Measuring Progress with Normalized Energy Intensity

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ABSTRACT

Energy standard ISO 50001 will require industries to quantify improvement in energy intensity to qualify for certification. This paper describes a four-step method to analyze utility billing, weather, and production data to quantify a company's normalized energy intensity over time. The method uses 3-pararameter change-point regression modeling of utility billing data against weather and production data to derive energy signature equations. The energy signature equation is driven by typical weather and production data to calculate the 'normal annual consumption', NAC, and divided by typical production to calculate 'normalized energy intensity" NEI. These steps are repeated on sequential sets of 12 months of data to generate a series of 'sliding' NEIs and regression coefficients. The method removes the effects of changing weather and production levels, so that the change in energy intensity is a sole function of changing energy efficiency. Deficiencies of other methods of calculating NEI are identified. The method is demonstrated in a case study example.

INTRODUCTION

Global climate change caused by high atmospheric CO_2 concentrations has caused many institutions to institute policies aimed at lowering carbon emissions. One such institution is the International Organization for Standardization (ISO). ISO is now developing an energy management standard for manufacturers, ISO 50001, which is similar in structure to its well-known quality management standard, ISO 9001, and environmental management standard 14001. ISO 50001 is expected to affect as much as 60% of global energy use, was recently approved as a Draft International Standard, and could be published as a full International Standard as soon as early 2011. ISO 50001 will provide a framework for industrial plants, commercial buildings or entire organizations to manage energy (ISO 2010). In order to receive certification under ISO 50001, industrial facilities will have to demonstrate a reduction in energy intensity normalized for weather and production. This method will provide a way for plants to track their energy intensity over time in units of energy per part. This is useful not only as a potential way to achieve ISO 50001 certification, but also as a way to communicate energy performance in readily understood units, energy per part produced.

This paper describes a four-step method to analyze utility billing, weather, and production data to understand a company's energy intensity over time. The method uses regression modeling of utility billing data against weather and production data. The regression models are then driven with typical weather and production data to calculate the 'normal annual consumption', NAC. These steps are repeated on sequential sets of 12 months of data to generate a series of 'sliding' NACs and regression coefficients. The NACs for fuel use and electricity use are then combined and divided by typical production to produce the 'normal energy intensity', NEI. These steps are repeated on sequential sets of 12 months of data to generate a series of 'sliding' NEIs and regression coefficients. The method can quantify changes in energy intensity with the effects of changing weather or production removed, so that the change in energy intensity reflects changes in energy efficiency.

OVERVIEW OF THE METHOD

The method of using 'sliding' NEI analysis to quantify plant energy intensity is accomplished through four sequential steps. These steps are discussed individually below.

DESCRIPTION OF DATA AND SOFTWARE TOOLS

Utility bills are widely available, are generally accurate, and measure the total quantity of fuel and electricity used by facilities. Because of these attributes, the method uses utility bills as the principle source of energy use data. The method can be used with sub-metered data; however, sub-metered data may not capture interaction effects between systems and thus may not capture the total change in energy efficiency. In addition, the method can also be used with data measured over shorter time intervals, such as hourly or daily data. However, it has been shown that regression models of short time-interval energy data and monthly energy data versus temperature and production generate similar coefficients (Carpenter et al., 2009); thus, the use of short time-interval data for measuring long term changes in energy intensity does not appreciably change the results.

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 from the University of Dayton Average Daily Temperature Archive (Kissock 1999). Typical weather data is derived from TMY2 data files (NREL 1995). 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 for a 1-year period.

This method also uses both actual and typical production data. Actual production data is generally available from facility management or accounting departments. Typical production data can be derived from historical averages, budgeted values, or projected production. The case studies illustrating the method use historical averages for typical production.

