Seasonality and Weather Effects on Electricity Loads: Modeling and Forecasting

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Abstract

We wish to investigate climate change-driven effects on electricity demand and production. We model hourly loads for the electricity region and the individual electric utilities of the Pennsylvania, New Jersey, and Maryland Interconnection (PJM) from January 1st, 1998 through April 30th, 2001. We create a database of hourly electricity loads for PJM, by individual utilities and in aggregate. We then estimated a set of hourly forecasting models incorporating autoregressive components, heating and cooling degree temperature effects and trading day variation for holidays and weekends. We use the models' short-run elasticities to perform a simulation of a 2°F increase in daily temperature, finding a small but positive impact on electricity demand.

We first link specific demand effects to hypothesized climate change, utilizing forecasts of end-use equipment stock and electric load shape. These models then project long run responses to climate change.

We model hourly loads for the Pennsylvania, New Jersey, and Maryland Interconnection, PJM, electricity region and the individual electric utilities in that region from January 1st, 1998 through April 30th, 2001. PJM is the largest centrally dispatched electric system in North America and the third largest in the world behind France and Tokyo. PJM was the first Independent System Operator (ISO) in the United States. The PJM service area includes all or part of Delaware, the District of Columbia, Maryland, New Jersey, Pennsylvania, and Virginia. Nearly 9% of the U.S. population resides in the service territory. The peak energy and total energy consumed represents about 7.5% of the national total. Nearly 8% of the nation's generating capacity is located in PJM. Planners at the ISO and owners of generators need to forecast 24-48 hours ahead. Estimates of seasonal and temperature sensitivities are crucial in those projections. We build hourly models by load region and evaluate the forecasts 24-48 hours ahead.

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Outline

I. Introduction

The role of climate change-driven effects on electrical energy demand and production is the focus of this modeling effort. We are undertaking two general tasks. The first requires detailed, disaggregated models that can link hypothesized climate change perturbations to specific demand effects in the residential and commercial sectors. This requires consideration of end-use equipment penetration, load shape forecasting, and creation of detailed (one-hour) short-term forecasts. The end-use and load shape forecasts will be used to explore general relationships between climate and energy use on a regional scale. These models will be used in developing long-term projections of human adaptation to climate change and variability. These projections will then be translated into hourly load forecasts that fully reflect the variability of loads and their correlations with the meteorological conditions that also affect pollutant transport and transformation. These forecasts will be used to analyze interactions between climate, pollution, and energy use on a detailed temporal scale. In the second general task, we will consider the impact of unique events and conduct econometric analyses of the effects of pollution alerts on hourly electricity usage.

II. Literature Review (very brief)

The objective is to produce hourly models of electricity load (consumption) for the electricity dispatch and generation model. These will be used to construct load duration curves.

In general, aggregate analyses have found that commercial and residential uses are much more sensitive to temperature increases than industrial uses, justifying the focus of this proposal on the former. These studies have usually concluded that climate warming would produce a few percentage point increase in cooling requirements, and a similar decrease in heating requirements (Scott et al., 1994; Morris et al., 1996; Sailor and Munoz, 1997); the canceling of the two effects often implies that the net impact on annual energy use may be relatively small (e.g., Darmstadter, 1993). As an example of such a study, Baxter and Calandri

(1992) projected that a 1.9^{o} C warming would increase California's annual electricity requirements by 2.6%. What is more relevant, however, is how that change is distributed within the year. In particular, the greatest increases are likely to occur during weekdays during the air conditioning season, precisely at those times that tropospheric ozone violations occur. For instance, Baxter and Calandri's (1992) analysis indicates that their assumed 1.9^{o} C increase would magnify peak summer electricity demands by 3.7%. It is possible that the proportional increase during periods of high ozone may be even higher; however, no studies have analyzed climate's effect on energy demands on a fine enough temporal scale to consider this possibility. One of this project's purposes is to fill that gap.

