Development of Short-term Demand Forecasting Model
And its
Application in Analysis of Resource Adequacy

For discussion purposes only
Draft

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Introduction

In this paper we will present the methodology, testing and results from short-term forecasting model developed by Northwest Power and Conservation Council. We also present the methodology and application of this modeling system to the Resource Adequacy analysis. Theoretical discussions are presented in the appendix section.

Before we start it is necessary that we define what we mean by weather-normalized and temperature-sensitive load. Weather-normalized load is load under "normal" temperature conditions. The term "temperature-sensitive load" as used here has a meaning somewhat different than its usual meaning: 'Temperature-sensitive load' means <u>deviation</u> in load resulting from <u>deviations</u> in temperature from normal for a given day or hour."

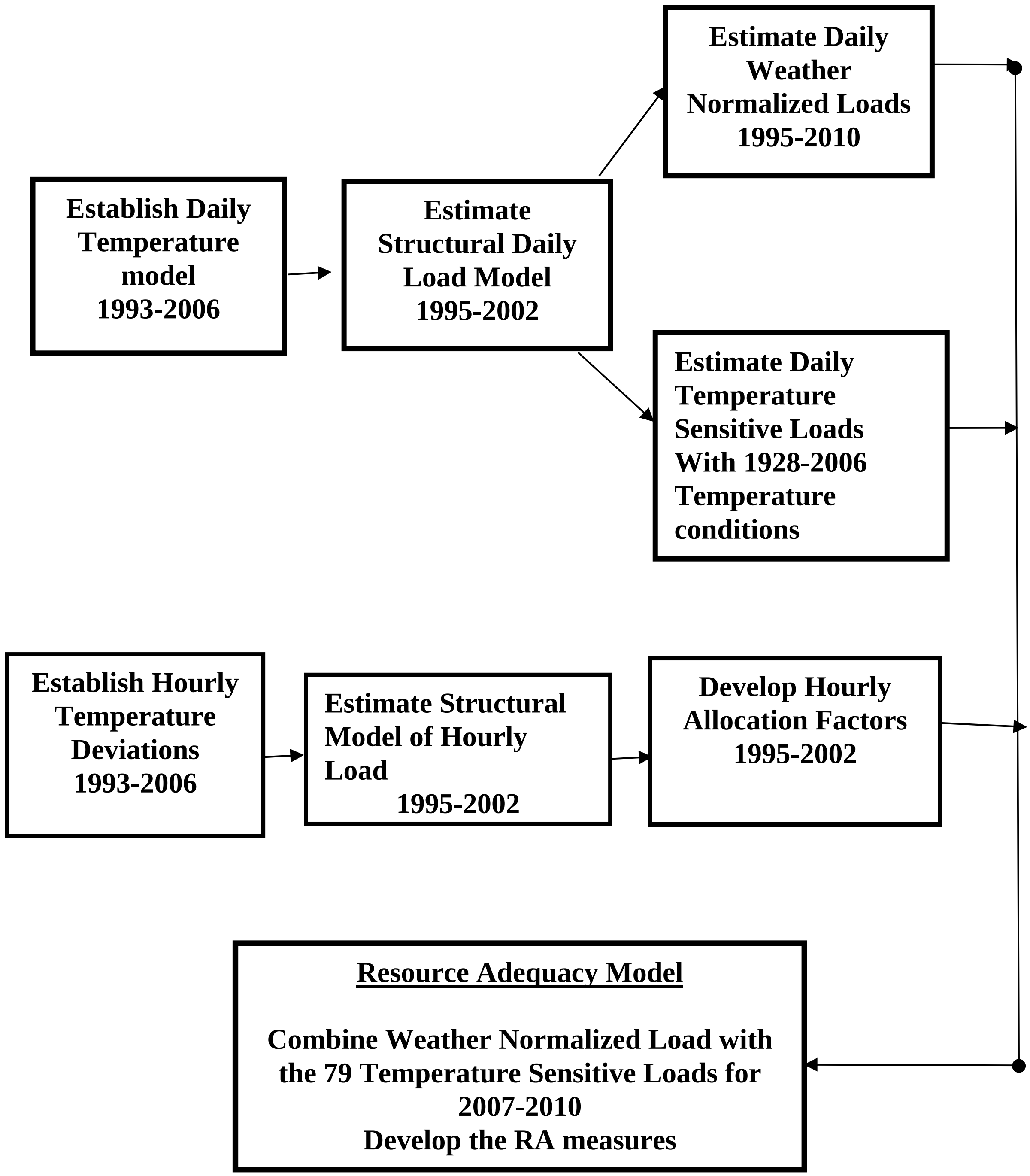
Methodology:

Using econometrically estimated relationships between loads and temperatures, in a three step process, we developed and applied the short-term forecasting model to Resource Adequacy analysis. These steps are presented below.

1. Developed Daily Load Model
    a. Using daily average temperature for the region we estimated daily deviations from mean for each day from January 1, 1928- December 31, 2006.
    b. Using the daily temperature deviations and a limited number of trends, seasonal and cyclical variables we estimated the structural model for daily loads.
    c. Using daily structural model for daily load and removing non-temperature related variables; we estimated the temperature-sensitive portion of daily load for daily temperature conditions the region has experienced in the past 79 years, from 1/1/1928 through 12/31/2006.
    d. Using the non-temperature related variables we forecasted weather-normalized daily load for 2007-2010.

2. Developed the Hourly Load Model
    a. Using hourly temperature for 1993-2006, we estimated the hourly deviations from mean temperature for the region
    b. Using the hourly temperature deviations and the same trend, seasonal and cyclical variables as in the daily model we estimated the structural model for hourly loads.
    c. Using the hourly model and excluding the holiday and the economic trend variables we estimated hourly loads for 1995-2002. These hourly loads were then used to develop 8760 hourly allocation factors.
    d. The hourly allocation factors were used to allocate daily forecast for weather-normalized loads and temperature-sensitive loads into total hourly loads.

3. Application to Resource Adequacy
    a. Using the 79 years of daily temperature observations, we Developed 79 different hourly load forecasts for each day in 2007 through 2010, using the 79 temperature-sensitive loads.
    b. Selected a Sustained Peaking Period, 5 weekdays and 10 hours per day.
    c. For each month coincident peak and average loads in the Sustained Peak Period were calculated. Peak load and energy load for all months were ranked and top 5th percentile load were used as the loads for resource adequacy purposes.



Application of Short-term Hourly Load Forecasting Model to Resource Adequacy

Preliminary Weather-Normalized Load Forecast for 2007-2010

After we estimated, tested and refined the daily model we produced a preliminary forecast. Using Global Insights quarterly employment forecast for the four states of Oregon, Washington, Montana, and Idaho we forecast weather-normalized loads for 2007-2010. The following table shows long and short-term forecasts for annual energy as well as short-term forecast for peak load. Figures for 2000-2004 in the long-term model are actual figures, whereas for the short-term model they are backcast.

Comparison of 5th Power Plan Forecast and Short-Term Forecast

	Council's Long-Term Model Forecast					Short-Term Model	(Weather-Normalized)
	Low	Med lo	Medium	Med hi	High	Energy MWa	Peak Load MW
2000			19,187			19,547	25,949
2001			18,671			18,906	23,616
2002			18,696			19,454	23,666
2003			19,124			19,560	23,694
2004			19,699			19,829	23,824
2005	18,738	19,428	20,092	20,732	22,040	20,138	24,057
2006	18,748	19,571	20,343	21,102	22,592	20,408	24,323
2007	18,764	19,727	20,607	21,496	23,170	20,613	24,367
2008	18,778	19,880	20,868	21,901	23,777	20,773	24,664
2009	18,810	20,053	21,151	22,322	24,413	20,919	24,800
2010	18,853	20,242	21,460	22,758	25,078	21,052	24,934

Comparison of short-term forecast results with the 5th Plan forecasts finds that although the short-term and long-term forecasts are based on totally different analytical approaches, the resulting forecasts are fairly consistent. The following table shows percent difference between the two models over the next four years.