The algorithms used to generate multi-variable change point models are described in Kissock et al., 2006. These methods have been incorporated into software applications used for this analysis (Kissock 2005; Kissock, 2006)

STEP 1: DEVELOPING ENERGY SIGNATURE MODELS

The first step of the method is to create statistical models of each facility's electricity and fuel use as functions of weather and production using utility billing data, actual weather data, and actual production data. In many industrial facilities, the weather dependence of energy use can be accurately described using a three-parameter change-point model. Three-parameter change-point models describe the common situation when cooling (heating) begins when the air temperature is more (less) than some building balance temperature. For example, consider the common situation where electricity is used for both air conditioning and production-related tasks such as lighting and air compression. During cold weather, no air conditioning is necessary, but electricity is still used for production purposes. As the air temperature increases above some balance-point temperature, air conditioning electricity use increases as the outside air temperature increases (Figure 1a). The regression coefficient β_1 describes non-weather dependent electricity use, and the regression coefficient β_2 describes the rate of increase of electricity use with increasing temperature, and the regression coefficient β_3 describes the change-point temperature where weather-dependent electricity use begins. This type of model is called a three-parameter cooling (3PC) change point model. Similarly, when fuel is used for space conditioning and production-related tasks, fuel use can be modeled by a three-parameter heating (3PH) change point model (Figure 1b).

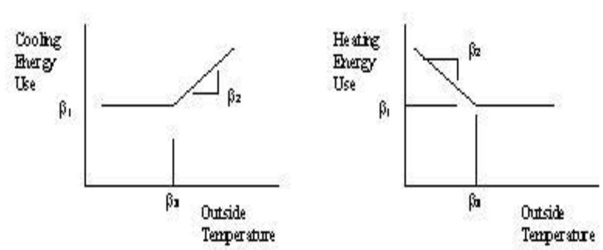


Figure 1- (a) 3PC (cooling) and (b) 3PH (heating) regression models

These basic change-point models can be extended to include the dependence of energy use on the quantity of production by adding an additional regression coefficient. The functional forms for best-fit multi-variable three-parameter change-point models for cooling energy use, E_C, (3PC-MVR) and heating energy use, E_H, (3PH-MVR), respectively, are:

$$E_C = \beta_1 + \beta_2 (T - \beta_3)^+ + \beta_4 \cdot P \qquad (1)$$

$$E_H = \beta_1 - \beta_2 (\beta_3 - T)^+ + \beta_4 \cdot P \qquad (2)$$

where β_1 is the constant term, β_2 is the temperature-dependent slope term, β_3 is the temperature change-point, and β_4 is the production dependent term. T is outdoor air temperature and P is the quantity of production. The superscript + notation indicates the parenthetic term evaluates to zero when the value of the enclosed term is negative.

The use of a single regression coefficient, β_4, and a single metric of production, P, is arbitrary; additional terms can be added to account for multiple products. The number of production variables needed to characterize plant energy use depends on the plant and process. In many plants, such as auto assembly plants or foundries, the relationship between energy use and production is accurately characterized by a single variable. In other plants with a heterogeneous product mix, multiple variables for the most energy-intensive products may be needed. In this paper, the method is demonstrated using one production variable; however, the methodology is unchanged with the addition of production variables.

In Equations 1 and 2, the β_1 term represents energy use that is independent of both weather and production, such as lighting energy use in plants with limited daylighting. The $\beta_2 \cdot (T - \beta_3)^+$ or $-\beta_2 \cdot (\beta_3 - T)^+$ term represents outdoor air temperature-dependent energy use. Because several studies have shown that outdoor air temperature is the single most important weather variable for influencing energy use in most buildings, this is referred to as weather-dependent energy use. (Fels 1986b; Kissock et al. 1998) In cases for which the weather dependent term represents space-conditioning energy use, the coefficient, β_2, represents the overall building load coefficient, UA, divided by the efficiency of the space conditioning equipment, η. In the case of 3PC or 3PC-MVR models, this coefficient is referred to as the cooling slope (CS). Similarly, in the case of 3PH or 3PH-MVR models, this coefficient is referred to as the heating slope (HS). The coefficient, β_3, represents the building balance temperature, which is the outdoor air temperature below which heating energy is used or above which cooling energy is used. The $\beta_4 \cdot P$ term represents production-dependent energy use. Using these terms, these simple regression equations can statistically disaggregate whole-plant energy use into independent, weather-dependent and production-dependent components. The interpretation and use of this technique is called Lean Energy Analysis (Kissock and Seryak, 2004a; Kissock and Seryak, 2004b and Patil et al. 2005, Kissock and Eger, 2006; Eger and Kissock, 2007) and is useful for identifying energy saving opportunities, measuring energy effects of productivity changes, developing energy budgets, and measuring energy savings.

