UNDERSTANDING MANUFACTURING ENERGY USE THROUGH STATISTICAL ANALYSIS

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ABSTRACT
Energy in manufacturing facilities is used for direct production of goods, space conditioning, and general facility support such as lighting. This paper presents a methodology for statistically analyzing plant energy use in terms of these major end uses. The methodology uses as few as 60 data points that are relatively easy for most plants to obtain. Multivariable change-point models of electricity and natural gas use as functions of outdoor air temperature and production data are then developed. The statistical models can be used to predict energy use for energy budgeting, measure savings, determine cost structures, and diagnostic purposes. Moreover, in many cases, the statistical models are able to subdivide plant energy use into facility, space-conditioning and production-related components. These breakdowns suggest the savings potential from reducing non-production and space-conditioning energy use. A detailed case study example is used to demonstrate the method and discuss interpretations of the results.

SYNOPSIS OF DEVELOPMENT OF STATISTICAL MODELS OF ENERGY USE

Beginning in the 1980s, statistical modeling has been used to understand energy use in buildings. The Princeton Scorekeeping Method, PRISM, pioneered the practice of automatically fitting variable-base degree-day (VBDD) models to residential utility data (Fels, 1986; Fels et al. 1995). PRISM employs three primary types of statistical models: “heating only” (HO), “cooling only” (CO) and “heating and cooling” (HC). The heating-only and cooling-only models describe residential energy use in terms of three regression variables alpha, beta and tau, which also have physical significance in thermodynamic models of building energy use.

Alpha, α, is a regression constant that describes average non-weather related energy use, such as electricity use for lighting and plug loads or natural gas use for cooking and domestic hot water. Tau, τ, is the base outdoor air temperature used to compute the heating or cooling degree days. The value of tau is determined by an automated search algorithm within PRISM that regresses building energy use against degree-days computed with different balance point temperatures, and selects the model with the best fit. Tau represents the building’s balance-point temperature. In the case of a heating-only model, tau represents the outdoor air temperature below which space heating is needed and above which only non-weather dependent energy use is required. Similarly, in the case of a cooling-only model, tau represents the outdoor air temperature above which space cooling is needed and below which only non-weather dependent energy use is required. Beta, β, is the regression coefficient that describes the quantity of space-conditioning energy required per cooling or heating degree day. In thermodynamic models of building energy use, beta represents the building’s overall conductance divided by the efficiency of the heating or cooling equipment.

The PRISM approach to modeling residential building energy use proved to be highly effective; the normalized annual energy consumption, NAC, of most residential buildings could be determined within +10% and the R^2 value of most regression fits was greater than 90% (Fels, 1986).

The PRISM variable-base degree-day method also produces acceptable fits between commercial building energy use and outdoor air temperature (Rabl et al., 1992; Rabl and Rialhe, 1992; Kissock and Fels, 1995). However, commercial heating and cooling systems are different that residential systems, and these differences result in different relationships between energy use and temperature than the relationships prescribed by the variable-base degree day method (Kissock, 1993). Large commercial buildings are typically comprised of several zones with different heating and cooling requirements. To maintain comfort within the different zones, supply air is typically cooled to a dew-point temperature of about 55 F then reheated as needed for each zone. Thus, many commercial buildings use both heating and cooling energy year round, and, as a consequence, have no balance-point temperature which defines where heating or cooling is not needed. In addition, heating and cooling energy use may vary non-linearly with outdoor air temperature depending on whether the air distribution system delivers a constant or variable amount of supply air to the zones, and depending on the latent cooling load.

To account for these effects, four-parameter change-point (CP) models of cooling and heating energy use as functions of outdoor air temperature were developed (Schrock and Claridge, 1989; Ruch and Claridge, 1992; Kissock et. al, 1993b). Four-parameter change-point models find linear relationships between energy use and temperature both above and below an outdoor air change-point temperature. Thus, four-parameter are highly effective at modeling energy use in buildings where energy use is temperature-dependent over the entire range of outdoor air temperatures, but increases above or below some outdoor air temperature due to increased space-conditioning loads. In contrast, VBDD models only model the temperature-dependence of energy over part or the range of outdoor air temperatures, and assume that energy use is constant over the remaining outdoor air temperatures. In addition to four-parameter models, three-parameter and five-parameter change-point models were also developed that are analogous to the PRISM HO, CO models, but use different algorithms for finding the best-fit regression coefficients (Kissock et al. 1992; Kissock et al. 1994; Kissock et al., 1998; Kissock, 2000).

The PRISM and change-point models described so far are effective at modeling the variation in building energy use with outdoor air temperature, but are not capable of considering the variation in building energy use caused by other factors such as changing occupancy, scheduling or system controls. Thus, the primary way to account for other factors when using PRISM or change-point models was to separate the energy use data into groups and build separate models for each group of data. Unfortunately, this approach is both cumbersome and useful only when sufficient energy-use data for each type of type of occupancy, schedule or system control are available.

