USING STRUCTURAL TIME SERIES MODELS
For Development of
DEMAND FORECASTING FOR ELECTRICITY
With
Application to Resource Adequacy Analysis

December 31, 2014

INTRODUCTION

In this paper we present the methodology, results and an application of the short-term modeling system at the Council for resource adequacy analysis.

Methodology:

Using econometrically estimated relationships between loads and temperatures, used in a three step process we developed the short-term forecasting model then applied it for Resource Adequacy analysis.

1. Developed Daily Load Model

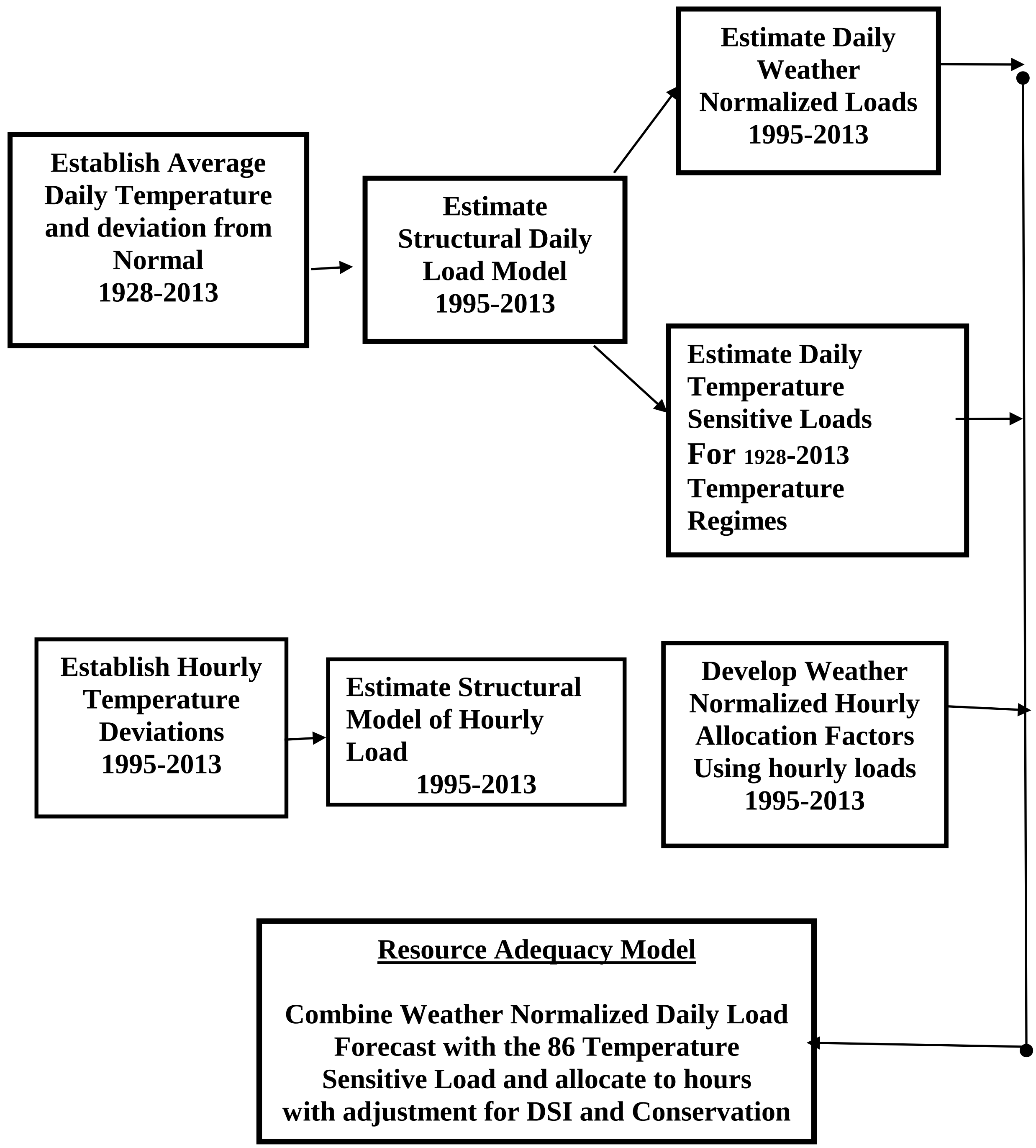
    a. Using daily average temperature for the region we estimated daily deviations from mean for each day from January 1, 1928- December 31, 2013.
    b. Using the daily temperature deviations and a limited number of trend seasonal and cyclical variables we estimated the structural model for daily loads
    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 condition for January 1, 1928 through December 31, 2013.
    d. Forecasted Weather-Normalized daily load for desired forecast period.

2. Developed the Hourly Load Model

    a. Using hourly temperature, 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 1995-2013. These hourly loads were then averaged over historic period 1995-2013 and 24 factors for each day (8760 hourly allocation factors) were developed.
    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 of the Short-term Forecasting Model to Resource Adequacy

    a. Developed 86 different hourly load forecasts for forecast period by combining the weather-normalized load for the hour and each one of the 86 weather-sensitive loads for that hour.



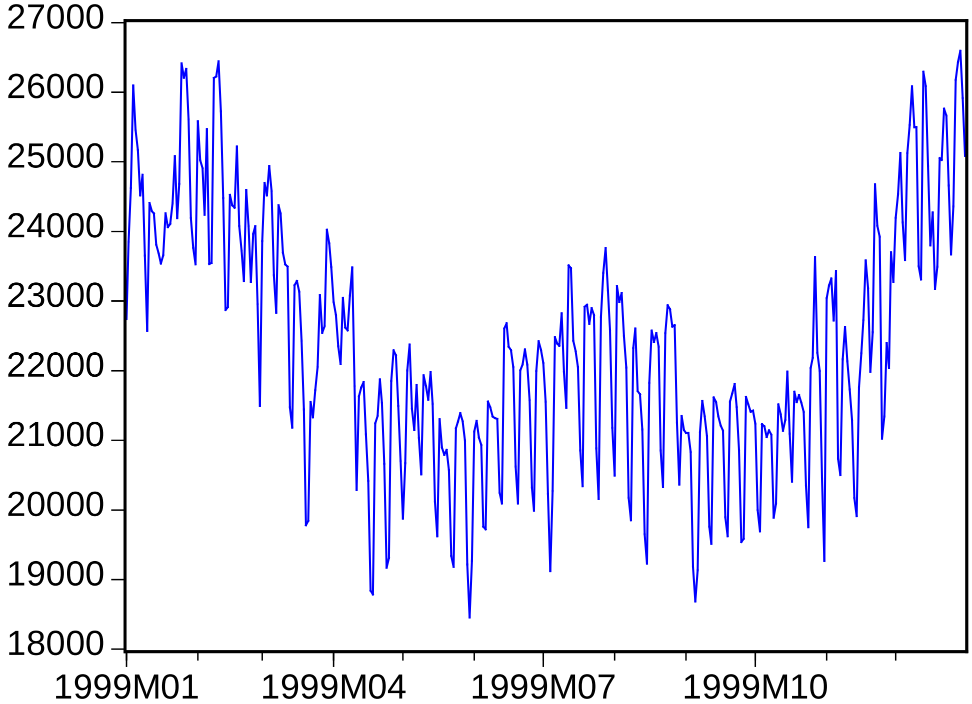
Application of Short-term Hourly Load Forecasting Model to Resource Adequacy

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. Figures 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 which reoccurs on a weekly basis. There are also variations that occur on a regular basis but are of lower frequency during the year. Consumption on holidays is usually lower than that on 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:

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

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. Hannan [1963], Jorgenson [1964 and 1967], Harvey and Sheparrd, [1993], and Dziegielewski and Opitz [2002] recommend use of Fourier series of sine and cosine terms as a continuous function of time to express these seasonal patterns.

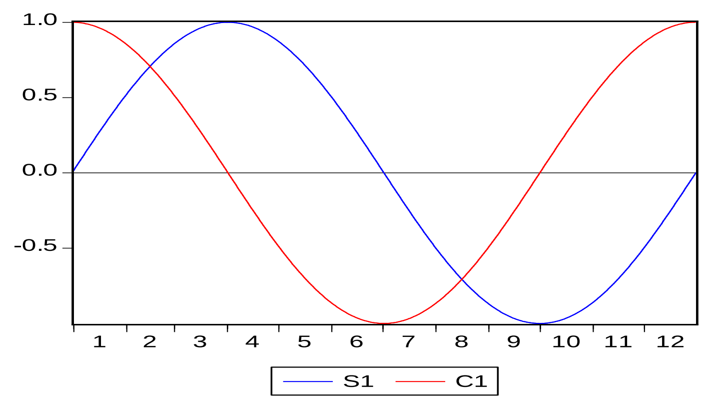
For daily load data these variables can be constructed as

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

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

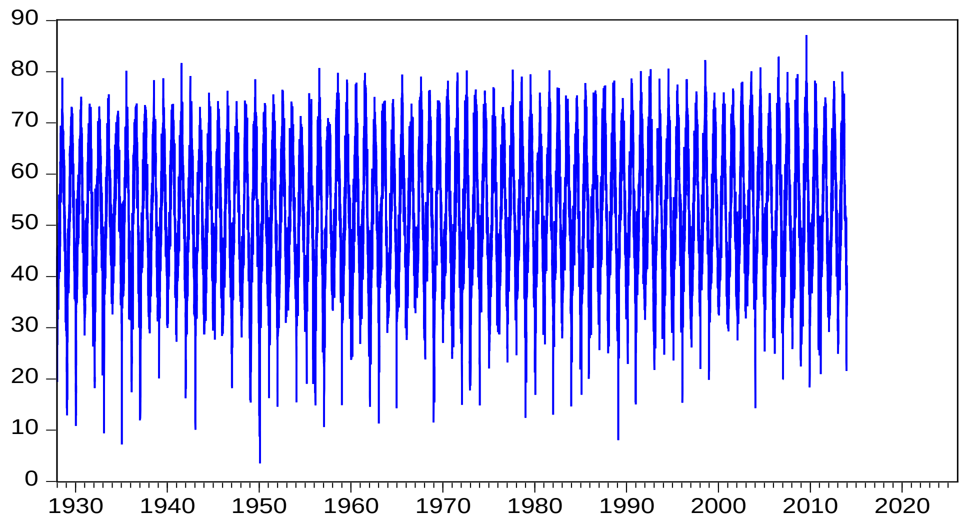
Figure 2. Fourier Series Sine and Cosine Harmonics with One Cyle Per Year



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 which are above and beyond seasonal variations.