STEP 2: NORMALIZE ANNUAL ENERGY CONSUMPTION

Utility bills show the actual annual energy consumption during a billing period. However, that energy consumption might be affected by unusual weather or production. This makes it difficult to assess a facilities energy performance over time when weather or production changes. Both of these problems can be eliminated by driving the energy signature model with "typical" weather and production. 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 and typical production data from historical records. Thus, NAC represents the "noise-free" energy use of a facility after changes due to abnormal weather and production variances have been removed. As such, NAC reveals the true energy characteristics of facilities and manufacturing processes, and allows comparison of facility energy use over time.

STEP 3: SLIDING NAC ANALYSIS

The change in energy characteristics of a manufacturing facility can be determined by comparing the facility's NAC during sequential 12-month periods. This is called a 'sliding' NAC analysis. To calculate the 'sliding' NAC, an energy-signature model is created for each set of 12 sequential months, and then driven with typical weather from a TMY2 file and typical production from a typical independent variable (TIV) file to create a sequence of NACs. The sliding NAC analysis illustrates how the building's fundamental energy use characteristics change over time. Figure 2 shows a graphical representation of how a 'sliding' NAC is calculated using the sequential dataset.

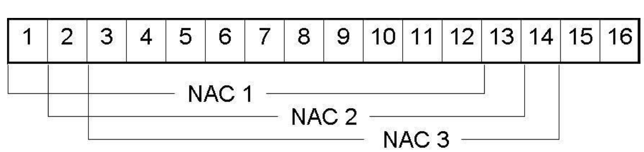


Figure 2-Graphical representation of sliding NAC

STEP 4: COMBINE ENERGY STREAMS AND DIVIDE BY TYPICAL PRODUCTION

Once the NAC is calculated for plant electricity and fuel, the Normal Energy Intensity (NEI) can be calculated. To calculate the 'sliding' NEI, the 'sliding' NAC for electricity and fuel are converted into common units and summed. The sum of the energy streams is then divided by the typical production value to create sequential NEIs.

CASE STUDY

The following case study illustrates the method when both weather and production influence plant energy intensity. Because of a corporate initiative to lower plant energy intensity, the plant in this case study made an effort to lower its energy intensity and track it on a monthly basis by dividing their total energy use each month by the total production for the month. They noticed, however, that their energy intensity would increase during shutdown months when production was low and during summer months because part of the plant was air conditioned. Therefore they are an ideal case study to illustrate the effectiveness of this method.

Figure 3 shows a time trend of total plant energy use and production. Inspection of the graph shows that production dropped off significantly in late 2008, corresponding to the start of the recession. At the same time, energy use dropped, but to a lesser extent. Because unnormalized energy intensity is total energy divided by production, the plant's unnormalized energy intensity increased significantly when the economy receded.

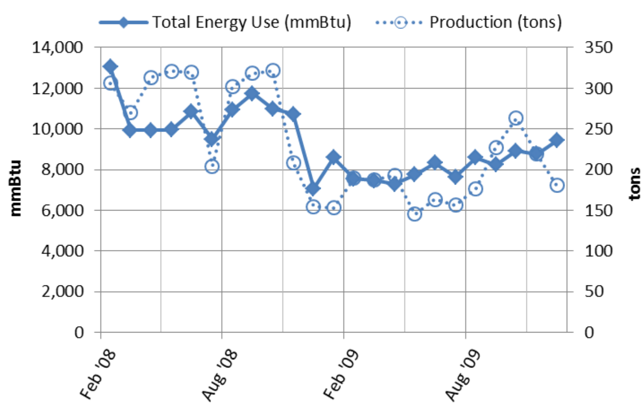
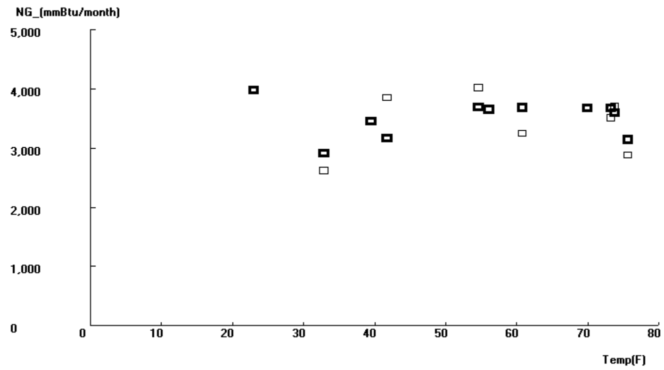
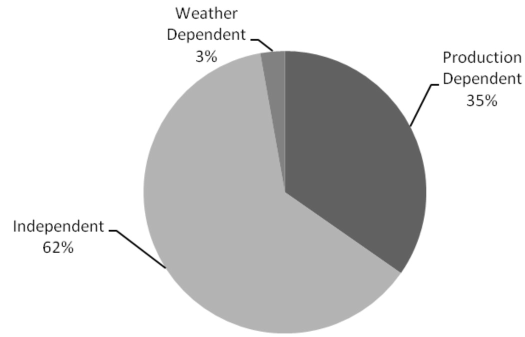