To compensate for this limitation, Sonderegger (1997; 1998) extended the VBDD method for modeling building energy use to include other factors using a two-step approach. First, building energy use is regressed against heating or cooling degree days with different base-temperatures until the base temperature which gives the best fit is identified. Next, the heating or cooling degree days calculated with this best-fit temperature are included in a multivariable regression model with other factors that may influence energy use.

Similarly, Kissock (Kissock et al., 2003; Haberl et al., 2003) extended the temperature change-point models described above to include additional independent variables. The resulting change-point multivariable regression (CP-MVR) models automatically find the best fit in a single step, and incorporate the advantages of the change-point approach over the VBDD approach as explained above. These CP-MVR models are used by US-EPA Energy Star Buildings program (Kissock, 1997) to weather normalize building energy use and in the ASHRAE Inverse Modeling Toolkit (Kissock et al., 2001) in support of measurement and verification efforts.

This paper describes the application of CP-MVR models to understanding industrial energy use. Model algorithms and the application of the models to building energy use are described in the previous references. The models are effective because they were explicitly developed to model energy use that varies with both weather and other factors, such as production, as does industrial energy use. The application of these models to industrial energy use is demonstrated using a case study from a manufacturing plant that used natural gas and electricity for both production and space-conditioning.

CASE STUDY

<u>Overview</u>

In the plant to be considered, electricity is used for production-independent purposes such as such as lighting, to power production machinery, and for air conditioning. Natural gas is used for production-independent purposes such as heating aluminum hold furnaces, to melt aluminum to produce parts, and for space heating.

Thus, electricity and natural gas use vary with both the quantity of parts produced and with outdoor air temperature. By analyzing the relationships between energy use, production and outdoor air temperature, empirical models can be developed for predicting both electricity and natural gas use as functions of the quantity of parts produced and outdoor air temperature. These models can be used to breakdown both electricity and natural gas use into facility, production-dependent and space conditioning components. Facility energy use is energy use that is independent of production or weather. Production-dependent energy use varies with the quantity of parts produced. Space conditioning energy use varies with weather, as characterized by outdoor air temperature.

The empirical models can be also be used to predict future energy costs for budgeting, to establish baseline energy use to measure energy savings, and for many other purposes. This case study describes the development of statistical models to predict electricity and natural gas use as functions of outdoor air temperature and quantity of parts produced, and compares the models to sub-metered data.

Source Data

The source data for the development of the models are monthly electricity use, natural gas use, production and outdoor air temperature. Electricity and natural gas use are from utility billing data. Average temperatures are available from many sources including the UD/EPA Average Daily Temperature Archive, which posts average daily temperatures from 1995 to present for over 300 cities around the world (http://www.engr.udayton.edu/weather/). Production data are logged by most companies. Monthly electricity use, natural gas use and production are normalized by the number of days in the data period to remove the influence of variable-length data periods from the analysis.

Software

The software used to develop the models is Enertel Analysis (Kissock, 2000). Enertel Analysis integrates the previously laborious tasks of data processing, graphing and statistical modeling in a user-friendly, graphical interface. The multivariable change-point models described above are included in Enertel Analysis. These models enable users to quickly and accurately determine baseline energy use, predict future energy use, understand factors that influence energy use, calculate retrofit savings, and identify operational and maintenance problems.

Statistical Analysis of Electricity Use

Figure 1 shows monthly electricity use and average outdoor air temperature during 2002. The graph shows that electricity is slightly higher during summer and early fall, when the outdoor air temperatures are higher and air conditioning loads are greatest. In the fall, electricity use declines steeply; however, it is unlikely that the dramatic reduction in electricity use is caused solely by the cooler air temperatures since electricity use during the first part of the year remained relatively high despite similarly cold temperatures. Thus, outdoor air temperature appears to have some influence on electricity use, but does not appear to be the sole influential variable.

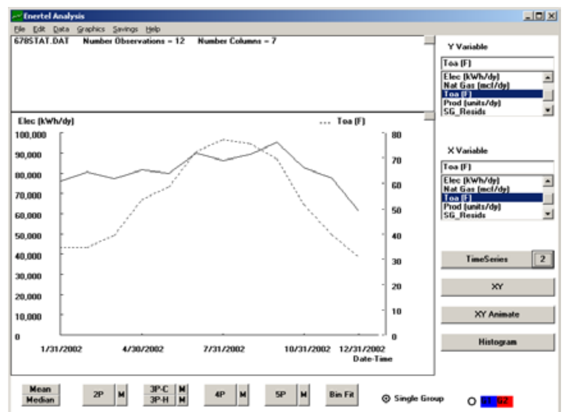

Figure 1. Monthly electricity use and average daily temperatures during 2002.

Figure 2 shows monthly electricity use and the quantity of units produced each month during 2002. The two trends appear to be relatively well correlated, frequently rising and falling in unison. However, summer electricity use is distinctly higher than electricity use during the rest of the year. Thus, both production and outdoor air temperature appear to significantly influence electricity use.

