Proceedings of ES2007
Energy Sustainability 2007
June 27-30, 2007, Long Beach, California

ES2007-36080

TARGETING RESIDENTIAL ENERGY ASSISTANCE

Gregory Raffio, Ovelio Isambert, George Mertz, Charlie Schreier, Kelly Kissock

Building Energy Center, Department of Mechanical and Aerospace Engineering
University of Dayton, 300 College Park, Dayton, Ohio 45469-0238

ABSTRACT

This paper describes a four-step method to analyze the utility bills and weather data from multiple residences to target buildings for specific energy conservation retrofits. The method is also useful for focusing energy assessments on the most promising opportunities. The first step of the method is to create a three-parameter change-point regression model of energy use versus weather for each building and fuel type. The three model parameters represent weather independent energy use, the building heating or cooling coefficient and the building balance-point temperature. The second step is to drive the models using typical TMY2 weather data to determine Normalized Annual Consumption (NAC) for each fuel type. The third step is to create a sliding NAC with each set of 12 sequential months of utility data. The final step is to benchmark the NACs and coefficients of multiple buildings to identify average, best and worst energy performers, and how the performance of each building has changed over time. The method identifies billing errors, normalizes energy use for changing weather, prioritizes sites for specific energy-efficiency retrofits and tracks weather-normalized changes in energy use. The principle differences between this method and previously defined ones are that this method seeks to use inverse modeling proactively to identify energy saving opportunities rather than retroactively to measure energy savings, it tracks changes in building performance using sliding analysis, and it uses comparisons between multiple buildings to extract additional information. This paper describes the method, then demonstrates the method through a case study of about 300 low-income residences. After applying the method, targeted buildings were visited to determine the accuracy of the method at identifying energy efficiency opportunities. The case study shows that over 80% of the targeted buildings presented at least one of the expected problems from each type of retrofit.

Introduction

Today, companies, governments, and individuals are reducing their energy use for both environmental and economic reasons. This paper describes a four-step method to analyze the utility bills and weather data from multiple residences to target buildings for specific energy conservation retrofits. It enables analysts to identify buildings with the greatest energy saving opportunities from a broader group of buildings, prior to visiting the sites. Further, it clearly identifies the best type of retrofit, and how the buildings energy use performance changes over time. Thus, it is able to derive a significant quantity of actionable information from simple utility bills and readily available weather data.

The method of regressing utility billing data against weather data presented here is a derivation of the PRInceton Scorekeeping Method, PRISM [1], with a few important differences. First, the method presented here uses change-point models [2, 3] instead of the variable-base degree-day models used by PRISM. Second, this method uses TMY2 data, rather than an average of 10 years of data, as ‘typical’ weather. The interpretation of regression coefficients, also builds on early work by Goldberg and Fels [4] and by Rabl [5], Rabl et al. [6] and Reddy, [7]. Principle differences between this work and the aforementioned papers are that this work seeks to use inverse modeling proactively to identify energy saving opportunities rather than retroactively to measure energy savings, this work tracks changes in building performance using sliding analysis, and this work uses comparisons between multiple buildings to extract additional information.

Overview of the Method

The first step of the method is to create statistical three-parameter models of each building’s electricity and fuel use as functions of outdoor air temperature using data from utility bills and actual weather data. These models represent the energy signatures of the building, and the three model coefficients represent weather-independent energy use, building balance temperature and the total heating/cooling coefficient. The building balance temperature is the outdoor air temperature below/above which space heating/cooling begins. The total heating/cooling coefficient is the quotient of the building heat gain coefficient, UA, and the efficiency of the space heating/cooling equipment. The weather-independent energy use is the base fuel and electricity use which is not affected by outdoor air temperature.

The second step is to drive the energy signature models with typical weather data from TMY2 files [8] to determine energy use in a ‘normal’ weather year. This is called the Normalized Annual Consumption (NAC). The NAC removes the noise associated with changing weather from the utility billing data.

The third step is to determine an energy-signature model and NAC for each set of 12 sequential months of utility billing data. The resulting ‘sliding NACs’ show how weather-independent energy use changes over time. In addition, the ‘sliding coefficients’ show how independent energy use, the balance temperature and the heating/cooling coefficient change over time.

The fourth step is to compare the NACs and coefficients of multiple buildings to identify average, best and worst energy performers. For example, buildings with high weather-independent fuel use are good targets for hot-water heater retrofits. Buildings with high balance temperature are good targets for programmable thermostats. Buildings with high heating/cooling coefficients are good targets for envelope or high-efficiency space conditioning equipment retrofits.

This information is also useful when conducting energy assessments to identify problem areas even in advance of the site visit. Finally, the benchmarking process enables the user to quantify the ‘average’ performance of all the buildings, and to quantify how that ‘average’ changes over time.

Description of Data and Software Tools

Utility bills are widely available and accurately describe the amount of fuel or electricity delivered to buildings. Thus, this method uses utility bills as the principle source of energy use data. In addition, it is sometimes useful to normalize building energy use by occupancy, floor area or other variables. If deemed useful, energy use from billing data should be normalized prior to further analysis.