Figure 3- Plant monthly energy use and production

Figure 4a shows the 3PH-MVR model of natural gas use as a function of outdoor air temperature and production. Model coefficients and goodness-of-fit statistics are shown in Table 1. An R^2 of 0.51 and CV-RMSE of 9.9% indicates the 3PH-MVR model is able to account for about half of the variation in fuel use. From the 3PH-MVR model, natural gas energy use can be disaggregated into constituent components according to the model coefficients. Figure 4b shows this disaggregated breakdown. Independent natural gas use accounts for about 62% of the total. Weather-dependent natural gas use accounts for about 3% of the total. Production-dependent natural gas use accounts for about 35% of the total. These data indicate that the majority of natural gas use in the facility is either independent or production dependent.



(a)



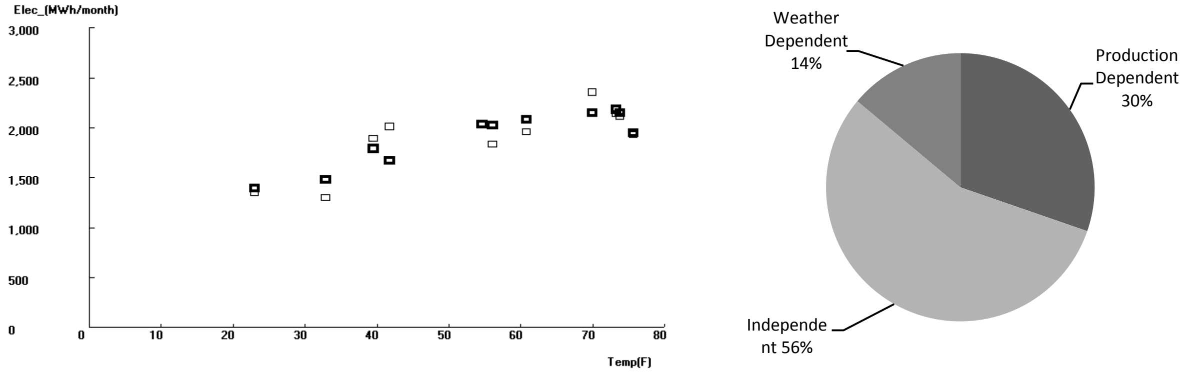
(b)

Figure 4- (a) 3PH-MVR model of fuel use as a function of weather and production (light squares indicate the actual energy use and dark squares indicate predicted energy use) and (b) natural gas energy use breakdown

Table 1- 3PH-MVR model coefficients and statistical indicators

Coefficient	**Description**	**Units**	**Value ± Standard Error**
R^2			0.51
CV-RMSE			9.9%
β_1	Independent Fuel	mmBtu/mo	2,201.2
β_2	Temp. Dependent	mmBtu/mo-F	-11,364
β_3	Balance Temp.	F	23.05
β_4	Prod. Dependent	mmBtu/ton	4.65

Figure 5a shows the 3PC-MVR model of electricity use as a function of outdoor air temperature and production. Model coefficients and goodness-of-fit statistics are shown in Table 2. An R^2 of 0.75 and CV-RMSE of 9.4% indicates the 3PC-MVR model is able to account for most of the variation in electricity use. From the 3PC-MVR model, electricity use can be disaggregated into constituent components according to the model coefficients. Figure 5b shows this disaggregated breakdown. Independent electricity use accounts for about 56% of the total. Weather-dependent electricity use accounts for about 14% of the total. Production-dependent electricity use accounts for about 30% of the total. These data indicate that the majority of natural gas use in the facility is either independent or production dependent.