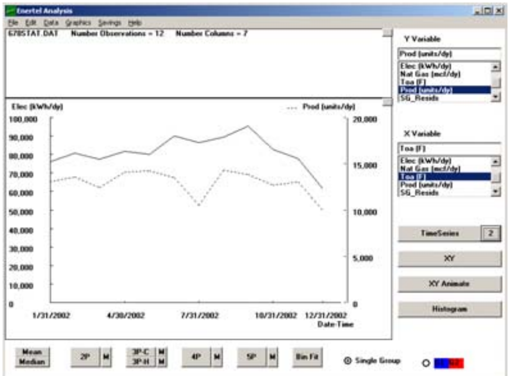

Figure 2. Monthly electricity use and number of units produced during 2002.

Statistical regression models can be developed which quantify the influence of outdoor air temperature and production on electricity use. Figure 3 shows a three-parameter cooling (3PC) change-point model of monthly electricity use as a function of outdoor air temperature. Three-parameter change-point models are so named because they have three coefficients; Ycp is temperature-independent energy use, Xcp is the outdoor air temperature above which space cooling energy use increases, and X1 is the additional electricity use for space cooling per degree of outdoor air temperature. In Figure 3, the flat section of the model on the left indicates temperature-independent electricity use, Ycp, when no air conditioning is needed. At outdoor air temperatures above the change-point temperature, Xcp, of about 32 F, electricity use begins to increase with increasing outdoor air temperature and air conditioning load. The slope of the line, X1, indicates the how much additional electricity is consumed as the outdoor air temperature increases.

To assess if this is a good model of electricity use, the R2 and CV-RMSE statistics should be considered. R2 is a non-dimensional measure of the influence of the independent variable(s). It can be thought of as the fraction of variation of the dependent variable that is explained by the independent variable(s). Low R2 values indicate that the independent variable(s) are not very influential and should be excluded from the model. The model's R2 of 0.67 indicates that temperature is indeed an influential variable. CV-RMSE is a non-dimensional measure of the scatter of data around the model. The model's CV-RMSE of 6.4% indicates that the model provides a good fit to the data.

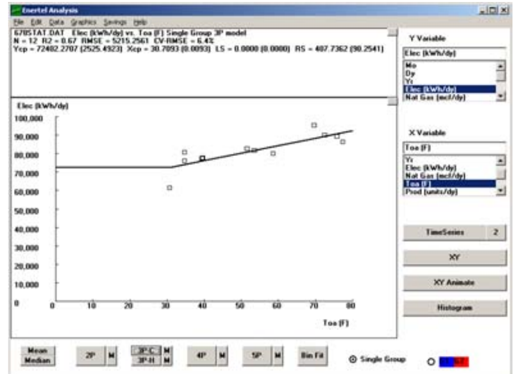

Figure 3. Three-parameter cooling (3PC) change-point model of monthly electricity use as a function of outdoor air temperature.

Despite the relatively good fit of the outdoor air temperature model shown in Figure 3, inspection of Figure 2 indicated that production also influences electricity use. Figure 4 shows a two-parameter model of electricity use as a function of number of units produced. The model shows a trend of increasing electricity use with increased production. However, the model R2 is 0.32, which indicates that production alone is a poor indicator of electricity use.

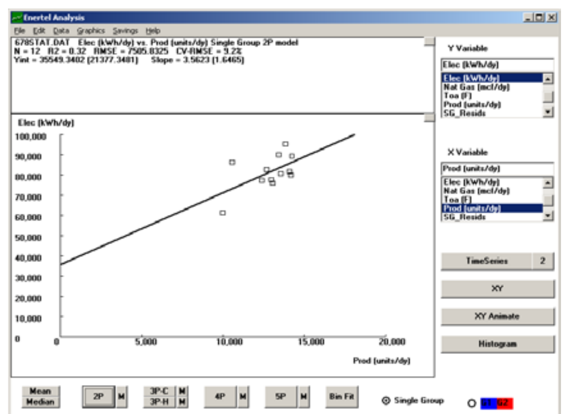

Figure 4. Two-parameter model of monthly electricity use as a function of quantity of units produced.

Clearly, the best model for predicting electricity use would include both outdoor air temperature and production. Figure 5 shows the regression results of a three-parameter cooling model of electricity use as a function of outdoor air temperature, that also includes production as an additional independent variable. This model is called a 3PC-MVR model since it includes the capabilities of both a three-parameter cooling model of energy use versus temperature, plus a multivariable-regression model (MVR). In

Figure 5, the measured electricity use (light squares) and predicted electricity use (bold squares) are plotted against outdoor air temperature. It is seen that the measured and predicted electricity use are almost on top of each other for each monthly temperature, which graphically indicates that the model is a good predictor of electricity use. The model's R2 of 0.82 and CV-RMSE of 5.1% are improvements over the previous models that attempted to predict natural gas use using air temperature of production independently. In addition, the coefficient that describes natural gas use per unit of production, X2, is now positive as expected. Thus, this model provides a very good fit to the data.

