CD indices of 8.3 and 0 and XHD indices of 0 and 3.5, respectively. Additionally, low order Fourier frequencies are 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

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

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

where *m* represents the numerical month number (i.e., 1 = Jan, 2 = Feb, .., 12 = Dec). Note that low order Fourier frequencies are also used to describe seasonal variation in the residual variance component of our system (wholesale) total and peak load equations.

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

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

2.3. Historical and forecasted inputs: economic and weather effects

The annual values of our historical and forecasted economic indices are reported on Demand Form 2.1 in our 2013 CEC IEPR submission packet. Annual PCPI data have been obtained from the US Bureau of Economic Analysis (http://www.bea.gov), while monthly employment statistics have been obtained from the CA Department of Finance (http://www.labormarketinfo.edd.ca.gov). As previously stated, both sets of data correspond to the Riverside-Ontario-San Bernardino metropolitan service area.

All SumCD, SumXHD, MaxCD3 and MaxHD weather indices for the Riverside service area are calculated from historical average daily temperature levels recorded at the UC Riverside CIMIS weather station (http://wwwcimis.water.ca.gov/cimis). Forecasted average monthly weather indices have been derived from a detailed simulation study using our dynamic time series temperature models (back-calibrated to six years of CIMIS weather data); these forecasted monthly indices are shown in Table 2.2. Note that these average monthly values are used as weather inputs for all 2013-2024 forecasts.

Table 2.2. Expected average values (forecast values) for 2013-2024 monthly weather indices; see Table 2.1 for weather index definitions.

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

3. System Load and Peak Forecast Models

3.1 Monthly system total load model

The regression component of our monthly total system load forecasting model is a function of our two economic drivers (PCPI and EMP), two calendar effects that quantify the number of weekdays (SumMF) and weekend days (SumSS) in the month, two weather effects that quantify the total monthly cooling and extended heating degrees (SumCD and SumXHD), and four low order Fourier frequencies (Fs(1), Fc(1), Fs(2) and Fc(2)). Additionally, the heterogeneous residual variance (mean square prediction error) component is defined to be a function of two low order Fourier frequencies (Fs(1) and Fc(1)). Mathematically, the model is defined as

$$
\begin{aligned}
y_t = \beta_0 + \beta_1[PCPI_t] + \beta_2[EMP_t] + \beta_3[SumMF_t] + \beta_4[SumSS_t] + \beta_5[SumCD_t] \\
+ \beta_6[SumXHD_t] + \beta_7[Fs(1)_t] + \beta_8[Fc(1)_t] + \beta_9[Fs(2)_t] + \beta_{10}[Fc(2)_t] + h_t\sigma^2
\end{aligned}
$$

Eq. 3.1

where

$$h_t = \exp \; \alpha_1[Fs(1)_t] + \alpha_2[Fc(1)_t] \; .$$ Eq. 3.2

In Eq. 3.1, y_t represents the RPU monthly total system load (GWh) for the calendar ordered monthly observations and forecasts (t=1 → Jan 2003, t=264 → Dec 2024) and the seasonally heterogeneous residual errors are assumed to be Normally distributed and temporally uncorrelated. Eqs. 3.1 and 3.2 were simultaneously optimized using restricted maximum likelihood estimation (SAS AutoReg Procedure).

All input observations that reference historical time periods are assumed to be fixed (i.e., measured without error) during the estimation process. For forecasting purposes, we treated the forecasted economic indices 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

$$Var(\hat{y}_t) = \hat{h}_t\hat{\sigma}^2_{MSPE} + Var \;\; \hat{\beta}_5[SumCD_t] + \hat{\beta}_6[SumXHD_t]$$ Eq. 3.3

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

3.2 System load model statistics and forecasting results

Table 3.1 shows the pertinent model fitting and summary statistics for our total system load forecasting equation. The equation explains approximately 99% of the observed variability associated with the monthly 2003-2011 system loads and all input parameter estimates are statistically significant below the 0.01 significance level.

The estimates for the seasonal variance components are shown at the bottom of Table 3.1. These components define how the model mean square error (MSE) changes across the calendar months. An analysis of the variance adjusted model residuals suggests that these errors are also Normally distributed, devoid of outliers and temporally uncorrelated; implying that our modeling assumptions are likewise reasonable.

The 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); note that an increase in one cooling degree raises the forecasted load four times as quickly as a one heating degree increase. Additionally, weekdays contribute slightly more to the monthly system load, as opposed to Saturdays and Sundays (i.e., the SumMF estimate is > than the SumSS estimate). Finally, RPU system load is expected to increase as either the area wide PCPI and/or employment indices improve over time (i.e., both economic parameter estimates are > 0).

Figure 3.1 shows the observed (blue points) versus calibrated (green line) system loads for the 2004-2011 timeframe. Nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines) and the observed versus calibrated load correlation exceeds 0.995. Figure 3.2 shows the forecasted monthly system loads for 2013 through 2024, along with the corresponding 95% forecasting envelope. This forecasting envelope encompasses both model and weather uncertainty, while treating the projected economic indices as fixed inputs. Note that there is considerable uncertainty associated with summer forecasts due to the increased uncertainty surrounding summer weather patterns.

Table 3.2 shows the forecasted monthly RPU system loads for 2013, along with their forecasted standard deviations. Once again, these standard deviations quantify both model and weather uncertainty. The 2013 forecasts project that our annual system load should be 2280.2 GWh, assuming that the RPU service area experiences typical weather conditions throughout the year.

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

Gross Monthly Demand Model (Jan 2003 - Sept 2011): GWh units
Forecasting Model: includes Weather & Economic Covariates (w/Fourier Effects)

Dependent Variable: GWhload Load (GWh)

Number of Observations Read	408
Number of Observations Used	105
Number of Observations with Missing Values	303

Weight: ht_1 (structured seasonal pattern)

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	74178	7417.84754	811.33	<.0001
Error	94	859.42504	9.14282		
Corrected Total	104	75038			

Root MSE	3.02371	R-Square	0.9885
Dependent Mean	170.72617	Adj R-Sq	0.9873
Coeff Var	1.77109		

Parameter Estimates

Regression Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	-149.11524	12.08573	-12.34	<.0001	0
PCPI	PCPI ($1,000)	1	2.99745	0.22027	13.61	<.0001	1.39787
Emp_CC	Labor (100,000)	1	3.78635	0.49617	7.63	<.0001	1.39314
sumMF	# Mon-Fri	1	5.52385	0.34037	16.23	<.0001	1.52376
sumSS	# Sat-Sun	1	4.93892	0.41948	11.77	<.0001	1.41986
sumCD	Sum CD's	1	0.16940	0.00733	23.12	<.0001	8.25305
sumHD	Sum XHD's	1	0.04716	0.01135	4.15	<.0001	2.88153
Fs1	Fs(1)	1	-4.52967	0.80873	-5.60	<.0001	3.74366
Fc1	Fc(1)	1	-7.22947	1.10550	-6.54	<.0001	7.03532
Fs2	Fs(2)	1	2.29214	0.66905	3.43	0.0009	2.79596
Fc2	Fc(2)	1	2.28435	0.47897	4.77	<.0001	1.44241