Average Daily Regional Temperature 1929-2013



Northwest Temperature Profile Summary

	Highest single day Temperature occurred in	Lowest single day Temperature occurred in
January	1935	1950
February	1932	1950
March	2004	1955
April	1998	1936
May	1986	1965
June	1992	1962
July	2009	1955
August	1977	1956
September	1988	1972
October	1987	1935
November	2006	1955
December	2012	1968
1929-2013 Annual	2009	1950

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 corresponds 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 which 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 throughout 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. 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 which 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.

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 log-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.

$$\log L = \alpha + \beta S + \gamma C + \omega W + \delta Emp + \varepsilon R + \theta I + u \qquad \textbf{(4)}$$

where L is the hourly or daily demand for electricity; *S and c are seasonal variables,* W is 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. Some of the variables that their coefficients had probability of 0.1 and higher were dropped. The EViews results for the daily load are presented below. It should be noted that dependent variable is regional load net of Direct Service Industry loads. This adjustment to loads was made to provide a more robust estimate of the underlying relationship between load and temperature. Inclusion of DSI load would have introduced large disturbance in loads. DSI load is forecasted separately and added as a flat load to the forecast.

In the table below are showing the structural coefficients for all variables. It should be noted that although shown as a single table, in fact there are 365 structural equation presented below. That is because each variable has 365 values depending on the temporal value for the day.

Dependent Variable: LOG(LOAD-DSI_LOAD)

Method: Least Squares
Date: 09/15/14 Time: 15:47
Sample: 1/01/1928 12/31/2020 IF @YEAR>1994
Included observations: 6938
Convergence achieved after 8 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C1	0.089331	0.001506	59.33430	0.0000
C2	0.067614	0.001483	45.59589	0.0000
S1	0.016762	0.001503	11.15019	0.0000
S2	0.029529	0.001498	19.71680	0.0000
S3	-0.019945	0.001455	-13.70421	0.0000
C1_W	-0.038399	0.000335	-114.6754	0.0000
C2_W	-0.017436	0.000243	-71.76301	0.0000
S1_W	0.020180	0.000334	60.33051	0.0000
S2_W	0.017156	0.000245	69.94726	0.0000
C1_W*C1	0.010235	0.000474	21.58375	0.0000
C2_W*C1	0.005179	0.000344	15.04930	0.0000
S2_W*C1	-0.002925	0.000347	-8.422812	0.0000
C1_W*S1	0.001947	0.000473	4.112704	0.0000
S1_W*S1	-0.001513	0.000473	-3.197535	0.0014
D_JUL4	-0.082677	0.004083	-20.24948	0.0000
D_LBD	-0.067118	0.004136	-16.22935	0.0000
D_MEMD	-0.073460	0.004150	-17.70208	0.0000
D_NYD	-0.052855	0.004175	-12.65842	0.0000
D_TG	-0.075589	0.004151	-18.21139	0.0000
D_XMAS	-0.060912	0.004089	-14.89564	0.0000
RESILOG	-0.064568	0.004658	-13.86148	0.0000
RESILOG*C1	-0.353046	0.006429	-54.91454	0.0000
RESILOG*C2	0.139059	0.005360	25.94507	0.0000
RESILOG*S1	-0.158495	0.006080	-26.06818	0.0000
RESILOG*S2	0.165025	0.006217	26.54270	0.0000
RESILOG(-1)	-0.036034	0.004425	-8.143734	0.0000
RESILOG(-1)*C1	-0.078942	0.006047	-13.05414	0.0000
RESILOG(-1)*S2	0.016144	0.005879	2.746180	0.0060
RESILOG^2*S2	-0.099096	0.016250	-6.098009	0.0000
LOG(REGION_EMP)	0.440705	0.019668	22.40761	0.0000
@YEAR=1998	-0.028181	0.004619	-6.101422	0.0000
@YEAR=2001	-0.023738	0.004600	-5.160393	0.0000
C	6.066012	0.170675	35.54135	0.0000
AR(1)	0.451210	0.011622	38.82370	0.0000
AR(2)	0.320528	0.011568	27.70870	0.0000

R-squared	0.963865	Mean dependent var	9.883843
Adjusted R-squared	0.963687	S.D. dependent var	0.106320
S.E. of regression	0.020260	Akaike info criterion	-4.955279
Sum squared resid	2.833531	Schwarz criterion	-4.920749
Log likelihood	17224.86	Hannan-Quinn criter.	-4.943375
F-statistic	5415.673	Durbin-Watson stat	1.969198
Prob(F-statistic)	0.000000		

Inverted AR Roots	.84	-.38

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.

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

RESILOG ^2 are the temperature variables in quadratic form.

RESILOG (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 indicated autocorrelation in the residuals. The Breusch-Godfrey Serial Correlation LM test of 2 lags, also indicated that there is a potential AR(2) process in the error term. To remedy the autocorrelation problem, the model was run with AR(2) process. The results indicated that both terms are significant and the inverted AR roots are within the unit circle. The BG LM test after adding AR(2) process indicated that there is no AR problem in the error term. However, ARCH LM test indicated that there is auto-regressive conditional heteroskedasticity in the error term.

In order to remedy the problem, the model was run with GARCH(2,1) process. The final results, shown in previous 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 indicated that the error terms do not exhibit additional AR or ARCH problem. The results also exhibited a strong predictive power with highly significant explanatory variables.

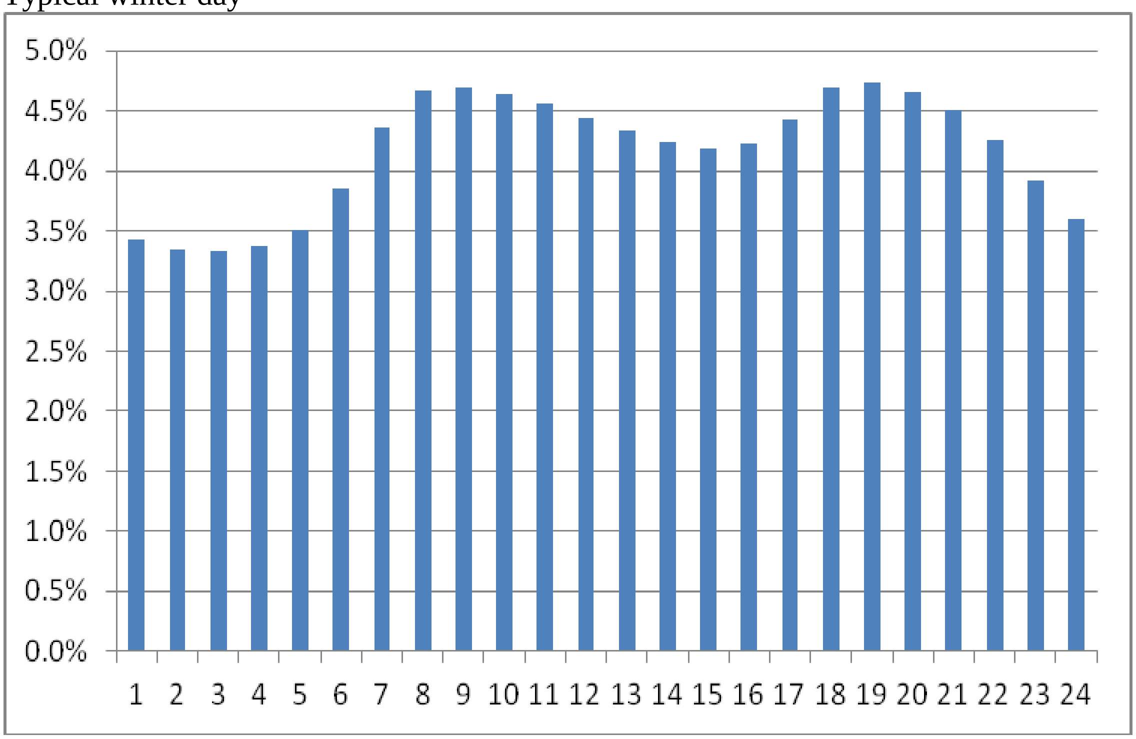
Decomposition of the Effects

One of the advantages of the model is that it allows decomposition of demand into the effects of different variables. For instance, the log linear combination of the variables with the exception of temperature variables would result in an estimate of weather normalized load. The log 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.

