Quantifying the Statistical Importance of Utilizing Regression over Classic Energy Intensity Calculations for Tracking Efficiency Improvements in Industry

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ABSTRACT

In the United States, manufacturing facilities accounted for about 32% of total domestic energy consumption in 2014. Robust energy tracking methodologies are critical to understanding energy performance in manufacturing facilities. Due to its simplicity and intuitiveness, the classic energy intensity method (i.e. the ratio of total energy use over total production) is very widely adopted. However, the classic energy intensity method does not consider the variation of other relevant parameters (i.e. product type, feedstock type, weather, etc.). Furthermore, the energy intensity method assumes that facilities' base energy consumption (energy consumption at zero production) is zero, which rarely holds true. Therefore, it is commonly recommended to utilize regression models rather than the energy intensity approach for tracking improvements at the facility level. Unfortunately, it is challenging for some energy managers to understand why regression models are statistically better than the classic energy intensity method. While anecdotes and qualitative information may convince some, many have major reservations about the accuracy of regression models and whether it is worth the time and effort to gather data and build quality regression models. This paper will explain why regression models are theoretically and quantitatively more accurate for tracking energy performance improvements. Based on the analysis of data from 114 manufacturing plants over 12 years, this paper will present quantitative results on the importance of utilizing regression models over the energy intensity methodology. This paper will also document scenarios where regression models do not have significant relevance over the energy intensity method.

Introduction

In the United States, industrial facilities accounted for about 32% of total national energy consumption in 2014 (EIA 2015). Improving energy efficiency of industrial facilities benefits companies financially, mitigates energy-related business risks, and protects the environment by reducing greenhouse gas emissions. To improve facilities' energy efficiency, companies have implemented energy conservation projects and adopted or advanced energy management systems. To demonstrate energy savings from energy conservation projects and assess the effectiveness of energy management systems, methodologies are required to accurately track the energy performance of manufacturing facilities (ISO 2011; 2014).

The simplest approach is to compare the annual total energy consumption on utility bills. This is the least accurate methodology as it does not consider the variation in products types, production, scheduling or manufacturing processes. It only, to some extent, considers weather by comparing similar time periods.

To minimize the influence of all relevant factors, many measurement and verification protocols and energy tracking methodologies had been proposed (ASHRAE 2014; Kissock 2006; Lammers 2011; Goldstein 2013; NEEA 2013; US DOE 2016; Therkelsen 2016). One approach is to use classic energy intensity (CEI) which involves simply dividing annual total energy use by annual total production of plants. Due to its simplicity and intuitiveness, this classic energy intensity method is very widely adopted in industry. This is definitely some improvement from the annual total energy consumption comparison; however, this simple energy efficiency metric has some major flaws. As explained in the next section, using CEI comparison to track energy performance fundamentally assumes that the base energy consumption (energy consumption with no production) is zero. In other words, it is assumed that the relationship between total energy and production can be represented by a straight line through origin with the slope as the ratio of annual total energy consumption over production. Unfortunately, this zero base energy assumption very rarely holds valid, because supporting energy systems or major manufacturing equipment almost never unloads perfectly with production due to technological and operational limitations (US DOE 2015).

A better approach is to utilize monthly energy (or shorter time periods) and production data to generate linear regression models to represent the relationship between energy consumption and production. These regression models can be used to normalize production and even other parameters that affect energy consumption. Unfortunately, it is challenging for some facility energy managers to understand why regression models are statistically better than utilizing the CEI method. While anecdotes and qualitative information may convince some, many have major reservations about the accuracy of regression models and whether it is worth the time and effort to gather data and build quality regression models.

This paper will first explain why regression models are engineeringly and statistically more accurate for tracking energy performance improvements. Then based on the analysis of 586 sets of manufacturing plants monthly electricity and production data from114 manufacturing plants over 12 years, this paper will present quantitative results on the importance of utilizing regression models over CEI methodology.

