The Impact of Daylight Savings Time on Electricity Consumption in Indiana

Joseph Basconi, advised by Dr. Jeffrey Kantor

University of Notre Dame

Department of Chemical and Biomolecular Engineering

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Introduction

One of the arguments for observing Daylight Savings Time (DST) is that extending the hours of sunlight later into the day reduces the need for artificial lighting in the evening, and thereby decreases electricity consumption during the summer months. This report describes a retrospective study on how the observation of DST has affected electricity consumption in Indiana, following the state's adoption of DST in April 2006. The analysis was patterned after similar studies done in 2001 by the California Energy Commission and the Indiana Fiscal Policy Institute, which forecasted the impact that proposed changes to DST would have on electricity consumption. The study uses a model that relates hourly electric load to a variety of explanatory variables that contribute to electricity usage throughout the course of the day. Upon analyzing the individual effects of the different contributing factors, we found that Daylight Savings Time had an overall net effect of reducing electricity consumption, by as much as 320 MW a day in Central Indiana counties. While the advancement of time by one hour increases electricity usage in the morning hours, this effect is outweighed by reduced consumption in the later hours of the day.

Background

On April 28, 2005, Indiana state legislators decided that all Indiana counties would officially adopt Daylight Savings Time beginning in April 2006. Up until this time, Indiana was one of three US states that did not adjust its clocks to DST during the summer. The majority of its counties stayed on Eastern Standard Time throughout the entire year, while some counties neighboring Chicago, IL in the northwest and Evanston, IN in the southwest belonged to the Central Time Zone and did observe Daylight Savings Time.

Indiana's decision to adopt DST throughout the state and align its counties with either the Eastern or Central Time Zones was not without controversy. In northern Indiana, for example, counties with connections to the Chicago economy preferred to be on Central Time, while others communities closer to Fort Wayne, IN were in favor of Eastern Time. After much debate, the state placed the majority of its counties on Eastern Time, and six counties in the northwest and eleven counties in the southwest on Central time. Effective April 2, 2006 the entire state would observe summer Daylight Savings Time in accord with the rest of the country.

One of the arguments for Daylight Savings Time is that adjusting the clock one hour ahead during the summer months saves electricity by altering daily consumption patterns. Additionally, DST can shift electricity consumption away from peak demand times when electricity is most expensive, thereby reducing utility costs. In 2001, the California Energy Commission published a report entitled "Effects of Daylight Savings Time on California Electricity Use." Their study simulated electricity consumption under two different DST scenarios that lawmakers had proposed to help the state cope with an energy shortfall. The Commission reported that "marginal amounts of electricity" could be saved either by extending DST into the winter months, or by advancing the clock by two hours in the summer to observe "Double Daylight Savings Time."[1] Under both scenarios, electricity consumption would increase during the morning hours and would decrease in the evening to produce a net savings over the course of day. Additionally, the state would save millions of dollars because DST would shift some of the evening consumption away from the peak demand time when rates are the highest.

Later in 2001, the Indiana Fiscal Policy Institute (IFPI) replicated the California study to simulate the effect of DST in Indiana. In contrast to the California results, this study predicted that Indiana electricity usage would increase in the morning hours and decrease in the evening. The IFPI did not draw a definitive conclusion on the overall effect that DST would have on electricity consumption, but recommended that further analysis be done.

[1] California Energy Commission, May 2001.

Approach to Analysis

The approach taken for this project was to follow the statistical model used in the California and Indiana studies in 2001, in which hourly electric load is related to many different predictor variables. By fitting a regression model to a data set that included days both before and after the adoption of Daylight Savings Time in Indiana, we hoped to understand the effect that DST had on electricity consumption.

Before implementing a mathematical model, the raw electric load data was plotted to give a preliminary picture of how electricity usage had fluctuated from January 2004 through May 2007. The average hourly electric load was plotted for each month, and we compared the hourly consumption patterns for the years before the adoption of DST, 2004 and 2005, and the years after DST, 2006 and 2007. We also plotted the average hourly electric load for the weeks that preceded and followed a change in DST, for the years 2006 and 2007. These comparisons were useful in that they illustrated how consumption patterns for DST days differed from the patterns for Standard Time days. However, simply comparing the differences in electric load for DST and Standard Time does not accurately describe the effect that DST has on electricity consumption, as a variety of other variables also contribute to electric load. For example, extreme high or low temperatures increase the demand for heating or cooling, the presence or absence of sunlight dictates the need to turn on lights, and the number of people employed and the day of the week reflect the electricity demands of businesses and industry.

In order to analyze the effect of DST on electricity consumption independent of other contributing factors, we employed the statistical model used in the California and Indiana studies. The model consists of a system of twenty-four linear equations, one for each hour of the day, in which hourly electric load is related to explanatory variables representing the unique conditions of that time of the day. These variables include whether or not Daylight Savings Time is in effect, whether or not it is a workday, average monthly employment in the area, the weather conditions at the time, and the presence of sunlight or twilight at the time (a detailed discussion of the weather and lighting variables can be found in Appendix B). The California and Indiana studies did not include a daylight savings time variable; rather they performed multiple regression on the data set to generate model coefficients for each hour of the day, and then shifted these coefficients to the previous hour's data to simulate the electric load under the conditions of Daylight Savings Time. Our retrospective study includes data from the years both before and after the change to DST, and thus includes an additional DST variable that represents whether or not DST is observed at time of the year.

Using this type of regression model allowed us to isolate the effects of individual contributors and study how each of these effects changed over the course of the day. In the case of the workday variable, one would expect its impact to be much greater at 2 P.M., when most businesses are operating on workdays, than at 2 A.M., when businesses are typically closed regardless of the day of the week. We also were interested in the net effect of the different variables, particularly the DST variable, over a twenty-four hour day.