The method uses both actual and typical weather data. Actual average daily temperatures for 157 U.S. and 167 international cities from January 1, 1995 to present are available free-of-charge over the internet from the University of Dayton Average Daily Temperature Archive [9]. Typical weather data is derived from TMY2 data files [8]. TMY2 files contain typical meteorological year (TMY) data sets derived from the 1961-1990 National Solar Radiation Data Base (NSRDB). These files include typical hourly values of solar radiation, ambient temperature, ambient humidity and wind speed over a 1-year period.

During the first step of this method, utility data is regressed with actual average daily temperature data to identify building energy signature models. These models describe the relationship between building energy use, outdoor air temperature, and other influential variables such as floor area and occupancy. Building energy signature models can be created with several statistical software tools. This work used the ETrackerC software [10]. ETrackerC is capable of performing the entire analysis described here on multiple sites.

Step 1: Energy Signature Models

The first step of the method is to combine utility data with average daily temperature data. It is recommended that at least three years of billing and daily temperature data are used in order to track building energy performance over time. Average daily temperatures should be combined to calculate the average outdoor air temperature during each billing period. Figure 1 shows three years of monthly natural gas use and the average outdoor air temperature during each billing period for an example residence.

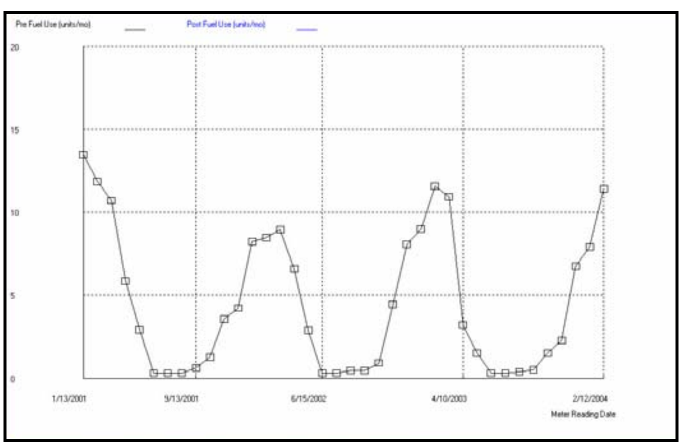

Figure 1a. Natural gas use for 3 years

The energy use and weather data are then regressed to identify energy signature model for each type of energy use. Figure 2 shows the three-parameter heating (3PH) model for the example residence. In this graph, the natural gas use is plotted on the vertical axis and outdoor air temperature is plotted on the horizontal axis. This model shows how natural gas use varies with outdoor air temperature.

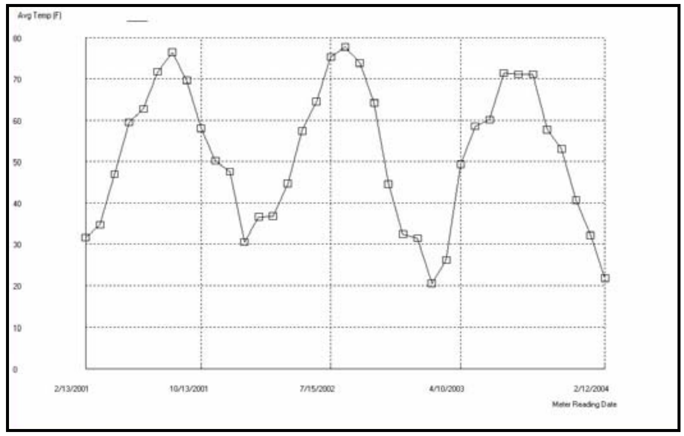

Figure 1b. Average Temperatures for 3 years Multi-Variable Change-Point Models Three Parameter Heating Model

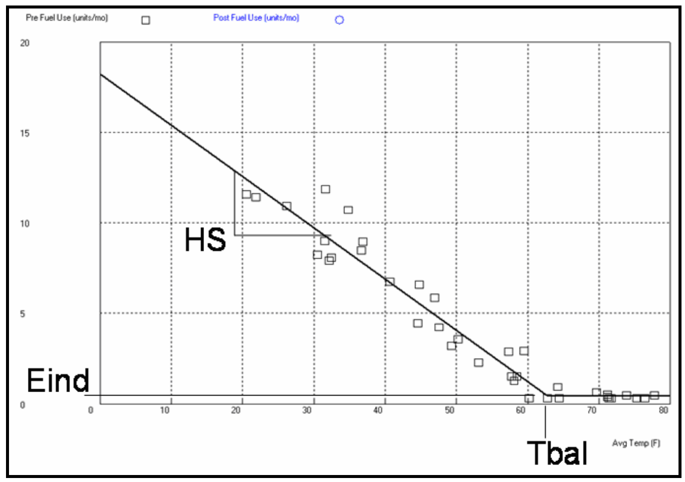

Figure 2. 3PH energy model

In a 3PH model, the coefficients represent the weather-independent natural gas use (Eind), the building balance temperature (Tbal), and the total heating coefficient, or heating slope (HS). The building balance temperature is the outdoor air temperature below which space heating begins. The total heating coefficient is the quotient of the building heat gain coefficient (UA) and the efficiency of the space heating equipments (Eff). Thus, the heating coefficient is shown in Equation 1.