Theoretical Background

Engineering Perspective

The classic energy intensity method uses one single number, the ratio of annual total energy consumption to production, to represent one whole year's energy performance characteristics and perform year-to-year energy performance comparisons. For example, the annual energy consumption and production of year 1 and 2 are TE_1, TP_1, TE_2, and TP_2, respectively. The energy savings (ES) percentage from year 2 to 1 will be:

$$ES(\%) = 1 - (TE_2/TP_2)/(TE_1/TP_1) \qquad (1)$$

CEI is a basic production normalization approach. It is apparent that the only variable considered in CEI is production. More importantly, this production normalization approach also implicitly assumes that the relationship between production and energy consumption is linear with zero base energy consumption (the energy consumption with no production) and a slope of the ratio of annual total energy over production. To some facility energy managers, this assumption is obscure and hard to understand. To illuminate this major underlying assumption, Equation (1) is expanded to its full version as illustrated below.

To make a relatively fair comparison on energy performance for two years with different production rates, one logic thought is to compare the projected energy consumption if both years has the same production rates – the norm production rate (TP_N).

Year 1 energy consumption for the norm production rate will be:

$$TE_{N1} = TE_1/TP_1 \times TP_N \qquad (2)$$

Year 2 energy consumption for the norm production rate will be:

$$TE_{N2} = TE_2/TP_2 \times TP_N \qquad (3)$$

The energy savings percentage from year 2 to year 1 is:

$$ES(\%) = 1 - (TE_2/TP_2 \times TP_N)/(TE_1/TP_1 \times TP_N) \qquad (4)$$

After canceling TP_N, Equation (4) becomes Equation (1).

$$ES(\%) = 1 - (TE_2/TP_2)/(TE_1/TP_1) \qquad (1)$$

Equations 2 to 4 show the how Equation (1) is obtained. For equations (2) and (3), please note that when TP_N is zero, the TE_{N1} and TE_{N2} will be zero. In other words, if the production is zero, the energy consumption will be zero. This almost never holds true for any manufacturing plants, because manufacturing systems and supporting energy systems almost never perfectly unload with production rate due to current technology and operation limitations. In fact, base energy consumption for most manufacturing facilities can be up to 40% of its full load energy consumption (DOE 2015).

Statistical Perspective

As described above, the CEI approach assumes that the relationship between production and energy consumption is linear with zero intercept (i.e. zero base energy consumption) and with a slope of the ratio of annual total energy over production. In other words, this approach uses a linear regression through the origin to represent the relationship between energy consumption and production. From a statistical perspective, linear regression through the origin is not always the most accurate way to represent the relationship. Figure 1 shows the comparison between a linear relationship through the origin with a slope of the ratio of total electricity use over production (i.e. CEI) and the least squares one variable linear regression (LSOVLR) model for an automobile assembly plant.