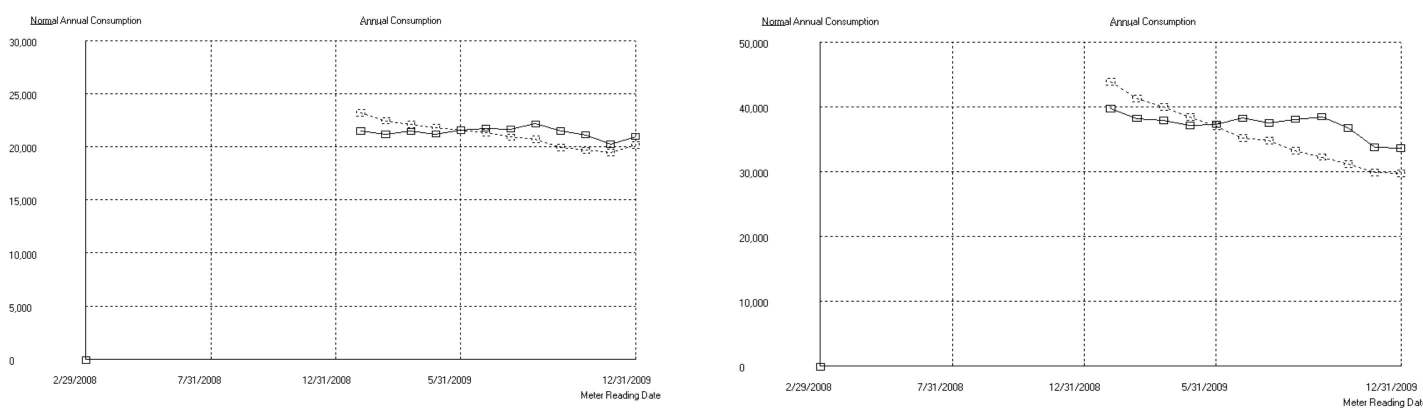
(a) (b)

Figure 5- (a) 3PC-MVR model of electricity use as a function of weather and production (light squares indicate the actual energy use and dark squares indicate predicted energy use) and (b) electricity use breakdown

Table 2- 3PC-MVR model coefficients and statistical indicators

Coefficient	**Description**	**Units**	**Value ± Standard Error**
R^2			0.75
CV-RMSE			9.4%
β_1	Independent	MWh/mo	1,061.86
β_2	Temp. Dependent	MWh /mo-F	8.38
β_3	Balance Temp.	F	22.96
β_4	Prod. Dependent	MWh/ton	2.20

Figure 6 shows the ‘sliding’ NAC (solid lines) and actual use (dashed lines) for both electricity and natural gas over a 24 month period. For both electricity and natural gas, the actual consumption starts high and intersects the NAC around the fifth month. After that, actual consumption stays below the NAC for the remainder of the time period.



(a) (b)

Figure 6- (a) Sliding actual facility electricity use and NAC analysis and (b) Sliding actual facility fuel use and NAC analysis

The individual NACs are then combined and divided by typical production to achieve plant NEI. The unnormalized energy intensity is the monthly energy use divided by the production for that month. Figure 7 shows the 'sliding' NEI (solid line) and unnormalized energy intensity (dashed line). Unnormalized energy intensity increases by about 10%. In contrast, NEI remains fairly constant before dropping towards the end of the time period. In total, plant NEI declined by about 7% during the year. Thus, unnormalized energy intensity suggests that the plant became much less energy efficient, when in fact it became more energy efficient.

The biggest reason for the discrepancy between the NEI and unnormalized energy intensity is the decrease in production experienced in late 2008. The baseline energy signature models indicated that plant natural gas and electricity use is largely independent of weather and production. Thus, plant energy use did not drop significantly when production declined. When a slightly reduced energy use is divided by a significantly reduced production value, a high unnormalized energy intensity is the result. On the other hand, NEI, eliminates these effects to show the true change in energy intensity.