Percent Difference in forecasts from short-term and long-term models

	Low	Med low	Medium	Med high	High
2007	10%	4%	0.0%	-4%	-11%
2008	11%	4%	-0.5%	-5%	-13%
2009	11%	4%	-1%	-6%	-14%
2010	12%	4%	-2%	-7%	-16%

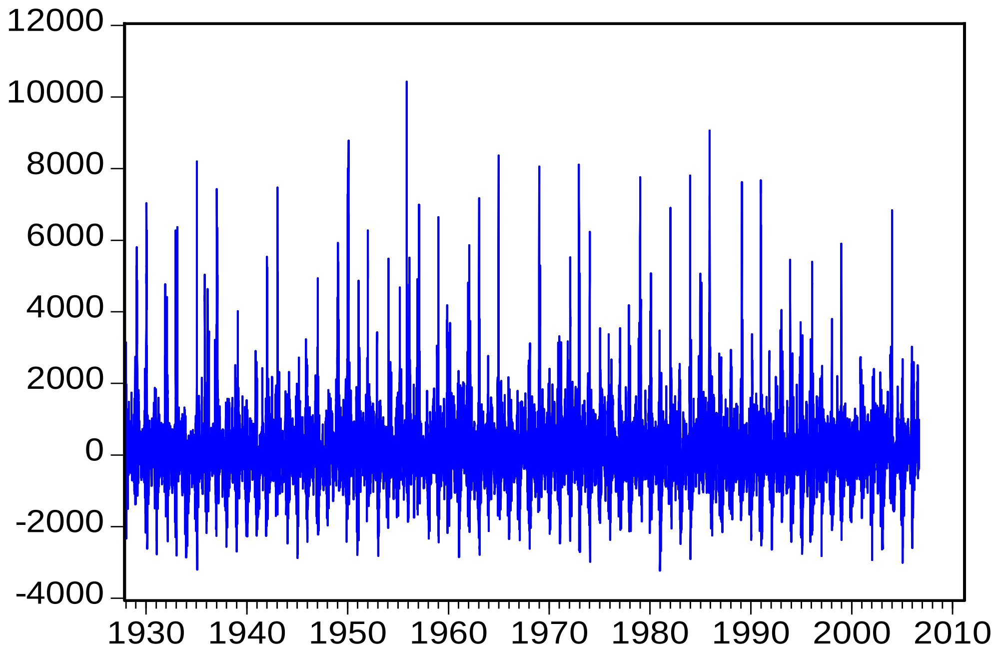
Our recent biennial assessment showed that weather-normalized actual load is in the medium-low to medium range of the long-term forecast.

Forecasting Temperature Sensitive Loads under Various Temperature conditions

One of the advantages of the short-term model is that it allows decomposition of demand into the effects of different variables. For instance, the linear combination of the variables with the exception of temperature variables would result in an estimate of weather normalized load. The linear combination of the temperature variables on the other hand, estimates the effect of temperature fluctuations above and beyond the seasonal variations on demand. This useful feature of the model allows simulation of load under different historical experienced weather conditions. For instance, by adding an array of experienced weather effects to the weather normalized demand in a specific year, one explores different scenarios of demand based on weather.

Using the daily model and daily regional temperatures from 1928-2006, we estimated the temperature sensitive (TS) portion of the load for each day. The estimated TS loads show what the forecasted load would be if the region experiences past temperatures.

Load Fluctuation due to 1928-2006 Daily Temperature Deviations from Norm. (MWa)