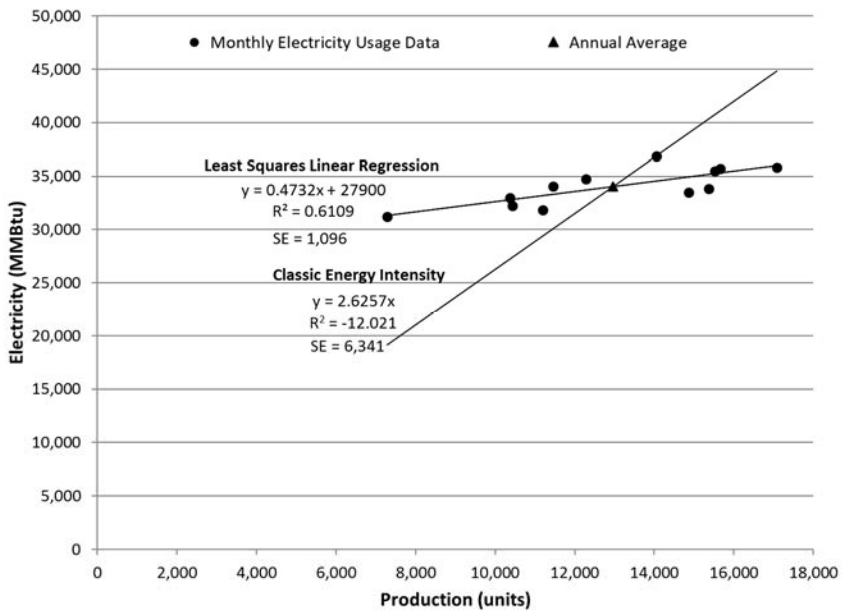

Figure 1. CEI vs. LSOVLR

From Figure 1, it can be observed that LSOVLR graphically is a more accurate representation of the relationship between energy consumption and production than the CEI approach for this manufacturing plant. Statistically, the values of R^2 (Coefficient of Determination) and SE (Standard Error of Regression) also quantitatively demonstrates that LSOVLR is more accurate than CEI for this specific case.

Data Analysis

Manufacturing Plants Energy Usage Data

To demonstrate the advantage of LSOVLR over CEI, 586 sets of monthly electricity and production data have been analyzed. This data set includes 12 years (2005-2016) of data from 114 manufacturing plants. The nine manufacturing subsectors included in this data set are shown in Table 1.

Table 1. Manufacturing Subsectors of Energy Usage Data Sets

NAICS	Manufacturing Subsectors
324	Petroleum and Coal Products Manufacturing
325	Chemical Manufacturing
331	Primary Metal Manufacturing
333	Machinery Manufacturing
334	Computer and Electronic Product

	Manufacturing
335	Electrical Equipment, Appliance, and Component Manufacturing
336	Transportation Equipment Manufacturing
337	Furniture and Related Product Manufacturing
339	Miscellaneous Manufacturing

SE Ratio

R^2 and Standard Error of Regression (SE) are two most common goodness-of-fit statistical measures. R^2 basically is the percentage of the dependent variable variation that can be explained by a linear model (Montgomery 2012). SE represents the average distance between the actual values and the regressions output (Frost 2014). In other words, SE intuitively shows the how close the predicted values are to the observed values.

$$Standard\ Error\ of\ Regression\ (SE) = \sqrt{\frac{\sum\left(Y_i - \widehat{Y_i}\right)^2}{n-p}}$$

Where:
Y_i = Actual sample values
$\widehat{Y_i}$ = Predicted sample values
n = Number of samples
p = Number of variables not including the intercept

Due to its intuitiveness, SE is adopted as the method to decide how well a linear regression model fits data. To compare the statistical error of CEI method and LSOVLR, when the SE ratio of CEI over LSOVLR is greater than 1.1, it is interpreted that LSOVLR improved accuracy. When the SE ratio is less than 1.1, it is interpreted that LSOVLR does not significantly improve accuracy. Some measurement and verification protocols (e.g. ASHRAE 2014) have uncertainty requirement of equal to or less than 10% and use 10% savings as approach selection threshold. Therefore, this paper selects SE ratio threshold of 1.1 for demonstration purpose. SE ratio threshold can be less or greater than 1.1 depending on the energy performance tracking accuracy requirements by facilities and measurement and verification protocols to comply. Please note that selecting different SE ratio thresholds might affect the conclusions.

Figure 2 shows the SE ratio of CEI over LSOVLR for various plant annual electricity uses. It can be observed that SE ratio ranges from about 1.0 to 3.0 for almost all plant sizes (electricity consumption perspective). For some plants with electricity consumption around 1.0×10^6 MMBtu, the SE ratio can be up to 9.6. It is also interesting that for plants with electricity consumption more than 1.0×10^5 MMBtu and less than 2.0×10^6 MMBtu, the SE ratio is relatively greater than smaller or larger plants, this might be worth future investigation.