HS = UA/Eff **(Equation 1)**

The heating slope is negative because heating energy use increases with decreasing outdoor air temperature. Using this model, the natural gas use can be estimated using Equation 2. The superscript $^+$ indicates that the value of the parenthetic quantity is zero when it evaluates to a negative quantity.

Gas Use = Eind – HS (Tbal – Toa)$^+$ **(Equation 2)**

Three Parameter Cooling Model

Figure 3 shows an analogous model of electricity use versus outdoor air temperature. In this graph, the electricity use is plotted on the vertical axis and outdoor air temperature is plotted on the horizontal axis.

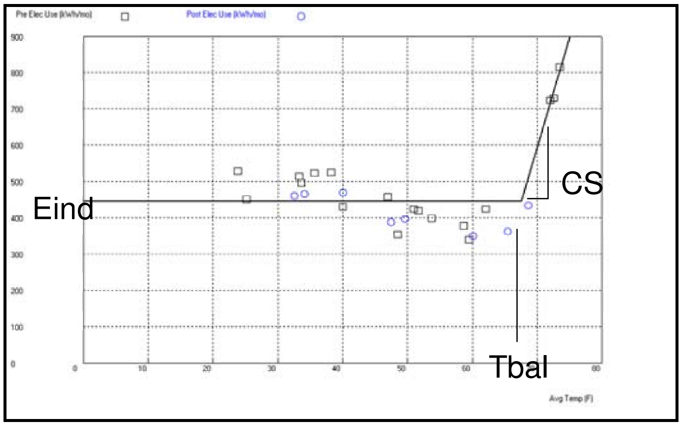

Figure 3. 3PC energy model

In a three-parameter cooling (3PC) model, the coefficients represent the weather-independent electricity use (Eind), the building balance temperature (Tbal), and the total cooling coefficient, or cooling slope (HS). The cooling slope is positive because electricity use for air conditioning increases with increasing outdoor air temperature. Using this model, electricity use can be estimated using Equation 3. .

Elec Use = Eind + CS (Toa – Tbal)$^{+}$ (Equation 3)

Interpretation of Coefficients

A primary strength of this method is that the model coefficients have physical meaning. In a 3PH model, Eind represents weather independent energy use. In 3PH models of gas use, this is often related to hot water heater efficiency and the hot water heater temperature set point. In 3PC models of electricity use, Eind generally represents the general household electricity use from lights and electrical appliances. The balance temperature (Tbal) represents the outdoor air temperature below or above which space conditioning begins. Tbal is a function of the thermostat setpoint temperature (Tsp) the internal loads from electricity use, solar gain and people (Qint) and the building load coefficient UA (Equation 4).

Tbal = Tsp – Qint/UA (Equation 4)

The heating and cooling slope (HS and CS) are the quotient of the building load coefficient and heating/cooling equipment efficiency. The building load coefficient is determined by envelope insulation and air infiltration through the envelope. The heating and cooling slopes are very important since they cause the most significant change in natural gas and electricity use with the outdoor air temperature.

Analyzing the physical meaning of energy signature model coefficients and their relationship to building characteristics enables specific problems to be identified. For example, buildings with high weather-independent fuel use are targets for hot-water heater retrofits, such as reducing hot water set point temperature, fixing hot water leaks, and replacing inefficient water heaters. Buildings with high balance temperatures are targets for programmable thermostats. Buildings with high heating/cooling coefficients are targets for envelope or space conditioning equipment retrofits.

Step 2: Normalize Annual Energy Consumption

In order to compare or benchmark multiple buildings located in different sites, or to compare the energy use of a single building during different time periods energy signature models should be normalized for weather. Utility bills show the actual annual energy consumption during a billing period. However, that energy consumption might be affected by unusual weather, making it difficult to assess the building's energy performance. Similarly, it is difficult to compare the energy performance of buildings located in different climates. Both of these problems can be eliminated by driving the energy signature model with "typical" weather. The resulting annual energy use is called the Normalized Annual Consumption, (NAC). To calculate the NAC, the energy signature models developed in Step 1 are driven with typical weather data from TMY2 files. Figure 4 shows a graphical example of the steps required to calculate the NAC of the example building.