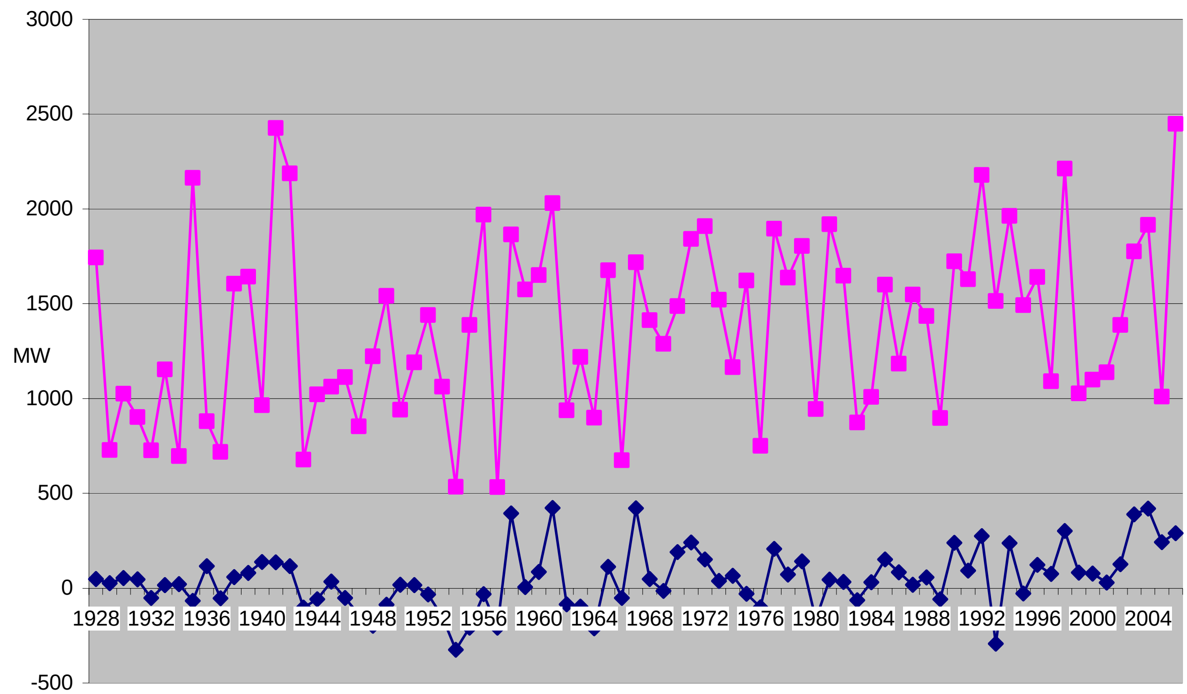


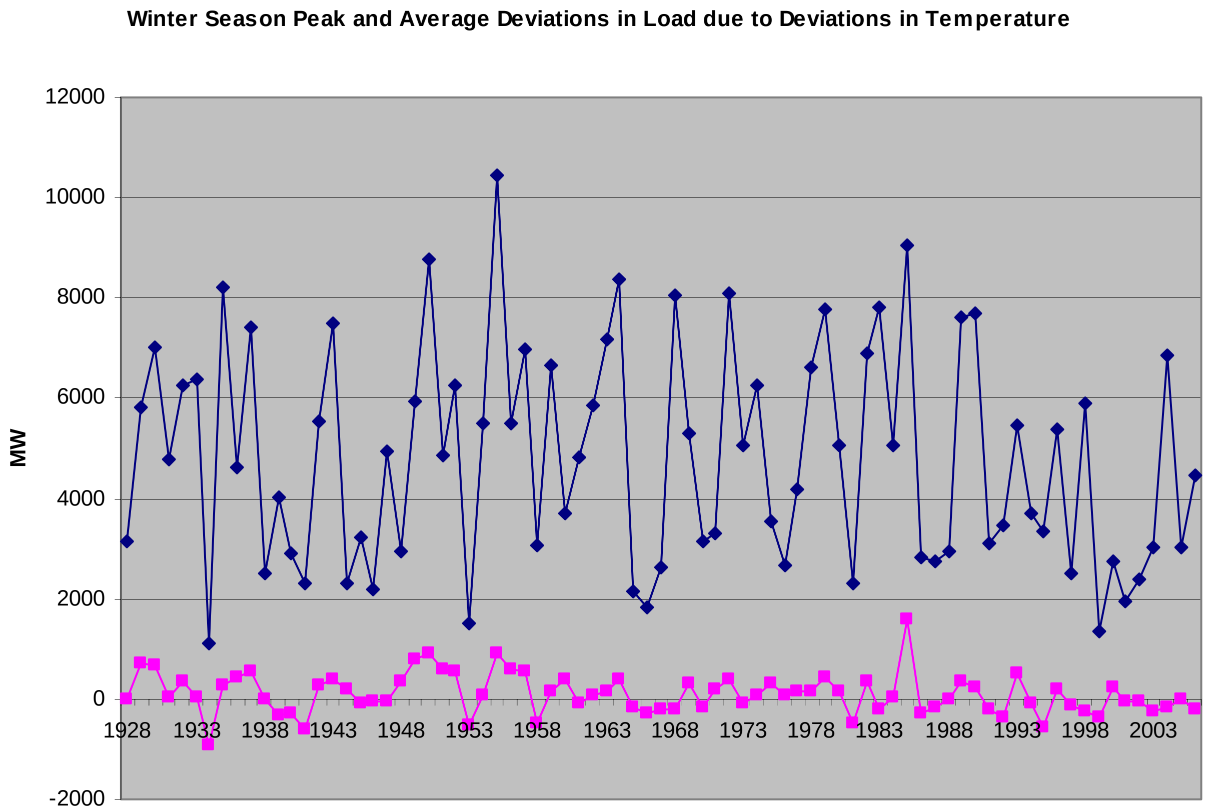
To give a summary view of this information, in the following table we have extracted highest and lowest additions and reductions to daily load due to daily temperature deviations from daily mean temperature. For example, we see that if the region is exposed to temperature profiles similar to November 1955, coldest November in the past 79 years, then regional peak load will be higher by 10,433 MWa. For the July daily loads we observe that if the region faces a temperature profile similar to what it experienced on July 24th in 2006, then regional daily load would go up 2449 MWa.

Change in Temperature Sensitive portion of Regional Load due to Temperature Deviations in the past 79 year

	Average Daily Temperature	Normal Load for 2007 MWa	Year of Extreme Temp Event	Deviation of Daily Temp. From Mean	Change in Daily Load (MWa)	Total Load MWa
January	35	23,533	1950	-33	8,784	32,317
February	39	22,622	1950	-30	8,149	30,771
March	43	21,165	1955	-23	4,685	25,850
April	49	19,767	1936	-16	3,450	23,217
May	57	19,245	1965	-12	1,466	20,711
June	62	19,759	1992	16	2,178	21,937
July	68	20,559	2006	14	2,449	23,008
August	67	20,274	1992	12	1,929	22,203
September	62	19,017	1988	-12	1,364	20,381
October	53	19,735	1935	-17	4,453	24,188
November	45	21,871	1955	-26	10,433	32,304
December	37	23,484	1964	-24	8,365	31,849

The following graphs show maximum and average daily MWa due to deviations in temperature.





We observe weather induced fluctuations in load are greater in winter than summer.

Application of the Daily and Hourly Models to Resource Adequacy

An application of the model developed above is the development of regional hourly loads under a wide range of temperature conditions. In this report, we discuss development of three metrics for resource adequacy.

1- Single hour peak load in the sustained peaking period
2- Maximum average load in the sustained peaking period
3- Average of average load in the sustained peaking period

To develop above three load measures we take the following steps.

1- Define Sustained Peaking Period (SPP)

The sustained peaking period was defined as 10 hours per day for 5 weekdays (50 hours per week). During the winter months (November, December, January, February, March) the 50-hours consisted of two sets of 5 consecutive hours over 5 weekdays. The first period starting at 7 am going to 11 am and the second period starting at 3 pm and ending at hour 7 pm. During the summer months (June, July, August and September) the 50 hour consists of 10 consecutive hours, starting at 10 am and ending at hour 7 pm. Saturday and Sundays are excluded from sustained peaking period. Each hour in a day is assigned a multiplier of 0 (exclude) or 1 (include) in the sustained peaking period. Other definitions of sustained peaking period can be developed (ie, 6 hours/day for 5 days).

2- Determine hourly Weather normalized load for the sustained peaking period

For each day during 2007-2010, we estimate the weather-normalized load then multiply it by the hourly allocation factor and sustained peaking period multiplier for that day.

3- Determine hourly temperature-sensitive load

For each day during 2007-2010 we estimate 79 temperature-sensitive loads (reflecting the historic 1928-2006 temperature experience for that day). Daily loads are multiplied by hourly allocation factors and sustained peaking period multiplier for that day.

4- Determine hourly total load

Weather normalized and temperature-sensitive loads for each hour are added

5- Generate metrics for resource adequacy

We developed three measures:

1. Single hour peak load during a month during sustained peaking period. This measure is in MW units.
2. Maximum of average loads during sustained peaking period. This is a capacity/energy hybrid measure is expressed in units of energy, MWa.
3. Average load during the sustained peaking period.

6-Rank the Loads

For each month we would have 79 values for these three sets of measurements. Each set is independently ranked. For each set, ranking of 1 indicates the load under the worst temperature condition, highest load. Ranking of 39 indicates the load under average weather condition. For resource adequacy assessment analysis, we used a ranking of 4 indicating 5^{th} percentile or 1 in 20 year case. In the table below we present, the coincident peak and average regional net load for 2007 under worst, average and top 5^{th} percentile weather conditions. Note that the ranking for each measure is independent from the other measures.

	2007 1 in 79 year event			2010 1 in 79 year event		
	Single Hour Peak Load During Sustained Peaking Period	Maximum of Average Load during Sustained Peaking Period	Average Load during Sustained Peaking Periods	Single Hour Peak Load During Sustained Peaking Period	Maximum of Average Load during Sustained Peaking Period	Average Load during Sustained Peaking Periods
	MW	MWa	MWa	MW	MWa	MWa
January	36,506	32,895	30,027	36,688	32,521	29,672
February	36,357	33,928	27,881	36,267	31,987	27,852
March	29,990	26,766	24,340	31,146	27,177	25,062
April	25,406	22,501	21,919	27,394	25,035	22,203
May	23,842	21,600	21,122	24,159	22,016	21,501
June	25,694	23,983	22,206	25,986	24,778	22,751
July	27,295	25,162	23,700	27,513	25,437	24,173
August	26,205	24,714	23,458	26,882	25,022	24,004
September	23,443	22,066	21,262	24,209	23,254	22,034
October	28,863	22,443	21,638	27,173	24,057	22,027
November	37,593	33,124	26,727	36,882	32,283	27,032
December	37,102	31,744	27,969	37,699	33,717	28,689