The model took the form of twenty-four simultaneous equations relating hourly electric load to nineteen different explanatory variables, plus a constant term. Matlab was used to estimate coefficients for each of the parameters by the method of least squares. We also used Matlab's "stepwise" function to improve the model by removing parameters that were not statistically significant based on their p-values. The estimated coefficients were fitted to the data to predict the load for each individual hour, and the predictions were compared with the actual hourly loads to validate the quality of the model. We then analyzed the DST coefficient as it changed throughout the day to understand its hourly impact on electricity consumption. By summing the twenty-four DST coefficients of the different hours of the day, we were able to estimate the net effect of DST on electricity consumption at a 95 percent confidence level.

In the future, we plan to use the tool of Seemingly Unrelated Regressions (SUR) to model the data and improve upon the least squares model. Employed by both the California and Indiana studies in 2001, the SUR method is an iterative process that generates improved estimates for the model coefficients by accounting for correlations between the error terms of the different equations. Because the factors that determine electricity consumption are strongly correlated from one hour to then next, the SUR is a useful tool for this type of problem. Details on the specifics of the regression model can be found in Appendix A.

Data Sources and Data Sets

The data for this study include all hours of the days ranging from January 1, 2004 through the summer months of 2007, depending on the load data provided by the utility. This time period allows an analysis of electricity consumption both before and after the adoption of DST. Hourly electric load data was obtained from three out of the top five electricity providers in Indiana: Duke Energy, Vectren Energy, and Northern Indiana Power and Light Company (NIPSCO), though not all data sets were appropriate for analysis. Monthly employment data was obtained online from www.statsIN.com, a website maintained by the University of Indiana Kelly Business School. Hourly weather data and sunrise, sunset, twilight begin, and twilight end times for six stations throughout the state were purchased from the Weather Bank, a commercial meteorological service. Details on the specifics of the variables and data sets can be found in Appendices B and C.

Results

Electric Load Plots

Before using the regression model, we created several plots of the raw electric load data to gain a preliminary understanding of how Daylight Savings Time affected electricity usage from 2004 to 2007. While many factors besides DST contribute to the amount of electricity consumed, the plots did reveal certain trends that distinguished Standard Time days from DST days. Load data for each of the 24 hours were averaged over each of the 12 months, and the monthly averages for the different years were compared, as seen in the plots of January and May in Figure 1.

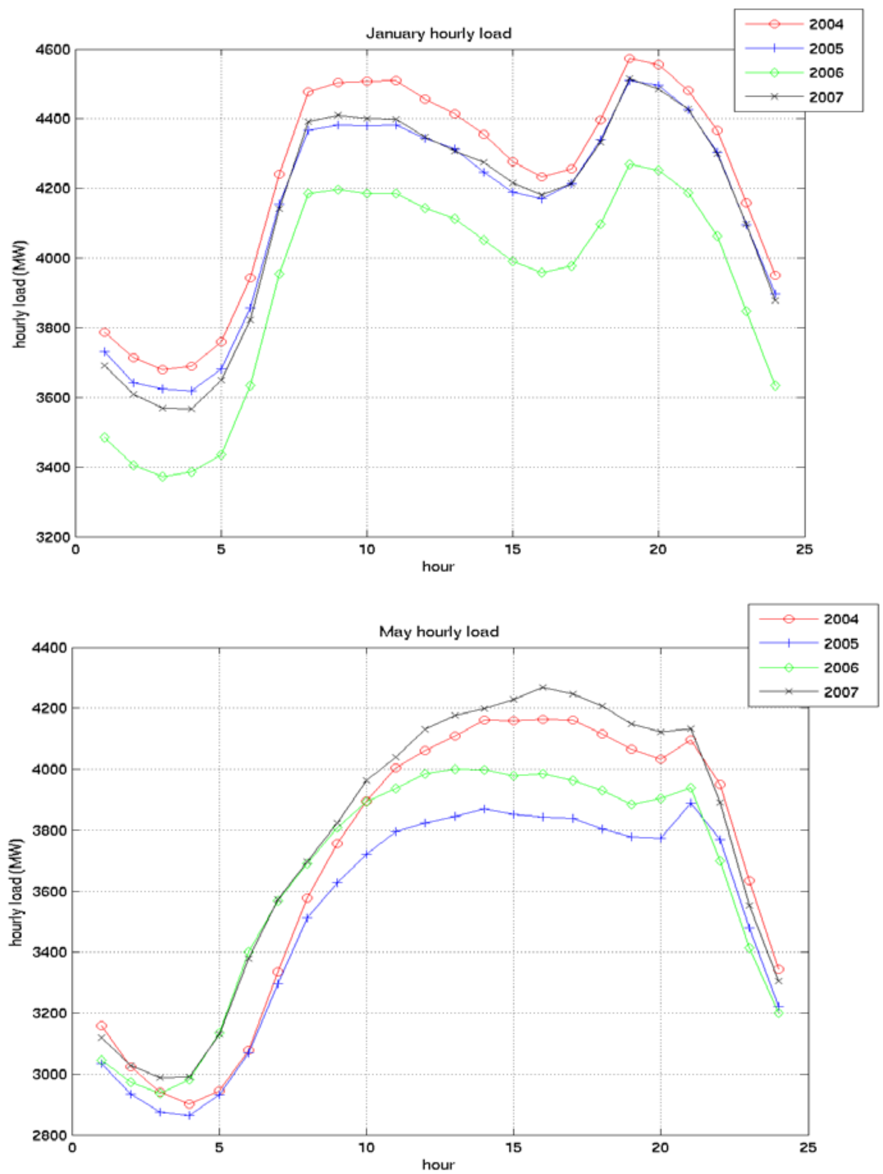

Figure 1: Hourly load plots for January (no DST observed) and May (DST observed in 2006 and 2007)

During January, a typical winter month when DST does not occur, the electric load plots for each of the four years follow roughly the same pattern, with peaks in the morning and evening hours coinciding with each other. The common shape of the plots for the different years shows that no factor in January significantly altered the daily pattern of electricity consumption. While total consumption clearly varies with each year, no conclusions can be made on how DST impacts total electricity usage because many other factors also contribute to the hourly load.