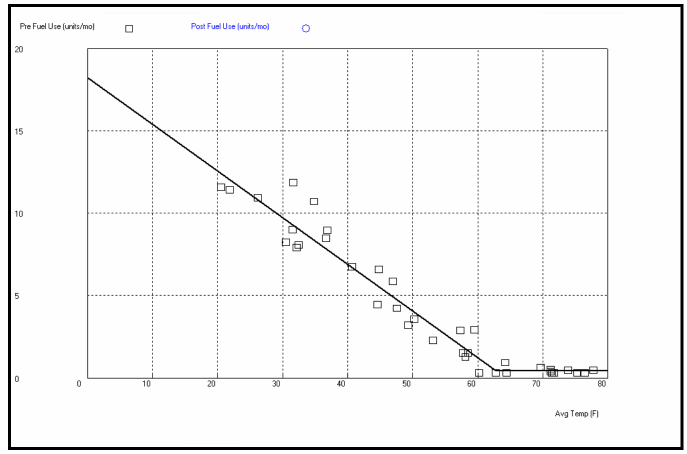

Figure 4a. Energy signature model

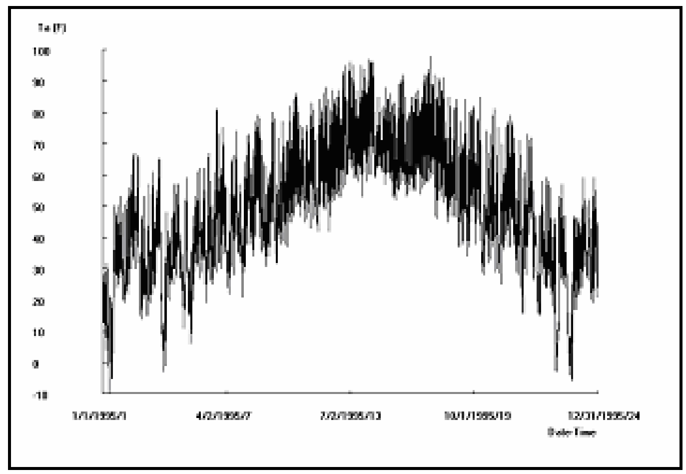

Figure 4b. Typical weather data

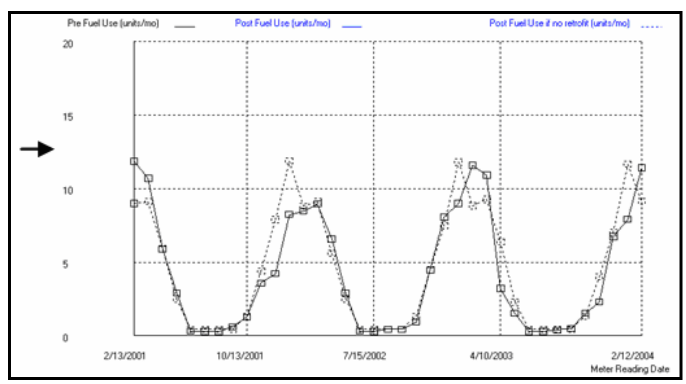

Figure 4c. NAC

Figure 4. Combining 3PH energy model (a) with typical weather data (b) to derive NAC (c)

Figure 4_a shows the energy signature model. Figure 4_b shows the one year of hourly outdoor air temperatures from a TMY2 data file. Figure 4_c shows monthly actual consumption and normalized consumption over three years. The actual consumption is represented by the continuous line and the normalized consumption is characterized by the dashed line. The differences between actual and normalized consumption are caused by abnormally warm or cold weather.

Thus, NAC represents the noise-free energy use of a building after changes due to abnormal weather have been removed. As such, NAC reveals the true energy characteristics of buildings, and allows comparison of building energy use between buildings in different climates and over time.

Step 3: Sliding NAC Analysis

The best way to compare the change in energy characteristics of buildings is by comparing the buildings' NAC during sequential 12-month periods. This is called a 'sliding' NAC analysis. To do so, an energy-signature model is created for each set of 12 sequential months, and then driven with typical weather from a TMY2 file to create a sequence of NACs. Figure 5 shows how the building's energy signature model and NAC are computed for sequential 12-month data periods over two years. The sliding NAC analysis illustrates how the building's fundamental energy use characteristics change over time. When these changes are caused by energy conservation retrofits, this sliding analysis provides an accurate measurement of the energy savings. In addition, it can measure persistence of the savings.

Figure 6 shows the sliding NAC over three years for the example residence. In this residence, a different set of occupants moved in every year. The dashed line is the actual annual consumption (AC); the solid line is the NAC. During the first year, both AC and NAC remain steady. The NAC is greater than the AC, which means that the weather was unusually mild. However, during the second year the AC increases, which appears to indicate that the building became noticeably *less* energy efficient. However, the NAC decreases, which shows that the building actually became *more* energy efficient during the second year. This example shows both the power and necessity of using NAC to understand building energy performance over time.

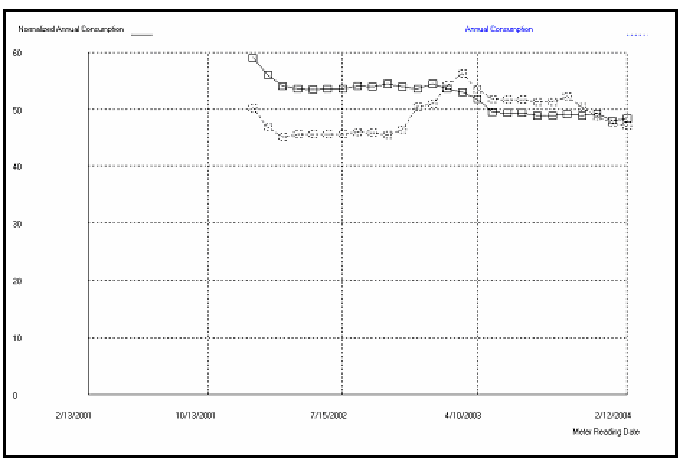

Figure 6. Sliding NAC analysis of typical Dayton residence

However, even more information can be extracted from this analysis by tracking the values of the model coefficients over time. Changes in NAC are caused by changes in model coefficients. Thus, a sliding analysis of model coefficients can identify the cause of a change in NAC. Figure 7 shows how heating slope (HS) and NAC vary over time. The dashed line is the heating slope and the solid line is the NAC. The HS remains steady over time. Thus, the reduction in NAC is not caused by an improvement to the building's envelope or space heating equipment.