	2007 with Average Condition			2010 with Average Condition		
	Single Hour Peak Load During Sustained Peaking Period	Maximum of Average Load during Sustained Peaking Period	Average Load during Sustained Peaking Periods	Single Hour Peak Load During Sustained Peaking Period	Maximum of Average Load during Sustained Peaking Period	Average Load during Sustained Peaking Periods
	MW	MWa	MWa	MW	MWa	MWa
January	30,726	27,051	25,615	30,544	27,879	26,218
February	28,261	25,826	24,761	28,763	25,892	25,040
March	26,988	24,022	22,990	27,140	24,456	23,493
April	23,999	21,379	20,914	24,540	22,168	21,402
May	22,795	21,019	20,721	23,344	21,558	21,204
June	23,716	22,680	21,842	24,343	22,850	22,227
July	25,202	23,767	23,097	25,524	24,228	23,510
August	24,611	23,378	22,612	25,058	23,648	23,085
September	22,427	21,422	21,079	22,926	22,301	21,697
October	24,066	21,457	20,991	24,258	22,157	21,474
November	27,664	24,951	23,570	28,049	24,950	23,897
December	29,787	27,010	25,903	30,291	27,590	26,167

	2007 With 1 in 20 year event			2010 With 1 in 20 year event		
	Single Hour Peak Load During Sustained Peaking Period	Maximum of Average Load during Sustained Peaking Period	Average Load during Sustained Peaking Periods	Single Hour Peak Load During Sustained Peaking Period	Maximum of Average Load during Sustained Peaking Period	Average Load during Sustained Peaking Periods
	MW	MWa	MWa	MW	MWa	MWa
January	35,522	31,371	28,885	35,745	32,190	29,316
February	32,468	29,625	26,870	33,578	29,847	27,374
March	29,369	25,834	23,868	29,538	26,475	24,301
April	25,196	22,176	21,380	25,624	23,159	22,128
May	23,593	21,540	21,025	23,964	21,853	21,442
June	24,790	23,369	22,108	25,437	23,610	22,571
July	26,356	24,869	23,628	26,863	25,215	24,045
August	25,622	24,313	23,109	26,140	24,585	23,753
September	23,194	21,786	21,219	23,643	22,907	21,864
October	26,193	22,402	21,373	26,089	23,380	21,980
November	31,030	27,431	24,737	31,984	27,846	25,285
December	35,262	30,159	27,608	37,187	31,643	27,600

Sensitivity of Resource Adequacy to Sustained Peaking Period definition

In the previous case the forecasted loads excluded weekend loads. To test the sensitivity of loads to the period definition we included weekends in the analysis.

In that 1 in 20 event case we observe the following:

- Single hour peak does not change in majority of cases, except December where peak load increases by 200 MW.
- The maximum of average load during sustained peaking period goes up by between 27-1700 MWa.
- The average during sustained peaking period goes down between 184-653 MWa.

Weekends included	2007 Weekends included			Delta		
	Hour Peak Load During Sustained Peaking Period	Maximum of Average Load during Sustained Peaking Period	Average Load during Sustained Peaking Period	Single Hour Peak Load During Sustained Peaking Period	Maximum of Average Load during Sustained Peaking Period	Average Load during Sustained Peaking Period
	MW	MWa	MWa	MW	MWa	MWa
January	35,522	31,784	28,910	-	412	(184)
February	32,468	29,928	26,344	-	302	(162)
March	29,369	26,189	23,393	-	354	(267)
April	25,196	22,416	21,068	-	240	(295)
May	23,593	21,567	20,509	-	27	(471)
June	24,790	23,369	21,686	-	-	(653)
July	26,356	24,869	23,054	-	-	(545)
August	25,622	24,313	22,737	-	-	(375)
September	23,194	22,319	20,841	-	534	(378)
October	26,193	22,914	21,025	-	513	(584)
November	31,030	27,810	24,262	-	379	(538)
December	35,461	31,863	27,006	199	1,704	(597)

Other sensitivity tests can be performed.

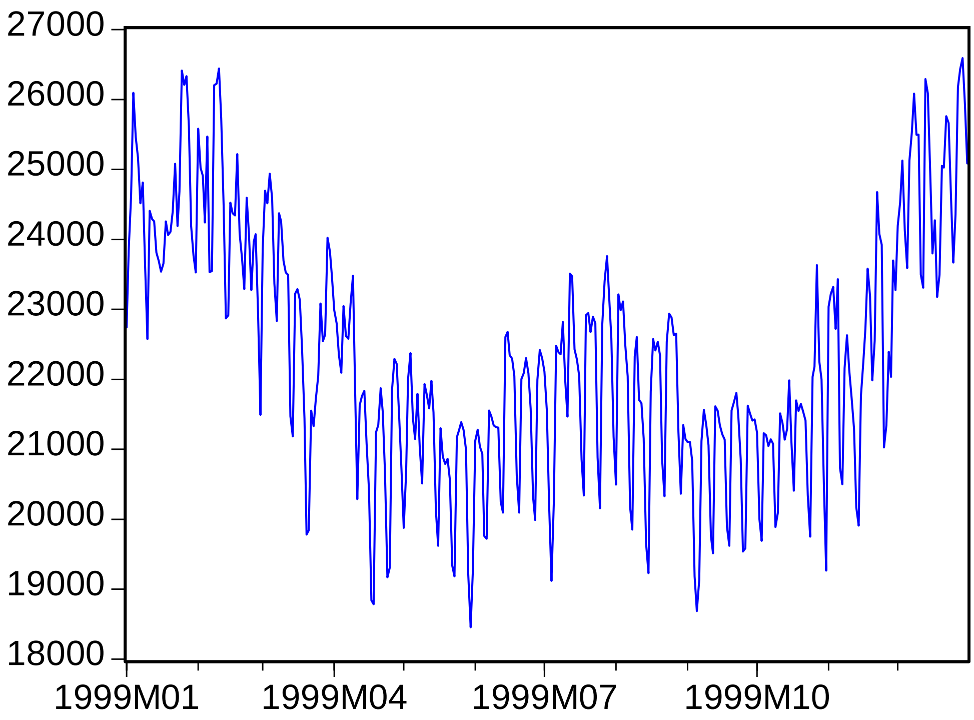
Appendix

Structural Model

Various studies have shown that time-series data can be decomposed into trend, cyclical, seasonal, and irregular components. This technique is very useful in time-series demand studies and allows the researcher to isolate the recurring variations in demand, i.e., seasonal, from variations that are due to changes in short-term and long-term factors that derive demand.

Time-series data for hourly and daily consumption of electricity exhibit these behaviors. In cold climates space heating increases the overall consumption of electricity in winter. By the same token, in warm climates space cooling creates higher consumption in summer. Figure 1 exhibit such seasonal patterns for daily electricity consumption for the region.

Figure 1- Daily Regional Load for 1999



In addition to the overall seasonal variation in consumption, the data exhibit variations that are of shorter durations. For instance, on closer inspection one can observe a regular pattern that reoccurs on a weekly basis. There are also variations that occur on a regular basis but are of lower frequency during the year. For example, consumption on holidays which is usually lower than regular days, which fall into this category. On a longer time horizon, overall consumption of electricity is also affected by changes in demographic and economic factors in the service area. The irregular variations are mainly due to daily changes in the weather and errors in measurement.

A structural time series model was adopted to represent the demand for electricity in the region. The general specification of the demand model is represented by:

$$L = f(S, W, DE, I) \qquad \textbf{(1)}$$

Where :

L = net average hourly or daily electricity load in the region
S = variables depicting seasonal variations in load,
W = weather variables generated via a regression model as explained below,
DE = demographic and economic variables, and
I = indicator or dummy variables.

Seasonal Variables

The daily electricity load in any year exhibits a distinct W-shaped seasonal pattern. The load is generally high during winter, drops in spring and fall, and increases, although, not as much as winter, during the summer. We have used Fourier series of sine and cosine terms as a continuous function of time to express these seasonal patterns.