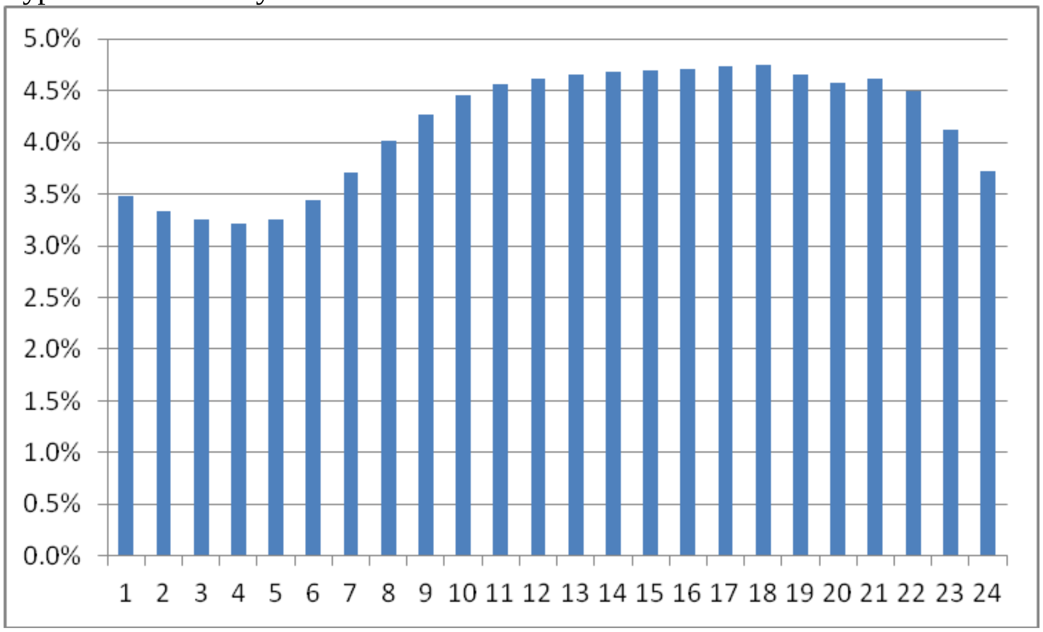
Development of Hourly Model

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. Same tests and refinements we had made to the daily model were done for the hourly model. The coefficients for additional hours are presented in the appendix. The 24 hourly allocation factors for each day we can now develop and hourly forecast of loads. In the following two graphs we can see value of allocation factors for a day in winter and a summer day. Note that area under the curve sums up to 1. Using these factors we are allocating the daily weather normalized energy into hourly weather normalized loads prior to application of temperature sensitivity factors.

Typical winter day



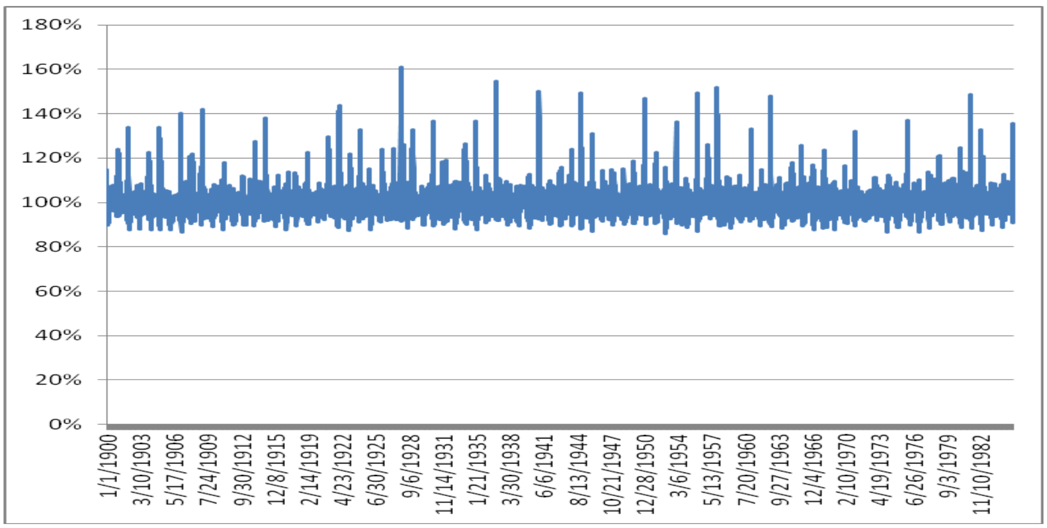
Typical summer Day



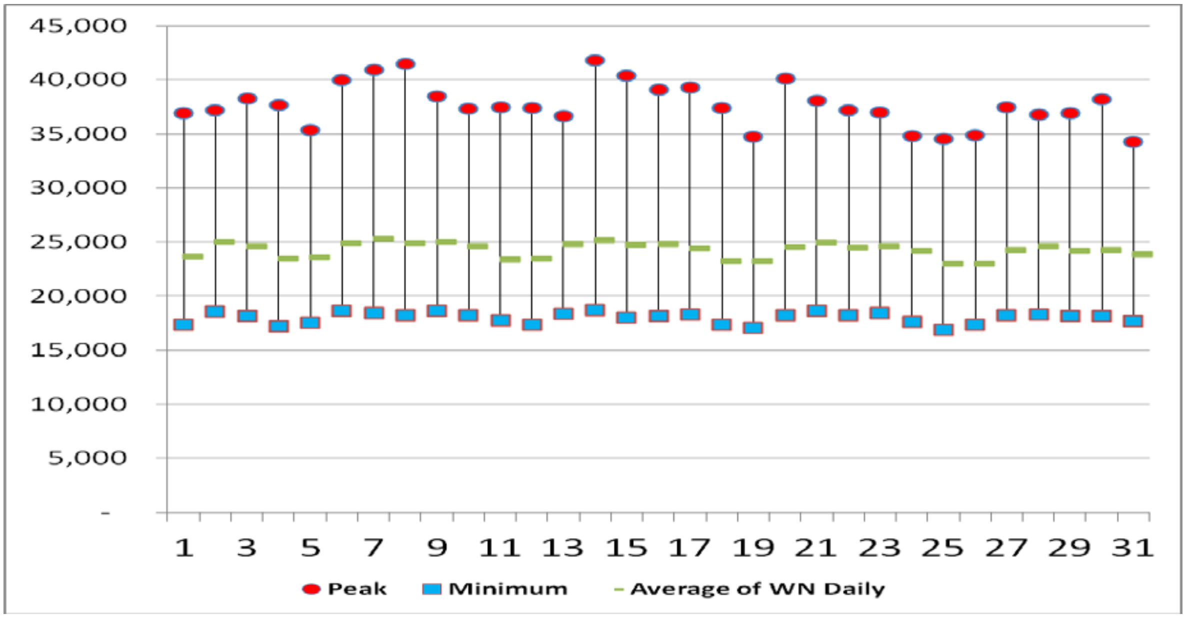
Forecasting Temperature Sensitive Loads under Various Temperature conditions

Using the daily load model and daily regional temperatures from 1928-2013 we can estimate the temperature sensitive (TS) portion of the load for each day. The estimated TS loads show percent change in loads if the region experiences past temperatures. Under certain conditions weather normalized average load for a day can increase by over 60% due to change in temperature.

Weather Sensitive Regional Load 1928-2013 (Percent change in WN Daily Load)



In the following table and graph we have extracted average, highest and lowest loads for one month, January 1-31, for the forecast year 2020. January, weather normalized loads that average about 24,377 MWa, depending on weather-year, can have a single hour peak of 41,814 and single hour minimum load of 18,673 MW.



Day in January	Peak hour	Minimum load	Average of WN Daily
1	36,943	17,327	23,655
2	37,193	18,578	25,059
3	38,286	18,138	24,655
4	37,679	17,195	23,491
5	35,380	17,538	23,582
6	39,965	18,608	24,911
7	40,917	18,446	25,296
8	41,490	18,261	24,894
9	38,469	18,637	25,004
10	37,327	18,232	24,592
11	37,441	17,768	23,414
12	37,415	17,380	23,484
13	36,661	18,344	24,792
14	41,814	18,673	25,159
15	40,382	18,047	24,742
16	39,119	18,140	24,844
17	39,312	18,281	24,427
18	37,435	17,358	23,237
19	34,766	17,065	23,288
20	40,098	18,246	24,577
21	38,054	18,655	24,930
22	37,202	18,208	24,501
23	37,016	18,411	24,600
24	34,838	17,606	24,182
25	34,555	16,854	22,982
26	34,862	17,342	23,013
27	37,447	18,237	24,286
28	36,814	18,316	24,630
29	36,897	18,141	24,194
30	38,197	18,150	24,292
31	34,291	17,661	23,878

Appendix

Data: Five datasets were used for this analysis.

1. Hourly regional load (BA) for 1995-2013 from Northwest Power Pool, and WECC
2. Daily temperature for PDX, SEATAC, Boise and Spokane 1929-1990
3. Hourly temperatures for 1990-2013 from Western Regional Climate Center
4. Monthly employment data for 1995-2006 from Bureau of Labor Statistics
5. Forecast of employment by state from Global Insight.
6. Hourly Direct Service Industry aggregate load data for 1993-2006 from Bonneville Power Administration
7. Forecast of DSI load from White-book 2013.

Hourly regional load data for the footprint of Northwest Power and Conservation Planning includes hourly loads for the states of Idaho, Oregon and Washington in their total and the western part Montana state. Hourly loads were net of Direct Service Industries loads. Hourly temperature data were for four regionally representative sites (Portland airport, Boise Airport, Spokane airport, Seattle airport).

Following is the representation of the coefficient and their values used in development of hourly allocation factors. Estimate of weather normalized hourly loads, excluding temperature, employment and indicator variables were used to develop 8760 average allocation factors.