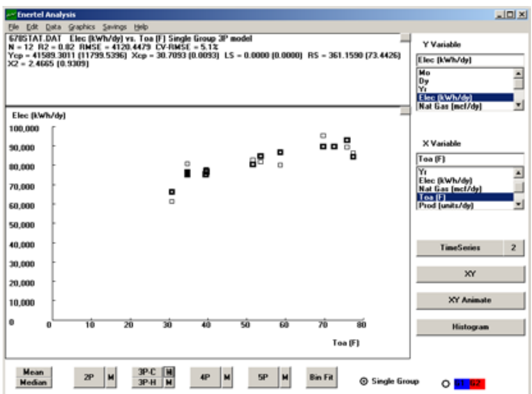

Figure 5. Results of three-parameter cooling model of electricity use as function of both outdoor air temperature and production. Measured electricity use (light squares) and predicted electricity use (bold squares) are plotted against outdoor air temperature.

Figure 5 also shows the regression coefficients and the standard error of each regression coefficient used to create the model. These values of these coefficients are shown in Table 1. The ratio of the standard error of a coefficient to the coefficient is called the "coefficient of variation of the standard error" or CV-SE. The CV-SE is a non-dimensional measure of the uncertainty with which a coefficient is known. High CV-SE values indicate that the model was not able to precisely quantify the value of this coefficient. Low values of CV-SE indicate that the coefficient is known with a high level of precision. In either case, however, the value of the regression coefficient is the best estimate of the true value of the coefficient that can be determined from the available data.

Coefficient	Value	Std Err	CV-SE
Ycp (kWh/dy)	41,589	11,799	0.28
Xcp (F)	30.7093	0.0093	0.00
RS (kWh/dy-F)	361	73.44	0.20
X2 (kWh/dy-unit)	2.4665	0.9359	0.38

Table 1. Regression coefficients a three-parameter cooling multivariable-regression (3PC-MVR) model of plant electricity use. Ycp represents facility use, Xcp represents the temperature at which air conditioning begins, RS represents the variation in air conditioning electricity use with outdoor air temperature and X2 represents the variation in electricity use with production.

Inspection of the CV-SEs in Table 2 indicates that X2, which represents electricity use per unit of production, is known with less certainty than the other coefficients. This suggests that if this number were to be used in isolation, it should be used with the knowledge that this number is not known with a high degree of precision. On the other hand, when all coefficients are used together in the 3PC-MVR model, the model's overall CV-RMSE of 5.1% indicates that uncertainty associated with the electricity use predicted by the model is much lower. In general, most multivariable regression models follow this pattern. The uncertainty associated with individual model coefficients is greater than the uncertainty associated with the overall model. Thus, when model coefficients are used to breakdown total energy use into various components, the uncertainty with which each component is known is relatively high. However, when the model is used to predict overall energy use, the uncertainty of the predicted overall energy use is generally much smaller.

Using the regression coefficients from Figure 5 and Table 1, the equation for predicting electricity use, E, as a function of outdoor air temperature Toa and quantity of units produced, P, with a 3PC-MVR model is:

$$E = Ycp + RS \times (Toa - Xcp)^{+} + (X2 \times P) \quad (1)$$

$$\begin{aligned} E\ (kWh/dy) &= 41{,}589\ (kWh/dy) \\ &+ 361.159\ (kWh/dy\text{-}F) \times [Toa\ (F) - 30.7093\ (F)]^{+} \\ &+ 2.4665\ (kWh/dy\text{-}unit) \times P\ (units) \end{aligned}$$

where the superscript + on the parenthetic term indicates that the value of the term is zero when the enclosed quantity, (Toa – Xcp), is negative.

In Equation 1, the total electricity use, E, is the sum of the three terms that represent non-production electricity use, temperature-dependent electricity use (air conditioning), and production-dependent electricity use. Thus, electricity use can be broken down into the following components.

$$\text{Fac} = 41{,}589 \text{ (kWh/dy)} \quad (2)$$
$$\text{AC} = 361.16 \text{ (kWh/dy-F)} \times [\text{Toa (F)} - 30.71 \text{ (F)}]^{+} \quad (3)$$
$$\text{Prod} = 2.4665 \text{ (kWh/dy-unit)} \times \text{P (units)} \quad (4)$$

Equations 1, 2, 3 and 4 can easily be entered into a spreadsheet to estimate total electricity use, and electricity use by each component \ (Figure 6). Inspection of Figure 6 shows reasonably good agreement between actual plant-wide electricity use and the electricity use predicted by Equation 1. Of course, least-squares regression guarantees that, when averaged over the entire year, predicted electricity use exactly equals actual electricity use.

Equation 1 can be used to predict future electricity use for budgeting or other purposes based on projections of production and outdoor air temperature. Although no one can foretell future weather, it is relatively easy to bracket projected electricity use by driving the model with temperature data from years with above-average and below-average temperatures. Equation 1 can also be used as a baseline for measuring savings from energy conservation retrofits. To “measure” retrofit savings, simply compare actual electricity use from after the retrofit to the electricity use predicted by Equation 1 when driven with the temperatures and production data from after the retrofit. In addition, Figure 6 clearly shows the increase in air conditioning electricity use throughout the summer and the reduction in production electricity use associated with the July and December plant shutdowns.