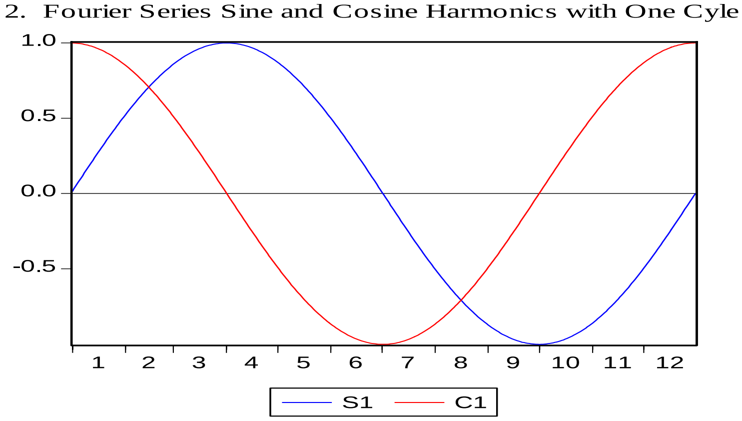
For daily load data these variables can be constructed as

$$S_{it} = \sin\left(\frac{2\pi it}{DIY}\right) \text{and } C_{it} = \cos\left(\frac{2\pi it}{DIY}\right) \qquad \textbf{(2)}$$

where i is the number of cycles within each year, t is the day of the year, and DIY is the number of days in the year, i.e., 365 days and 366 for leap years.

For instance S_1 and C_1 (t subscript is dropped to avoid clutter) complete one full Sine and Cosine cycle and S_2 and C_2 complete two full cycles within a year. Figure 2 shows S_1 and C_1 cycles during a period of one year. The sine wave starts at zero, while the cosine wave at 1.

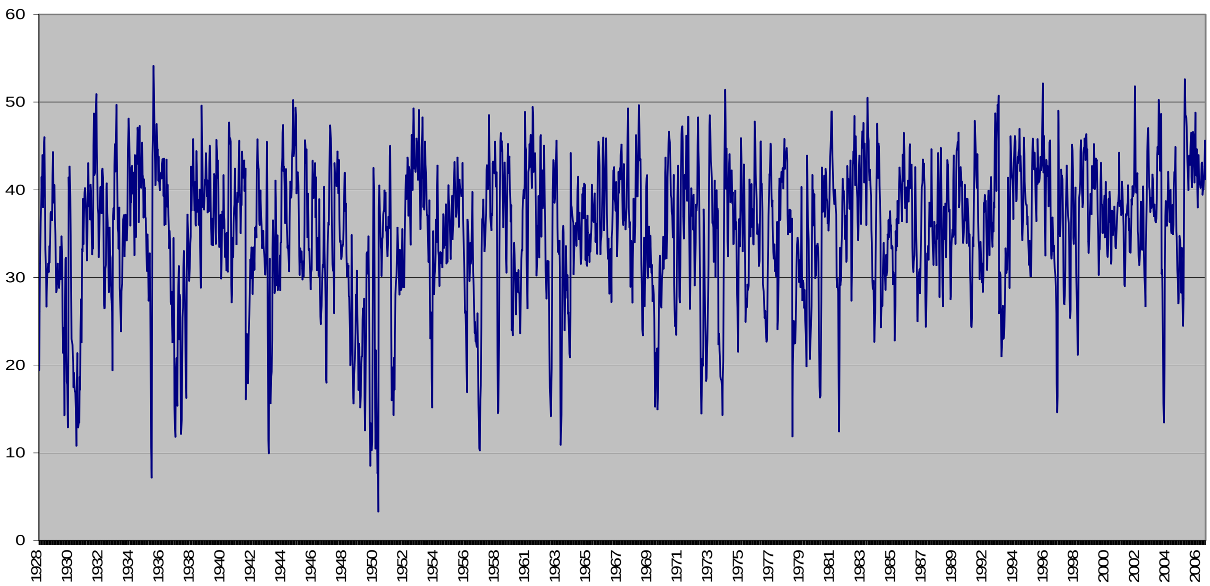
Figure 2. Fourier Series Sine and Cosine Harmonics with One Cyle Per Year



Weather Variables

Weather is the most important driving factor in hourly and daily loads. Air temperature determines the level of electricity use for space heating and cooling. Obviously, weather is governed by a seasonal pattern as well. In fact the seasonal pattern in weather leads to the seasonal variations in load. However, since we are including Fourier series to explain the seasonal pattern in load, using air temperature directly as explanatory variable would entangle the seasonal load pattern with the daily temperature variation. In order to resolve such problem, seasonal pattern should be removed from air temperature as well. This amounts to expressing the hourly and daily temperatures as deviations from historical mean of each hour and each day of the year over the entire available daily temperature data. This can also be achieved by regressing hourly and daily temperatures against a set of Fourier series that explain seasonal variations in temperature. Such a regression model practically estimates the conditional hourly and daily mean of temperature over the entire data. The residuals of the regression model are the deviations from the historical mean and by design are devoid of seasonal pattern. When used as explanatory variables in the load model, the residuals explain variations in load due to hourly and daily temperature change that are above and beyond seasonal variations.

Average Daily Regional Temperature 1928-2006



Northwest Temperature Profile Summary

	Warmest	Coldest
January	1935	1950
February	1932	1950
March	2004	1955
April	1998	1936
May	1998	1965
June	1992	1962
July	2006	1955
August	1977	1956
September	1988	1972
October	1987	1935
November	2006	1955
December	1980	1968

There are several important issues that have to be considered in constructing the temperature variables. The most important issue is that electricity exhibits both positive and negative relationship with temperature. In winter, load increases as temperature drops; this constitutes a negative relation. In summer, however, a rise in temperature increases the load; this constitutes a positive relation. This behavior reflects a nonlinear relationship that can be explained as a temperature effect on load interacted with seasonality. The second issue is the lag effect of temperature on load. Usually, it takes a few consecutive cold or hot hours or days to increase the load. To reflect this effect, we need to include temperature variables with lags. The third issue is the possible nonlinear effect of temperature on load. Beyond certain levels, changes in temperature do not affect load as much as before reaching those levels. This exhibits a quadratic relationship between temperature and load.

In order to generate the temperature variables, first we regress the temperatures against the Fourier series. We include six sine and cosine harmonics as explanatory variables plus a constant term. Then we compute the residuals of the regression equation as depicted by:

$$TR_0 = T_0 - \left(\hat{\alpha} + \sum_{i=1}^{6} \hat{\beta}_i S_i + \sum_{j=1}^{6} \hat{\gamma}_j C_j \right) \qquad \textbf{(3)}$$

T_0 and TR_0 are contemporaneous temperature and deviation from conditional mean temperature respectively. Multiplying TR_0 by the Fourier series of lower harmonics, i.e., S_1, S_2, C_1, and C_2 would provide us with seasonally interacted temperature variables. These variables allow the model to explain both positive and negative relationship between the load and temperature during the year. Different lags of *TR* and *TR* in squared form are used to depict the lagged and quadratic effects of temperature on load.

Periodic Weekly and Indicator Variables

Figure 1 also, shows that there are periodic weekly variations in load that correspond to the days of the week. The load is usually lower on weekends. This periodicity can be depicted in the model by either a set of indicator (dummy) variables that represent the days of the week or by a set of Fourier series variable that oscillate within a seven-day range. Since including too many dummy variables could increase risk of multicollinearity, weekly Fourier series are included instead. There is also the issue of seasonal changes in the weekly variations. That is also addressed by including the weekly variables interacted with the seasonal harmonic variables S_1, S_2, C_1, and C_2.

There are regular and or irregular variations in load that are sporadic in nature. For example, load usually drops during the holidays which are scattered through out the year, are often observed on different dates, and do not follow a seasonal pattern. There could also be other sudden shifts in consumption for a longer duration, which cannot be explained by seasonal, weather, or demographic and economic variables. A set of indicator explanatory variables is included in the model to explain these events. The variables take the value of 1 during the event and 0 otherwise.