Variance Effect	Label	DF	Parameter Estimate	Standard Error
Fs1	Fs(1)	1	-0.3923	0.2867
Fc1	Fc(1)	1	-0.4679	0.2393

Durbin-Watson D	1.763
Number of Observations	105
1st Order Autocorrelation	0.087

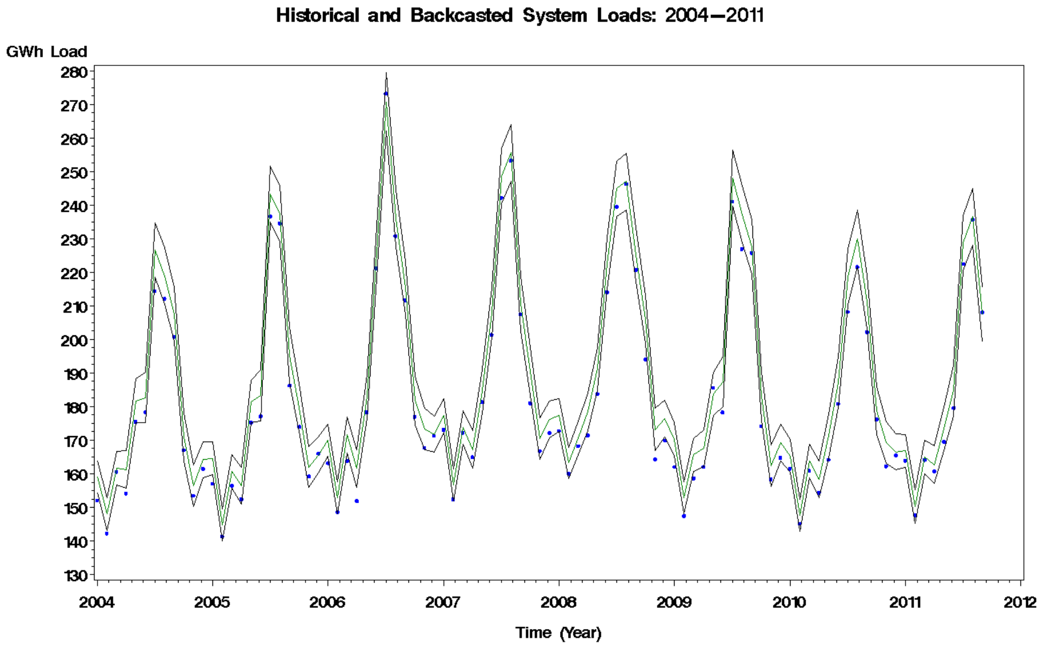

Figure 3.1. Observed and predicted total system load data (2004-2011), after adjusting for known weather conditions.

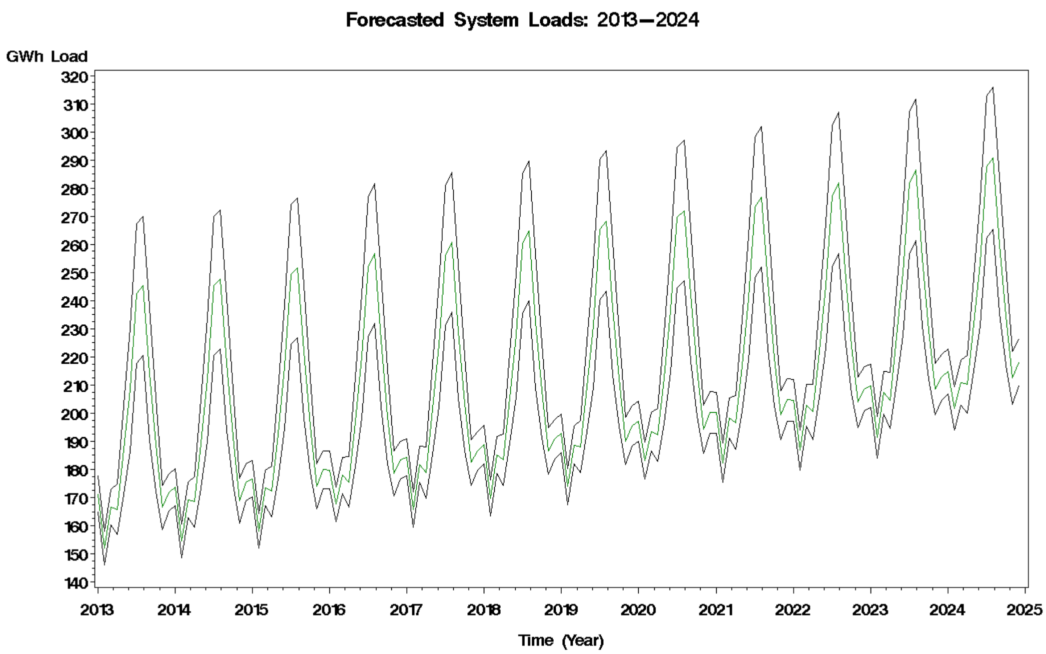

Figure 3.2. Forecasted monthly total system loads for 2013-2024; 95% forecasting envelopes encompass both model and weather uncertainty.

Table 3.2. 2013 monthly total system load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Load (GWh)	Std.Dev (GWh)
JAN	171.22	3.22
FEB	152.00	3.01
MAR	166.62	3.13
APR	165.83	4.47
MAY	187.03	7.90
JUN	208.56	10.99
JUL	242.46	12.38
AUG	245.29	12.38
SEP	214.18	11.79
OCT	188.74	8.34
NOV	166.54	3.93
DEC	171.70	3.26
Annual TOTAL	2280.19	

3.3 Monthly system peak model

The regression component of our monthly system peak forecasting model is a function of our two economic drivers (PCPI and EMP), three weather effects that quantify the total monthly cooling needs, maximum three-day cooling requirements (i.e., 3-day heat waves) and the maximum single day heating requirement (SumCD, MaxCD3 and MaxHD, respectively), and six lower order Fourier frequencies (Fs(1), Fc(1), Fs(2), Fc(2), Fs(3) and Fc(3)). Once again, the heterogeneous residual variance (mean square prediction error) component is defined to be a function of low order Fourier frequencies (four frequencies in this model: Fs(1), Fs(2), Fc(1) and Fc(2)). Mathematically, the model is defined as

$$y_t = \beta_0 + \beta_1[PCPI_t] + \beta_2[EMP_t] + \beta_3[SumCD_t] + \beta_4[MaxCD3_t] + \beta_5[MaxHD_t] \\ + \beta_6[Fs(1)_t] + \beta_7[Fc(1)_t] + \beta_8[Fs(2)_t] + \beta_9[Fc(2)_t] + \beta_{10}[Fs(3)] + \beta_{11}[Fc(3)] + h_t\sigma^2$$

Eq. 3.4

where

$$h_t = \exp\ \alpha_1[Fs(1)_t] + \alpha_2[Fc(1)_t] + \alpha_3[Fs(2)] + \alpha_4[Fc(2)]\ .$$ 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 → Jan 2004, t=252 → Dec 2024) and the seasonally heterogeneous residual errors are assumed to be Normally distributed and temporally uncorrelated. Eqs. 3.4 and 3.5 were again simultaneously optimized using restricted maximum likelihood estimation (SAS AutoReg Procedure).