During May, a summer month in which DST does occur, the load plots for the DST years of 2006 and 2007 are clearly shifted one hour ahead of the non-DST years 2004 and 2005. This shift is most noticeable in the early morning hours of 5 A.M. and 6 A.M. when electricity usage climbs sharply as people begin waking up and turning on lights and appliances. The advancement of the clock under DST delays the morning light by one hour, thus advancing the demand for early-morning electricity by one hour. A second observation on consumption patterns in May is that the evening peak around 7 P.M. to 8 P.M. is broader during DST and sharper during Standard Time. This finding may be attributed to DST delaying the need to turn on lights in the evening by one hour, and in the process shifting some demand away from a time when there is already a high demand due to activities that people typically do at this time. It is important to note that these explanations assume that people base their daily schedules and consumption habits on the time of day it is, rather than whether it is dark or light outside, a factor that changes throughout the year. It is assumed that people will wake up and turn on lights at 6:30 A.M. because they have work at 8:00, regardless of how light it is outside.

As seen in Figure 2, similar consumption patterns are found in the plots of average load for the weeks that precede and follow changes to and from DST. The clocks change from Standard Time to DST in the spring of 2006 and 2007, and from DST to Standard Time in the fall of 2006. Averaged over only one week of data, these plots are highly dependant on the weather conditions of the week, which sometimes mask changes in consumption patterns that arise due to DST. Still, the plots help verify the trends observed in Figure 1, as the weeks in which DST is observed appear to have the morning peak shifted one hour earlier.

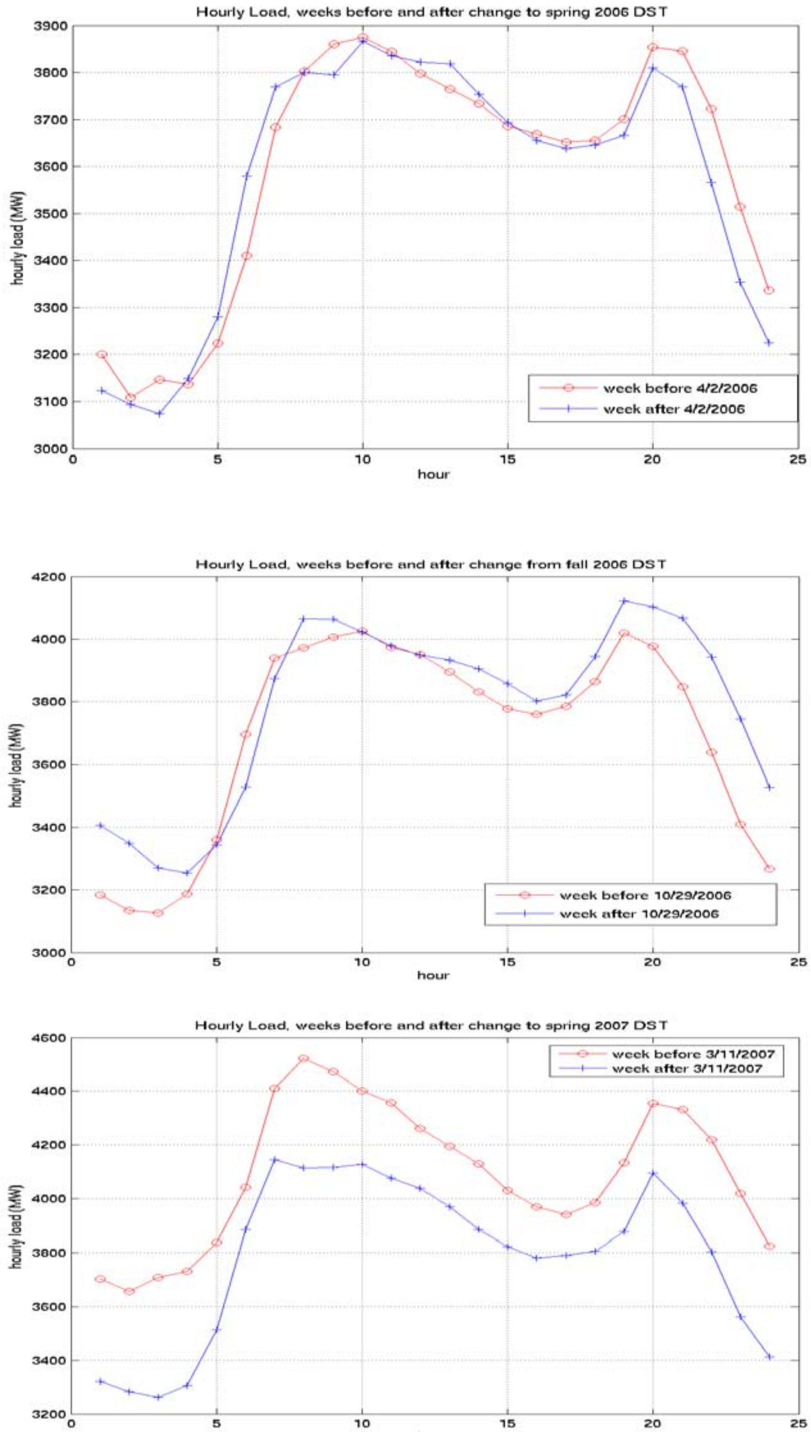

Figure 2: Electric load for weeks preceding and following changes in DST.

Regression Analysis: whole data set

While plotting the load data provided evidence that DST moves the early morning peak ahead one hour and broadens the evening peak, a regression model was necessary to determine exactly how these shifts in consumption patterns affected the amount of electricity used over the course of the day. We designed a model that related hourly electric load to a variety of explanatory variables: whether or not DST was observed, whether or not it was a workday, average monthly employment, the weather conditions at the time, and the amount of sunlight and twilight in the hours of that day. The variables used in this model are further discussed in Appendix B.