Demographic and Economic Variables

Demographic and economic variables usually explain the overall long-term trend in the load. Growth in population, employment, and overall income tend to increase demand for electricity. Increases in price and conservation tend to reduce the overall demand.

Economic and demographic variables tend to move together. An economic boom in a region usually leads to higher employment, higher income, higher prices and eventually higher population. The collinearity among these variables is also rooted in the economic and demographic forecasting models. For instance, the models that generate population forecast usually have employment and other economic factors as explanatory variables. As a result, including too many demographic and economic variables in the load model creates multicollinearity problem that renders the estimates of the coefficients of these variables unreliable. Hence, only seasonally adjusted employment is included in the model as a proxy for both demographic and economic growth. Average revenue per MWH is also included as a proxy for the overall electricity rates.

Functional Form

The functional form used to model the variations in daily and hourly electricity demand includes linear, quadratic, and interaction explanatory variables. However, the regression model is linear in terms of the coefficients that are to be estimated. Equation 4 shows the compact representation of the functional form for the hourly and daily load models.

$$L = \alpha + \beta S + \gamma C + \omega W + \delta Emp + \varepsilon R + \theta I + u \quad (4)$$

where *L* is the hourly or daily demand for electricity; *S* and *W* are Seasonal and Weather variables as explained in the above; *Emp* is seasonally adjusted employment, R is electricity rate, *I* are the indicator or dummy variables, and *u* is the error term of the regression model with the usual normality assumptions.

RESULTS

The econometric package EViews is used for estimating the temperature deviation and demand equations. First the model included all the 12 sine and cosine harmonics. The temperature in several lags and square form along with the interactions with lower harmonics were included. Variables whose coefficients had probability of 0.1 and higher were dropped. The EViews results for the daily load are presented below.

Dependent Variable: LOAD-DSI_LOAD
Method: ML - ARCH
Date: 01/25/07 Time: 11:13
Sample: 1/01/1928 12/31/2010 IF @YEAR>1994
Included observations: 2920
Convergence achieved after 67 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(38) + C(39)*RESID(-1)^2 + C(40)*RESID(-2)^2 + C(41)*Garch(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
D_JUL4	(1,731)	189.5079	-9.136754	0%
D_LBD	(1,499)	92.00543	-16.29748	0%
D_MEMD	(1,481)	107.9352	-13.72359	0%
D_NYD	(1,614)	174.1133	-9.272446	0%
D_TG	(1,323)	411.1183	-3.217924	0%
D_XMAS	(1,622)	183.6491	-8.831728	0%
REGION_EMP	1.71	0.198843	8.620886	0%
@YEAR=1998	(351)	94.67767	-3.70749	0%
@YEAR=2001	(528)	103.1417	-5.118015	0%
C1	1,863	53.31991	34.94773	0%
C2	1,256	47.37592	26.51397	0%
S1	368	46.42008	7.926398	0%
S2	568	49.54786	11.46658	0%
S3	(297)	44.54812	-6.661273	0%
C1_W	(763)	8.33318	-91.51546	0%
C2_W	(355)	6.294594	-56.38888	0%
S1_W	395	7.899264	50.00602	0%
S2_W	335	6.247335	53.61837	0%
C1_W*C1	140	12.11839	11.55939	0%
C2_W*C1	67	9.547819	7.041855	0%
S2_W*C1	(29)	9.422439	-3.090226	0%
C1_W*S1	59	10.89229	5.449212	0%
S1_W*S1	(19)	10.33189	-1.799731	7%
S2_W*S1	(17)	8.066175	-2.089665	4%
TR_REG2006	(65)	2.419012	-26.87382	0%
TR_REG2006*C1	(135)	3.401913	-39.82292	0%
TR_REG2006*C2	14	2.88931	4.957074	0%
TR_REG2006*S1	(53)	2.938516	-17.97745	0%
TR_REG2006*S2	51	3.459968	14.87239	0%
TR_REG2006(-1)	(26)	2.302774	-11.19596	0%
TR_REG2006(-1)*C1	(54)	3.536495	-15.34349	0%
TR_REG2006(-1)*S2	14	3.287518	4.278953	0%
TR_REG2006^2	4	0.2637	13.38994	0%
TR_REG2006^2*S2	(2)	0.361335	-5.955325	0%
C	9,771	1098.18	8.897219	0%
AR(1)	0.33	0.017651	18.85595	0%
AR(2)	0.47	0.017512	26.99943	0%
	Variance Equation			
C	2,679	1149.851	2	2%
RESID(-1)^2	0.18	0.040261	4	0%
RESID(-2)^2	(0.13)	0.04125	(3)	0%
GARCH(-1)	0.94	0.017739	53	0%

R-squared	96%	Mean dependent var	19,192
Adjusted R-squared	96%	S.D. dependent var	2,021
S.E. of regression	389	Akaike info criterion	15
Sum squared resid	4.36E+08	Schwarz criterion	15
Log likelihood	-21376.53	F-statistic	1,898
Durbin-Watson stat	1.92	Prob(F-statistic)	0

Inverted AR Roots	0.87	-0.54

The variables are defined as follows:

S(i) and C(i) are continuous sine and cosine wave variables that explain seasonal variations in electricity demand. The number (i) indicates the frequency of oscillation within a year.

S(i)_W and C(i)_W are continuous sine and cosine wave variables that explain weekly variations in electricity demand. The number (i) indicates the frequency of oscillation within a week.

D_JUL4, D_LBD, D_MEMD, D_NYD, D_TG, and D_XMAS are indicator variables that represent 4th of July, Labor Day, Memorial Day, New Year's Day, Thanksgiving Day, and Christmas Day respectively.

TR_REG06(i) are the daily temperature variables which are corrected for the conditional daily mean. The daily lags are indicated by (i).

TR_REG06^2 are the temperature variables in quadratic form.

TR_REG06(i)*S(j) and TR_REG06(i)*C(j) are the interaction of temperature variables with seasonal variables. The indices (i) and (j) represent lags in temperature variable and number of harmonics in the Fourier series respectively.

REGION_EMP is regional annual employment level in the service area, used as a proxy for economic conditions.

@YEAR=1998 and @YEAR=2001 are indicator variables that explain sudden drop in demand that are not explained by other variables.

The adjusted R-squared of 0.96 indicates a high degree of explanatory power of the model. However, DW statistics indicates autocorrelation in the residuals. The Breusch-Godfrey Serial Correlation LM test of 2 lags also indicates that there is a potential AR(2) process in the error term. To remedy the autocorrelation problem, the model is run with AR(2) process. The results indicate that both terms are significant and the inverted AR roots are within the unit circle. The BG LM test after adding AR(2) process indicates that there is no AR problem in the error term. However, ARCH LM test indicates that there is auto-regressive conditional heteroskedasticity in the error term.

In order to remedy the problem, the model is run with GARCH(2,1) process. The final results include the Bollerslev-Wooldridge robust standard errors and covariance to remedy the other potential forms of heteroskedasticity. The BG test and ARCH LM tests both indicate that the error terms do not exhibit additional AR or ARCH problem. The results also exhibit a strong predictive power with highly significant explanatory variables.

To evaluate fit of the model we used the daily load data from 1995-2002 and compared actual and fitted values. The following two tables show result of comparison. In general the model does well in forecasting daily peak loads for winter and summer months. If temperature forecast is accurate the forecasted peak loads are small and model does well in forecasting the date of peak load as well. For those peak days that the model missed the date, the magnitude of peak load error is rather small. The column heading "error in identifying Peak" shows the error in days and magnitude of error.