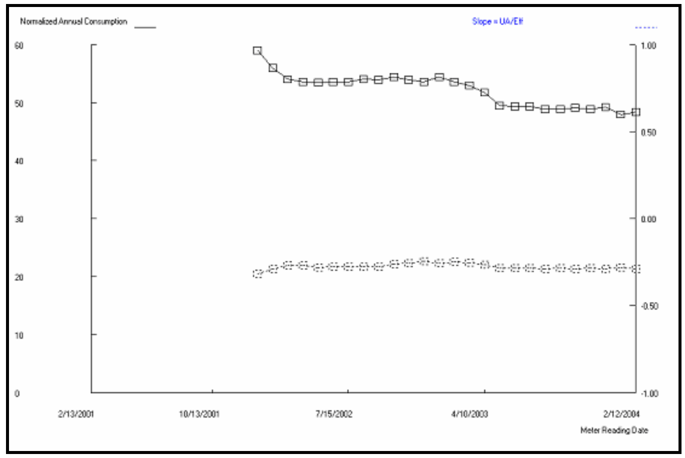

Figure 7. Sliding NAC analysis compared to heating slope

Figure 8 shows how weather-independent energy use (Eind) and NAC vary over time. The dashed line is Eind and the solid line is NAC. Although Eind varies over time, in this building Eind is too small to have a significant effect on NAC. Thus, in this case, the reduction in NAC is not caused by the variations in Eind.

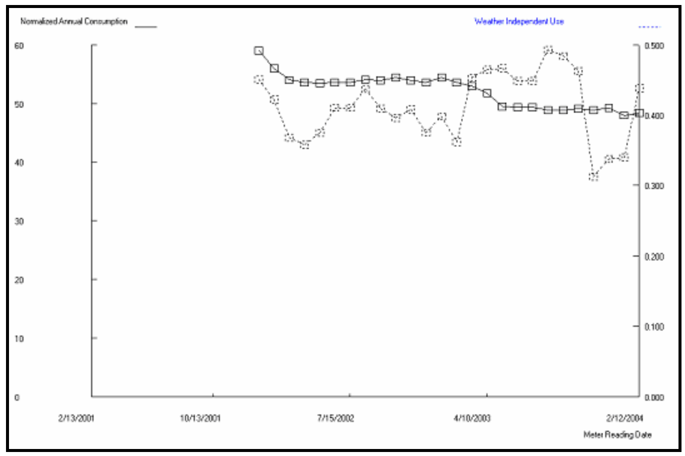

Figure 8. Sliding NAC analysis compared to independent energy use

Figure 9 shows how the building's balance-point temperature (Tbal) and NAC vary over time. The dashed line is Tbal and the solid line is NAC. The graph shows that after one year, the balance temperature was lowered, which caused the decrease in NAC. Thus, the reduction in NAC was caused either by a reduction in the thermostat set-point temperature or a dramatic increase in internal loads, which is unlikely. Thus, this analysis was able to identify how the building's fundamental energy use changed over time and the cause of this change.

Thus, sliding NAC and coefficient analysis provides a powerful lens through which a building's fundamental energy performance can be understood, and without which it is almost impossible to perceive what is happening. In addition, sliding analysis enables accurate measurement of changes and energy savings from energy conservation retrofits.

<table>
<tr><td>Sliding NAC Analysis Data Set</td><td colspan="12">Data set 1</td><td colspan="12">Data set n</td></tr>
<tr><td>Months</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td></tr>
<tr><td>Data set (Year)</td><td colspan="12">Year 1</td><td colspan="12">Year n</td></tr>
<tr><td>Months</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td></tr>
<tr><td>Sliding NAC Analysis Data Set</td><td></td><td colspan="12">Data set 2</td><td colspan="11"></td></tr>
</table>

Figure 5. Graphical representation of sliding NAC

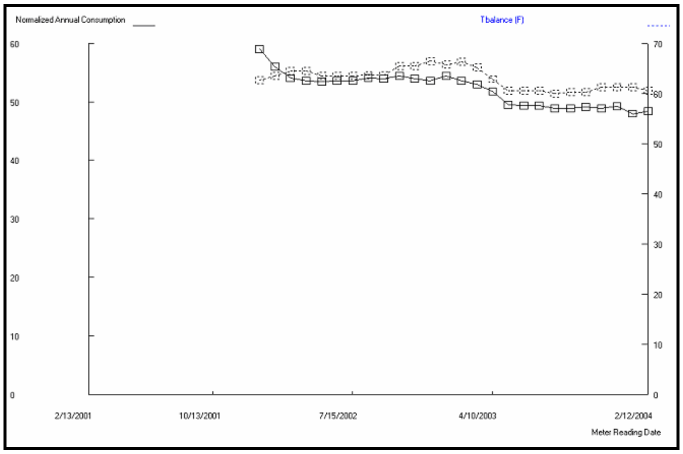

Figure 9. Sliding NAC analysis compared to balance point temperature

Step 4: Benchmarking NAC and Coefficients

In the fourth step of this method, the NAC and the model coefficients are benchmarked against other buildings to identify best and worst energy performers. In essence, benchmarking provides another dimension to the analysis, and reveals another type of actionable information.