The first analysis on the Duke Energy data set was done using the "regress" Matlab function, which estimates coefficients and the 95 percent confidence intervals for each parameter in the model. The regression was done using the method of least squares, so that all parameters were left in the model, regardless of their p-values. After obtaining 480 coefficient estimates, one for each of twenty parameters for each of the twenty-four hours of the day, the model coefficients were "fit" to the explanatory data to estimate the load for each unique hour in the data set. Ideally, the model should predict load values that are equal to the actual load values, and a plot of predicted vs. actual load should be linear. As seen in Figure 3, the hourly loads predicted by our model have a roughly linear relationship with the actual loads, though there is some noise in the data. The quality of this fit, along with the model's R squared statistic of 0.867, led us to keep the model as an effective tool for analysis. Details on the set-up of the regression model may be found in Appendix A.

Of primary interest for this study were the hourly coefficients of the DST variable (β_{DST}). Several of the DST betas had 95 percent confidence intervals that included zero, and therefore were not statistically significant. Mindful of this limitation, we plotted all twenty-four values to see how Daylight Savings Time could contribute to electric load throughout the day. As seen in Figure 4, the effect of the DST variable on electric load changes considerably over the course of the day. Because the regression model was coded with 1 for DST days and 0 for Standard Time days, positive coefficients represent hours when Daylight Savings Time increased electric load and negative coefficients reflect hours when DST decreased load. The plot reveals that DST significantly increases electricity consumption during the morning hours, by a much as 200 MW at 6 A.M. This provides evidence that the shifted morning peak time observed in Figure 1 has a direct effect on the amount of electricity consumed during the morning hours. Shifting the clock one hour ahead for DST leads to increased electricity demand in the morning, as people use more artificial lighting in response to the "delayed" rising of the sun.

The β_{DST} values become negative beginning at 11 A.M., and thus it is likely that DST decreases electricity consumption during these midday and afternoon hours, though the null hypothesis cannot be rejected for all of these hours. The coefficients become positive again in the evening at 7 P.M. and 8 P.M., then take on larger negative values during the late night and early morning hours. The positive β_{DST} values during the evening hours may help explain the effect of the broadening of the evening peak observed in Figure 1. The regression model predicts that DST slightly increases electricity usage in the evening by altering the consumption patterns of this time of day, just as it significantly increases morning usage by shifting sunrise back one hour.

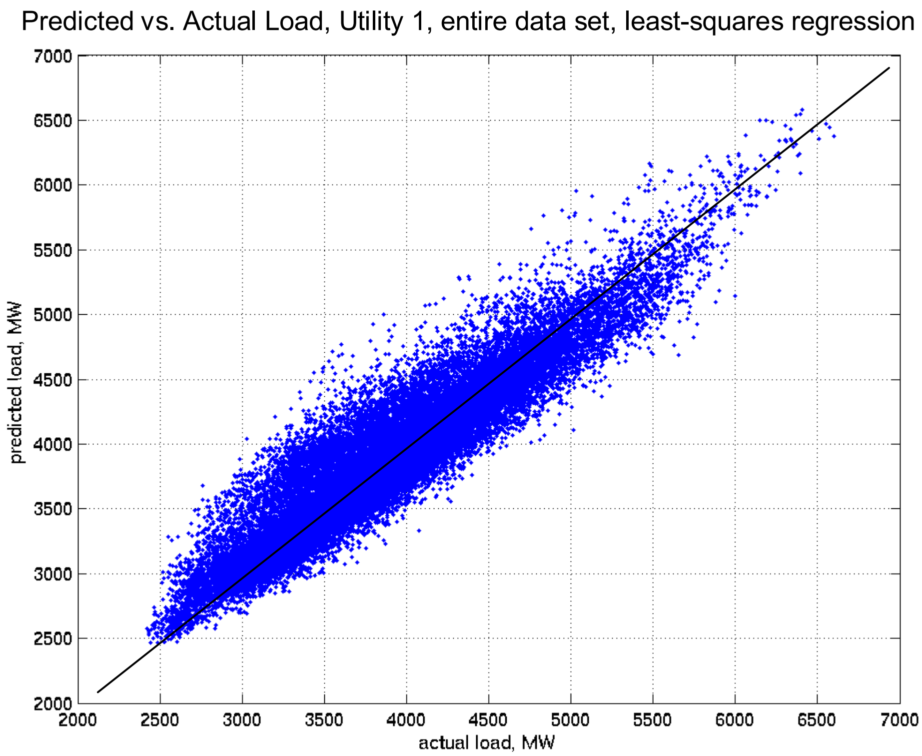

Figure 3

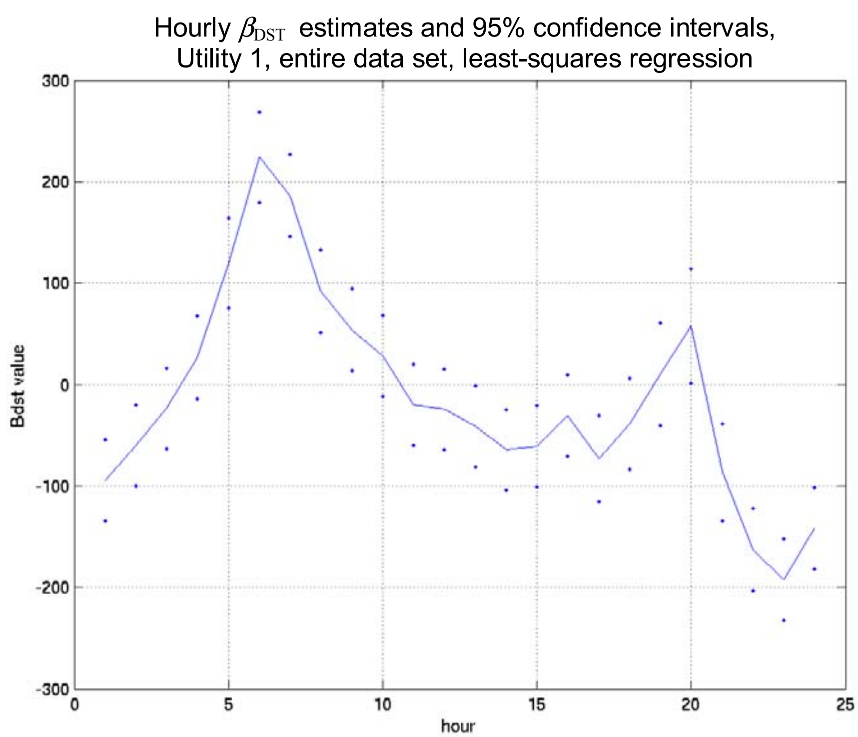

Figure 4

The net effect of Daylight Savings Time was found by summing the β_{DST} values for each hour of the day. The β_{DST} coefficient over the course of the day had a net total of -316.59 and was statistically significant, with a 95 percent confidence interval of -524.18 to -108.99. Thus, the model predicted that Daylight Savings Time reduced electricity consumption by an average of approximately 317 MW a day, as the increased demand in the morning was more than outweighed by decreased usage throughout the rest of the day.