Figure 3 shows that, for 152 data sets, the SE ratio is equal to or less than 1.1. In other words, for these data sets, using CEI does not compromise much accuracy. There are 265 data sets for which the SE ratio is greater than 1.1 and less than or equal to 2.0. This means for these data sets LSOVLR has considerably improved accuracy. For the other 169 data sets, SE ratio is greater than 2.0 and for some data sets, the SE ratios are up to 9.6 (Fig. 2). For these data sets, CEI will not be recommended because of significantly compromised accuracy. In summary, from SE perspective, LSOVLR greatly improves accuracy for 74% (434) of the studied data sets and CEI and LSOVLR has similar accuracy for 26% (152) of these data sets.

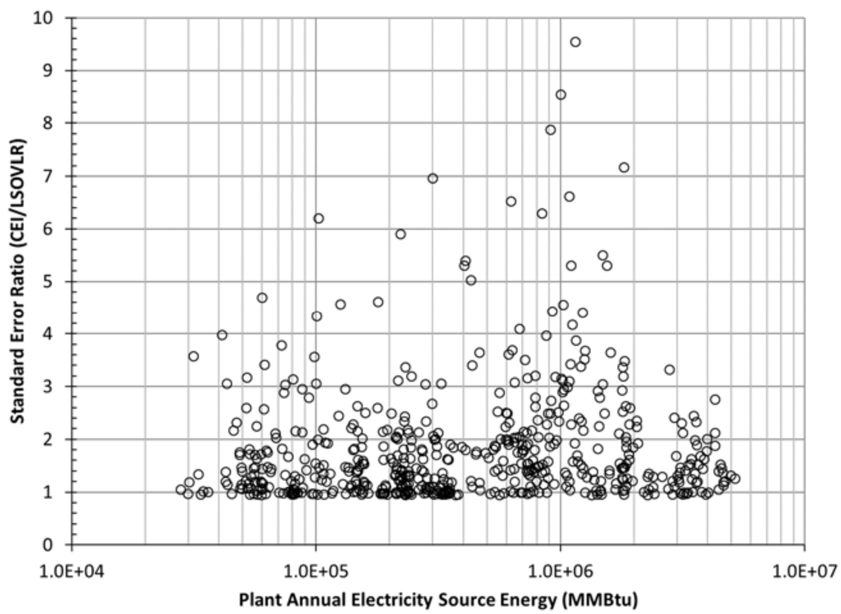

Figure 2. SE Ratio CEI over LSOVLR

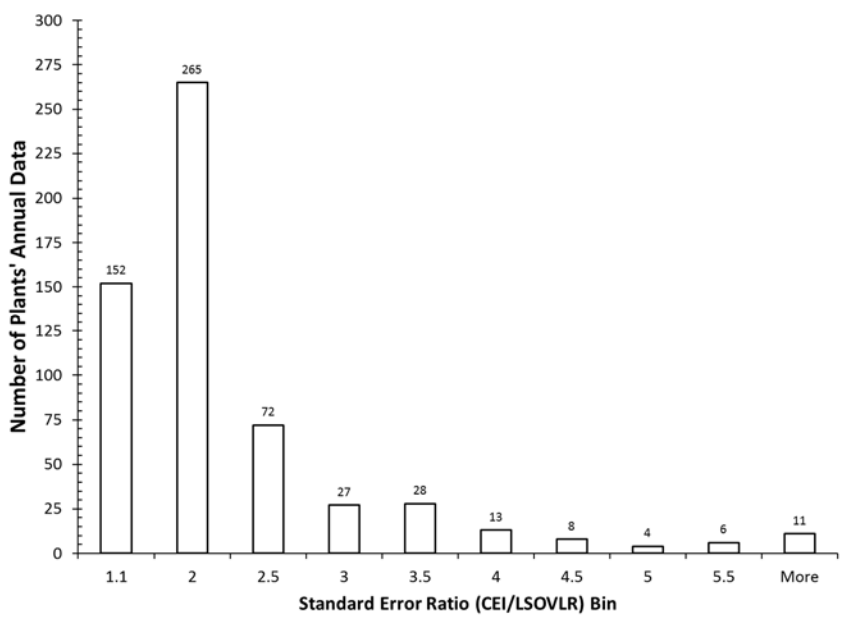

Figure 3 SE Ratio Distribution

P-value of Intercept

As mentioned before, CEI is basically a one variable linear relationship with the intercept of zero and the slope of the ratio of annual total energy over total production. For LSOVLR, by minimizing the sum of the squares of the errors between projected and actual sample values, the intercept and slope are determined with some consideration of the monthly energy and production variation. In other words, the fundamental differences between CEI and LSOVLR are the methodologies of obtaining linear relationship's intercepts and slopes.

The p-value of intercept tests the hypothesis that the intercept equals to zero (Kutner 2003). The smaller the p-value is; the more likely the intercept is non-zero or the more likely the assumption of zero intercept in CEI is not true. On the other hand, the p-value of slope tests the hypothesis that the slope equals to zero. Since CEI approach only assumes the intercept of zero, only the p-value of intercept has been examined in this study.

Figure 4 shows the intercept p-values for the studied data sets. It can be observed that for almost all plant sizes (electricity consumption perspective), intercept p-value ranges from 0 to 1.0. Unlike SE ratio distribution, there is not much p-value range variation between plant sizes. From Figure 5, for 80% (469) of these data sets, the intercept p-value is less than 0.1. In other words, for these data sets, it is very likely that the intercept of zero hypothesis is invalid. On the hand, for other 20% (117) of these data sets, the intercept of zero hypothesis can be valid or it is highly uncertain that the intercept is zero.