One way to convey this information is to plot NAC and the change in NAC for multiple buildings on orthogonal coordinates. The change in NAC is shown in Equation 5.

(NAC_1 – NAC_n)/NAC_1 (Equation 5)

Figure 10 shows NAC on the horizontal axis and change in NAC on the vertical axis for 260 low income residences. Buildings on the right side of the chart are the biggest energy users and buildings on the left are the lowest. Buildings near the top of the chart have experienced the greatest reduction in NAC, while the normalized energy consumption of buildings near the bottom has increased. In addition, the mean NAC and change in NAC are shown as lines through the center of each distribution.

This graph conveys a wealth of actionable information for energy managers or analysts. For example, on the horizontal axis, high energy buildings are targets for energy assistance; while low energy buildings can serve as goals or examples of what can be achieved. Similarly, buildings with large energy increases may be experiencing equipment malfunctions or inadvertent changes in operations; while buildings with reducing energy use are examples of improving energy efficiency. The mean NAC defines the center of the distribution and provides a metric for defining "typical" performance and the distribution of performance across all buildings. The mean change in NAC indicates the magnitude of change in the energy performance of the entire group of buildings, and can be a solid indicator of the success of energy efficiency efforts across large groups of buildings.

Similar plots can be constructed for the model coefficients. As in the case of a single building, analysis of the model coefficients shows why and how NAC has changed. Figure 11 shows HS on the horizontal axis and change in HS on the vertical axis for 260 low income residences. Buildings on the right have the largest heating slopes are targets for building envelope and space conditioning equipment retrofits, while buildings on the left demonstrate best practices. Similarly, buildings near the bottom have experienced significant deterioration in the building envelope or space conditioning equipment.

In summary, the fourth step is to compare the NACs and coefficients of multiple buildings to identify average, best, and worst energy performers. Buildings with high weather-independent fuel use are good targets for hot-water heater retrofits, or in the case of electricity, high efficiency lighting and appliances. Buildings with high balance temperature are good targets for programmable thermostats. Buildings with high heating/cooling coefficients are good targets for envelope or high-efficiency space conditioning equipment retrofits. The center and distribution of all of these indices of performance can be determined, as well as the change in these indices.

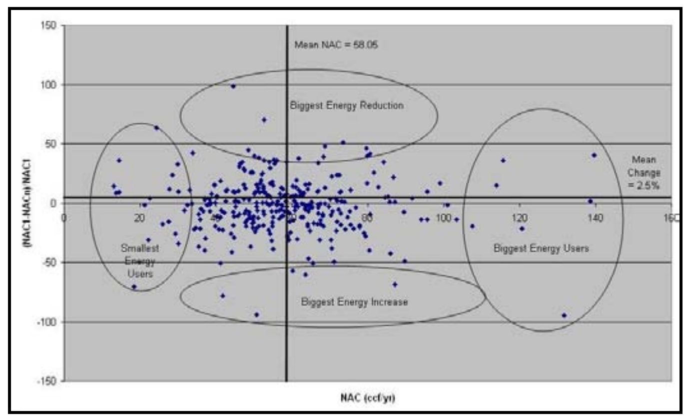

Figure 10. NAC and change in NAC for 260 sites

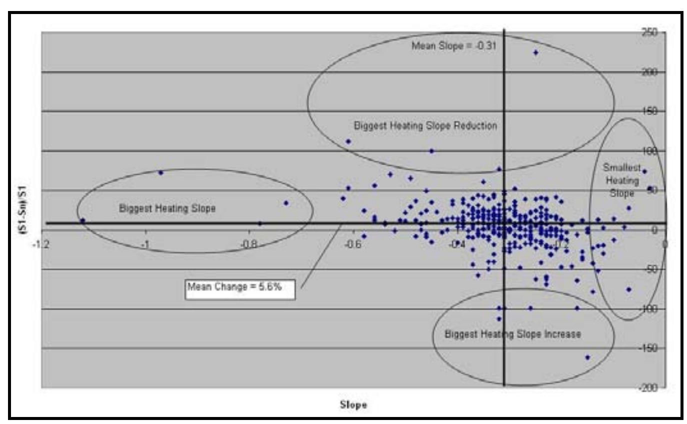

Figure 11. Heating slope and change in heating slope for 260 buildings

Case Study: Sorted NAC and Model Coefficients

The method and selected results are demonstrated in the following case study of 260 student residences at the University of Dayton. Most of these houses were built in the early 1900s as housing for factory workers. The houses have minimal insulation and high infiltration rates. Currently UD spends nearly $1 million per year on gas and electricity for the student neighborhood. A significant portion of this cost is due to irresponsible energy practices [11]. These houses provide a good test for targeted residential energy assessment and the measuring the resulting savings

The base data were derived from utility bills between 2/12/2001 and 2/12/2004. Actual and typical weather data was taken from the Average Daily Temperature Archive [9] of the University of Dayton and from the TMY2 file for Dayton, Ohio. 3PC and 3PH energy signature models were developed for each of the 260 houses. In this particular case, only the 3PH results are presented.