For example, for January 1995 model forecasted January 5th to be the peak day, whereas the actual peak day was on January 4th. Model error for Date of peak was one day. Magnitude of error was 0.8%.

Comparison of the Actual & Fitted Daily Peak Loads - Winter

		Peak Daily Load		Date of Peak Day		Error in identifying Peak	
Year	**Month**	**Actual**	**Fitted**	**Actual**	**Fitted**	**Date**	**Percent MW**
1995	1	24,709	24,911	1/4/1995	1/5/1995	1	0.8%
1996	1	27,944	27,552	1/31/1996	1/30/1996	(1)	-1.4%
1997	1	25,195	25,364	1/27/1997	1/14/1997	(13)	0.7%
1998	1	25,678	25,646	1/12/1998	1/12/1998	-	-0.1%
1999	1	23,681	23,424	1/25/1999	1/26/1999	1	-1.1%
2000	1	24,072	24,312	1/12/2000	1/11/2000	(1)	1.0%
2001	1	24,724	24,388	1/16/2001	1/17/2001	1	-1.4%
2002	1	24,468	24,542	1/29/2002	1/29/2002	-	0.3%
1995	11	21,378	21,044	11/2/1995	11/2/1995	-	-1.6%
1996	11	22,146	22,159	11/21/1996	11/21/1996	-	0.1%
1997	11	20,382	20,418	11/19/1997	11/26/1997	7	0.2%
1998	11	21,537	20,650	11/30/1998	11/24/1998	(6)	-4.1%
1999	11	21,800	21,631	11/22/1999	11/23/1999	1	-0.8%
2000	11	24,063	24,004	11/17/2000	11/16/2000	(1)	-0.2%
2001	11	22,554	21,629	11/28/2001	11/27/2001	(1)	-4.1%
2002	11	21,977	22,413	11/26/2002	11/26/2002	-	2.0%
1995	12	24,427	23,817	12/8/1995	12/8/1995	-	-2.5%
1996	12	24,341	24,392	12/18/1996	12/19/1996	1	0.2%
1997	12	23,371	23,812	12/22/1997	12/22/1997	-	1.9%
1998	12	29,619	29,267	12/21/1998	12/21/1998	-	-1.2%
1999	12	23,709	23,880	12/29/1999	12/29/1999	-	0.7%
2000	12	25,967	26,110	12/13/2000	12/13/2000	-	0.5%
2001	12	22,896	22,866	12/10/2001	12/4/2001	(6)	-0.1%
2002	12	22,553	23,041	12/19/2002	12/20/2002	1	2.2%

Comparison of the Actual & Fitted Daily Peak Loads - Summer

		Peak Daily Load		Date of Peak Day		Error in identifying Peak	
Year	**Month**	**Actual**	**Fitted**	**Actual**	**Fitted**	**Date**	**Percent MW**
1995	6	19,245	19,577	6/30/1995	6/30/1995	-	1.7%
1996	6	18,861	19,025	6/19/1996	6/20/1996	1	0.9%
1997	6	18,627	18,669	6/25/1997	6/26/1997	1	0.2%
1998	6	18,905	19,026	6/30/1998	6/30/1998	-	0.6%
1999	6	19,880	19,667	6/15/1999	6/29/1999	14	-1.1%
2000	6	21,398	21,183	6/28/2000	6/28/2000	-	-1.0%
2001	6	19,572	19,492	6/21/2001	6/21/2001	-	-0.4%
2002	6	21,277	20,851	6/26/2002	6/26/2002	-	-2.0%
1995	7	20,126	20,401	7/19/1995	7/18/1995	(1)	1.4%
1996	7	20,818	20,847	7/25/1996	7/24/1996	(1)	0.1%
1997	7	19,183	19,262	7/16/1997	7/29/1997	13	0.4%
1998	7	21,587	21,932	7/27/1998	7/28/1998	1	1.6%
1999	7	20,931	21,056	7/28/1999	7/27/1999	(1)	0.6%
2000	7	21,612	20,981	7/31/2000	7/31/2000	-	-2.9%
2001	7	19,351	19,996	7/10/2001	7/10/2001	-	3.3%
2002	7	21,822	21,419	7/11/2002	7/11/2002	-	-1.8%
1995	8	19,258	19,527	8/4/1995	8/1/1995	(3)	1.4%
1996	8	19,810	19,734	8/9/1996	8/13/1996	4	-0.4%
1997	8	19,377	19,635	8/6/1997	8/5/1997	(1)	1.3%
1998	8	20,656	20,689	8/13/1998	8/13/1998	-	0.2%
1999	8	20,395	20,666	8/2/1999	8/3/1999	1	1.3%
2000	8	20,834	21,419	8/1/2000	8/1/2000	-	2.8%
2001	8	18,932	19,607	8/10/2001	8/9/2001	(1)	3.6%
2002	8	21,005	20,954	8/14/2002	8/13/2002	(1)	-0.2%

Development of Hourly Model

Estimation of hourly model was similar to the daily model in that we start with establishing hourly deviations in temperature then used this temperature deviation as an explanatory variable along with the other cyclical and seasonal and dummy variables. We developed a model consisting of 24 equations, one equation for each hour, individually estimated. We performed the same tests and refinements for the hourly model as we did for the daily model.

Testing the Hourly Model

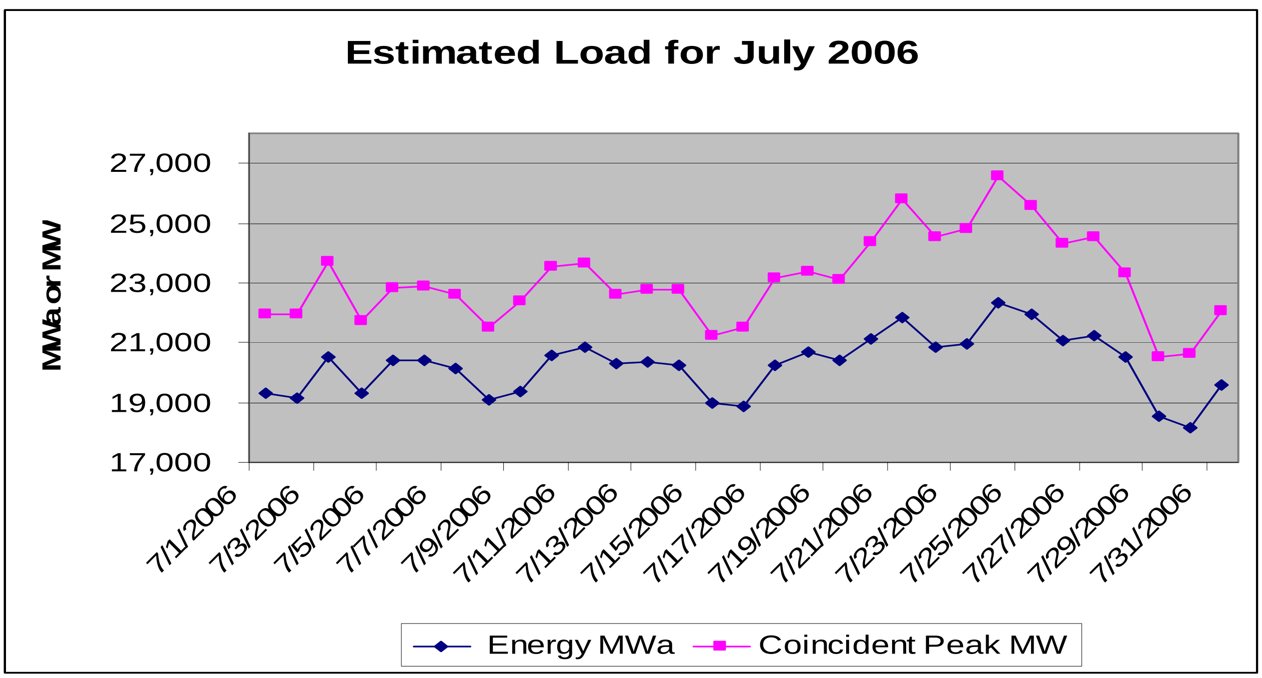
A comparison of actual and backcasted values for 1995- 2002 hourly energy, peak load, peak day and peak hour for each month, shows that MAPE for the energy is less than 0.015% and MAPE for peak hourly demand is about 2.8%. In general model does well in predicting the timing of winter peaks.