Dependent Variable: NETLOAD?
Method: Pooled EGLS (Cross-section weights)
Date: 12/05/13 Time: 15:45
Sample (adjusted): 1/04/1993 12/31/2012
Included observations: 7264 after adjustments
Cross-sections included: 24
Total pool (unbalanced) observations: 172792
Iterate coefficients after one-step weighting matrix
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)
Convergence achieved after 18 total coef iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D_JUL4	-1185.641	64.30247	-18.43850	0.0000
D_LBD	-980.0113	64.78643	-15.12680	0.0000
D_MEMD	-989.8201	64.76786	-15.28258	0.0000
D_NYD	-738.2337	65.47278	-11.27543	0.0000
D_TG	-1303.940	64.87077	-20.10057	0.0000
D_XMAS	-997.7110	64.80521	-15.39554	0.0000
@YEAR=1998	-766.7517	120.3747	-6.369707	0.0000
@YEAR=2001	-761.1993	122.2241	-6.227898	0.0000
REGION_EMP	0.171466	0.075788	2.262453	0.0237
C2_W*C1	59.80913	5.609430	10.66225	0.0000
S1_W*C1	5.902467	8.287388	0.712223	0.4763
S2_W*C1	-22.13679	5.659197	-3.911649	0.0001
C1_W*S1	18.72279	8.296423	2.256731	0.0240
S1_W*S1	-36.97107	8.290788	-4.459295	0.0000
S2_W*S1	-13.18845	5.644785	-2.336396	0.0195
C1_W*S2	-22.81696	8.304629	-2.747499	0.0060
C2_W*S2	-20.96164	5.604585	-3.740087	0.0002
_01--C1	1485.933	64.50306	23.03663	0.0000
_02--C1	1554.112	61.22806	25.38235	0.0000
_03--C1	1659.929	58.89461	28.18473	0.0000
_04--C1	1784.697	61.47821	29.02975	0.0000
_05--C1	1952.342	66.96553	29.15444	0.0000
_06--C1	2347.408	70.40840	33.33989	0.0000
_07--C1	2900.922	60.84939	47.67380	0.0000
_08--C1	3068.587	58.67724	52.29604	0.0000
_09--C1	2762.603	63.94686	43.20154	0.0000
_10--C1	2305.627	63.24268	36.45682	0.0000
_11--C1	1865.682	59.66209	31.27080	0.0000
_12--C1	1440.324	57.86995	24.88897	0.0000
_13--C1	1087.959	57.27284	18.99607	0.0000
_14--C1	815.5500	56.68582	14.38720	0.0000
_15--C1	646.8005	57.17546	11.31255	0.0000
_16--C1	728.6135	57.19006	12.74021	0.0000
_17--C1	1303.225	59.64749	21.84878	0.0000
_18--C1	2128.205	59.36441	35.84985	0.0000
_19--C1	2490.711	59.88944	41.58848	0.0000
_20--C1	2385.256	59.65859	39.98178	0.0000
_21--C1	1946.722	61.61219	31.59637	0.0000
_22--C1	1502.605	70.88997	21.19630	0.0000
_23--C1	1419.576	80.30297	17.67775	0.0000
_24--C1	1440.299	80.24746	17.94822	0.0000
_01--C2	1189.005	61.02900	19.48262	0.0000
_02--C2	1062.995	58.09901	18.29626	0.0000
_03--C2	981.8846	56.22731	17.46277	0.0000

_04--C2	900.1198	58.54852	15.37391	0.0000
_05--C2	760.2919	63.99317	11.88083	0.0000
_06--C2	481.4482	68.04631	7.075302	0.0000
_07--C2	326.1130	59.86088	5.447848	0.0000
_08--C2	560.9345	57.72522	9.717322	0.0000
_09--C2	900.6584	61.97440	14.53275	0.0000
_10--C2	1184.936	61.07622	19.40094	0.0000
_11--C2	1385.785	57.91865	23.92640	0.0000
_12--C2	1509.335	56.39463	26.76380	0.0000
_13--C2	1576.814	55.97258	28.17119	0.0000
_14--C2	1618.611	55.50289	29.16265	0.0000
_15--C2	1676.808	56.04004	29.92161	0.0000
_16--C2	1766.929	56.08892	31.50228	0.0000
_17--C2	2010.991	58.46616	34.39581	0.0000
_18--C2	2166.233	58.24596	37.19113	0.0000
_19--C2	1790.160	58.70941	30.49188	0.0000
_20--C2	1326.506	58.34743	22.73461	0.0000
_21--C2	1240.796	60.05101	20.66236	0.0000
_22--C2	1498.433	68.19895	21.97150	0.0000
_23--C2	1532.830	74.99727	20.43847	0.0000
_24--C2	1354.281	73.73790	18.36615	0.0000
_01--S1	307.2628	64.59222	4.756963	0.0000
_02--S1	360.4869	61.28716	5.881933	0.0000
_03--S1	436.5883	58.94654	7.406513	0.0000
_04--S1	533.3918	61.53065	8.668718	0.0000
_05--S1	651.6386	67.02060	9.722959	0.0000
_06--S1	854.7435	70.48161	12.12718	0.0000
_07--S1	1097.238	60.83119	18.03742	0.0000
_08--S1	1117.803	58.69641	19.04381	0.0000
_09--S1	885.2496	63.99353	13.83342	0.0000
_10--S1	592.6587	63.32513	9.358981	0.0000
_11--S1	338.9853	59.74414	5.673951	0.0000
_12--S1	113.2963	57.90064	1.956736	0.0504
_13--S1	-64.83185	57.32367	-1.130979	0.2581
_14--S1	-229.0409	56.72519	-4.037728	0.0001
_15--S1	-370.1870	57.20520	-6.471213	0.0000
_16--S1	-465.4453	57.29363	-8.123857	0.0000
_17--S1	-555.9324	59.69693	-9.312579	0.0000
_18--S1	-473.3705	59.37893	-7.972028	0.0000
_19--S1	-228.7603	59.92267	-3.817591	0.0001
_20--S1	-75.75072	59.69937	-1.268870	0.2045
_21--S1	108.5714	61.63616	1.761489	0.0782
_22--S1	229.7414	70.99856	3.235859	0.0012
_23--S1	250.7354	80.41624	3.117970	0.0018
_24--S1	226.1305	80.36828	2.813678	0.0049
_01--S2	448.7915	61.18626	7.334841	0.0000
_02--S2	422.9207	58.23205	7.262679	0.0000
_03--S2	389.4440	56.35279	6.910821	0.0000
_04--S2	352.1528	58.71464	5.997701	0.0000
_05--S2	280.8354	64.16986	4.376438	0.0000
_06--S2	181.3536	68.25085	2.657163	0.0079
_07--S2	81.46889	59.92830	1.359439	0.1740
_08--S2	103.0762	57.92341	1.779526	0.0752
_09--S2	215.2815	62.19313	3.461500	0.0005
_10--S2	361.5173	61.27690	5.899733	0.0000
_11--S2	467.9164	58.08821	8.055274	0.0000
_12--S2	566.1583	56.54126	10.01319	0.0000
_13--S2	646.1300	56.09888	11.51770	0.0000
_14--S2	717.6843	55.63189	12.90059	0.0000
_15--S2	767.1975	56.13658	13.66662	0.0000
_16--S2	759.5240	56.24722	13.50332	0.0000
_17--S2	650.8912	58.58221	11.11073	0.0000
_18--S2	653.7131	58.36912	11.19964	0.0000
_19--S2	773.6513	58.84849	13.14650	0.0000