As seen in Figure 4, several of the β_{DST} values have confidence intervals that include 0, meaning the β_{DST} for that hour actually may not be a positive or negative contributor to electric load as the plot depicts. To eliminate parameters from the model that were not statistically significant, the Matlab regression tool of "Stepwise" was used to generate new parameter estimates. Stepwise includes all parameters with p-values less than 0.05 and removes parameters with p-values greater than 0.10. Fitting the new coefficients to the data set did little to change the predicted hourly load, as we obtained nearly the same relationship between predicted and actual loads as seen in Figure 3. Stepwise removed six of the β_{DST} values from the model, and the net total of the remaining coefficients was -324.85, for an average net savings of approximately 325 MW a day. The 95 percent confidence interval for this total, -474.08 to -159.09, was an improvement over the least-squares regression.

Regression Analysis: Data Set including possible DST days

The data set used for the initial analysis included 29880 hours spanning from January 2004 to May 2007. The years of 2004 and 2005 had no DST, whereas 2006 and 2007 marked the beginning of DST in Indiana. Taking a different approach to the regression model, we created a new data set using the DST days of 2006, and the corresponding summer days of 2004 and 2005 that would have been DST had the time change been observed then (data for the entire DST period of 2007 was not available at the time of the study, July 2007). Fitting the least-squares regression model to this new set yielded results that deviated from the analysis of the entire set. As seen in Figure 5, the new model predicted hourly loads that were closer to the actual loads than the model for the entire data set. The more linear relationship between the actual and predicted loads indicates that the model may have improved. Additionally, the R squared statistic improved from 0.87 for the model of the entire data set, to 0.91 for the new model.

However, the plot of the new β_{DST} values shown in Figure 6 shows that at many hours, DST is less of a negative contributor to electric load, and there is less certainty that it decreases consumption at these times. These observations are reflected in the reduced net β_{DST} value over the course of the day and the wider 95 percent confidence interval: β_{DST} had a value of -308.97 with an interval of -638.94 to 20.99. However, the total β_{DST} value is close to the value obtained using the whole data set, and the larger confidence interval may simply be a result of using a smaller, more error-sensitive data set for the regression.