The result of using load duration curves in a long-run production simulation model is a set of estimates of average cost and emissions by generating unit type for a given period of time. This will permit a general assessment of the strength of the linkage between regional climate change and emissions of criteria pollutants. However, because of the high correlation between time varying electricity demands (and thus emissions) and the meteorological conditions that influence ambient pollutant concentrations, the impact of that linkage upon concentrations and ensuing health effects must be based upon a detailed chronological simulation of both power system operations and pollutant transport and transformation. Utility experience across the U.S. shows that variations in weekday demands are most strongly associated with temperature, although wind, humidity, and cloud cover are also factors that are frequently considered in short-term models [Liu et al., 1996]. Typically, 80% or more of the variation is associated with weather, and for systems we have studied, peak electric demands in the summer can easily vary by 25% or more because of day-to-day changes in temperature [Hobbs et al., 1998].

III. Data

We have collected hourly loads for the Baltimore Gas & Electric Company (BGE) load region within the Pennsylvania, New Jersey, and Maryland Interconnection, PJM, from January 1st, 1998 through April 30th, 2001. The source for the historical data is from the PJM web-site http://www.pjm.com/market_system_data/system/historical.html. BGE has been operating for more than 180 years. It services more than 1.1 million electric customers and 580,00 gas customers. The load region is about 2,300 square miles including Baltimore City and all or part of 10 central Maryland counties. Figure 1 shows the BGE load region. BGE was a traditional vertically integrated utility that generated and delivered electricity until July 1st, 2000. Constellation Energy Group, the holding company formed a year earlier for BGE, transferred the generating to two competitive affiliates. There are 1,200 miles of transmission lines and more than 21,000 miles of overhead and underground distribution lines in the load region.

PJM is the largest centrally dispatched electric system in North America and the third largest in the world behind France and Tokyo. PJM was the first Independent System Operator (ISO) in the United States. The PJM service area includes all or part of Delaware, the District of Columbia, Maryland, New Jersey, Pennsylvania, and Virginia. Nearly 9% of the U.S. population resides in the service territory. The peak energy and total energy consumed represents about 7.5% of the national total. Nearly 8% of the nation's generating capacity is located in PJM.

We assembled the hourly database for BGE from the PJM website. Table 1 presents summary statistics for hourly loads from January 1st , 1998 through April 30th, 2001. There are 1216 individual hours. The highest average loads are between 7pm and 10pm (hours 19-21) and are above 4,000Mw. The lowest average hourly loads are in the early morning 3am to 6am; they are nearly 1.2Mw lower. The standard deviation of loads is lowest during the early morning period. While the highest ranges above 700Mw between 3pm and 6pm. The maximum hourly loads above 6,000 Mw is from 2pm to 10pm, during this period the range from maximum to minimum is 3,200 to 3,500Mw. In the early morning period, the range is only 2,000 to 2,500Mw.

Hourly load statistics for January and July separately are given in Table 2. The respective load curves are graphed in Figures 2 and 3. Several interesting patterns emerge. As expected average hour loads in the morning hours until about 9am are higher in January or winter. They average 5%-20% higher with the largest differential at 7am, 3,970Mw against 3,262Mw. This is a function of the overnight temperatures and the start of the day effects. The same is true for the standard deviation. Starting about 11am through 11pm average loads and standard errors are higher in July. The differential extends to more than 1,000Mw in the afternoon and narrows to 400Mw in the late evening. Maximum loads in July are 1,000Mw larger than in June during the 11am to 11pm period. Plots of the load curves reveal further differences between January and July other than just magnitudes. In each figure, the monthly mean or average, maximum, and minimum load for a particular year is plotted. The load curves in January (and other winter months) appear to have two peaks. While in July there is a single large hump.

Weather and temperature data was obtained from the NOAA data web-site, http://www.ncdc.noaa.gov/ . The weather station at Baltimore/Washington International Airport, WBAN#724060 and Call Sign KBWI, is the collection site in BG&E study region. While there are several other weather stations in the region, we decided to collect information from this one because of its central location to the population center(s) within the utility's service territory. The sample includes 29,184 hourly observations. There are 868 missing observations, about 3% of the total number. Appendix A details provides details about the hourly temperature series. (We collected data on wind speed, direction, and cloud cover, but did not use it the analysis here.)