_20--S2	746.9352	58.58206	12.75024	0.0000
_21--S2	635.0713	60.18316	10.55231	0.0000
_22--S2	511.6036	68.34744	7.485336	0.0000
_23--S2	463.6223	75.25268	6.160875	0.0000
_24--S2	439.4833	73.95026	5.942959	0.0000
_01--S3	-454.7865	56.32820	-8.073869	0.0000
_02--S3	-414.0268	53.82388	-7.692251	0.0000
_03--S3	-388.2288	52.51192	-7.393155	0.0000
_04--S3	-379.9883	54.53349	-6.967980	0.0000
_05--S3	-371.1564	59.86996	-6.199376	0.0000
_06--S3	-328.9765	64.68795	-5.085591	0.0000
_07--S3	-212.3144	58.45246	-3.632258	0.0003
_08--S3	-232.4914	56.52248	-4.113256	0.0000
_09--S3	-319.3857	59.26117	-5.389460	0.0000
_10--S3	-396.5939	58.06040	-6.830712	0.0000
_11--S3	-439.4743	55.46079	-7.924053	0.0000
_12--S3	-468.6803	54.35605	-8.622412	0.0000
_13--S3	-485.1338	54.16063	-8.957315	0.0000
_14--S3	-503.4850	53.86521	-9.347127	0.0000
_15--S3	-543.9694	54.40716	-9.998122	0.0000
_16--S3	-595.9449	54.59437	-10.91587	0.0000
_17--S3	-716.3338	56.87004	-12.59598	0.0000
_18--S3	-684.4485	56.66594	-12.07866	0.0000
_19--S3	-587.0711	57.07033	-10.28680	0.0000
_20--S3	-545.4333	56.56948	-9.641830	0.0000
_21--S3	-582.8699	57.83105	-10.07884	0.0000
_22--S3	-583.3880	64.37874	-9.061813	0.0000
_23--S3	-555.8209	68.16024	-8.154621	0.0000
_24--S3	-509.0720	65.74291	-7.743376	0.0000
_01--C1_W	-267.5683	6.989070	-38.28383	0.0000
_02--C1_W	-272.1547	6.811595	-39.95462	0.0000
_03--C1_W	-282.3645	6.973530	-40.49089	0.0000
_04--C1_W	-334.5848	7.028812	-47.60190	0.0000
_05--C1_W	-566.4901	7.906965	-71.64444	0.0000
_06--C1_W	-1144.531	9.911880	-115.4707	0.0000
_07--C1_W	-1840.162	12.98099	-141.7583	0.0000
_08--C1_W	-1822.774	12.92682	-141.0072	0.0000
_09--C1_W	-1237.969	9.703690	-127.5771	0.0000
_10--C1_W	-831.5526	8.957371	-92.83445	0.0000
_11--C1_W	-695.0581	9.152635	-75.94076	0.0000
_12--C1_W	-671.7705	9.569634	-70.19814	0.0000
_13--C1_W	-728.1660	9.981983	-72.94804	0.0000
_14--C1_W	-804.1546	10.36682	-77.57003	0.0000
_15--C1_W	-839.7219	10.66553	-78.73234	0.0000
_16--C1_W	-834.1777	10.82174	-77.08348	0.0000
_17--C1_W	-799.0068	11.11148	-71.90824	0.0000
_18--C1_W	-756.6119	11.40428	-66.34457	0.0000
_19--C1_W	-720.4374	11.14018	-64.67018	0.0000
_20--C1_W	-667.5244	10.51503	-63.48289	0.0000
_21--C1_W	-628.0090	9.761633	-64.33442	0.0000
_22--C1_W	-564.2121	8.945820	-63.06991	0.0000
_23--C1_W	-459.4684	7.667150	-59.92688	0.0000
_24--C1_W	-357.6492	6.932512	-51.59013	0.0000
_01--C2_W	-59.66911	4.804033	-12.42063	0.0000
_02--C2_W	-70.25746	4.629394	-15.17638	0.0000
_03--C2_W	-87.07267	4.670516	-18.64305	0.0000
_04--C2_W	-121.5651	4.534907	-26.80652	0.0000
_05--C2_W	-248.4724	5.008745	-49.60771	0.0000
_06--C2_W	-529.7076	6.814116	-77.73680	0.0000
_07--C2_W	-874.2130	9.461561	-92.39628	0.0000
_08--C2_W	-912.6708	9.611061	-94.96047	0.0000
_09--C2_W	-696.1811	7.316929	-95.14662	0.0000
_10--C2_W	-538.2147	6.734087	-79.92393	0.0000
_11--C2_W	-475.3660	6.872378	-69.17053	0.0000

_12--C2_W	-442.7756	7.140678	-62.00749	0.0000
_13--C2_W	-425.9663	7.360618	-57.87100	0.0000
_14--C2_W	-432.0508	7.586794	-56.94775	0.0000
_15--C2_W	-424.2031	7.768535	-54.60529	0.0000
_16--C2_W	-403.2811	7.830230	-51.50309	0.0000
_17--C2_W	-349.1299	7.939816	-43.97204	0.0000
_18--C2_W	-278.1526	7.953799	-34.97104	0.0000
_19--C2_W	-196.6847	7.562056	-26.00942	0.0000
_20--C2_W	-104.2876	6.866785	-15.18725	0.0000
_21--C2_W	-55.23337	6.146659	-8.985916	0.0000
_22--C2_W	-71.29142	5.527923	-12.89660	0.0000
_23--C2_W	-151.1987	4.944062	-30.58188	0.0000
_24--C2_W	-176.3993	4.747346	-37.15746	0.0000
_01--S1_W	-158.4281	6.995188	-22.64816	0.0000
_02--S1_W	-117.4261	6.819904	-17.21814	0.0000
_03--S1_W	-75.00381	6.981570	-10.74312	0.0000
_04--S1_W	-16.56922	7.037422	-2.354445	0.0186
_05--S1_W	118.2286	7.916846	14.93380	0.0000
_06--S1_W	413.3099	9.922458	41.65398	0.0000
_07--S1_W	757.1641	12.99371	58.27159	0.0000
_08--S1_W	750.9479	12.93880	58.03843	0.0000
_09--S1_W	488.0788	9.708947	50.27104	0.0000
_10--S1_W	317.8758	8.955855	35.49363	0.0000
_11--S1_W	293.2386	9.147402	32.05704	0.0000
_12--S1_W	326.9291	9.559454	34.19956	0.0000
_13--S1_W	406.4613	9.970843	40.76499	0.0000
_14--S1_W	472.5948	10.35342	45.64624	0.0000
_15--S1_W	509.8250	10.65177	47.86296	0.0000
_16--S1_W	534.8371	10.80706	49.48961	0.0000
_17--S1_W	573.2780	11.09578	51.66631	0.0000
_18--S1_W	659.7610	11.38269	57.96178	0.0000
_19--S1_W	740.3404	11.11429	66.61161	0.0000
_20--S1_W	788.1744	10.49129	75.12656	0.0000
_21--S1_W	749.8583	9.741292	76.97729	0.0000
_22--S1_W	558.7757	8.930058	62.57246	0.0000
_23--S1_W	289.9059	7.654530	37.87377	0.0000
_24--S1_W	125.2916	6.921869	18.10084	0.0000
_01--S2_W	-141.2931	4.837224	-29.20954	0.0000
_02--S2_W	-99.18874	4.664932	-21.26263	0.0000
_03--S2_W	-58.78400	4.704551	-12.49513	0.0000
_04--S2_W	-1.043813	4.568587	-0.228476	0.8193
_05--S2_W	131.4103	5.040584	26.07046	0.0000
_06--S2_W	422.0204	6.836602	61.72956	0.0000
_07--S2_W	764.4826	9.472865	80.70236	0.0000
_08--S2_W	776.2779	9.619891	80.69509	0.0000
_09--S2_W	530.0012	7.329385	72.31182	0.0000
_10--S2_W	368.8753	6.747410	54.66917	0.0000
_11--S2_W	335.1832	6.886101	48.67532	0.0000
_12--S2_W	345.4977	7.154051	48.29400	0.0000
_13--S2_W	395.9981	7.375622	53.69013	0.0000
_14--S2_W	440.8337	7.602117	57.98829	0.0000
_15--S2_W	448.4057	7.780692	57.63056	0.0000
_16--S2_W	438.2087	7.846470	55.84787	0.0000
_17--S2_W	414.7918	7.955175	52.14113	0.0000
_18--S2_W	413.6501	7.971988	51.88795	0.0000
_19--S2_W	415.5183	7.581575	54.80632	0.0000
_20--S2_W	408.8849	6.886838	59.37194	0.0000
_21--S2_W	383.2526	6.167045	62.14526	0.0000
_22--S2_W	312.0781	5.551209	56.21804	0.0000
_23--S2_W	211.8157	4.971292	42.60779	0.0000
_24--S2_W	134.9277	4.776903	28.24586	0.0000
_01--TR_REG_01	-59.77330	1.395910	-42.82030	0.0000
_02--TR_REG_02	-73.98792	1.339499	-55.23551	0.0000
_03--TR_REG_03	-83.60957	1.350667	-61.90240	0.0000