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

$$Var(\hat{y}_t) = \hat{h}_t \hat{\sigma}^2_{MSPE} + Var\left(\hat{\beta}_3[SumCD_t] + \hat{\beta}_4[MaxCD3_t] + \hat{\beta}_5[MaxHD_t]\right) \qquad \text{Eq. 3.6}$$

where $\hat{\sigma}^2_{MSPE}$ represents the model calculated mean square prediction variance and the second variance term captures the uncertainty in the average weather forecasts. As before, the second variance term was approximated via simulation after the parameters associated with the SumCD, MaxCD3 and MaxHD 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 again explains approximately 99% of the observed variability associated with the monthly 2004-2011 system peaks.

The estimates for the seasonal variance components are shown at the bottom of Table 3.3. These components define how the model mean square error (MSE) changes across the seasons. As with the system load residuals, an analysis of the variance adjusted, peak model residuals suggests that these errors are Normally distributed, devoid of outliers and temporally uncorrelated.

The regression parameter estimates shown in the middle of Table 3.3 imply that monthly system peaks increases as each of the weather indices increase (SumCD, MaxCD3 and MaxHD), but the peaks appear to be primarily determined by the MaxCD3 index. (Recall that this index essentially quantifies the maximum cooling degrees associated with 3-day summer heat waves.) RPU system peaks are also expected to increase as either the area wide PCPI and/or employment indices improve over time (i.e., both economic parameter estimates are > 0). Additionally, not every individual Fourier frequency parameter estimate is statistically significant, although their combined effect significantly improves the forecasting accuracy of the model.

Figure 3.3 shows the observed (blue points) versus calibrated (green line) system loads for the 2004-2011 timeframe. Nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines) and the observed versus calibrated load correlation exceeds 0.989. Figure 3.4 shows the forecasted monthly system peaks for 2013 through 2024, along with the corresponding 95% forecasting envelope. This forecasting envelope again encompasses both model and weather uncertainty, while treating the projected economic indices as fixed inputs. As with the system loads, there is considerable uncertainty associated with summer peak forecasts due to the increased uncertainty surrounding summer weather patterns.

Table 3.4 shows the forecasted monthly RPU system peaks for 2013, along with their forecasted standard deviations. Once again, these standard deviations quantify both model and weather uncertainty. The 2013 forecasts project that our maximum monthly system peak should be about 573 MW and occur in August, assuming that the RPU service area experiences typical weather conditions throughout the year. Note that this represents a 1-in-2 temperature forecast, respectively.

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

Monthly Peak Load Model (Jan 2004 - Sept 2011): MW units
Forecasting Model: includes Weather & Economic Covariates (w/Fourier Effects)

Dependent Variable: Peak Peak (MW)

Number of Observations Read	396
Number of Observations Used	93
Number of Observations with Missing Values	303

Weight: ht_2 (structured seasonal pattern)

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	1687851	153441	639.10	<.0001
Error	81	19447	240.08946		
Corrected Total	92	1707299			

Root MSE	15.49482	R-Square	0.9886
Dependent Mean	341.16118	Adj R-Sq	0.9871
Coeff Var	4.54179		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	101.85807	37.75270	2.70	0.0085	0
PCPI	PCPI ($1,000)	1	4.21152	1.18698	3.55	0.0006	1.27497
Emp_CC	Labor (100,000)	1	5.06463	2.14415	2.36	0.0206	1.25466
sumCD	Sum CD's	1	0.11549	0.04624	2.50	0.0145	24.33037
maxCD3	Max 3-day CD	1	2.67030	0.22273	11.99	<.0001	16.86261
maxHD	Max XHD	1	1.39419	0.56402	2.47	0.0155	4.56153
Fs1	Fs(1)	1	-27.05680	4.85113	-5.58	<.0001	4.78835
Fc1	Fc(1)	1	-38.88293	6.41692	-6.06	<.0001	13.62696
Fs2	Fs(2)	1	6.62555	3.78128	1.75	0.0835	2.89319
Fc2	Fc(2)	1	-3.97387	2.90112	-1.37	0.1745	2.39228
Fs3	Fs(3)	1	4.06101	2.57365	1.58	0.1185	2.15623
Fc3	Fc(3)	1	5.36904	2.31039	2.32	0.0226	1.85533

Variance Effect	Label	DF	Parameter Estimate	Standard Error
Fs1	Fs(1)	1	-0.7997	0.3304
Fc1	Fc(1)	1	-0.3527	0.3274
Fs2	Fs(2)	1	-1.1602	0.3503
Fc2	Fc(2)	1	-0.5508	0.3273

Durbin-Watson D	1.994
Number of Observations	93
1st Order Autocorrelation	-0.028

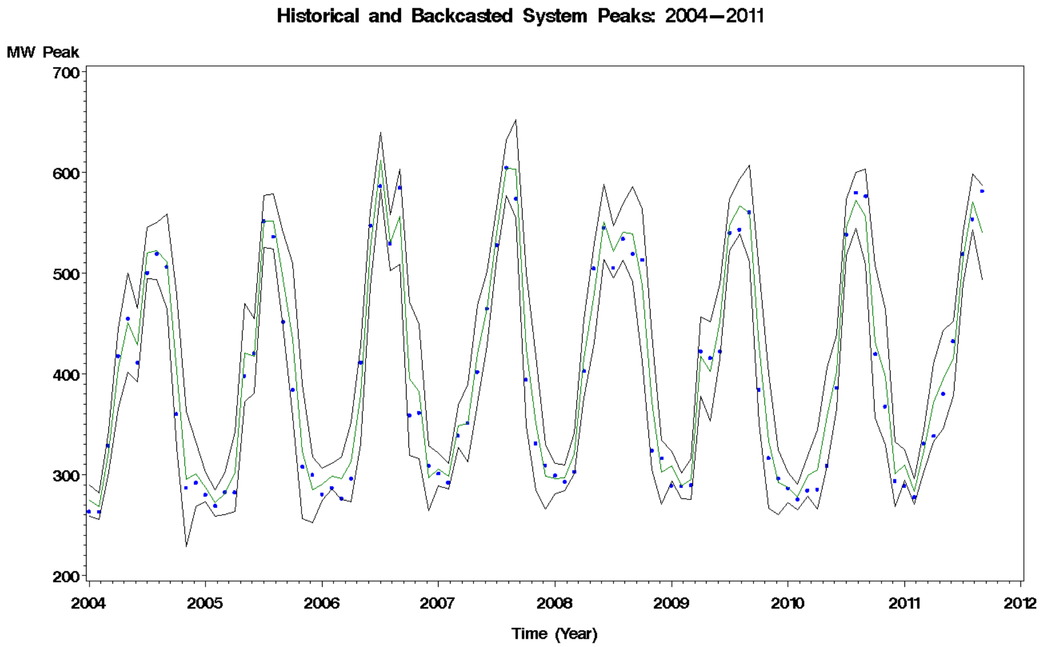

Figure 3.3. Observed and predicted system peak data (2004-2011), after adjusting for known weather conditions.