Since we are primarily interested in more extreme weather conditions we focus here on the months of January and July in the sample period. Table 3 contains the hourly temperature summary statistics for the two months respectively. Clearly for July, the highest temperatures are experienced from 1pm-4pm (13:00-16:00) and the coolest temperatures from 3am-5am. Warming begins between 6am and 8am and appears to increase faster than the cooling decreases in the late afternoon and evening. In January, the warmest temperatures are experienced between 1pm-4pm and the coolest from 4pm-8pm.

Electricity consumption models are typically based on transformations of the temperature data into heating-degree day and cooling-degree day measures. These represent the impact of temperature fluctuations on electricity load in winter for heating needs and cooling needs in the summer. Heating degree measures are expressed in terms of the difference between 65F and temperatures below, while cooling-degree measures are the difference from 72F and temperatures above. When temperatures exceed the respective upper or lower bound the measures are scored as zero. Hourly degree-day statistics are given Table 4 for January and July respectively. The hourly pattern is similar to that in the raw temperature data.

Figures 4 and 5 plot the average of the hourly load curve and the average degree-day variables together for particular sub-samples in the same graph. Figure 4 contains four graphs for January 1998, 1999, 2000, and 2001. Figure 5 contains three graphs for July 1998, 1999, and 2000. Both demonstrate the importance of time of day and heating and cooling degree effects.

A “camel back” effect is the best way to describe the January load curve. Loads start increasing about 6am and have their first peak an hour or two later. This peak is about 25%-30% higher than the low at night. Then they decline about 10% until about 4pm. After which loads increase to their second and larger peak around 7pm. This peak is about 10% higher than the morning one. Loads decline dramatically after 10pm to the night time low(s). The heating degree-days curve has a single valley with a trough around 2pm. Between 10pm and 8am heating degree-day needs are at their highest, but they are offset by the decline in human and economic activity.

A single trough characterizes the July load curve graphs, in Figure 5, in the early morning, 4am to 6am, coincident with the lowest cooling degree-day needs. As mentioned earlier, loads and cooling-degree day needs increase dramatically between 7am and 11am. Cooling-degree day needs begin falling after 2pm-3pm. But the load curve persists near the peak until the evening and does not really begin to decline until about 10pm. There was a fair amount of variation in cooling degree averages across the three years; Summer 1998 and 1999 were much warmer than Summer 2000.

IV. Models

We specify hourly load models of electricity consumption for the Baltimore Gas and Electric region within PJM using the seasonal sub-samples of data from January 1st, 1998 through April 30th, 2001. The individual hourly models have been estimated using ordinary least squares. The results from these models will be compared against those from a panel data model and an artificial neural network model to be developed in the future. In addition, we will compare the results for the PJM models with other publicly available hourly load models. MetrixND 3.0 (2001) and Eviews 4.1 are the software used for estimating the models and constructing the forecasts.

Electricity loads are dependent on recent time of day and previous hour load effects, seasonal and daily weather patterns, weekday vs. weekend effects, and holidays. These latter two effects are known as trading day variation effects and are modeled using 0-1 dummy variables. A list of the deterministic variables is provided in Table 5.

We use a simple standard seasonal time series modeling approach (Diebold 2001 and Abraham and Ledolter 1983) .The general model for each hour, h, in the summer is specified as follows:

$$Log(Load_{ht}) = \beta_0 + \sum_{i=1}^{7} \beta_i \, Day_{iht} + \sum_{j=1}^{3} \delta_j \, Month_{jht} + \sum_{j=1}^{4} \alpha_j \, Month_{jht} * CDD_{jht} + \sum_{j=1}^{4} \gamma_j \, Month_{jht} * CDD_{jht}^{2} + \phi(L) \, Log(Load_{ht}) + e_{ht}$$

The hourly models for the winter are specified similarly. Time subscripts are denoted using “h” and “t”. The “h” refers to the particular hour and “t” refers to the day in the sample. A white noise random disturbance term, e, is added onto the end of the equation. Dummy variables are used for capturing the day of the week and months. The hourly models are normalized on Mondays in June for the cooling-degree day models (and January for the heating degree day models.) There are seven dummy variables for Day; these include the remaining six days of the week plus a holiday dummy variable. The three monthly dummy variables capture the level effects for July, August, and September in the cooling-degree day models (and February, March, and December in the heating degree day models.)