_04--TR_REG_04	-92.85344	1.309599	-70.90220	0.0000
_05--TR_REG_05	-107.1361	1.444563	-74.16506	0.0000
_06--TR_REG_06	-125.7986	1.941249	-64.80291	0.0000
_07--TR_REG_07	-139.7315	2.723944	-51.29750	0.0000
_08--TR_REG_08	-131.5747	2.818497	-46.68258	0.0000
_09--TR_REG_09	-113.2044	2.193655	-51.60539	0.0000
_10--TR_REG_10	-92.15802	1.994607	-46.20359	0.0000
_11--TR_REG_11	-79.25287	2.001886	-39.58911	0.0000
_12--TR_REG_12	-68.17944	2.003556	-34.02922	0.0000
_13--TR_REG_13	-62.13751	1.985121	-31.30162	0.0000
_14--TR_REG_14	-57.64076	1.971493	-29.23711	0.0000
_15--TR_REG_15	-54.34259	1.944370	-27.94868	0.0000
_16--TR_REG_16	-55.91336	1.927322	-29.01090	0.0000
_17--TR_REG_17	-58.17450	1.967510	-29.56758	0.0000
_18--TR_REG_18	-61.33371	2.005095	-30.58893	0.0000
_19--TR_REG_19	-61.41710	1.967094	-31.22225	0.0000
_20--TR_REG_20	-60.93655	1.873358	-32.52797	0.0000
_21--TR_REG_21	-58.18997	1.754348	-33.16901	0.0000
_22--TR_REG_22	-55.46563	1.621057	-34.21572	0.0000
_23--TR_REG_23	-55.66954	1.462940	-38.05319	0.0000
_24--TR_REG_24	-60.23575	1.391150	-43.29924	0.0000
_01--TR_REG_01*C1	-100.8906	1.991228	-50.66754	0.0000
_02--TR_REG_02*C1	-97.86202	1.924666	-50.84622	0.0000
_03--TR_REG_03*C1	-95.98081	1.948334	-49.26300	0.0000
_04--TR_REG_04*C1	-92.44104	1.891265	-48.87790	0.0000
_05--TR_REG_05*C1	-91.82613	2.092896	-43.87515	0.0000
_06--TR_REG_06*C1	-89.54254	2.838399	-31.54685	0.0000
_07--TR_REG_07*C1	-93.37141	3.987340	-23.41697	0.0000
_08--TR_REG_08*C1	-107.9247	4.040983	-26.70753	0.0000
_09--TR_REG_09*C1	-118.3079	3.034247	-38.99085	0.0000
_10--TR_REG_10*C1	-121.6450	2.727834	-44.59397	0.0000
_11--TR_REG_11*C1	-121.6726	2.740342	-44.40052	0.0000
_12--TR_REG_12*C1	-122.6446	2.768793	-44.29533	0.0000
_13--TR_REG_13*C1	-127.9928	2.762655	-46.32962	0.0000
_14--TR_REG_14*C1	-138.8092	2.771487	-50.08476	0.0000
_15--TR_REG_15*C1	-150.3333	2.771152	-54.24939	0.0000
_16--TR_REG_16*C1	-160.8767	2.768045	-58.11923	0.0000
_17--TR_REG_17*C1	-163.9893	2.839360	-57.75575	0.0000
_18--TR_REG_18*C1	-158.5402	2.887526	-54.90521	0.0000
_19--TR_REG_19*C1	-149.2763	2.795576	-53.39734	0.0000
_20--TR_REG_20*C1	-141.7412	2.622767	-54.04262	0.0000
_21--TR_REG_21*C1	-136.7888	2.457528	-55.66114	0.0000
_22--TR_REG_22*C1	-132.5320	2.296831	-57.70212	0.0000
_23--TR_REG_23*C1	-119.4459	2.086244	-57.25406	0.0000
_24--TR_REG_24*C1	-106.8091	1.997195	-53.47956	0.0000
_01--TR_REG_01*S2	33.11912	1.938425	17.08559	0.0000
_02--TR_REG_02*S2	28.99469	1.858021	15.60515	0.0000
_03--TR_REG_03*S2	30.60919	1.852301	16.52495	0.0000
_04--TR_REG_04*S2	29.92715	1.785071	16.76525	0.0000
_05--TR_REG_05*S2	32.88233	1.970739	16.68528	0.0000
_06--TR_REG_06*S2	36.20334	2.650635	13.65837	0.0000
_07--TR_REG_07*S2	40.32821	3.696837	10.90884	0.0000
_08--TR_REG_08*S2	42.69053	3.806409	11.21544	0.0000
_09--TR_REG_09*S2	43.11780	2.988476	14.42802	0.0000
_10--TR_REG_10*S2	42.28796	2.806225	15.06934	0.0000
_11--TR_REG_11*S2	41.05581	2.818115	14.56854	0.0000
_12--TR_REG_12*S2	40.72696	2.805631	14.51615	0.0000
_13--TR_REG_13*S2	41.00264	2.751833	14.90012	0.0000
_14--TR_REG_14*S2	42.09547	2.715799	15.50021	0.0000
_15--TR_REG_15*S2	43.78216	2.669808	16.39899	0.0000
_16--TR_REG_16*S2	47.24366	2.644296	17.86625	0.0000
_17--TR_REG_17*S2	52.37211	2.684404	19.50977	0.0000
_18--TR_REG_18*S2	54.64892	2.739451	19.94886	0.0000
_19--TR_REG_19*S2	56.01434	2.692763	20.80181	0.0000

_20--TR_REG_20*S2	54.09001	2.601526	20.79165	0.0000
_21--TR_REG_21*S2	46.07383	2.473043	18.63042	0.0000
_22--TR_REG_22*S2	37.51346	2.287403	16.40002	0.0000
_23--TR_REG_23*S2	34.25983	2.058558	16.64264	0.0000
_24--TR_REG_24*S2	31.45667	1.946161	16.16345	0.0000
_01--TR_REG_01(-1)	-18.60764	1.405141	-13.24255	0.0000
_02--TR_REG_02(-1)	-16.11293	1.351862	-11.91907	0.0000
_03--TR_REG_03(-1)	-17.80645	1.366098	-13.03453	0.0000
_04--TR_REG_04(-1)	-19.63098	1.325299	-14.81249	0.0000
_05--TR_REG_05(-1)	-20.90501	1.466355	-14.25645	0.0000
_06--TR_REG_06(-1)	-20.40652	1.975271	-10.33099	0.0000
_07--TR_REG_07(-1)	-23.07608	2.772219	-8.324048	0.0000
_08--TR_REG_08(-1)	-25.98232	2.856179	-9.096880	0.0000
_09--TR_REG_09(-1)	-22.42940	2.193633	-10.22477	0.0000
_10--TR_REG_10(-1)	-16.39053	1.986187	-8.252261	0.0000
_11--TR_REG_11(-1)	-10.75808	1.976381	-5.443326	0.0000
_12--TR_REG_12(-1)	-5.242295	1.984781	-2.641246	0.0083
_13--TR_REG_13(-1)	0.248939	1.962878	0.126823	0.8991
_14--TR_REG_14(-1)	5.633039	1.951745	2.886155	0.0039
_15--TR_REG_15(-1)	9.430789	1.932746	4.879477	0.0000
_16--TR_REG_16(-1)	11.63392	1.923952	6.046885	0.0000
_17--TR_REG_17(-1)	10.41321	1.968798	5.289121	0.0000
_18--TR_REG_18(-1)	5.103818	2.016355	2.531210	0.0114
_19--TR_REG_19(-1)	-0.789073	1.983241	-0.397870	0.6907
_20--TR_REG_20(-1)	-5.364833	1.879675	-2.854128	0.0043
_21--TR_REG_21(-1)	-9.770994	1.756857	-5.561632	0.0000
_22--TR_REG_22(-1)	-12.74185	1.625543	-7.838522	0.0000
_23--TR_REG_23(-1)	-12.19260	1.467569	-8.308026	0.0000
_24--TR_REG_24(-1)	-11.55893	1.395719	-8.281701	0.0000
_01--TR_REG_01(-1)*C1	-49.70842	1.990554	-24.97216	0.0000
_02--TR_REG_02(-1)*C1	-47.70520	1.925586	-24.77439	0.0000
_03--TR_REG_03(-1)*C1	-46.88870	1.951132	-24.03154	0.0000
_04--TR_REG_04(-1)*C1	-45.63097	1.894669	-24.08387	0.0000
_05--TR_REG_05(-1)*C1	-45.09991	2.100682	-21.46917	0.0000
_06--TR_REG_06(-1)*C1	-46.10282	2.849961	-16.17665	0.0000
_07--TR_REG_07(-1)*C1	-42.85680	3.999079	-10.71667	0.0000
_08--TR_REG_08(-1)*C1	-42.49820	4.049892	-10.49366	0.0000
_09--TR_REG_09(-1)*C1	-49.98615	3.022437	-16.53836	0.0000
_10--TR_REG_10(-1)*C1	-58.82861	2.723123	-21.60337	0.0000
_11--TR_REG_11(-1)*C1	-66.46393	2.739125	-24.26466	0.0000
_12--TR_REG_12(-1)*C1	-70.30761	2.773094	-25.35349	0.0000
_13--TR_REG_13(-1)*C1	-68.25884	2.769943	-24.64269	0.0000
_14--TR_REG_14(-1)*C1	-63.95550	2.782726	-22.98304	0.0000
_15--TR_REG_15(-1)*C1	-58.07493	2.787047	-20.83744	0.0000
_16--TR_REG_16(-1)*C1	-54.94641	2.785335	-19.72704	0.0000
_17--TR_REG_17(-1)*C1	-55.83228	2.859658	-19.52411	0.0000
_18--TR_REG_18(-1)*C1	-57.75031	2.906914	-19.86654	0.0000
_19--TR_REG_19(-1)*C1	-65.04337	2.805280	-23.18606	0.0000
_20--TR_REG_20(-1)*C1	-69.47256	2.623613	-26.47973	0.0000
_21--TR_REG_21(-1)*C1	-65.75678	2.450494	-26.83410	0.0000
_22--TR_REG_22(-1)*C1	-56.04601	2.283156	-24.54760	0.0000
_23--TR_REG_23(-1)*C1	-50.98966	2.064306	-24.70063	0.0000
_24--TR_REG_24(-1)*C1	-46.15730	1.988399	-23.21331	0.0000
_01--TR_REG_01(-1)*S1	-20.50732	1.973581	-10.39092	0.0000
_02--TR_REG_02(-1)*S1	-11.65344	1.924657	-6.054812	0.0000
_03--TR_REG_03(-1)*S1	-9.335365	1.944634	-4.800578	0.0000
_04--TR_REG_04(-1)*S1	-5.829795	1.900061	-3.068214	0.0022
_05--TR_REG_05(-1)*S1	-5.582269	2.080340	-2.683345	0.0073
_06--TR_REG_06(-1)*S1	-13.32385	2.723186	-4.892742	0.0000
_07--TR_REG_07(-1)*S1	-18.73577	3.728110	-5.025541	0.0000
_08--TR_REG_08(-1)*S1	-25.12593	3.875052	-6.484023	0.0000
_09--TR_REG_09(-1)*S1	-25.06936	3.038010	-8.251902	0.0000
_10--TR_REG_10(-1)*S1	-25.64495	2.772722	-9.249016	0.0000
_11--TR_REG_11(-1)*S1	-21.83721	2.732448	-7.991814	0.0000