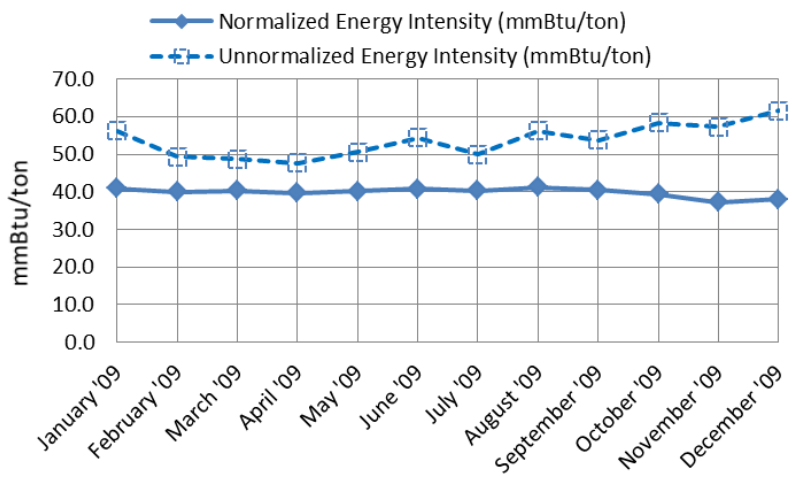


Figure 7- Sliding NEI analysis and unnormalized energy intensity

OTHER METHODS

It is tempting to use other simpler methods to determine how energy efficiency changes over time. However, as demonstrated below, these methods are typically affected by changing weather and production even when energy efficiency remains the same. Thus, they are not good measures of energy intensity.

UNNORMALIZED ENERGY INTENSITY

As shown in the preceding case study, unnormalized energy intensity, simply dividing actual energy use by actual production, is a poor indicator of energy efficiency since changes in weather and production cause changes in unnormalized energy intensity even if the energy efficiency of the plant remains unchanged. This effect also appears at a different facility shown in Figure 8 below, where the weather dependency of the unnormalized fuel energy intensity is obvious; energy use increases during winter and decreases during summer. Thus in this case, the unnormalized energy intensity is really a picture of the weather and not the energy efficiency of the plant.

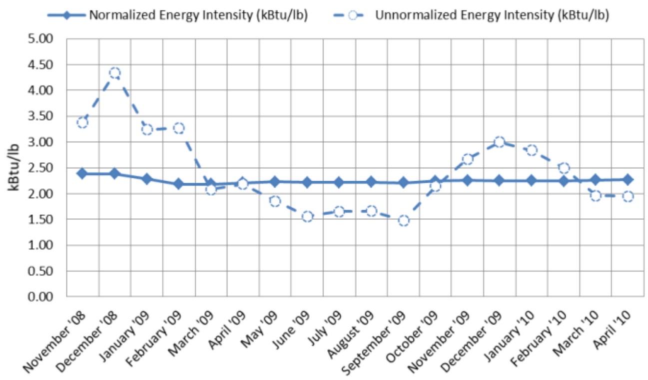


Figure 8- Sliding fuel NEI and unnormalized fuel energy intensity

SUMMING ENERGY STREAMS

When calculating total energy intensity in facilities that use multiple energy sources, such as electricity and fuel, it is convenient to add all energy sources together before calculating a single regression model of total energy use versus weather and production. Unfortunately, this practice results in the loss of important information, especially when the different energy sources of energy have different temperature dependencies, as most do.

Figure 9 shows how adding energy sources before statistical analysis can cause information about the how the plant uses energy to be lost. It is clear that both of the plant's energy sources have weather dependency. However it can also be seen that if the energy sources were combined before anyone analyzed the data, it would appear that plant energy use had no weather dependency. Thus, the regression model would not be able to account for, and remove the effects of, changing weather. Therefore all plant energy sources should be analyzed separately, then summed when calculating overall plant energy intensity.