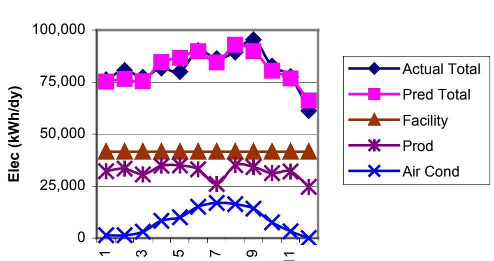

Figure 6. Time trends of actual and predicted electricity use by component versus month of the year.

In this plant, the electricity use of major electrical busses and motor control centers was sub metered; thus, the statistical and sub-metered breakdowns of electricity use can be compared. Sub-metered electricity use by exhaust fans, make-up air units, lighting and air compressors was summed to estimate production-independent electricity use. Air compressors are included in this group since their relatively poor part-load efficiencies makes their electricity use relatively independent of production. The chillers and production equipment were individually were sub metered. The sub-metered and statistical breakdowns of total electricity use are shown in Figures 7 and 8 respectively.

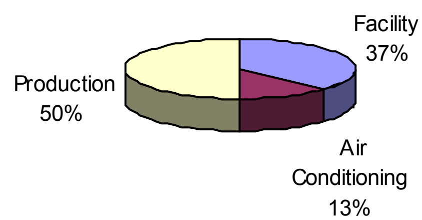

Figure 7. Fraction of total electricity use by component from sub metering.

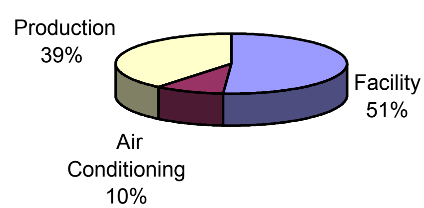

Figure 8. Fraction of total electricity use by component from statistical analysis.

Overall, there is a rough agreement between the sub-metered and statistical electricity use breakdowns in Figures 7 and 8. Both breakdowns indicate similar quantities of air conditioning electricity use. The slight difference may be due to the inherent uncertainty associated with the value of the regression coefficients. However, the difference may also indicate that some air conditioning electricity use is independent of outdoor air temperature, and is driven by internal loads. This interpretation is consistent with the type of air conditioning equipment in the plant. The majority of chilled glycol is sent to make-up air units that use 100% outdoor air. The energy required to chill this glycol should be dependent on outdoor air temperature. The rest of the chilled glycol is sent to fan-coil units that recirculate plant air near heat-generating equipment. The energy required to chill this glycol is much less dependent on outdoor air temperature. Thus, comparing the two breakdowns suggests that about

(13% - 10%) / 13% = 23%

of chiller electricity use is devoted to the fan coil units and the balance to the make-up air units.

The biggest discrepancy between the sub-metered and statistical electricity use breakdowns is between production and facility electricity use. The statistical breakdown suggests that facility electricity use is greater than indicated by the sub-metered data. Similarly, the statistical breakdown suggests that production electricity use is smaller than indicated by the sub-metered data. Most likely, this incongruity is because electricity use by some equipment on the "production" electrical busses does not vary linearly with production. For example, when pumps and fans are left running during non-production hours, their electricity use will not correlate with units of production.

In general, our interpretation of the incongruity between the breakdowns is not that the statistical breakdown is incorrect and should be calibrated to the sub-metered breakdown. Instead, we posit that the statistical analysis shows the true variation in electricity use as a function of production and temperature. Thus, the fact that sub-metered production electricity use is greater than statistical production electricity use points to an opportunity to reduce unnecessary production electricity use.

More generally, in the ideal plant, all electricity use would be proportional to production or devoted to space conditioning; facility electricity use, which is unrelated to production or space conditioning, would tend toward zero. In terms of the well-known principles of lean production, any activity that does not directly add value to the product is waste. Seen in this light, the goal is to reduce facility electricity use as low as possible. The fact that statistical analysis indicates that facility electricity use accounts for over half of all electricity use, and that production electricity use is 11% greater than statistical production electricity use, indicates a large potential for reducing electricity use. Several recommendations in this report address measures such as shutdown procedures and improving the performance of the compressed air system, which will help realize these potential savings. With diligence, even traditionally non-production related tasks such as lighting and air compression can become more related to production. For example, turning off lights in areas where production has stopped would decrease the fraction of facility electricity use and increase the fraction of production-dependent electricity use. Similarly, fixing air leaks and using air compressors with good part-load energy performance, would both save energy use and increase the fraction of production-dependent electricity use.

Statistical Analysis of Natural Gas Use

Figure 9 shows monthly natural gas use and average outdoor air temperature during 2002. The graph shows that natural gas use increases during cold months and decreases during warm months, however, some natural gas is used even during summer. Thus, outdoor air temperature appears to have some influence on natural gas use, but does not appear to be the sole influential variable.