Data and Model Screening

The 3PH signature models were sorted by R^2 values. Approximately 80% of the buildings had R^2 values greater than 0.80. In many cases, low R^2 were caused by one or more bad data points. It was found that of the original 20% of the houses with R^2 values less than 0.80, half of these were due to data errors. This result shows the ability of the simple 3PH models to accurately characterize gas consumption, and the use of the method to identify billing data errors. Removing houses with errant data resulted in a set of 260 houses. Figure 12 shows a plot of the R^2 values of each house model before and after data manipulation.

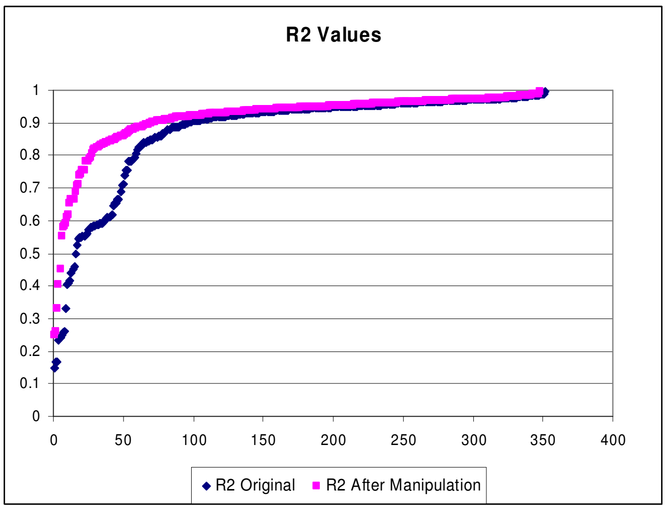

Figure 12. R^2 values before and after data manipulation

Targeting Houses for Energy Efficiency Improvements

Energy signature models and NACs were calculated for all houses, and the houses were sorted by NAC, HS, Eind and Tbal. In general, houses with the largest NACs are probably the most likely to benefit from energy efficiency improvements. However, sorting by HS, Eind and Tbal is a much more effective way to identify houses most likely to benefit from specific energy efficiency improvements.

For example, Figure 13 shows the fraction of the 25 houses with highest NAC that also show up in the top 25 houses sorted by each coefficient. About 80% of the 25 houses with highest NAC were also among the group with the top 25 heating slopes. This shows that poor insulation and low furnace efficiency are the two most significant problems identified in the case study. But perhaps more importantly, it shows that sorting by NAC alone would have missed 20% of the houses with poor building envelopes or space conditioning equipment. Moreover, 60% of the houses with independent energy use and 80% of the houses with highest balance point temperatures would have also been missed. This underscores the importance of sorting by coefficients to target houses for specific energy efficiency assistance. Sorted coefficient analysis makes it possible to accurately identify what type of retrofit is to be expected, even before visiting the building. This enables houses to be sorted by retrofit type, and maximize the efficiency of energy assistance.

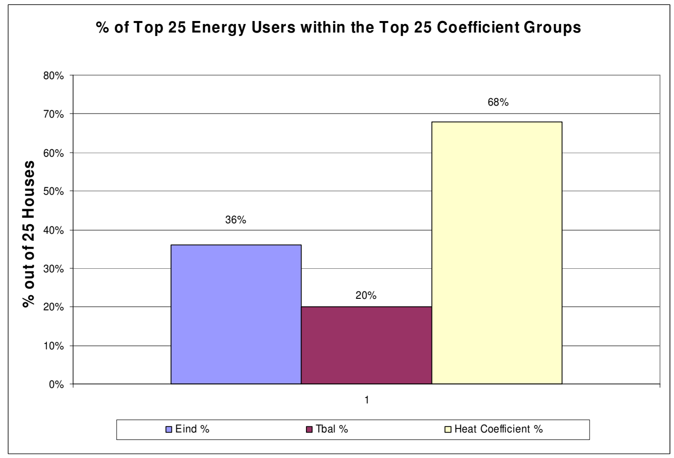

Figure 13. % of top 25 energy users within the top 25 coefficient groups

Case Study: Site Visits

Prioritization for Retrofits

Based on the sorted coefficient analysis, the 10 houses with the highest independent gas use, heating slope and balance-point temperature were visited. Each parameter suggests a different set of possibilities for what is happening in the house. The number of houses with the expected conditions were recorded.

High Independent Gas Use

In the case of natural gas, weather independent energy use (Eind) is primarily for hot water since hot water is used all year. High Eind generally indicates high water temperature set point, leaking hot water heater or pipes, or a low-efficiency water heater. Table 1 shows the frequency with which these issues were identified. Overall, 89% of the houses with high weather independent energy use presented at least one of the expected problems.

Table 1. Summary of case study results (Eind)

SUGGESTED ISSUES DRIVING HIGH Eind	% OF SIGNIFICANCE (OUT OF 10 HOUSES)
High water Temp. set point	67%
Low efficiency water heater	67%
Natural Gas stove (annual use will drive up the baseline and Ycp)	33%
Boiler (summer boiler instead of furnace	22%
At least 1	89%

High Balance Temperature

The balance point temperature, (Tbal) is a function of thermostat set point temperature, heat from humans, solar radiation and electricity use. High balance point temperature generally indicates high temperature set-point, no night setbacks, and low solar and/or internal gains. Table 2 shows the frequency with which these issues were identified. Overall, 100% of the houses with high balance-point temperatures presented at least one of the expected problems.