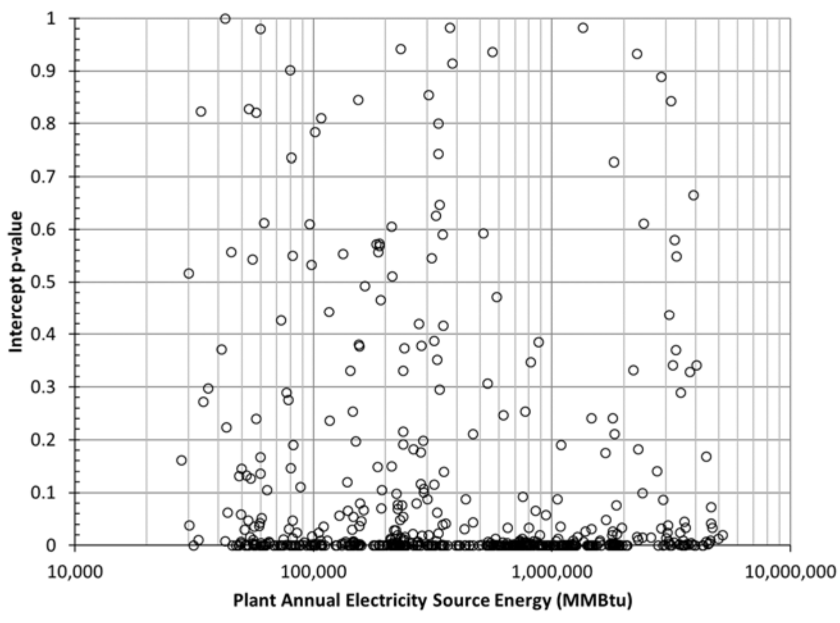

Figure 4. Intercept p-values

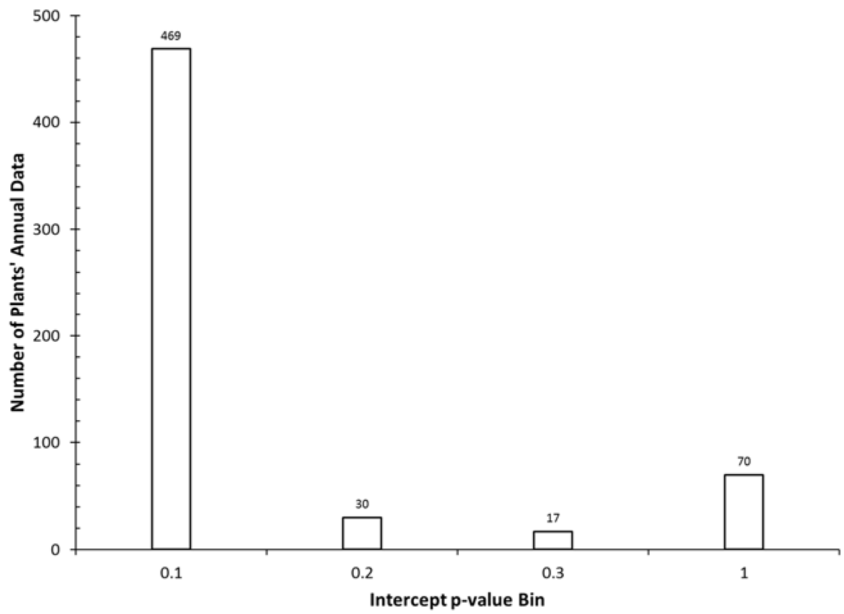

Figure 5. Intercept p-value bin distribution

SE Ratio and p-value of intercept

SE ratio compares the overall statistical errors of CEI and LSOVLR and p-value of intercept examines the hypothesis of zero intercept (i.e. zero base energy consumption) assumed by CEI. When the zero-intercept assumption is not valid, it is very likely the error of CEI will be more significant and the SE ratio of CEI and LSOVLR will be greater. In other words, there should be some correlation between SE ratio and p-value of intercept.

Figure 6 illustrates the correlation between SE ratio and p-value intercept. It can be observed that, for most data points, when p-value of intercept is less than 0.1, as p-value of the intercept decreases, SE ratio increases dramatically. In other words, when the assumption of zero intercept is more likely invalid, the accuracy of CEI will drop significantly. For outliers above the intercept p-value and SE ratio curve, their p-values are greater than 0.5 or the assumption of zero intercept is likely true, but their SE ratios are relatively high. This might be caused by the different slopes of CEI and LSOVRL. For outliers below the intercept p-value and SE ratio curve, their p-values is zero or the assumption of zero intercept is very likely untrue, but their SE ratios are relatively smaller. For these data points, even though LSOVRL makes more engineering sense, but LSOVRL's advantage is not demonstrated through SE ratio.

Figure 7 shows the data points distribution when considering both SE ratio and p-value of intercept. When SE ratio is greater than 1.1 and p-value of intercept is less than 0.1, LSOVLR is both more statistically accurate and made more engineering sense. 73% (428) of these data set fall into this category. When SE ratio is greater than 1.1 and p-value of intercept is greater than 0.1, even though the assumption of zero intercept might be valid, LSOVLR is still more statistically accurate. 1% (5) of these data points are in this category. When SE ratio is less than 1.1 and p-value of intercept is greater than 0.1, the assumption of zero intercept might be valid and LSOVLR does not significantly improve accuracy. 19% (112) of these data set is in this category. When SE ratio is less than 1.1 and p-value of intercept is less than 0.1, the assumption of zero intercept is very likely invalid, but LSOVLR does not significantly improve statistical accuracy. 7% (41) of these data set are in this category. In summary, for 81% (474) of the studied data sets, LSOVLR will be recommended to track facilities' energy performance because LSOVLR improves accuracy, or makes more engineering sense, or both. On the other hand, only 19% (112) of the studied data sets, CEI may be adopted to track facilities' energy performance.