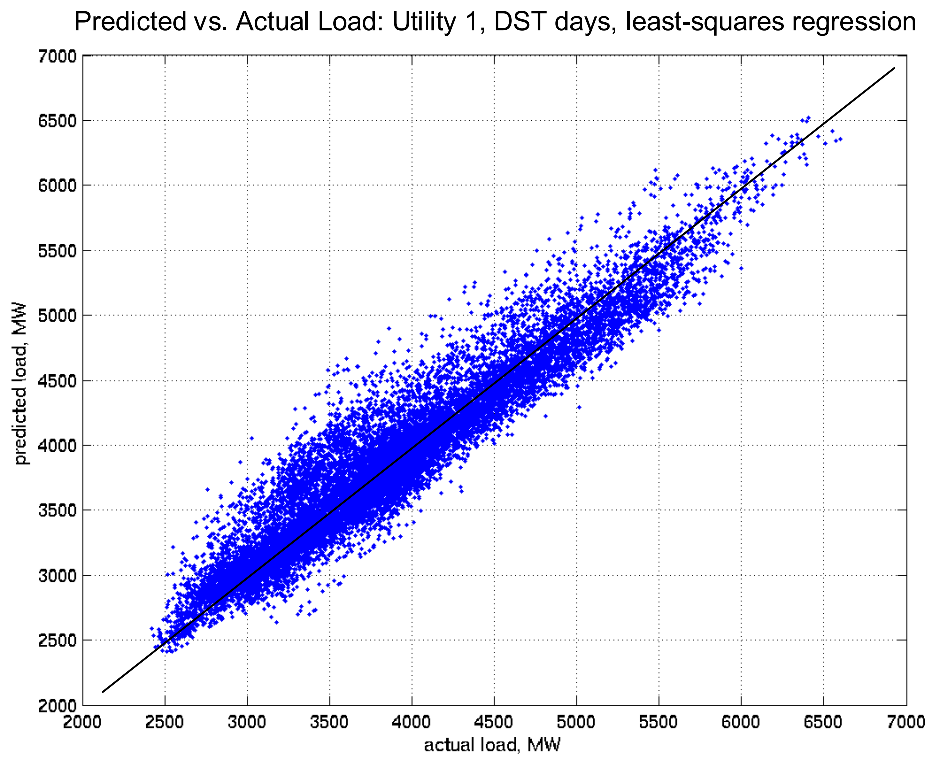

Figure 5

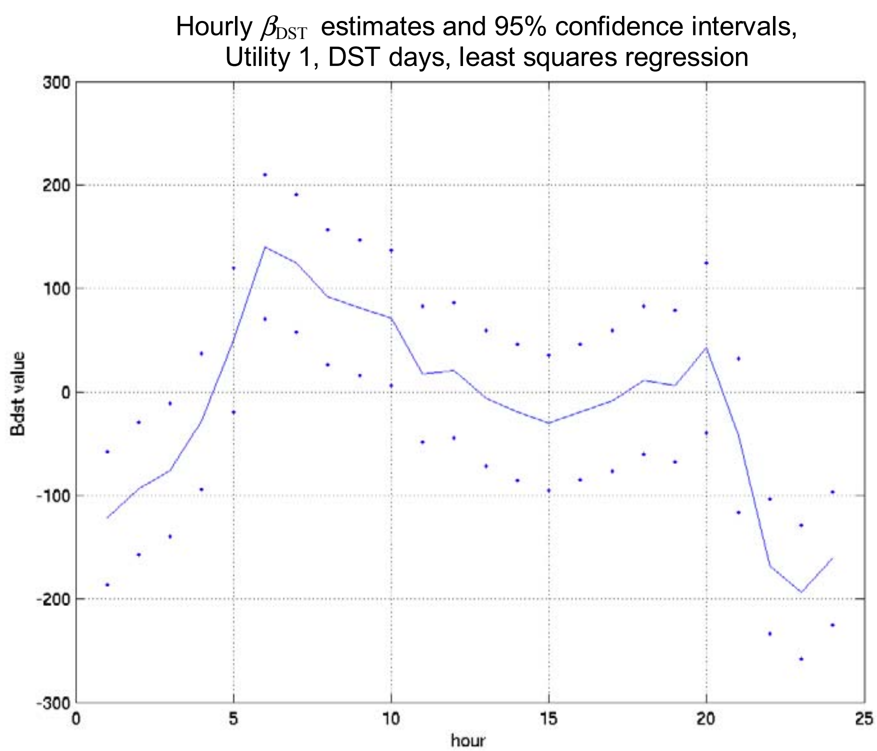

Figure 6

Regression Analysis: Modeling data for a second utility

A second analysis was performed on the Vectren Energy data set, primarily to compare the results of the original regression model with a model based on an entirely different data set. As discussed in Appendix C, Vectren's coverage area included counties that had observed Central Standard Time as well as Central Daylight Time for all four years, while Duke Energy served counties that had observed Eastern Standard Time year-round up until April 2006. Despite these differences, a similar data set was prepared for the Vectren load data, using employment, weather, and lighting data for Vectren's coverage area.

While less conclusive than the results on the first utility, the second regression model supported the finding that DST has a net effect of reducing electricity consumption over the course of the day. As seen in Figure 7, the model provided a reasonably good prediction of the actual load, though the relationship is clearly noisier than that of the first utility. The R squared value of 0.82 for the Vectren model, compared to a value of 0.87 for the Duke model, reflects this difference. The second model is a poorer predictor of actual load, likely because two counties in the utility's coverage area did not observe Central Time as the majority in the area did.

As seen in Figure 8, the hourly β_{DST} values for the second utility follow roughly the same pattern as the parameters of the first utility. Again, the DST coefficients in the morning are positive contributors to electric load, and the coefficients take on negative values throughout the rest of the day. The values for the evening hours of 7 P.M. and 8 P.M. deviate from the first model, as they are negative rather than positive throughout this period. Like the first model, some of the coefficients during the midday hours have confidence intervals that include 0, as there is a degree of uncertainty about the actual effect of DST at these hours. However, upon inspection of the β_{DST} plot, it seems likely that DST increases electricity usage in the morning hours and decreases consumption throughout the rest of the day.

Summing the coefficients to find the net effect of DST, the total β_{DST} has a value of -488.84 with a very small 95 percent confidence interval, -549.83 to -421.84. This result implies that DST significantly decreases electricity consumption within the service area, and thus supports the first model's findings. However, this net β_{DST} value is a less reasonable answer than the β_{DST} value obtained for the first utility. The model predicts an average savings of nearly 490 MW per day, for a utility whose hourly loads range from 400 to 1300 MW. It is unlikely that Daylight Savings Time actually saves this much energy for a small-size utility. Once again, prediction errors may be attributed to the fact that the data set was not ideally conditioned for this type of regression model. However, the results do support the initial findings that DST reduces electricity consumption over the course of the day.

Predicted vs. Actual Load: Utility 2, least-squares regression

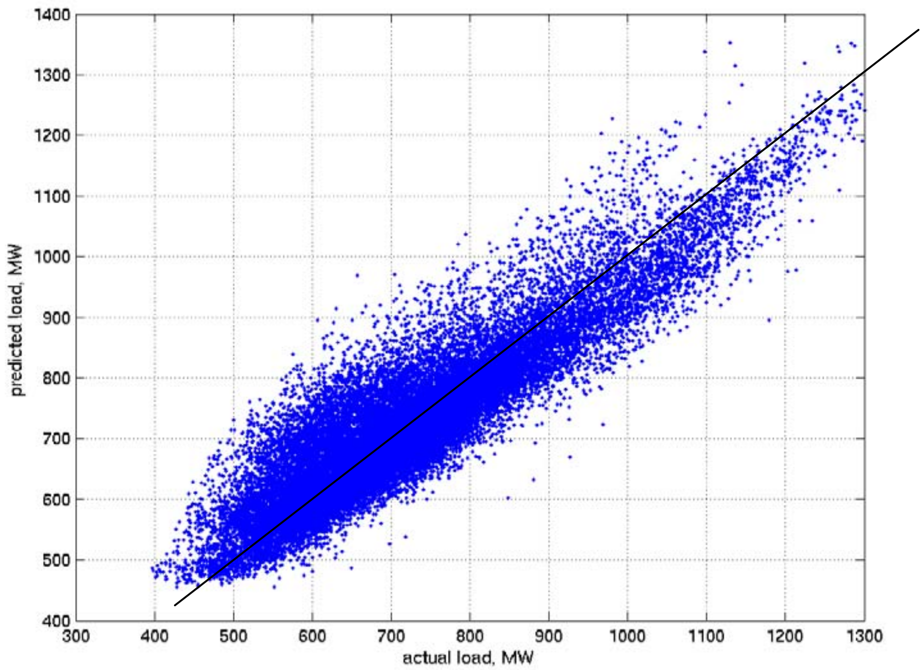

Figure 7

Hourly β_{DST} estimates and 95% confidence intervals,
Utility 2, least squares regression