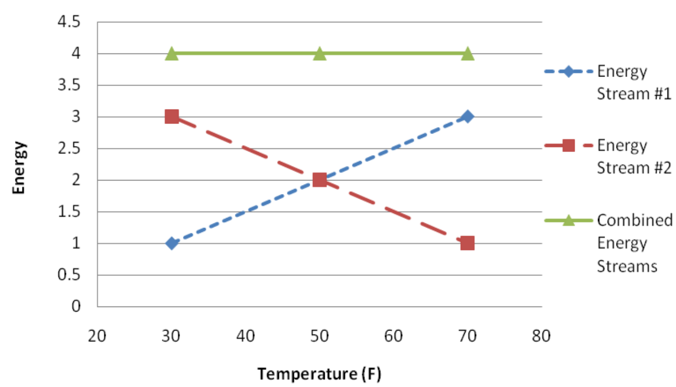


Figure 9- Effect of adding energy sources before statistical analysis

INCORRECT WEATHER AND PRODUCTION NORMALIZATION

Some methods for calculating plant energy intensity do not completely normalize for changes in weather and production. One such method is the Superior Energy Performance Default Method for calculating energy intensity (SEP, 2009). In the Default Method, the Key Performance Indicator (KPI) is the ratio of actual energy usage, E, to baseline usage that would have been expected with current production levels and external factors, $\hat{E}_b$.

$$KPI = \frac{E}{E_b}$$

Where $\hat{E}_b$ is determined from the regression model of baseline energy use. The energy intensity improvement, ΔEI, then is one minus the KPI.

$$\Delta EI = \frac{E_b - E}{E_b} = 1 - KPI$$

To understand how this method would show energy intensity improvement even when the plant's energy efficiency remains unchanged, consider the following example. Assume a plant uses energy according to the following formula.

$$E = \alpha + \gamma W + \phi P$$

Where E is the energy usage, α is the energy usage independent of production and weather, γ is the weather-dependent coefficient, W is the weather for the current period, ϕ is the production-dependent coefficient, and P is production for the current period. Assume that the baseline model yielded the following values for the coefficients: $\alpha_b = 100$, $\gamma_b = 2$, and $\phi_b = 5$. Now assume that insulation in the facility's envelope was increased, causing γ to drop from 2 to 1. Also assume that weather for the period was 250 and Production was 100.

Table 3 shows the calculation for KPI under these conditions. This yields a KPI of 0.7727. If the Default Method normalizes for changes in weather and production, then changing weather or production should not affect the KPI, and the KPI should remain constant at 0.7727.

Table 3- KPI calculation for weather related improvement

α	α_b	γ	γ_b	ϕ	ϕ_{base}	W	P		E	$\hat{E}_b$	KPI
100	100	1	2	5	5	250	100		850	1,100	0.7727

Now assume, that production, P, drops to 50. Table 4 shows the calculation for KPI under these conditions. This yields a KPI of 0.7059 when it should be 0.7727, a difference of 6.68%, even though the energy efficiency of the plant remains unchanged.

Table 4- KPI calculation for weather related improvement with change in production

α	α_b	γ	γ_b	ϕ	ϕ_{base}	W	P		E	$\hat{E}_b$	KPI
100	100	1	2	5	5	250	50		600	850	0.7059

Using this methodology, it is easy to construct many other situations involving changing weather and production cause the SEP Default Method to fail to properly normalize for changes in weather and production; hence, it cannot be depended on to verify plant energy intensity improvement. On the other hand, SEP also endorses two other methods for calculating plant energy intensity, the Backcast Method and the Standard Conditions Method. These methods are analogous to the method presented in this paper and effectively normalize plant energy use for changes in weather and production. Thus, we endorse the use of the Backcast and Standard Conditions methods for measuring improvements in energy intensity.

SUMMARY AND CONCLUSION

This paper describes a four-step method to analyze monthly utility billing, weather and production data to calculate a facility's normalized energy intensity. The method accurately describes changes in energy efficiency independent of changing weather and production, where simpler methods fail. However, a drawback in the method is the time delay between when energy efficiency improvements are made and when they completely manifest themselves in the NEI. For example, if energy intensity were decreased by 25% in the first month after the baseline period, NEI would not show a 25% reduction in energy intensity until 12 months after the initial reduction. This is because of the nature of sliding NAC analysis; in that all new calculated NAC's are computed with usage data from the previous 11 months.

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