The effect for a Tuesday in June on electricity load in hour h is given by $\beta_0 + \beta_1 + \alpha_1 * CDD + \gamma_1 * CDD^2$. The CDD terms are their mean values. The parameter β_1, represents the difference from Monday in June. Similarly, the electricity load in hour h on Fridays in July is captured by the expression $\beta_0 + \beta_5 + \delta_1 + \alpha_5 * CDD + \gamma_5 * CDD^2$. The Friday effect comes from the β_5 parameter and the δ_1 parameter captures the difference between July and June.

Heating-degree day and cooling-degree day effects were calculated using the hourly temperature recordings at the Baltimore Washington International Airport National Weather Station. Cooling-degree days, CDD, are defined as the difference between the temperature for that hour and 72F. If the maximum temperature did not exceed the threshold, the value for CDD is zero. Heating-degree days, HDD, are calculated as the difference between 65F and the temperature for the hour. If the minimum temperature was not below 65F, then a zero was assigned for HDD.

Heating and cooling driven loads may rise faster than linearly with increasing and decreasing temperature. We account for this by using squared terms for heating- and cooling-degree days. The general model allows for separate monthly temperature sensitivities through interacting the degree day measures with dummy variables for each month: June, July, August, and September in the cooling-degree day case and January, February, March, and December in the heating-degree day case.

Hourly loads are dependent on past loads; they are autocorrelated. The lagged polynomial operator, $\phi(L) = (L+L^2+L^3+L^{24})$ captures the effects from the previous three hours and for the same hour one day ago.

The general model has 23 parameters to estimate. We test a number of hypotheses on the deterministic variables, on the temperature sensitivities, and both jointly in an attempt to derive more parsimonious models. The hypotheses are explained below in Tables 6 and 8, using a three column format. The first column gives the number identifying the hypothesis; there are total of forty alternative hypotheses or simplifications of the unrestricted model specification. The second column explains the null hypothesis in words, and the last identifies the restrictions on the parameters.

Tables 7 and 9 present respectively the p-values associated with the likelihood ratio statistics for the HDD and CDD model hypotheses tests. Again the format for the tables is identical. The hypothesis number from Tables 6 and 8 is given in the first column. The next twenty-four columns are for each of the 24 hours. There are 40 alternative or restricted specifications of the maintained hourly model. Thus, we have a total of 960 hypotheses tested.

Because of the large amount of data in the table and the preference for presenting the results together, it is done so graphically. The graphical approach in Tables 7 and 9 is used to more easily identify a possible (general) class of model or models that are more parsimonious across all hours. A cell in the table is blank when the hypothesis cannot be rejected for that hour. When the hypothesis is rejected at the 10%, 5%, and 1% level an *, **, and *** is placed respectively in the cell. For example in Hour1 of Table 7, the "*" indicates that the first hypothesis, H0:1 is rejected at the 10% level. The null is that there are no day or holiday effects. Thus imposing this restriction significantly reduces the fit of the model. In Hour 2 of the same table, the second hypothesis, H0:3, has a blank cell. This implies that the null hypothesis (that there are no weekend effects for the winter season load model) cannot be rejected. One general result stands out - removal of deterministic effects for days and months reduces the explanatory power of the models. In the first 15 models and in models 32 through 38 where restrictions on the deterministic components are heaviest, there are rejections in more than two-thirds of the hourly models at the 1% and 5% level for both the heating and cooling degree-day experiments. Overall we found the hypotheses were not rejected in 38% of the winter season models and only 29% for the summer season models.