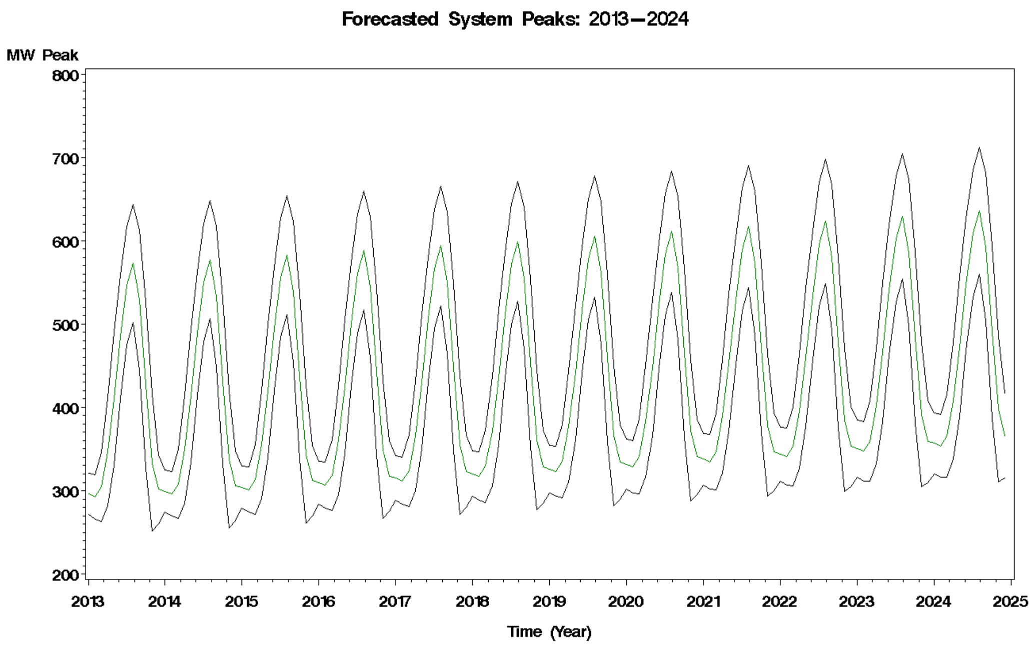

Figure 3.4. Forecasted monthly system peaks for 2013-2024; 95% forecasting envelopes encompass both model and weather uncertainty.

Table 3.4. 2013 monthly system peak forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Peak (MW)	Std.Dev (MW)
JAN	295.9	12.5
FEB	292.6	13.3
MAR	304.5	20.8
APR	346.3	32.4
MAY	410.7	39.9
JUN	484.9	37.0
JUL	546.1	35.5
AUG	573.0	35.4
SEP	529.0	42.1
OCT	427.1	49.6
NOV	333.6	41.3
DEC	301.5	20.8

3.5 Peak demand weather scenario forecasts

After calculating all of the 2013-2024 monthly peak forecasts and their corresponding standard deviation estimates (that incorporate weather uncertainty), additional peak demand forecasts for more extreme weather scenarios were produced. Under the assumption that these $\hat{y}_t$ forecasts can be probabilistically approximated using a Normal distribution, the following formulas were 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 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) quantiles 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 2013, our forecasted 1-in-5, 1-in-10, 1-in-20 and 1-in-40 peaks are 602.8, 618.4, 631.2 and 642.4, respectively. The weather scenario forecasts reported on our 2013 CEC Form 1.5 quantify these more extreme peak scenario projections through 2024.

4. Class-specific Retail Load Forecast Models

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

Second, RPU cannot currently analyze and estimate individual Commercial and Industrial forecasting models, because our Commercial versus Industrial classification schema was recently changed (over 2005 through 2007) by our Finance/Billing department. Instead, we have estimated a combined Commercial + Industrial load equation, produced combined forecasts using this equation and then split these forecasts into separate Commercial and Industrial predictions using a 0.31 Commercial / 0.69 Industrial load ratio metric historically derived from Jan 2007 through Dec 2010. This issue is discussed in more detail in section 4.2.

Finally, it is also important to note that we constrain the annual sum of our class specific, retail forecasts to be equal to 95% of our forecasted annual wholesale loads. (RPU internal distribution losses have averaged exactly 5.15% over the last 10 years.) This constraint is applied by determining a post-hoc, annual adjustment factor (f_R) computed as

$$f_R = \frac{0.9485(W)}{(R + C + I + O)} \qquad \text{Eq. 4.1}$$

where *R*, *C*, *I* and *O* represent our forecasted annual Residential, Commercial, Industrial and Other retail loads, and *W* represents or forecasted annual wholesale system load. Our final monthly retail load forecasts are then adjusted by this annual factor (to ensure that the Eq. 4.1 constraint holds). This process is done to force our (somewhat less accurate) retail load forecasts to align with our loss adjusted system load forecasts.

4.1 Monthly residential load model (retail sales)

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

$$\begin{aligned} y_t = \beta_0 + \beta_1[lag(EMP_t)] + \beta_2[(SumCD_t + lag(SumCD_t))/2] + \\ \beta_3[(SumXHD_t + lag(SumXHD_t))/2] + \beta_4[XMas_t] + \\ \beta_5[Fs(1)_t] + \beta_6[Fc(1)_t] + \beta_7[Fs(2)_t] + \beta_8[Fc(2)_t] + \sigma^2 \end{aligned} \quad \text{Eq. 4.2}$$

In Eq. 4.2, y_t represents the RPU monthly residential load (GWh) for the calendar ordered monthly observations and forecasts (*t*=1 → Jan 2003, *t*=264 → Dec 2024) and the homogeneous residual errors are assumed to be Normally distributed and temporally uncorrelated. Eq. 4.2 was optimized using ordinary least squares estimation (SAS Reg Procedure).