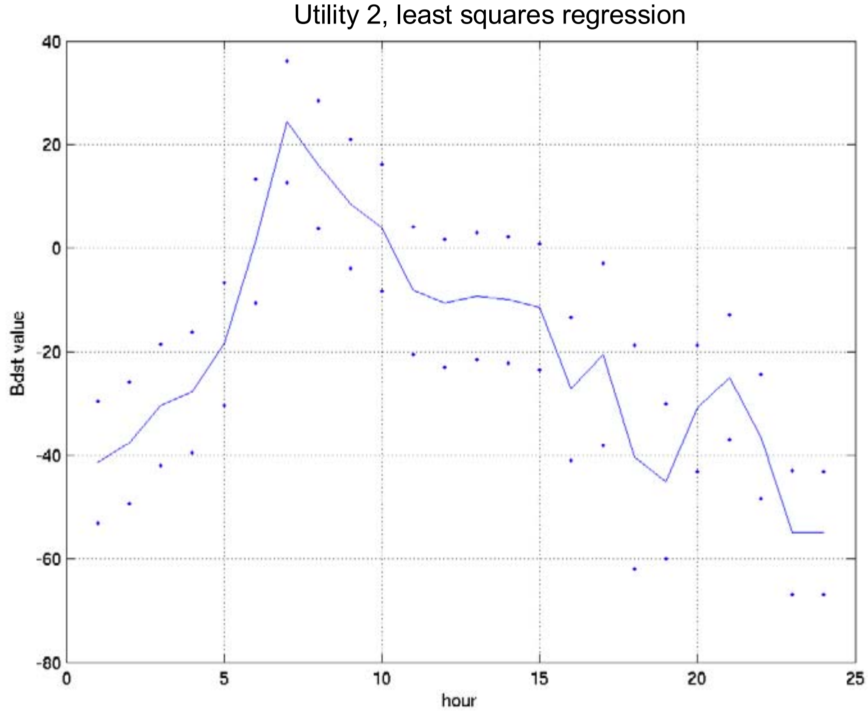

Figure 8

In Summary

The regression models indicate that DST does indeed reduce electricity consumption in Indiana over the course of the day. These savings may be as much as 320 MW per day for counties in Central Indiana. DST actually increases consumption in the morning hours by “delaying” sunrise by one hour, thereby increasing the need for artificial lighting in the morning. However, this increase is outweighed by reduced consumption during the later hours of the day and in the early morning. The regression model predicts that the impact of DST fluctuates throughout the day, and these changes coincide with the way in which DST alters daily consumption patterns, as show in the plots that compare non-DST load with DST load.

Further analysis is necessary to better understand how the broadening of the evening peak affects electricity consumption at this time. It would also be worthwhile to investigate the economic impact of Daylight Savings Time altering electricity consumption in Indiana. Additionally, it is possible that DST reduces electricity usage, but at the same time increases the consumption of other energy sources. An extra hour of sunlight in the evening may reduce electricity demand for artificial lighting, but also may increase the consumption of gasoline if more people are driving cars because it is still light outside. Further study on how DST affects total energy consumption, both on the state and national level, would provide insight on the true impact of Daylight Savings Time on our society.

Appendix A

Regression Model Details

The model used for analysis was patterned after the Seemingly Unrelated Regression (SUR) model created by the California Energy Commission and used by the Indiana Fiscal Policy Institute for their studies in 2001. The model consists of 24 simultaneous equations of the form:

$$MW_{ht} = a_h + b_h{*}DST_t + b_h{*}Workday_t + b_h{*}Employment_t + b_h{*}WeatherVariables_{ht} + b_h{*}LightingVariables_{ht} + u_{ht}$$

For each equation,

- there are 20 dependant variables, including the constant term a_h
- h indexes hour of the day
- t indexes the day of the data set
- MW_{ht} is hourly electric load for the utility, given in megawatts
- u_{ht} is a residual term
- DST_t has a value of 1 when daylight savings time is observed, and a value of 0 otherwise
- $Workday_t$ has a value of 1 for Monday through Saturday workdays, and a value of 0 for Sundays and major U.S. holidays
- $Employment_t$ is non-seasonally adjusted, average monthly employment in the utility's coverage area
- Hourly weather variables were averages for several cities spread throughout a given utility's coverage area. For Duke Energy, the weather variables represent the averages among Lafayette, Indianapolis, Bloomington, and Huntingburg. For Vectren Energy, the weather variable is simply the weather in Huntingburg. Details on the weather variables used can be found in the next section.
- Sunrise, sunset, twilight begin, and twilight end times were averaged over several cities in the same way as the weather variables.

In order to model the entire data set so that parameters would be estimated for each dependent variable for each hour of the day, the data was assembled in a matrix typically used for Seemingly Unrelated Regressions. Instead of using the same parameters for every series in the data set, the series were grouped into twenty-four groups representing each hour of the day, with a unique set of twenty parameters associated to each group. The matrix consisted of 29880 rows, one for each hour of the data set, and 480 columns, one for each dependent variable for each hour of the day. The method of least squares was used to estimate the vector of 480 β values, consisting of 24 groups of stacked parameter estimates, with 20 parameters for each hour.

Appendix B

Weather and Lighting Variables

In creating a regression model to describe hourly electric load, we sought to replicate the model used in the IFPI's 2001 study as closely as possible. At the same time, we tried to improve the predictive capability of the model by making several changes to the explanatory variables, including the addition of the DST variable, the addition of several temperature variables, and a different representation on lighting variables.