In the heating degree day model sample hypotheses 21, 31, 39, and 40 appear to have the fewest number of rejections of the null. *See 22, 25, 27, 28, 30 in particular 22 and 30.* The first imposes the restrictions that there are no individual March and December level effects for HDD and the January and February level HDD effects are likewise the same. The second restricts the individual HDD squared effects for December, March, January, and February to be the same; there were no restriction on the HDD level effects. Model 39 imposes symmetry for level and squared HDD effects for December and March and January and February. The last model restricts the HDD coefficients in levels and in squares to be the same for all months.

We calculated the Akaike Information Criterion and the Schwarz Criterion for all models as well. Models 21, 31, and 39 also were among the models with lowest Criterion scores. (These tables are available upon request.) Model 40 had the lowest (mean and median) SIC value for each hour. This reduces the estimated parameters from 23 to 17. We decided to continue with models 39 and 40. The former allows for asymmetric effects in HDD responses at the beginning and end of the winter season as compared with the middle. The latter says that the HDD sensitivities are the same across all the winter months. The regression results for these two models are presented in Table 10.

The cooling degree-day model sample empirical results reach similar conclusions. Again, we decided to keep continue with models 39 and 40. There are fewer significant restrictions in this sample than in the heating degree-day sample. Table 11 contains the regression results for the two models of summer electricity loads.

Tables 12 and 13 respectively present results for testing the symmetry effects in the heating and cooling degree-day sensitivities. There are seven columns in each table. Hours of the day are identified in the first column. The rows contain the results for each hour. Columns two through seven present three pairs of numbers for the tests. The first tests is for the null hypothesis that the degree-day sensitivity in levels for the pair December and March (June and September) is the same as January and February (July and August). The second test is whether the degree-day sensitivity in quadratic terms is the same across the monthly pairs. The third test is for both hypotheses together. The first column in each pair is the Wald Chi-square statistic and the second column is the associated p-value.

In general the heating degree-day sensitivities appear to depend on where in the winter season electricity consumers feel the cold. There is only one hour, 5pm, where the null hypotheses for similar effects are rejected; the December and March pair and the January and February pair both in levels and squared heating degree-day estimates are different. The rejections are at the 2% and 3% level respectively and at 7% jointly. There are marginal rejections, between 5% and 10%, at 3am, 3pm, 8pm, and 10pm. Symmetry appears to be rejected jointly at 1am and 1pm, but none of the individual symmetry tests is rejected at less than 20%. (This appears to be due to lack of significance of coefficients in one pair and not the other. The results are seen in the elasticity estimates below.) We can conclude that except for 5pm the winter season models are best specified without separate effects between the December and March pair and the January and February pair with respect to heating degree-day responses.

The summer season model(s) tests for symmetry in Table 13 tell a different story. Across the three tests, for level terms, quadratic terms, and both jointly, we find six rejections at the 5% level and two at the 10% level. In three cases the three tests are rejected at 5%: 9pm, 10pm, and 11pm. The joint test at 10pm is significant at 10% not 5%. At 6pm the individual rejections are less than 5% while the joint is only marginal at 5.5 %. In the morning between 9am and 10am and at noon the joint hypothesis is rejected, but cooling degree sensitivity appears to be driven more by the level effects and not the quadratic terms. We can refer back to the Figure 5 showing the load curve and average cooling degree-day variables. The morning effect is probably explained by the fact that loads have not reached their peaks so that level effects are most important. The persistence of high electricity consumption and cooling demand into the evening helps to bring in the quadratic terms into effect. The degree-day elasticities will need to take these factors into account. This can be interpreted as a possible start and end of season effect.

V. Elasticity Estimates

We compute elasticity estimates of the impact of a 1 degree Fahrenheit change in the heating and cooling degree-days on electricity loads for each hour. In general, elasticity estimates are not constant and change over the value of the variables of interest. Elasticities may be useful measures, because they are unit-free. Our hypothesis is that a fall in temperature in winter and rise in temperature in summer should have a net positive effect on electricity consumption. We expect the level effects to be positive and the quadratic effects can be positive or negative The scale-free measure will allow us to compare our elasticity estimates across utilities and regions.