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

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

4.2 Residential load model statistics and forecasting results

Table 4.1 shows the pertinent model fitting and summary statistics for our residential load forecasting equation. The equation explains about 96% of the observed variability associated with the monthly 2003-2012 residential loads and nearly all input parameter estimates are statistically significant below the 0.01 significance level. An analysis of the model residuals confirms that these errors are Normally distributed, devoid of outliers and temporally uncorrelated; implying that our modeling assumptions are reasonable.

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

Figure 4.1 shows the observed (blue points) versus calibrated (green line) residential loads for the 2003-2012 timeframe. Nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines); the observed versus calibrated load correlation equals 0.975. Figure 4.2 shows the forecasted monthly system loads for 2013 through 2022, along with the corresponding 95%

forecasting envelope. This forecasting envelope encompasses both model and weather uncertainty, while treating the projected economic indices as fixed inputs.

Table 4.2 shows the forecasted monthly RPU residential loads for 2013, along with their forecasted standard deviations. Once again, these standard deviations quantify both model and weather uncertainty. The 2013 forecasts project that our annual residential load should be 724.0 GWh, assuming that the RPU service area experiences typical weather conditions throughout the year.

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

Residential MWh Sales Model (Jan 2033 - Sept 2012)

Dependent Variable: Residential Load (GWh)

Number of Observations Read	456
Number of Observations Used	116
Number of Observations with Missing Values	340

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	26653	3331.63667	301.60	<.0001
Error	107	1181.96548	11.04641		
Corrected Total	115	27835			

Root MSE	3.32361	R-Square	0.9575
Dependent Mean	58.78005	Adj R-Sq	0.9544
Coeff Var	5.65432		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	8.69884	8.87162	0.98	0.3290	0
sum2CD	SumCD+lag(SumCD)	1	0.10111	0.00874	11.57	<.0001	13.00565
sum2HD	SumXHD+lag(SumXHD)	1	0.05280	0.01463	3.61	0.0005	2.94952
lagEmpCC	lag(EMP)	1	22.19667	5.61252	3.95	0.0001	1.10533
xmas	XMas Effect	1	9.55642	1.14899	8.32	<.0001	2.97416
s1	Fs(1)	1	-3.23920	1.14350	-2.83	0.0055	6.91401
c1	Fc(1)	1	-3.81151	1.13083	-3.37	0.0010	6.65583
s2	Fs(2)	1	3.58617	0.74500	4.81	<.0001	2.92578
c2	Fc(2)	1	-2.64973	0.65039	-4.07	<.0001	2.21120

Durbin-Watson D	2.688
Number of Observations	116
1st Order Autocorrelation	-0.354

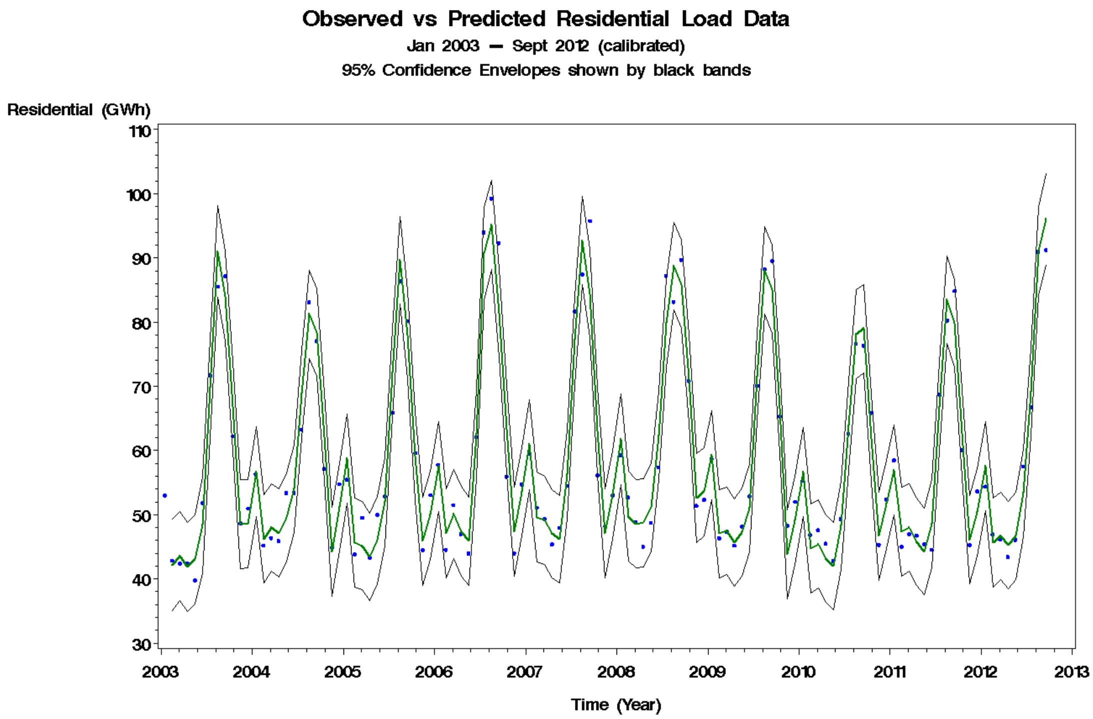

Figure 4.1. Observed and predicted residential load data (2003-2012), after adjusting for known weather conditions.