_12--TR_REG_12(-1)*S1	-19.66131	2.726913	-7.210098	0.0000
_13--TR_REG_13(-1)*S1	-19.08418	2.686133	-7.104705	0.0000
_14--TR_REG_14(-1)*S1	-17.44537	2.645623	-6.594051	0.0000
_15--TR_REG_15(-1)*S1	-16.74976	2.595937	-6.452299	0.0000
_16--TR_REG_16(-1)*S1	-16.79709	2.580725	-6.508673	0.0000
_17--TR_REG_17(-1)*S1	-14.35852	2.640532	-5.437738	0.0000
_18--TR_REG_18(-1)*S1	-12.83529	2.749195	-4.668744	0.0000
_19--TR_REG_19(-1)*S1	-11.68427	2.779173	-4.204227	0.0000
_20--TR_REG_20(-1)*S1	-11.66882	2.702202	-4.318264	0.0000
_21--TR_REG_21(-1)*S1	-12.56748	2.563709	-4.902070	0.0000
_22--TR_REG_22(-1)*S1	-11.70624	2.375302	-4.928316	0.0000
_23--TR_REG_23(-1)*S1	-14.92183	2.137559	-6.980780	0.0000
_24--TR_REG_24(-1)*S1	-15.04362	1.981825	-7.590792	0.0000
_01--TR_REG_01(-1)*S2	11.81265	1.959071	6.029717	0.0000
_02--TR_REG_02(-1)*S2	11.68610	1.889110	6.186033	0.0000
_03--TR_REG_03(-1)*S2	8.949235	1.898439	4.713996	0.0000
_04--TR_REG_04(-1)*S2	9.547404	1.835480	5.201585	0.0000
_05--TR_REG_05(-1)*S2	9.818007	2.027429	4.842591	0.0000
_06--TR_REG_06(-1)*S2	11.50587	2.733669	4.208947	0.0000
_07--TR_REG_07(-1)*S2	14.42370	3.839000	3.757150	0.0002
_08--TR_REG_08(-1)*S2	18.04585	3.966312	4.549782	0.0000
_09--TR_REG_09(-1)*S2	20.69229	3.045188	6.795076	0.0000
_10--TR_REG_10(-1)*S2	16.31185	2.810105	5.804712	0.0000
_11--TR_REG_11(-1)*S2	15.26996	2.817781	5.419143	0.0000
_12--TR_REG_12(-1)*S2	16.13493	2.825580	5.710308	0.0000
_13--TR_REG_13(-1)*S2	13.01594	2.804296	4.641428	0.0000
_14--TR_REG_14(-1)*S2	13.13545	2.782851	4.720142	0.0000
_15--TR_REG_15(-1)*S2	11.83387	2.747155	4.307681	0.0000
_16--TR_REG_16(-1)*S2	10.28567	2.737676	3.757083	0.0002
_17--TR_REG_17(-1)*S2	9.022716	2.796475	3.226460	0.0013
_18--TR_REG_18(-1)*S2	5.670518	2.866647	1.978101	0.0479
_19--TR_REG_19(-1)*S2	4.889180	2.798158	1.747285	0.0806
_20--TR_REG_20(-1)*S2	5.226651	2.637980	1.981308	0.0476
_21--TR_REG_21(-1)*S2	10.01943	2.469533	4.057219	0.0000
_22--TR_REG_22(-1)*S2	11.78643	2.279099	5.171530	0.0000
_23--TR_REG_23(-1)*S2	10.37142	2.054561	5.047999	0.0000
_24--TR_REG_24(-1)*S2	9.739140	1.950306	4.993646	0.0000
_01--TR_REG_01^2	2.400162	0.146987	16.32908	0.0000
_02--TR_REG_02^2	2.765248	0.140797	19.64003	0.0000
_03--TR_REG_03^2	2.916599	0.141842	20.56234	0.0000
_04--TR_REG_04^2	2.797644	0.136268	20.53052	0.0000
_05--TR_REG_05^2	2.862002	0.147506	19.40268	0.0000
_06--TR_REG_06^2	2.928524	0.195538	14.97676	0.0000
_07--TR_REG_07^2	2.964050	0.262400	11.29591	0.0000
_08--TR_REG_08^2	3.050046	0.269565	11.31472	0.0000
_09--TR_REG_09^2	2.936129	0.208143	14.10629	0.0000
_10--TR_REG_10^2	2.813491	0.197390	14.25344	0.0000
_11--TR_REG_11^2	2.927455	0.203366	14.39498	0.0000
_12--TR_REG_12^2	2.930368	0.199967	14.65426	0.0000
_13--TR_REG_13^2	2.919213	0.189476	15.40678	0.0000
_14--TR_REG_14^2	2.878947	0.179335	16.05343	0.0000
_15--TR_REG_15^2	2.872516	0.170734	16.82452	0.0000
_16--TR_REG_16^2	2.857704	0.163429	17.48594	0.0000
_17--TR_REG_17^2	2.693519	0.160667	16.76465	0.0000
_18--TR_REG_18^2	2.692181	0.166193	16.19917	0.0000
_19--TR_REG_19^2	2.495705	0.169153	14.75410	0.0000
_20--TR_REG_20^2	2.488121	0.174951	14.22184	0.0000
_21--TR_REG_21^2	2.571091	0.178169	14.43060	0.0000
_22--TR_REG_22^2	2.425240	0.169970	14.26866	0.0000
_23--TR_REG_23^2	2.428991	0.157106	15.46084	0.0000
_24--TR_REG_24^2	2.651681	0.149700	17.71330	0.0000
_01--C	15497.80	439.2400	35.28323	0.0000
_02--C	14999.44	438.9935	34.16780	0.0000
_03--C	14819.61	438.8079	33.77243	0.0000

_04--C	14931.60	438.9866	34.01379	0.0000
_05--C	15551.51	439.3893	35.39346	0.0000
_06--C	17018.57	439.6338	38.71078	0.0000
_07--C	19072.35	438.8459	43.46025	0.0000
_08--C	20455.71	438.7160	46.62631	0.0000
_09--C	20863.02	439.1474	47.50802	0.0000
_10--C	20899.36	439.1172	47.59402	0.0000
_11--C	20748.16	438.8481	47.27868	0.0000
_12--C	20450.88	438.7261	46.61423	0.0000
_13--C	20167.47	438.6670	45.97444	0.0000
_14--C	19918.95	438.6304	45.41171	0.0000
_15--C	19716.92	438.6572	44.94834	0.0000
_16--C	19739.77	438.6603	45.00013	0.0000
_17--C	20174.97	438.8246	45.97502	0.0000
_18--C	20783.24	438.7977	47.36405	0.0000
_19--C	21024.18	438.8308	47.90954	0.0000
_20--C	20930.73	438.8114	47.69870	0.0000
_21--C	20599.35	438.9529	46.92838	0.0000
_22--C	19649.97	439.7370	44.68574	0.0000
_23--C	18045.18	440.7038	40.94627	0.0000
_24--C	16449.53	440.7724	37.31978	0.0000
_01--AR(1)	0.621222	0.011802	52.63776	0.0000
_01--AR(2)	0.271939	0.011724	23.19517	0.0000
_02--AR(1)	0.639658	0.012108	52.82909	0.0000
_02--AR(2)	0.252034	0.011997	21.00777	0.0000
_03--AR(1)	0.659512	0.012203	54.04646	0.0000
_03--AR(2)	0.227060	0.012085	18.78798	0.0000
_04--AR(1)	0.720149	0.012527	57.48862	0.0000
_04--AR(2)	0.174321	0.012426	14.02898	0.0000
_05--AR(1)	0.744059	0.012422	59.89862	0.0000
_05--AR(2)	0.148811	0.012343	12.05672	0.0000
_06--AR(1)	0.601488	0.011762	51.13609	0.0000
_06--AR(2)	0.260147	0.011672	22.28818	0.0000
_07--AR(1)	0.448457	0.011274	39.77761	0.0000
_07--AR(2)	0.330425	0.011198	29.50865	0.0000
_08--AR(1)	0.399002	0.011036	36.15321	0.0000
_08--AR(2)	0.366535	0.010987	33.36090	0.0000
_09--AR(1)	0.389009	0.010632	36.58889	0.0000
_09--AR(2)	0.441703	0.010597	41.68149	0.0000
_10--AR(1)	0.402172	0.010632	37.82627	0.0000
_10--AR(2)	0.440380	0.010597	41.55519	0.0000
_11--AR(1)	0.399507	0.010658	37.48583	0.0000
_11--AR(2)	0.430848	0.010620	40.57124	0.0000
_12--AR(1)	0.410427	0.010786	38.05305	0.0000
_12--AR(2)	0.409195	0.010729	38.13810	0.0000
_13--AR(1)	0.437205	0.010972	39.84776	0.0000
_13--AR(2)	0.376829	0.010904	34.55825	0.0000
_14--AR(1)	0.451090	0.011111	40.60030	0.0000
_14--AR(2)	0.356468	0.011021	32.34561	0.0000
_15--AR(1)	0.459994	0.011223	40.98642	0.0000
_15--AR(2)	0.345247	0.011119	31.05092	0.0000
_16--AR(1)	0.473523	0.011350	41.72067	0.0000
_16--AR(2)	0.330999	0.011209	29.53049	0.0000
_17--AR(1)	0.501023	0.011492	43.59871	0.0000
_17--AR(2)	0.309435	0.011338	27.29191	0.0000
_18--AR(1)	0.544554	0.011729	46.42949	0.0000
_18--AR(2)	0.266075	0.011574	22.98984	0.0000
_19--AR(1)	0.595098	0.011914	49.95002	0.0000
_19--AR(2)	0.226832	0.011772	19.26799	0.0000
_20--AR(1)	0.661638	0.012097	54.69509	0.0000
_20--AR(2)	0.175830	0.011959	14.70276	0.0000
_21--AR(1)	0.725059	0.012290	58.99667	0.0000
_21--AR(2)	0.133148	0.012172	10.93930	0.0000
_22--AR(1)	0.771787	0.012483	61.82733	0.0000

_22--AR(2)	0.116484	0.012403	9.391642	0.0000
_23--AR(1)	0.732594	0.012501	58.60400	0.0000
_23--AR(2)	0.179421	0.012437	14.42639	0.0000
_24--AR(1)	0.641025	0.012035	53.26482	0.0000
_24--AR(2)	0.274463	0.011966	22.93727	0.0000

Weighted Statistics

R-squared	0.973660	Mean dependent var	20655.55
Adjusted R-squared	0.973584	S.D. dependent var	3652.622
S.E. of regression	589.1970	Sum squared resid	5.98E+10
F-statistic	12840.31	Durbin-Watson stat	2.045117
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.959744	Mean dependent var	19805.53
Sum squared resid	7.51E+10	Durbin-Watson stat	1.619703

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There has been some questions regarding the energy and peak hour forecast using the above methodology. One question has been

1) Is the weather normalized load (average annual energy) equal to the average of 86 years average annual energy? The answer is yes. Tables below show the weather normalized forecast as of 2014 for 2014-2020 loads. The weather normalized loads prior to 86 year temperature overlays is 20942 (net of DSI), with DSI 21715 average megawatts and the average of load after overlays is 21,766 average megawatts. Difference of 0.2%.