The hourly cooling degree-day elasticity in month j is defined as

$$E_{Chj} = (\alpha_{hj} + \gamma_{hj} * 2 * MCDD_{hj}) * MCDD_{hj} .$$

Heating degree-day elasticities are calculated using the same formula replacing the average CDD measure for that hour and month by the average heating degree-day measure. (The M in front of MCDD terms means that they are evaluated at their mean values.)

Table 14 shows the heating degree-day load elasticities for each hour across the symmetric and asymmetric model. If a coefficient estimate is not significant at 5%, then a zero is placed in that cell. The symmetric model for heating degree-days appeared most appropriate from the hypothesis test results in Table 12 with the possible exception of 5pm. The last column or sum reflects the impact from both level and squared effects in heating degree-days.

There were coefficient estimates significant at 5% in 21 of the 24 hours and sums were all positive. The level effect elasticity was significant between midnight and 7am and between 4pm and midnight (except between 7pm and 8pm); these are the coldest times of the day. In addition there was a positive level effect between 9am and 10am and a small negative between noon and 1pm. The later was outweighed by the quadratic effect. Quadratic effects were positive and significant between 8am and noon, 2pm and 3pm, and from 6pm to 8pm as well. The highest elasticities were in the early morning hours and between 6pm and 8pm. The former affect temperature effects while the latter captures household temperature and activity effects. For example between 6pm and 7pm the combined level and quadratic effect is 4.8% for a 1degree Fahrenheit increase in heating degree-day temperature.

The cooling degree-day elasticities in Table 15 have different characteristics from those of the winter season. In this case the asymmetric model results appeared to be the most appropriate. The responsiveness of June and September cooling degree-day coefficients was found to be different from the July and August coefficients. On net, all the hourly elasticities are positive. We found that level elasticity was statistically significant at 5% in 21 of 24 hours for the June and September pair and 18 of the 24 hours for the July and August pair. The portion of the elasticity associated with the quadratic term was negative and significant in 14 of the June and September measures and 13 of the July and August pair. An important point to take from this is that ignoring the quadratic term in the model specification would bias the elasticity estimates upward. We have two possible explanations (there maybe more) for the negative value. First, there is a limit on the cooling demand from the existing capital stock. Second, the utilities find ways to reduce the load response during very warm weather. The highest elasticities occur during the warmest portion of the day from 8am to 6pm. A surprising result is that the elasticity estimates appear at least numerically larger in most hours for June and September, as compared to July and August.

This may be due to the two reasons mentioned above and greater volatility in temperature. The average cooling degree value for June and September between 9am and 6pm ranges from 4 to 7.7 with a standard deviation from 5 to 6.9. The July and August values have about the same standard deviation range, 5.5 to 6.9 while the average cooling degree-day ranges from 7.8 to 12.15. In addition, the July and August values appear to approximate a normal distribution, the Jarque-Bera test cannot be rejected at 10%. The test is rejected for every hour in the June and September sample. There appear to be flatter tails to the distributions; that is more observations close to zero and maximum average values close to those in July and August. Thus, even though hourly loads are on average larger in July and August, they appear to be relatively more temperature sensitive in June and September. We illustrate several of these concepts in figures below.

The hourly elasticity estimates with electricity loads are presented in Figures 6 and 7 using a bar and line graph. The estimates are taken from the last column of Table 14 and represent the sum in the symmetric case for December, January, February, and March. The elasticities seem to coincide more with heating (and cooling) needs by households and businesses and not the level of the load per se. The winter load exhibits two peaks during the day, between 8:00-9:00 and 20:00-21:00, and two troughs, about 3:00 and 14:00. Figure 6 shows the (statistically significant) hourly heating degree-day elasticities with bars on the left axis and the loads with a line on the right hand axis. Heating degree-day sensitivities are consistently 2% or higher between midnight and 6am. There appears to be no temperature sensitivity between 6:00 and

8:00. The next two hours have a heating degree elasticity of 3%, which seems to coincide with the start of the business day. Then, elasticities settle down until about 17:00 when they start rising as people are arriving home and the temperatures drop at sunset. The heating degree-day sensitivity seems to move with the load curve in the evening.