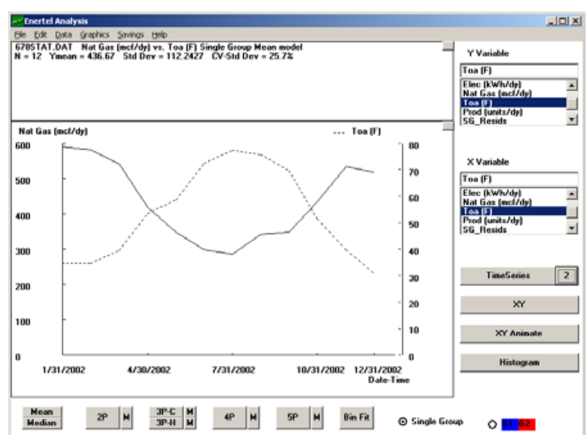

Figure 9. Monthly natural gas use and outdoor air temperature.

Figure 10 shows monthly natural gas use and number of units produced during 2002. The graph shows some correlation between production and natural gas use. For example, gas use declines during low-production months such as July and December.

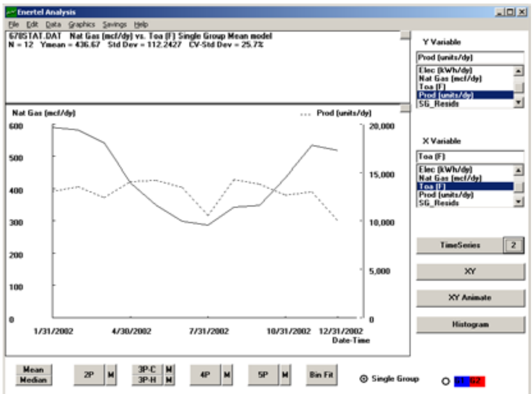

Figure 10. Monthly natural gas use and quantity of units produced.

Figure 11 shows a three-parameter heating (3PH) change-point model of monthly natural gas use as a function of outdoor air temperature. In Figure 11, the flat section of the model on the right indicates temperature-independent natural gas use, Ycp, when no space heating is needed. At outdoor air temperatures below the change-point temperature, Xcp, of about 66 F, natural gas use begins to increase with decreasing outdoor air temperature and increasing space-heating load. The slope of the line, X1, indicates the how much additional natural gas is consumed as the outdoor air temperature decreases. The model's R2 of 0.92 indicates that temperature is indeed an influential variable. The model's CV-RMSE of 7.5% indicates that the model provides a good fit to the data.

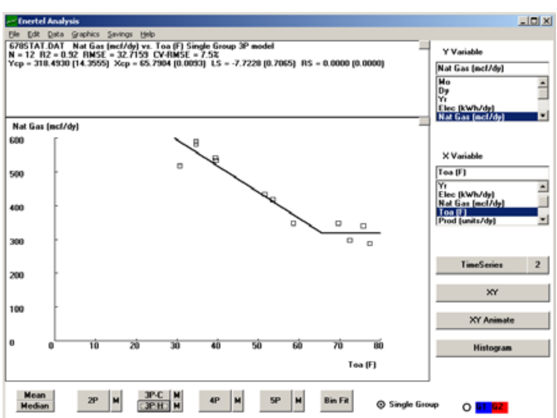

Figure 11. Three-parameter heating (3PH) change-point model of monthly natural gas use as a function of outdoor air temperature.

Despite the relatively good fit of the outdoor air temperature model shown in Figure 11, inspection of Figure 10 appears to indicate that production also influences natural gas use. Figure 12 shows a two-parameter model of natural gas use as a function of number of units produced. The model shows a trend of decreasing natural gas use with production, and a very low R2 = 0.02. This indicates that production alone is a poor indicator of natural gas use.

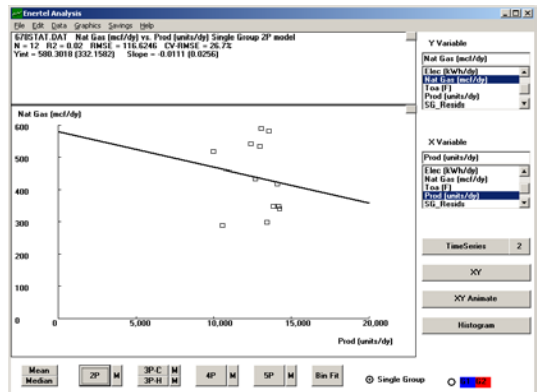

Figure 12. Two-parameter model of monthly natural gas use as a function of quantity of units produced.

Figure 13 shows the regression results of a three-parameter heating model of natural gas use as a function of outdoor air temperature, that also includes production as an additional independent variable. This model is called a 3PH-MVR model since it includes the capabilities of both a three-parameter heating model of energy use versus temperature, plus a multivariable-regression model (MVR). The model's R2 of 0.97 and CV-RMSE of 5.1% are improvements over either of the previous models that attempted to predict natural gas use using air temperature of production independently. Thus, this model provides a very good fit to the data. In addition, note that when combined with temperature data, the model coefficient for production (X2 = 0.0199) is now positive, indicating that gas use does indeed increase with increased production.