We also conducted a forecast for 2001 and 2002 using re-estimated model structure using 1995-2000 data only. Comparison of the actual loads and forecasted loads shows that hourly Mean Absolute Percent Errors is between 3%-4%.

Testing for July 2006 Heat wave

As another test of the model, we compared monthly total energy and peak hour loads for month of July 2005 with the figures reported by NWPP. Assuming that 50% of PacifiCorp load is in the region, and using a 98% coincident to non-coincident peak factor ratio we find that model under estimates energy by 1.4 % and over-estimates coincident peaks by 0.7%.

July 2006	Model	NWPP *	Delta
Energy MWa	20,237	20,518	-1.4%
Coincident Peak	26,564	26,382	0.7%
July monthly report from NWPP		26,920	MW non-coincident
Coincident factor		98%	



Coefficient Values from the 24 Hourly Models (select Hours)

NS signifies a Not Significant Variable (>10% insignificance)

Variable Description	HR 8	HR 9	HR 10	HR 17	HR 18	HR 19	HR 20
Labor Day	(3,891)	(2,863)	(1,896)	(1,543)	(1,299)	(1,091)	(907)
Menorial Day	(4,102)	(3,138)	(2,227)	(1,795)	(1,569)	(1,325)	(1,081)
4th of July	(2,808)	(2,441)	(2,036)	NS	(2,278)	(2,241)	(2,339)
New Year	(4,591)	(3,890)	(2,651)	(1,604)	(1,750)	(1,620)	(1,503)
Thanks Giving	(2,532)	(685)	NS	(3,509)	(4,092)	(3,931)	(3,538)
Christmas	(2,275)	(1,818)	(1,866)	(2,876)	(3,201)	(2,974)	(1,643)
Dummy Variables							
Drop in Load due to economic slowdown in 1998	(386)	(426)	(383)	(392)	(409)	(375)	(435)
Drop in Load due to economic slowdown in 2001	(618)	(611)	(585)	(523)	(581)	(634)	(608)
Economic Variables							
Impact of Seasonally Adjusted Employment in 1000s	1.5	1.5	1.5	1.9	2.0	2.1	2.3
Impact of Regional Annual Electricity Prices in $/MWH	(14)	(15)	(13)	NS	NS	NS	(12)
Annual Fourier Series							
Cosine wave- 1 cycle per year- Values between + 1 and -1	3,235	2,787	2,257	1,480	2,307	2,542	2,420
Cosine wave- 2 cycles per year- Values between + 1 and -1	583	862	1,092	2,000	2,109	1,658	1,204
Cosine wave- 3 cycles per year- Values between + 1 and -1	(199)	(157)	NS	237	NS	(249)	(180)
Cosine wave- 4 cycles per year- Values between + 1 and -1	(128)	(94)	NS	(142)	(269)	(192)	NS
sine wave- 1 cycle per year- Values between + 1 and -1	1,159	914	641	(421)	(308)	NS	NS
sine wave- 2 cycles per year- Values between + 1 and -1	NS	196	353	557	595	741	724
sine wave- 3 cycles per year- Values between + 1 and -1	(172)	(256)	(299)	(646)	(624)	(539)	(446)
WeekDay Variables (Fourier Series)							
Cosine wave- 1 cycle per weekr- Values between + 1 and -1	(1,891)	(1,220)	(759)	(838)	(809)	(770)	(702)
Cosine wave- 2 cycles per week- Values between + 1 and -1	(958)	(733)	(549)	(380)	(304)	(226)	(118)
sine wave- 1 cycle per weekr- Values between + 1 and -1	792	488	296	588	685	761	813
sine wave- 2 cycles per week- Values between + 1 and -1	839	544	346	438	449	460	448
Interaction of Weekly series and Annual Series							
Cosine wave for weekly series interacting with annual series	(187)	144	328	283	197	119	90
sine wave for weekly series interacting with annual series	154	NS	(103)	(84)	NS	NS	99
Cosine wave for weekly series interacting with annual series	NS	51	118	48	NS	NS	NS
Cosine wave for weekly series interacting with annual series	NS	NS	(68)	(67)	(74)	(62)	(61)
Cosine wave for weekly series interacting with annual series	NS	59	148	170	142	138	141
Cosine wave for weekly series interacting with annual series	NS	NS	(49)	(47)	(36)	NS	NS
sine wave for weekly series interacting with annual series	NS	NS	(49)	(58)	(48)	(44)	(48)
sine wave for weekly series interacting with annual series	131	NS	(135)	(138)	(69)	NS	NS
Hourly Temperature Deviation							
Daily Temperature Deviations	(97)	(83)	(68)	(89)	(75)	(48)	(42)
Daily Temperature Deviations interacting with cosine wave	(98)	(98)	(89)	(126)	(102)	(76)	(69)
Daily Temperature Deviation interacting with cosine wave	42	45	41	34	32	35	35
Impact from Previous Hour Temperature Deviations							
Previous Hour Temperature	(24)	NS	NS	(13)	(15)	(24)	(10)
Previous Hour Temperature interaction with annual Fouier series	NS	NS	NS	(23)	(37)	(44)	(38)
Previous Hour Temperature interaction with annual Fouier series	(33)	(28)	(25)	(62)	(52)	(41)	(40)
Previous Hour Temperature interaction with annual Fouier series	26	25	27	17	22	21	23
Impact of High Temperature Deviations							
Intensifying impact of high temperature deviations	2.1	2.2	2.2	2.2	2.0	1.7	0.8
Impact of Average Daily Temperature Deviations							
Average temperature for the day	NS	NS	NS	67	43	NS	(16)
Average temperature for the day interacting with Fourier Series	(60)	(74)	(84)	(86)	(35)	(61)	(70)
Average temperature for the day interacting with Fourier Series	(2)	(2)	(2)	31	(13)	(1)	(1)
Impact of Previous Day Temperature Deviations							
Average temperature for the previous day	(45)	(61)	(51)	NS	NS	15	NS
Average temperature for the previous day interacting with Fourier series	(60)	(74)	(84)	(86)	(60)	(45)	(36)
Average temperature for the previous day interacting with Fourier series	NS	NS	NS	31	26	NS	NS
Impact of Average Daily Temperature							
Intensifying impact of average daily temperature deviations	NS	NS	NS	NS	NS	NS	1.7
Intensifying impact of average daily temperature deviations interacting with FS	(1.3)	(1.0)	(0.9)	(1.0)	(1.5)	(1.6)	(2.0)
Intensifying impact of average daily temperature deviations interacting with FS	(1.7)	(2.0)	(1.8)	(1.0)	(0.9)	(0.9)	(1.0)
Constant Term for the equation	13,703	14,103	13,594	10,060	10,147	10,036	9,226
AutoRegressive Factor Lag 1	0.15	0.19	0.21	0.28	0.35	0.40	0.47
AutoRegressive Factor Lag 2	0.46	0.49	0.48	0.38	0.33	0.28	0.23
R-squared	95%	95%	94%	93%	95%	95%	95%