The following weather variables went into the model:

1. *Simple temperature (ºF):* Simple Temp = 0.9*(current hour's temp) + 0.1*(previous hour's temp)
2. *Quadratic temperature (ºF):* Quad. Temp = Simple Temp^2
3. *Cubic temperature (ºF):* Cubic Temp = Simple Temp^3
4. *Cooling temperature (ºF):* for temperatures over 60 ºF, cooling temp = temp – 60. All temperatures lower than 65 ºF take a value of 0.
5. *Heating temperature (ºF):* for temperatures below 60 ºF, heating temp = 60 – temp. All temperatures greater than 65 ºF take a value of 0.
6. *Separate temperature (ºF):* a weighted average of the temperatures of the previous hours, Separate Temp = 0.45*(avg. temp. 1 day lagged) + 0.35*(avg. temp 2 days lagged) + 0.1*(avg. temp. 3 days lagged)
7. *Humidity* (%)
8. *Barometric Pressure* (inches Hg)
9. *Wind Speed* (miles per hour)
10. *Precipitation* (inches)
11. *Visibility* (miles)
12. *Cloud Cover* (%)

The 2001 IFPI model included Simple Temp, Quadratic Temp, Cubic Temp, and Separate Temp, as well as most of the non-temperature weather variables listed above. In addition to these four temperature variables, we included cooling and heating temperature variables to our model to account for electricity demand due to cooling and heating needs. The "threshold temperature" at which people begin to cool and heat their homes and businesses was found by plotting hourly load versus the corresponding temperature for that hour. As shown in Figure 9, electric load begins to increase at temperatures both below and above 60 ºF. This may be attributed to increased use of air conditioning at temperatures above 60 ºF and increased use of heating at temperatures below 60 ºF. While other variables also contribute to cooling and heating needs, the cooling and heating temperatures provided a simple way to account for this type of electricity use.

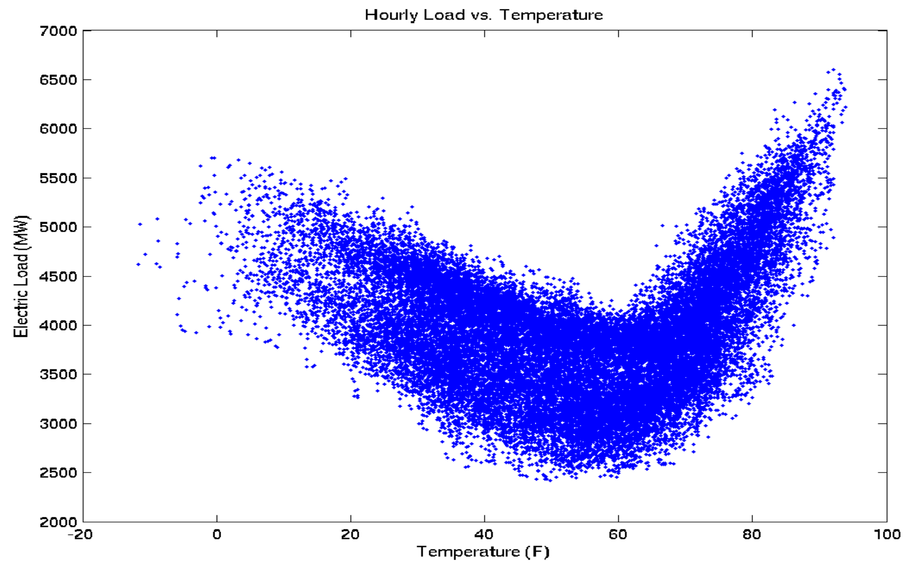

Figure 9

The following lighting variables went into the model:

1. *% sunlight for a sunrise hour*: For example, if sunrise occurred at 6:20 A.M., the 6th hour of this day would have a value of 67 (percent) for this variable. 40 minutes, or 67% of the 6th hour occurred after sunrise. All other hours of the day would have a value of 0 for this variable.

2. *% sunlight for a sunset hour*: For example, if sunrise occurred at 6:20 P.M., the 18th hour of this day would have a value of 33 (percent) for this variable. 20 minutes, or 33% of the 18th hour occurred before sunrise. All other hours of the day would have a value of 0 for this variable.

3. *% twilight for a twilight hour*: The percentage of a morning or evening hour that is twilight. For example, if twilight broke at 5:45 A.M. and sunrise occurred at 6:45 A.M., hour 5 for this day would have a value of 25 (25% of the hour occurred after twilight began), and hour 6 for this day would have a value of 75 (75% of the hour occurred before twilight ended with sunrise).

4. *% sunlight for all hours the day*: This variable includes the first two variables listed above for morning and evening hours, that is the percentage of a sunrise or sunset hour that is sunlight. For every hour in between sunrise and sunset, the variable has a value of 100, as 100% of the hour is sunlight. For every hour past sunset and before sunrise, the variable has a value of 0, as 0% of the hour is sunlight.

The last lighting variable is a different representation of light over the course of the day than the approach used in the California and IFPI models. The 2001 models included the actual sunrise, sunset, twilight begin, and twilight end times, as four different variables for every hour of the day in which these times occurred. The 2001 models also variable listed above that represent the percentage daylight of a sunrise or sunset hour and the percentage twilight of an hour containing. When our regression model included the actual sunrise, sunset, twilight begin and twilight end times, the DST variable took on very large negative values that were not consistent with the electricity production of the utilities. These four parameters were changed to the single sunlight variable that gives the percentage of each hour that is sunlight. This representation improved the predictive quality of the model and estimated much more reasonable values for the DST coefficients.

Appendix C

Data Sets

Though we had originally planned to analyze the effect of DST over the entire state of Indiana, this proved not possible when the coverage areas of the certain utilities included both counties that had originally observed DST and counties that adopted it in 2006. It would be difficult to represent two different time zones contributing to a single electric load with our model. Duke Energy's coverage area consists of sixty-nine counties in central Indiana that all changed from observing Eastern Standard Time year round to observing Daylight Savings Time beginning in April 2006, making it an ideal data set for studying the effects of DST.

Vectren Energy serves eight counties in southern Indiana that are all currently on Central Time. , Six counties have observed Central Standard and Daylight Time for years, while Posey and Pike Counties changed from year-round Eastern Standard Time to CST and CDT in April 2006. These differences would impact the electric load, however, the majority of Vectren's coverage area was consistent in its observation of Daylight Savings. With this limitation in mind, the Vectren data set was analyzed to see how it compared with the Duke data set.

NIPSCO's coverage area included many counties that observed CST and CDT, as well as many others that observed EST year-round until April 2006. With two different time zones both contributing to one electric load total, it would be difficult to accurately model electricity usage in relation to DST for this data set without subdividing the area into counties.