Cooling degree-day elasticities are smaller than heating degree-day ones even though the load is higher. The elasticities are taken from the last column of Table 15 and represent the sum in the symmetric case for June, July, August, and September. During the night, between 22:00 and 5:00, the elasticity is significant and about 0.5%-1.0%. This probably reflects the demand for comfort while sleeping even though this is the trough load period. Air conditioning demand is responsive on very hot nights. In the morning as temperatures and loads rise people go to work, and businesses open from hour 8 through hour 11, the elasticity averages about 1.5%. The load sensitivity is marginal for the next three hours as the temperature is just peaking and loads are approaching their peak. Starting at hour 15 through hour 18, the elasticity is greater than 1%. Between 6pm and 9pm the elasticity appears to be zero. This would seem counter-intuitive, but can probably be explained by offsetting effects. Residential demand for electricity is increasing while businesses are closing. In addition, the level of the temperature may by high; it is falling rather than rising.

VI. Simulation

We conducted two simulations for the impact of higher summer temperatures using the forecasts from the Intergovernmental Panel on Climate Change *(citation)*. The expectation is that temperatures could increase by 2 degrees Fahrenheit. The simulations look at two three day periods during July and August 2000 when cooling degree day needs were particularly high. The first was July 31st to August 2nd and the second was August 7th through August 9th. The hourly models are fit up through the day before each event and then forecasts are made for the next three days adjusting the cooling degree-day variables for a 2 degrees Fahrenheit increase. We compare the actual historical value against the forecast using the actual temperature values and the simulated forecasts with the adjusted cooling degree day variables.

The most important comparison we consider is the relative difference between the simulated forecast using the adjusted cooling degree values and the forecast using the actual cooling degree-day data. We examine the ratio for the two events in Figures 11 and 12. The figures show the ratio on an hourly basis each day during the two event periods respectively. The simulations do not show a very large impact on predicted loads; the effect is about 0.4% higher during the July 31st – August 2nd event and 0.55% higher in the August 7th- August 9th event. There is no impact from midnight to 6am or from the peak at 3pm to 7pm (15:00-19:00). The largest impacts are in the late morning and at sundown: 7pm to 9pm. These are the periods when there is the greatest change in electricity loads.

VII. Summary

This first interim report describes the progress on modeling the impact of climate change on electricity consumption behavior. The major accomplishment is the construction of an hourly data base of electricity loads for the Pennsylvania-New Jersey-Maryland Interconnection (PJM) in the aggregate and by utility control region. A standard set of hourly forecasting models has been estimated for the whole PJM accounting for autoregressive components, heating and cooling degree temperature effects, trading day variation for holidays and weekends. Short-run elasticities have been calculated for the heating degree day and cooling degree day effects. The forecasting power of the model has been evaluated and the (absolute) percentage errors range from one-half a percent to two percent of hourly loads. A simple simulation over two three-day events of particularly hot temperatures during July and August 2000 was performed. The experiment looks at the impact of a 2F increase in the daily temperature. We find a small but positive impact during the periods before and just after the peak in the daily electricity load.

There are several research areas we intend to work on testing and improving the models. The first area involves the collection of hourly temperature data for PJM and the utility control areas. At present we only have daily high and low temperatures. These two measures may not provide adequate resolution of the impact of temperature variability and its impact on electricity loads. Second, the specification of the model can be modified to try and capture more of the seasonal and temperature dynamics. The current set of hourly models covers PJM as a whole; the goal is to develop hourly models for each of the control regions. So far we have not been able to obtain loads by sector (residential, commercial, industrial, and other). This is another area for data collection and modeling we expect to report on in the future. The literature and our own experience suggests that the residential and commercial sector are more sensitive to climate variation than the industrial and other sectors.

The accomplishments for the short run transportation analysis are …

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