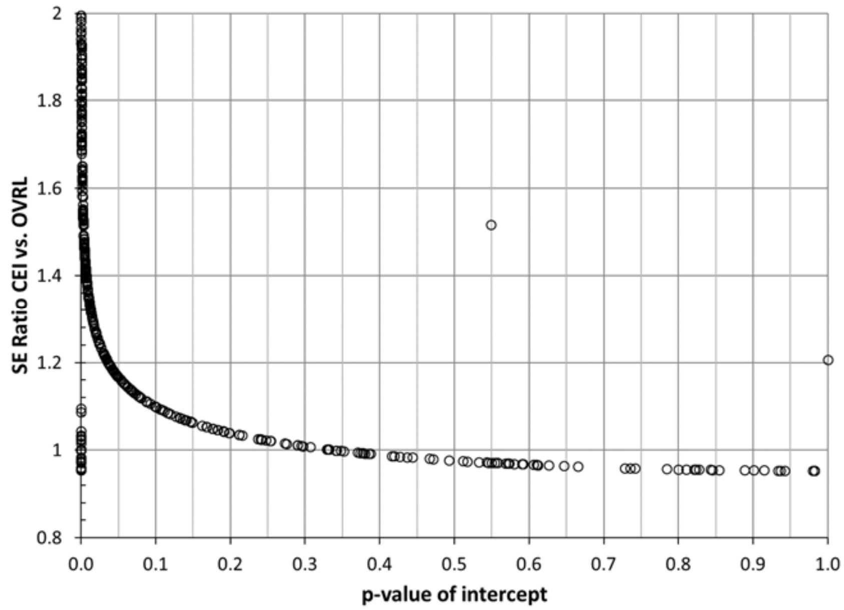

Figure 6. SE ratio and p-value of intercept

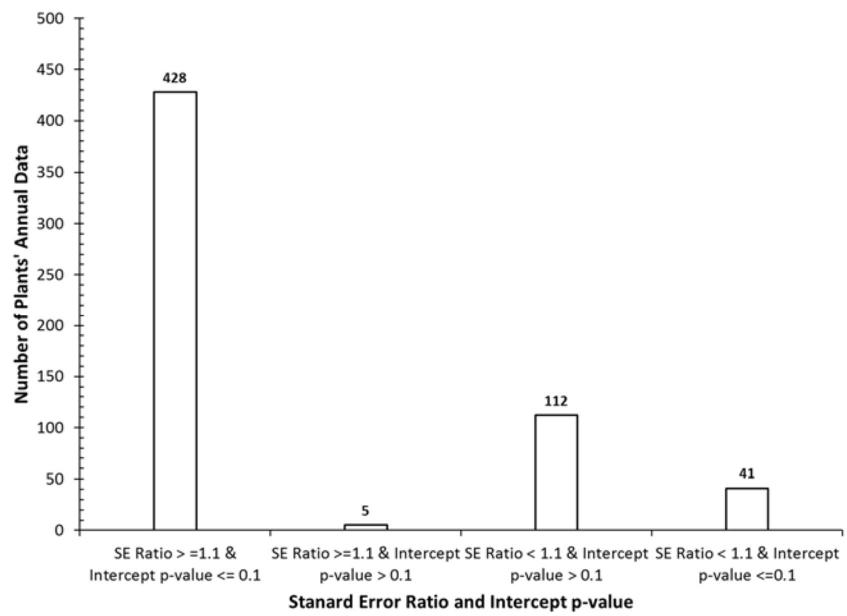

Figure 7. SE ratio and p-value of intercept bin distribution

Conclusions

This paper first has explained why CEI approach is fundamentally a linear relationship with zero intercept (zero base energy consumption) and a slope of the ratio of annual total energy consumption over production. Then 586 sets of monthly plants electricity and production data has been analyzed to quantitatively demonstrate the advantage of LSOVLR over CEI approach. It has been found that LSOVLR considerably improved accuracy for 74% (434) of the studied data sets while CEI and LSOVLR had similar accuracy for 26% (152) of these data sets. It has also been observed that for 80% (469) of these data sets, the intercept of zero assumption was very likely invalid and, for other 20% (117) of these data sets, intercept of zero assumption can be valid. Considering both SE ratio and p-value of intercept, for 81% (474) of the studied data sets, LSOVLR is a more accurate way to track facilities' energy performance as it either improves accuracy or makes more engineering sense or both. On the other hand, only 19% (112) of the studied data sets, CEI may be adopted to track facilities' energy performance.