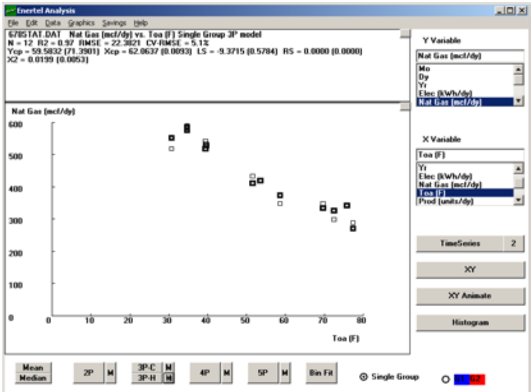

Figure 13. Results of three-parameter heating model of natural gas use as function of both outdoor air temperature and production (3PH-MVR). Measured natural gas use (light squares) and predicted natural gas use (bold squares) are plotted against outdoor air temperature.

Figure 13 also shows the regression coefficients and the standard error of each regression coefficient used to create the model. These values of these coefficients, and their interpretations, are shown in Table 2. Inspection of the CV-SE values in Table2 indicates that, as before, the uncertainty associated with individual model coefficients is greater than the uncertainty associated with the overall model. The large CV-SE for Ycp, facility gas use, is an indication that this value is not well defined by the regression analysis. However, unlike the CV-SE values of "slope" coefficients such as RS and X2, CV-SE values for X and Y change-points are dependent on the units and magnitude of the original data. For example, changing the units of temperature from degrees Fahrenheit to degrees Celsius would change CV-SE of Xcp and Ycp, but not RS and X2. Similarly, if facility natural gas use happened to be 100 mcf/day greater, the CV-SE of the Ycp would be lower. Thus, the interpretation of the uncertainty of the coefficient based on CV-SE is much more robust for slope coefficients than for change-point coefficients.

Coefficient	Value	Std Err	CV-SE
Ycp (mcf/dy)	59.58	71.39	1.20
Xcp (F)	62.06	0.0093	0.00
LS (mcf/dy-F)	-9.372	0.5784	0.06
X2 (mcf/dy-unit)	0.0199	0.0053	0.27

Table 3. Regression coefficients from three-parameter heating multivariable-regression (3PH-MVR) model of plant natural gas use. Ycp represents facility gas use, Xcp represents the temperature at which space heating begins, LS represents the variation in space heating gas with outdoor air temperature and X2 represents the variation in gas use with production.

Using the regression coefficients from Table 3, the equation for predicting natural gas use, NG, as a function of outdoor air temperature Toa and quantity of units produced, P, with a 3PH-MVR model is:

$$\begin{aligned} NG &= Ycp \\ &+ LS \times (Xcp - Toa)^{+} \\ &+ (X2 \times P)\ NG\ (mcf/dy) \end{aligned} \qquad (5)$$

$$\begin{aligned} NG &= 59.58\ (mcf/dy) \\ &+ 9.372\ (mcf/dy\text{-}F) \times [62.06\ (F) - Toa\ (F)]^{+} \\ &+ 0.0199\ (mcf/dy\text{-}unit) \times P\ (units) \end{aligned}$$

where the superscript + on the parenthetic term indicates that the value of the term is zero when the enclosed quantity, (Xcp - Toa), is negative. In Equation 5, the total natural gas use, NG, is the sum of the three terms that represent facility natural gas use, temperature-dependent natural gas use (space heating), and production-dependent natural gas use. Thus, natural gas use can be broken down into the following components.

$$\text{Fac NG} = 59.58\ (mcf/dy) \qquad (6)$$
$$\text{SH NG} = 9.372\ (mcf/dy\text{-}F) \times [62.06\ (F) - Toa\ (F)]^{+} \qquad (7)$$
$$\text{Prod NG} = 0.0199\ (mcf/dy\text{-}unit) \times P\ (units) \qquad (8)$$

Equations 5, 6, 7 and 8 can easily be entered into a spreadsheet to estimate total natural gas use, and natural gas use by each component.

Figure 14 shows the breakdown of natural gas use using these equations. Inspection of Figure 14 shows reasonably good agreement between actual plant-wide natural gas use and the natural gas use predicted by Equation 5. Equation 5 can be used to predict future natural gas use for budgeting or other purposes based on projections of production and outdoor air temperature. As before, it is relatively easy to bracket projected electricity use by driving the model with temperature data from years with above-average and below-average temperatures. Equation 5 can also be used as a baseline for measuring savings from energy conservation retrofits. In addition, Figure 14 clearly shows the increase in space heating gas use throughout the winter and the reduction in production natural gas use associated with the July and December plant shutdowns.

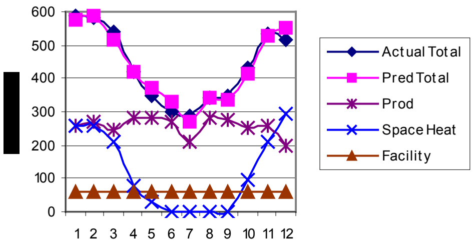

Figure 14. Time trends of actual and predicted natural gas use by component versus month of the year.