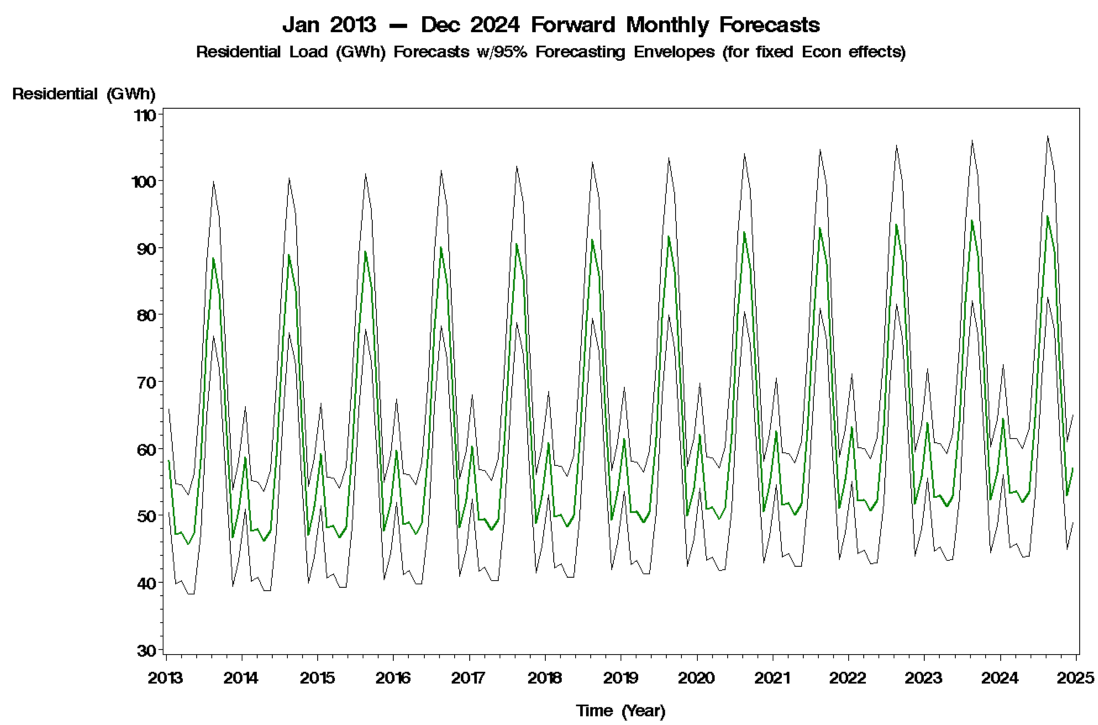

Figure 4.2. Forecasted monthly residential loads for 2013-2024; 95% forecasting envelopes encompass both model and weather uncertainty.

Table 4.2. 2013 monthly residential load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Load (GWh)	Std.Dev (GWh)
JAN	59.04	3.84
FEB	47.93	3.74
MAR	48.13	3.57
APR	46.38	3.69
MAY	47.98	4.50
JUN	59.11	5.48
JUL	77.38	5.75
AUG	89.76	5.79
SEP	84.43	5.63
OCT	65.06	4.56
NOV	47.33	3.61
DEC	51.44	3.69
Annual TOTAL	723.96	

4.3 Monthly commercial + industrial load model (retail sales)

Our composite monthly commercial + industrial load forecasting model is a function of two economic drivers (prior month PCPI and EMP), two current and prior weather effects that quantify the total monthly cooling and extended heating degrees (SumCD and SumXHD), and two low order Fourier frequencies (Fs(1) and Fc(1)). Mathematically, the model is defined as

$$y_t = \beta_0 + \beta_1[lag(EMP_t)] + \beta_2[lag(PCPI_t)] + \beta_3[(SumCD_t + lag(SumCD_t))/2] \\ + \beta_4[(SumXHD_t + lag(SumXHD_t))/2] + \beta_5[Fs(1)_t] + \beta_6[Fc(1)_t] + \sigma^2$$

Eq. 4.3

In Eq. 4.3, y_t represents the RPU combined monthly commercial + industrial load (GWh) for the calendar ordered monthly observations and forecasts (t=1 → Jan 2003, t=264 → Dec 2024) and the homogeneous residual errors are assumed to be Normally distributed and temporally uncorrelated. Eq. 4.3 was optimized using ordinary least squares estimation (SAS Reg Procedure).

Once again, all input observations that reference historical time periods were assumed to be fixed during the estimation process. Likewise, the forecasted economic indices are treated as fixed variables and the forecasted weather indices are again treated as random effects. As before, a first-order Delta method estimate of the forecasting variance was calculated in the usual manner.

In order to produce individual commercial and industrial load forecasts, it is necessary to split each monthly load prediction into two components. Upon examining the ratio of the monthly commercial (C) over the commercial + industrial (C+I) loads (i.e., C/[C+I]) since Januray 2007, we found that that this ratio has only varied from 0.295 to 0.338 (mean = 0.312, standard deviation = 0.012). Thus, we have assumed that 31% of each future load forecast represents commercial load, while the remaining 69% of each forecast represents industrial load. This simple post-hoc calculation facilitates the prediction of separate commercial and industrial retail load metrics, respectively.

4.4 Commercial + Industrial load model statistics and forecasting results

Table 4.3 shows the pertinent model fitting and summary statistics for our commercial + industrial load forecasting equation. The equation explains approximately 88% of the observed variability associated with the monthly 2003-2012 C+I loads. Note that although the heating degree effect is non-significant (t = 1.36, p=0.1754), we've elected to retain this weather variable in the equation. (Intuitively, a positive heating degree effect is both reasonable and expected.) Note also that an analysis of the model residuals confirms that these errors are Normally distributed, devoid of outliers and temporally uncorrelated.

The regression parameter estimates shown in the middle of Table 4.3 indicate that monthly residential load increases as either/both weather indices increase (SumCD and SumXHD); once again however, the heating degree effect cannot be judged to be statistically significant. As in the residential model, averages of each current and prior month weather indices are used as input variables in the forecasting equation (to account for the delayed billing effect). RPU C+I loads are also expected to increase as either/both the area wide PCPI and/or employment levels improve over time. Additionally, the impact of these estimated economic driver effects appear to be much more pronounced in this C+I equation, as opposed to the residential equation.

Figure 4.3 shows the observed (blue points) versus calibrated (green line) C+I loads for the 2003-2012 timeframe. Once again, nearly all of the calibrations fall within the calculated 95% confidence envelope (thin black lines); the observed versus calibrated load correlation equals 0.94. Figure 4.4 shows the forecasted monthly C+I loads for 2013 through 2024, along with the corresponding 95% forecasting envelope. This forecasting envelope encompasses both model and weather uncertainty, while treating the projected economic indices as fixed inputs. Note that our C+I loads are forecasted to grow at a 2.4% annual rate, once the local economy fully recovers.

Table 4.4 shows the post-hoc forecasted monthly commercial and industrial loads for 2013, along with their forecasted standard deviations. Once again, these standard deviations quantify both model and weather uncertainty. The 2013 forecasts project that our annual commercial and industrial loads should be 435.9 and 970.2 GWh, respectively, assuming that the RPU service area experiences typical weather conditions throughout the year and that the 31%/69% commercial/industrial load pattern continues to hold.

Table 4.3 Model summary statistics for the monthly commercial + industrial load forecasting equation.