Weather normalized net of DSI from Regression analysis prior to weather profiles overlays

Average of Load Net of DSI	
Year	Total
2014	20,343
2015	20,409
2016	20,556
2017	20,690
2018	20,795
2019	20,875
2020	20,942

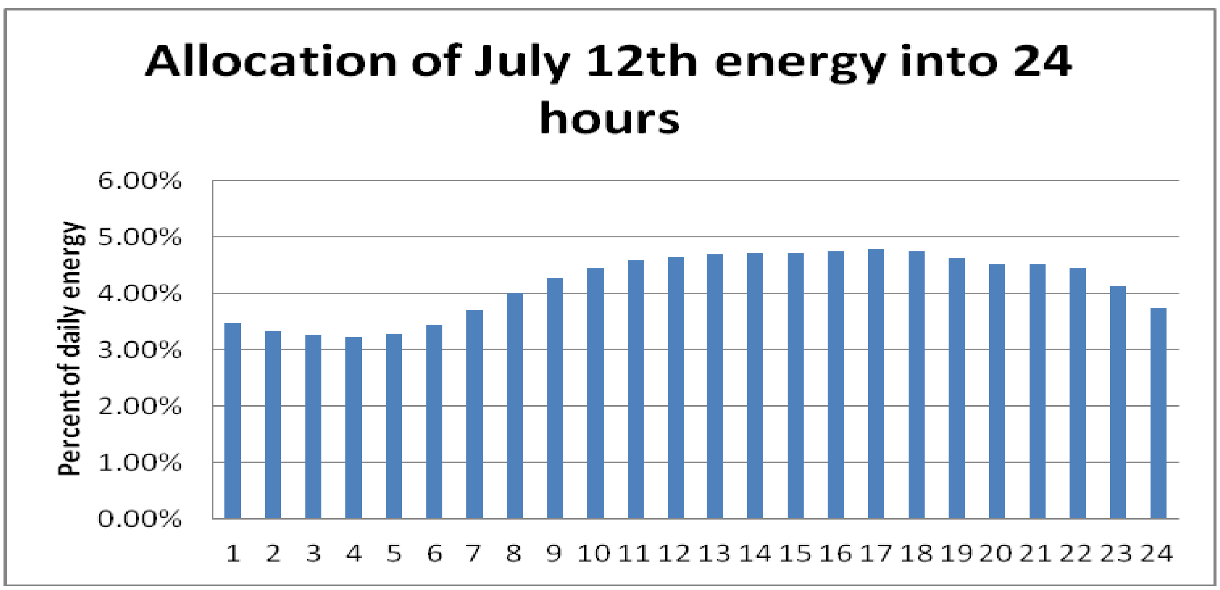
Comparison of average load weather normalized and average of 86 different loads with temperature overlay

	2020 Load forecast
WN load net of DSI (AMW)	20942
DSI (AMW)	773
WN load (AMW)	21,715
Load from Average of 86 years	21,766
Percent difference	0.2%

1) What is the relationship between historic and forecasted single hour peak for a given month or year? Should future forecast peak be larger than past observed peak load or should it be smaller. The answer is it depends.

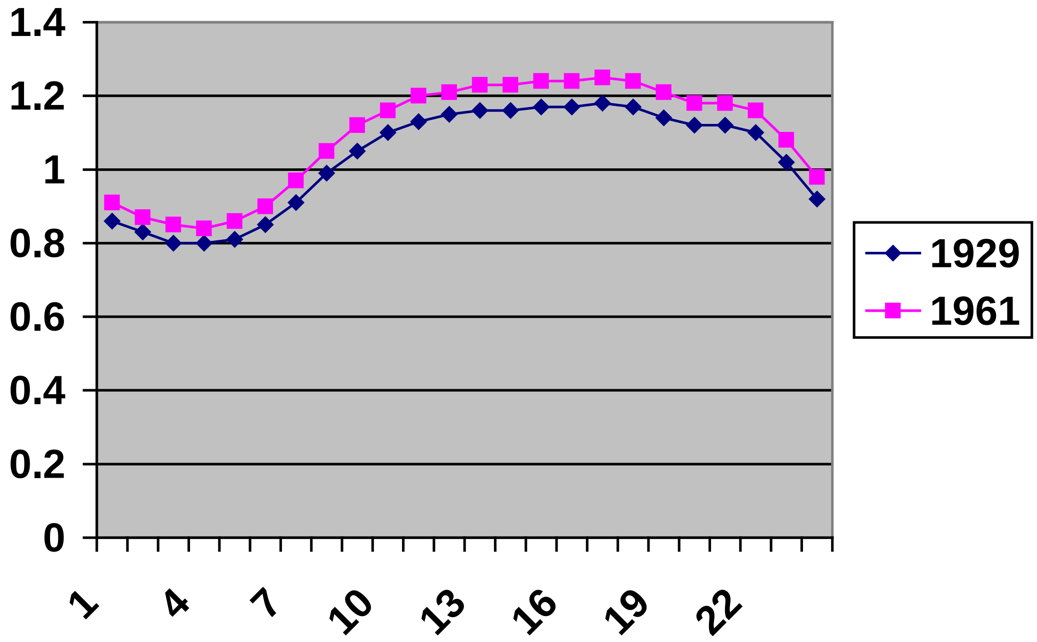
As was presented in the methodology discussion, every day in the forecast period consists of two layers load. A weather normalized load and one of the 86 different daily load overlays that were estimated based on the temperature profile for that day in the history. Saying this differently, let us take example of loads for July 12 2020. The weather normalized load for July 12th 2020 (net of DSI and after adjustment for conservation) is 19360 average megawatts. This day happens to be a Sunday. The WN load forecast knows that and has already adjusted down the load to reflect this fact. We see that next day Monday July 13th WN loads jump to 21033 average megawatts. So the weekday type, or holidays,… is already reflected in the weather normalized loads.

Step 1) Hourly Energy Allocation Factors
Now we need to add in the temperature sensitive loads induced by deviations from normal temperatures for July 12. We do this through a two step process. First using the 24 hourly profile for July 12 from the Hourly Model. Graph below shows these values for July 12. Each day in the year would have 24 values. Note that these hourly energy factors (% of daily load) are an average hourly shape factor developed using the methodology mentioned earlier (the hourly model).



Step 2) Temperature Sensitive Hourly load multiplier
Now we need to reflect the variation in load due various temperature profiles. Each one of the past July 12th (86 values for 1929-2013) will have a multiplier factors. Graph below shows two sets of these 24 hour values for July 12th 1929 and July 12th 1961.

The weather normalized load for the day July 12 is multiplied by each one of these factors. Note the range of multiplier values in this case are low as 80% (reduction in WN load) and as high as 130 percent (a 30% increase in loads).



To estimate the hourly loads for a July 12th we take, the WN load of 19360 aMW, multiply it by the hourly allocation factors from Step 2. For example, for the hour 1 in July 12th we multiply the 19360 by about 85% if year is 1929 and by 90% if year is 1961, we do this for the 24 hours in each day and each year. We then add the DSI loads to each hour load (we assume DSI load is not weather sensitive)

Load in a given Hour for a given day = WN Load * Temp sensitive hourly multiplier + DSI

Please note that temperature profiles have a continuous profile. So our methodology for incorporating the temperature sensitive loads also is on a continuous basis. We start each year on January 1 and end the year in December 31. Which weekday type each date falls in is captured in the weather normalized forecast. Also note that temperature sensitive loads are introduced into the weather normalized loads as a multiplier. This is due to the log-linear structure of the model.

Care should be taken in comparing Council's peak hour forecast with other forecasts. There can be significant differences due to coincident and non-coincident issue Council's forecast is regional and estimated for coincident peak. More importantly Council's model was designed to generate unique load for each day and then parse that into hourly loads, rather than averaging temperatures for a whole month and then determining the temperature sensitive load for the month. If one need to compare peak values generated from Council's model and other models, two approaches are possible; first approach is to compare the load for the same day. So, if we know the day that the peak is expected to occur, one can compare that load with the load for that day in the Council's model. The second approach is to compare Council's weather normalized peak load peak only.

So given the methodology of the hourly load forecast, there is no requirement that past peak loads be replicated in the future forecast. As shown growth in average energy from one year to next can be positive, whereas growth in peak loads forecast depends on timing of peaks. A given weather event in the past that had raised hourly loads does not create same load impact at the same day and hour in the future.

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