Table 2. Summary of case study results (Tbal)

SUGGESTED ISSUES DRIVING HIGH Tbal	% OF SIGNIFICANCE (OUT OF 10 HOUSES)
No night set backs	100%
High UA values (Low Insulation)	70%
At least 1	100%

High Heating Slope

The heating slope (HS) is the quotient of the building load coefficient and efficiency of the space conditioning equipment (Equation 1). In general, high HS indicates low furnace efficiency, poor insulation, and high infiltration rates. Table 13 shows the frequency with which these issues were identified. Overall, 80% of the houses with heating slopes presented at least one of the expected problems. Low furnace efficiency and high UA (low insulation) are the principal issues driving high HS values

Table 13. Summary of case study results (HS)

SUGGESTED ISSUES DRIVING HIGH HS	% OF SIGNIFICANCE (OUT OF 10 HOUSES)
Low furnace efficiency	70%
High UA value (Low R Value)	80%
At least 1	80%

This analysis shows that sorted coefficient analysis can effectively identify specific problems and energy saving opportunities.

SUMMARY AND CONCLUSIONS

This paper describes a four-step method to analyze monthly utility billing and weather data to target residential buildings for energy assistance programs and assessments. The first step of the method is to create three-parameter energy use models. The second and third steps are driving the models using TMY2 data to determine Normalized Annual Consumption (NAC), and creating a sliding NAC with each set of 12 sequential months of utility data. The final step is to benchmark the NACs and coefficients of multiple buildings to identify average, best and worst energy performers. This paper demonstrates the method through a case study of about 300 low-income residences. The principle differences between this method and previously defined ones are that method seeks to use inverse modeling proactively to identify energy saving opportunities rather than retroactively to measure energy savings, it tracks changes in building performance using sliding analysis, and it uses comparisons between multiple buildings to extract additional information.

After applying the four step method, targeted buildings were visited to determine the accuracy of the method. Of the houses visited, 89% of the high independent gas use houses, 100% of the high balance temperature houses, and 80% of the high heating slope houses had at least one significant issue as previously identified in the method. Of the high independent gas use houses, the most significant and frequent issues found were high hot water temperature setpoints (66%) and low efficiency hot water heaters (66%). Of the high balance temperature houses, the main issues found were no nighttime set-backs (100%) and high rate of infiltration (drafty houses) (70%). Finally, of the high heating slope houses, the issues were low furnace efficiency (70%) and high UA value (80%). The method is also helpful in identifying billing and transcription errors, which are significant problems for managers of multiple sites.

REFERENCES

[1] Boyle, Godfrey (ed), 2004, "Renewable Energy: Power for a Sustainable Future", 2nd Ed, Oxford UP.

[2] US EPA, 1994, http://www.epa.gov/globalwarming/climate/index.html.

[3] Fels, M., 1986, Energy and Buildings: Special Issue Devoted to Measuring Energy Savings: The Scorekeeping Approach, Vol. 9, Nums 1 & 2, February.

[4] Kissock, K., Reddy, A. and Claridge, D., 1998. "Ambient-Temperature Regression Analysis for Estimating Retrofit Savings in Commercial Buildings", *ASME Journal of Solar Energy Engineering*, Vol. 120, No. 3, pp. 168-176.

[5] Kissock, J.K., Haberl J. and Claridge, D.E., 2003. "Inverse Modeling Toolkit (1050RP): Numerical Algorithms", *ASHRAE Transactions*, Vol. 109, Part 2.

[6] Goldberg, M. and Fels, M., 1986, "Refraction of PRISM Results in Components of Saved Energy", Energy and Buildings, Vol. 9, Nums 1 & 2, February.

[7] Rabl, A., 1988, "Parameter Estimation in Buildings: Methods for Dynamic Analysis of Measured Energy Use", *ASME Journal of Solar Energy Engineering*, Vol. 110, pp. 52 - 62.

[8] Rabl, A., Norford, L. and Spadaro, J., 1986?, "Steady State Models for Analysis of Commercial Building Energy Data", *Proceedings of the ACEEE Summer Study on Energy Efficiency in Buildings,* Pacific Grove, CA, August, pp. 9.239-9.261.

[9] Reddy, A., 1989, "Identification of Building Parameters Using Dynamic Inverse Models: Analysis of Three Occupied Residences Monitored Non-Intrusively", Princeton University, Center for Energy and Environmental Studies Report No. 236, Princeton, NJ.

[10] National Renewable Energy Laboratory, 1995, "User's Manual for TMY2s", http://rredc.nrel.gov/solar/old_data/nsrdb/tmy2/.

[11] Kissock, J.K., 1999. "UD EPA Average Daily Temperature Archive", (http://www.engr.udayton.edu.weather).

[12]Kissock, J. K, 2006. http://www.engr.udayton.edu/faculty/jkissock/http/RESEARCH/informaticn.htm

[13] Seryak, J, 2004, "Energy Use in UD Campus Housing", Master's Thesis, Department of Mechanical and Aerospace Engineering, University of Dayton, Dayton, Ohio.