Future Work

CEI and LSOVLR are different approaches to obtain both intercept and slope. This paper only studied the p-value of the intercept and its correlation with SE ratios. Future work will include studying the effect of CEI and LSOVLR derived slopes on the SE values and model accuracy.

The findings in this paper support the improved accuracy of the LSOVLR approach under most circumstances and demonstrate that CEI is only potentially more beneficial for about 19% of the analyzed plants' energy data sets. Future work will analyze and evaluate under which plant-related circumstances (industry type, plant size, plant age, operation shifts, product types, etc) the CEI approach produces comparable results to the LSOVLR approach. Doing so will help facility energy managers understand where the CEI approach can be confidently used and where the LSOVLR approach may provide more accurate energy tracking results.

The conclusions are based on the SE ratio threshold of 1.1. Future work will also include the sensitivity study of SE ratio threshold.

Lastly, other future work includes expanding the comparison approach to incorporate advanced regression and energy tracking techniques (for example, comparing cumulative sum of differences for the CEI and LSOVLR approaches). This paper only analyzed the CEI versus a one-variable, production-based regression model. The authors will investigate the relative accuracy improvement of multi-linear models and non-linear models versus the CEI approach. In addition, the authors will explore categorizing the slope and intercept values by industry type to see if additional macro-trends can be identified.

Acknowledgments

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References

ASHRAE. 2014. ASHRAE Guideline 14 2014: Measurement of Energy, Demand, and Water Savings.

EIA. 2015. Monthly Energy Review (DOE/EIA-0035(2015/04)).

Frost, Jim. 2014. "Regression Analysis: How to Interpret S, the Standard Error of the Regression". The Minitab Blog, Minitab Inc. http://blog.minitab.com/blog/adventures-in-statistics-2/regression-analysis-how-to-interpret-s-the-standard-error-of-the-regression

Goldstein, D., J. Almaguer. 2013. Developing a Suite of Energy Performance Indicators (EnPIs) to Optimize Outcomes. Niagara Falls, NY. ACEEE Summer Study on Energy Efficiency in Industry 2013.

ISO. 2011. *ISO 50001 – Energy Management System Standard – Requirement with Guidance for Use*.

ISO. 2014. *ISO 50015 – Measurement and Verification of Organizational Energy Performance – General Principles and Guidance*.

Kissock, K., C. Eger. 2006. Measuring Industrial Energy Savings. Detroit, MI. Society of Automotive Engineers World Congress and Exposition 2006.

Kutner, M., C. Nachtsheim, J. Neter. 2004. *Applied Linear Regression Models*. New York City, NY: McGraw-Hill Education.

Lammers, N., F. Sever, B. Abels, K. Kissock. 2011. Measuring Progress with Normalized Energy Intensity. Detroit, MI, USA. Society of Automotive Engineers World Congress Conference 2011.

Montgomery, D. 2012. *Introduction to Linear Regression Analysis*. Hoboken, NJ: John Wiley & Sons, Inc.

NEEA (Northwest Energy Efficiency Alliance). 2013. *Energy Baseline Methodologies for Industrial Facilities.* Portland, OR. 2013.

Therkelsen, P., P. Rao, D. Sholes, B. Meffert, R. Green, S. Nimbalkar, A. McKane. 2016. The Value of Regression Models in Determining Industrial Energy Savings. Berlin, Germany. Industrial Efficiency Conference 2016.

US DOE. 2015. Quadrennial Technology Review.

US DOE. 2016. Superior Energy Performance Measurement and Verification, Washington DC.