Commercial / Industrial Sales Model (Jan 2003 - Sept 2012)

Dependent Variable: Comm+Indst Load (GWh)

Number of Observations Read	456
Number of Observations Used	116
Number of Observations with Missing Values	340

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	19145	3190.81975	136.93	<.0001
Error	109	2540.02790	23.30301		
Corrected Total	115	21685			

Root MSE	4.82732	R-Square	0.8829
Dependent Mean	109.78448	Adj R-Sq	0.8764
Coeff Var	4.39709		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	-28.92498	12.92552	-2.24	0.0273	0
sum2CD	SumCD+lag(SumCD)	1	0.05755	0.00761	7.56	<.0001	4.68245
sum2HD	SumXHD+lag(SumXHD)	1	0.02374	0.01740	1.36	0.1754	1.97791
lagPCPI	lag(PCPI)	1	3.55590	0.37604	9.46	<.0001	1.51256
lagEmpCC	lag(EMP)	1	17.87497	9.47739	1.89	0.0619	1.49404
s1	Fs(1)	1	-5.18813	1.21438	-4.27	<.0001	3.69636
c1	Fc(1)	1	-4.41963	1.12688	-3.92	0.0002	3.13304

Durbin-Watson D	2.378
Number of Observations	116
1st Order Autocorrelation	-0.190

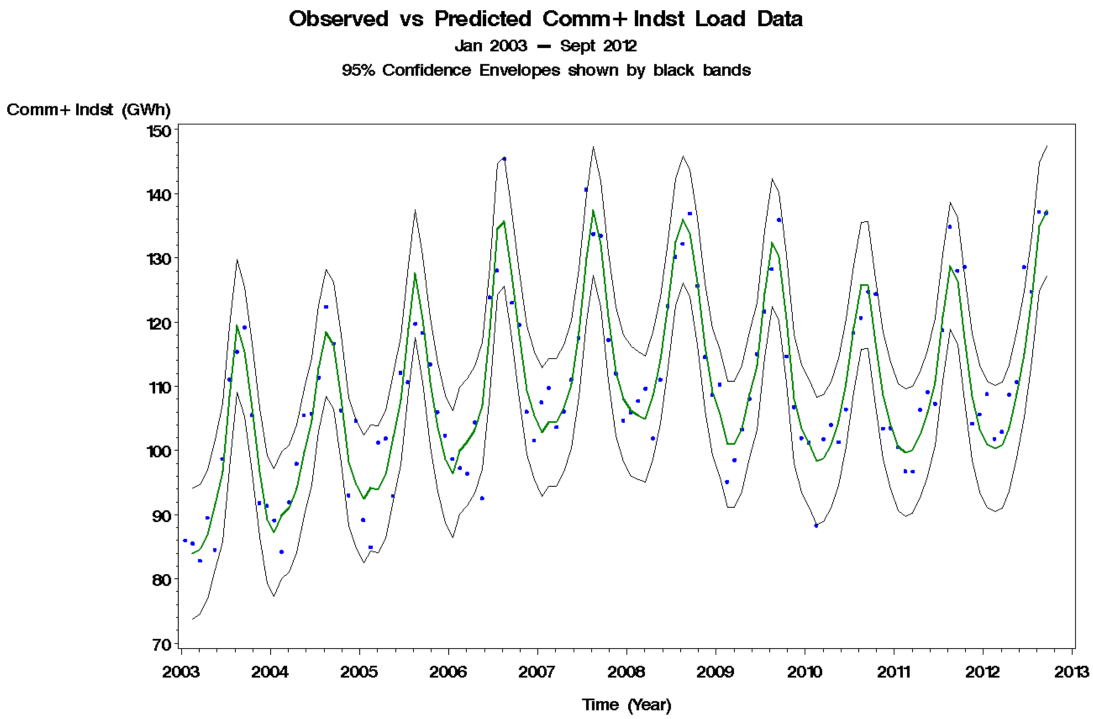

Figure 4.3. Observed and predicted C+I load data (2003-2012), after adjusting for known weather conditions.

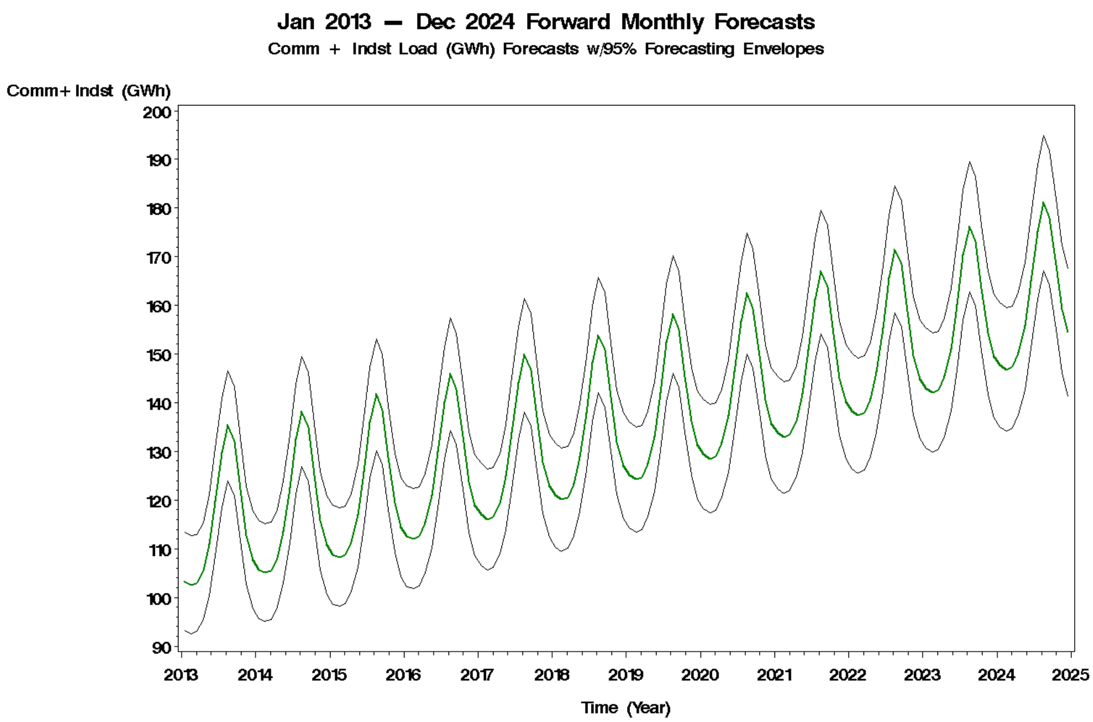

Figure 4.4. Forecasted monthly C+I loads for 2013-2024; 95% forecasting envelopes encompass both model and weather uncertainty.

Table 4.4. 2013 monthly commercial and industrial load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Comm Load (GWh)	Std.Dev (GWh)	Indst Load (GWh)	Std.Dev (GWh)
JAN	32.51	1.56	72.36	3.48
FEB	32.30	1.56	71.90	3.46
MAR	32.40	1.54	72.11	3.42
APR	33.20	1.54	73.89	3.44
MAY	34.88	1.62	77.64	3.60
JUN	37.65	1.71	83.81	3.81
JUL	40.83	1.74	90.87	3.88
AUG	42.61	1.75	94.84	3.90
SEP	41.58	1.73	92.55	3.85
OCT	38.48	1.63	85.65	3.62
NOV	35.51	1.55	79.04	3.46
DEC	33.93	1.56	75.52	3.46
Annual TOTAL	435.88		970.18	

4.5 Modeling and forecasting results for the Other customer class

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

Since January 2008, the monthly loads associated with the Other customer class have exhibited a fairly stable, seasonal pattern that appears to be independent of changing economic conditions. However, this pattern does show a marginal relationship with the observed monthly cooling degrees (SumCD), and two obvious outlier months (January 2009 and May 2011). As such, our load forecasting model for this customer class was defined to be a function of the current and prior month cooling degrees, two low order Fourier frequencies (Fs(1) and Fc(1)), and two indicator variables to account for the 01/09 and 05/11 outliers. The corresponding model estimation results (derived using ordinary least squares) are shown in Table 4.5; note that this equation describes 73% of the observed load variation.