In this plant, the natural gas use of major users was sub metered; thus, the statistical and sub-metered breakdowns of natural gas use can be compared. The sub-metered and statistical breakdowns of total natural gas use are shown in Figures 15 and 16 respectively. Both breakdowns indicate nearly identical quantities of space heating natural gas use. In addition, the statistical analysis was able to subdivide the remaining natural gas use into production-dependent and facility (non-production and non-temperature dependent) gas use. As before, in the ideal plant, all natural gas use would be proportional to production or outdoor air temperature, and facility natural gas use would tend toward zero. Thus, the statistical model suggests that about 14% of natural gas use is for non-production and non-space heating related tasks, and could present opportunities for reducing gas use.

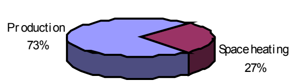

Figure 15. Fraction of total natural gas use by component from sub metering.

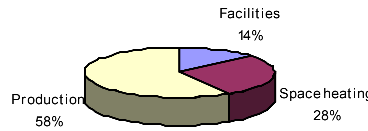

Figure 16. Fraction of total natural gas use by

SUMMARY

This paper presented a methodology and case study of how to statistically analyze plant energy data and interpret the results. The methodology used only 60 data points that are relatively easy for most plants to obtain. Multivariable three-parameter change-point models of electricity and natural gas use as functions of outdoor air temperature and production data were developed. The resulting statistical models were able to predict plant-wide electricity natural gas use with CV-RMSE of less than 6%. The statistical models can be used to accurately predict energy use for budgeting, measuring savings or diagnostic purposes. In addition, the statistical models were able to breakdown plant energy use into facility, space-conditioning and production-dependent components. In general, the breakdowns were consistent with sub-metered data and known plant operations. Further, the breakdowns suggested the savings potential from reducing non-production and space-conditioning energy use.

REFERENCES

Fels, M. 1986. "PRISM: An Introduction", *Energy and Buildings*, Vol. 9, pp. 5-18.

Fels, M., Kissock, J.K., Marean, M. and Reynolds, C., 1995. "PRISM (Advanced Version 1.0) Users Guide", Center for Energy and Environmental Studies, Princeton University, Princeton, NJ, January.

Kissock, K, Claridge, D.E., Haberl, J.S. and Reddy, T.A., 1992. "Measuring Retrofit Savings For the Texas LoanSTAR Program: Preliminary Methodology and Results", *Solar Engineering, 1992: Proceedings of the ASME-JSES-SSME International Solar Energy Conference*, Lahaina, HI, April.

Kissock, K., Agami, R, Haberl, J. and Claridge, D., 1993b. "EModel: A New Tool for Analyzing Building Energy Use Data", Proceeding of the

National Industrial Energy Conference, Houston, TX.

Kissock, K., 1993. "A Methodology to Measure Energy Savings in Commercial Buildings", Ph.D. Dissertation, Mechanical Engineering Department, Texas A&M University, College Station, TX, December.

Kissock, K, Xun, W., Sparks, R., Claridge, D., Mahoney, J. and Haberl, J., 1994. "EModel Version 1.4de", Copyright Texas A&M University, Energy Systems Laboratory, Department of Mechanical Engineering, Texas A&M University, College Station, TX, December.

Kissock, K. and Fels, M., 1995. "An Assessment of PRISM's Reliability for Commercial Buildings", *Proceedings of the National Energy Program Evaluation Conference*, Chicago, IL, August.

Kissock, K. 1997. "Tracking Energy Use and Measuring Savings Using WWW Weather Data and New ETracker Software". *Cool Sense National Forum on Integrated Chiller Retrofits*, San Francisco, September 23-24.

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

Kissock, J.K., 2000, "Enertel Analysis: Data Analysis Software", Version 1.0, Dayton, OH.

Kissock, K., Haberl, J. and Claridge, D., 2001, "Development of a Toolkit for Calculating Linear, Change-point Linear and Multiple-Linear Inverse Building Energy Analysis Models", Final Report, ASHRAE 1050-RP, December.

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

Haberl. J., Sreshthaputra, A., Claridge, D.E. and Kissock, J.K., 2003. "Inverse Modeling Toolkit (1050RP): Application and Testing", *ASHRAE Transactions*, Vol. 109, Part 2.

Rabl, A., Norford, L. and Spadaro, J., 1992. "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.

Rabl, A and A, Rialhe. 1992. "Energy Signature Models for Commercial Buildings: Test With Measured Data And Interpretation", *Energy and Buildings*, Vol. 19, No. 2, pp. 143 - 154.

Ruch, D. and Claridge, D., 1992. "A Four-Parameter Change-Point Model for Predicting Energy Consumption in Commercial Buildings", *ASME Journal of Solar Energy Engineering*, Vol. 114, No. 2, pp. 77 -83.

Schrock, D. and Claridge, D., 1989, "Predicting Energy Usage in a Supermarket", *Proceedings of the Sixth Symposium on Improving Building Systems in Hot and Humid Climates*, Dallas, TX, October.

Sonderregger, R. 1997. "Energy Retrofits in Performance Contracts: Linking Modeling and Tracking". *Cool Sense National Forum on Integrated Chiller Retrofits*, San Francisco, September 23-24.

Sonderegger, R. A., 1998. "Baseline Model for Utility Bill Analysis Using Both Weather and Non-Weather-Related Variables", *ASHRAE Transactions*, Vol. 104, No. 2 , pp. 859-870.