Table 4.6 shows the monthly load forecasts for 2013 along with their forecasted standard deviations. As with all previous forecasts, these standard deviations quantify both model and weather uncertainty. However, the weather uncertainty in these forecasts is minimal, since the estimated weather effect is quite trivial. Also, these forecasts do not grow over time, since the forecasting equation for this latter customer class includes no economic driver variables.

Table 4.5 Model summary statistics for our monthly "other" load forecasting equation.

Other (Non-RCI) Sales Model: [2008-2012]

Dependent Variable: Other Load (GWh)

Number of Observations Read	396
Number of Observations Used	57
Number of Observations with Missing Values	339

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	2.99293	0.59859	27.58	<.0001
Error	51	1.10700	0.02171		
Corrected Total	56	4.09993			

Root MSE	0.14733	R-Square	0.7300
Dependent Mean	2.64630	Adj R-Sq	0.7035
Coeff Var	5.56736		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	2.57210	0.04561	56.39	<.0001	0
sum2CD	SumCD+lag(SumCD)	1	0.00074	0.00035	2.12	0.0391	5.23393
s1	Fs(1)	1	-0.13548	0.05345	-2.53	0.0144	3.74182
c1	Fc(1)	1	0.16743	0.04290	3.90	0.0003	2.41099
outlier1	[Jan 2009]	1	0.57151	0.15154	3.77	0.0004	1.03943
outlier2	[May 2011]	1	-0.62683	0.15235	-4.11	0.0001	1.05056

Durbin-Watson D	1.542
Number of Observations	57
1st Order Autocorrelation	0.191

Table 4.6. 2013 monthly other customer class load forecasts for RPU; forecast standard deviations include both model and weather uncertainty.

Month	Load (GWh)	Std.Dev (GWh)
JAN	2.71	0.14
FEB	2.57	0.14
MAR	2.43	0.14
APR	2.35	0.14
MAY	2.34	0.14
JUN	2.44	0.14
JUL	2.62	0.14
AUG	2.81	0.14
SEP	2.92	0.14
OCT	2.94	0.14
NOV	2.90	0.14
DEC	2.83	0.14
Annual TOTAL	31.86	

4.6 Final post-hoc forecasting alignment

As described earlier at the beginning of section 4, a post-hoc correction factor was applied to all retail forecasts. This correction factor (calculated via Eq. 4.1.) was used to constrain the annual sums of our retail load forecasts to equal our (loss adjusted) system load forecasts. These annual adjustment factors ranged from 1.016 (2013) to 0.975 (2024), respectively.

Our final annual, class-specific adjusted retail forecasts are reported on Demand Form 1.a in our 2013 CEC IEPR submission packet. The monthly 2013-2024 forecasts for our three primary retail customer classes are also shown in Figure 4.5. Note that two general features are apparent. First, our forecasted residential loads exhibit a much more pronounced reaction to summer temperature effects. This pattern reflects the increased load associated with running residential air conditioning units during the June-September summer season in the RPU service territory. Second, the forecasted 10-year load growths associated with our commercial and industrial classes are significantly higher than our forecasted residential load growth. Assuming that the local economy fully recovers, there is a much greater potential for increased commercial and industrial growth in our service territory. The potential for new residential development is far more restricted, given current Riverside City zoning regulations (and City Council adopted slow-growth initiatives).

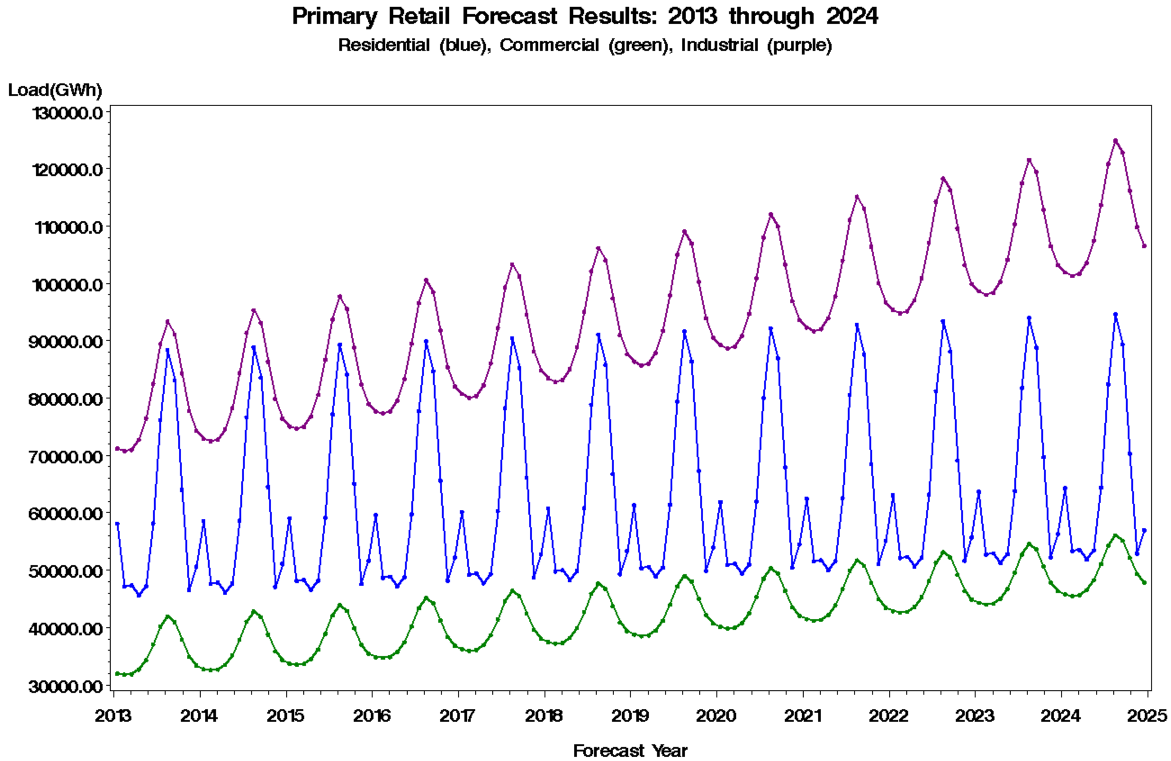

Figure 4.5. RPU monthly retail load forecasts (Jan 2013 - Dec 2024) for the residential, commercial and industrial customer classes.