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Comparison of One- and Two-Variable Linear Regression Models and Classic Energy Intensity for Energy Performance Tracking of Two Manufacturing Sectors

Authors List

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Comparison of One- and Two-Variable Linear Regression Models and Classic Energy Intensity for Energy Performance Tracking of Two Manufacturing Sectors

Abstract

Manufacturing facilities consumed about 32% of total domestic energy in the United States in 2016. To evaluate the energy savings achieved through the implementation of energy conservation projects and to establish powerful arguments for future projects, accurate energy performance tracking methods are necessary. The classic energy intensity method (i.e., the ratio of annual total energy over annual total production) is the means most widely used to measure savings because it can be understood and calculated easily. This method considers the variation in production rates to some extent; however, it fundamentally assumes facilities' base energy consumption (energy consumption at zero production) to be zero, which rarely holds true. Furthermore, this method does not consider variations in other relevant parameters, such as weather conditions. Therefore, the regression models approach is commonly recommended to track energy performance improvements. However, because it requires more data and statistical expertise, the regression models approach has been adopted by only a few facilities, and many others suspect it is not worth the effort for their specific cases. For this reason, the improved accuracy this approach offers needs to be demonstrated. By analyzing 477 monthly energy (electricity and natural gas) data sets, this study quantitatively compared the accuracy of classic energy intensity, one-variable (production only) linear regression models, and two-variable (i.e., production and weather) linear regression models for two manufacturing sectors (primary metal and transportation equipment manufacturing). Results showed that significant improvements in accuracy were achieved with one-variable regression models when compared with the classic energy intensity method and with two-variable regression models when compared with one-variable regression models. These improvements were demonstrated using the p-values of intercept, cooling degree days, and heating degree days. Based on these results, to achieve a good balance between accuracy improvements and resources requirements, one-variable (production only) linear regression models for electricity consumption and two-variable (production and heating degree days) linear regression models for natural gas consumption are recommended for both sectors in the case of limited resources. Facilities can also use the results to decide which approaches fit better in their cases.

Keywords

energy efficiency; energy intensity tracking; energy performance baselining; energy performance tracking; manufacturing facility; linear regression modeling

1. Introduction

In the United States, manufacturing facilities consumed about 32% of total domestic energy in 2016 [1]. Improving the energy efficiency of these facilities enhances national energy independency, reduce greenhouse gas emissions, and increase company competitiveness. However, the lack of reliable data regarding energy savings has hindered the implementation of energy efficiency projects, and without such information, companies have postponed new and replacement investments [2, 3].

Because of the importance of quantifying energy savings generated from energy conservation measures, numerous measurement and verification (M&V) protocols have been developed. International Performance Measurement and Verification Protocol (IPMVP), ASHRAE Guideline 14, and Superior Energy Performance (SEP) M&V Protocol for Industry are referred to most frequently. IPMVP establishes the framework for computing energy savings achieved by energy efficiency projects in commercial and industrial facilities [4]. ASHRAE Guideline 14 covers the details on instrumental and data management, measurement types, uncertainty determination procedure, and regression techniques [5]. SEP M&V Protocol defines the procedure to verify energy performance improvement for Superior Energy Performance program facilities [6]. Many regional and program-specific M&V protocols and guidelines are derived from these national or international protocols.

Many studies have been performed on methodologies used to track energy savings and performance improvements in facilities. The simplest approach is to compare the annual total energy consumption on utility bills, but this is a very inaccurate methodology as it does not consider variations in products types, production rates, scheduling, or manufacturing processes. It only considers weather to some extent by comparing savings during similar time periods. To minimize the effects of relevant factors, other methodologies have been proposed and used, including multi-variable regression models and their variations [3, 7, 8, 9], sliding normalized energy intensity [10], neural network model [11, 12, 13, 14], and calibrated energy models [15, 16].

Currently the most widely adopted methodology is classic energy intensity (CEI), which simply divides total annual energy use by total annual production of plants. The advantages of CEI are its simplicity and intuitiveness. This methodology also considers the variation in production rates to some extent, which makes it an improvement over simple comparison of annual energy consumption on utility bills. However, this methodology fundamentally assumes that the relationship between the annual energy consumption and the production rate can be represented by a straight line through origin (i.e., intercept is zero), with the slope as the ratio of the annual energy consumption over the annual production rate [17]. In other words, it assumes that when the production rate is zero, the energy consumption is zero as well. Because of technological and operational limitations of manufacturing plants, the supporting energy systems and major manufacturing equipment very rarely load and unload perfectly with the production rate [18]. Therefore, the assumption of zero base energy consumption almost never holds valid.

A more accurate methodology is to use monthly energy consumption (or shorter time periods of energy consumption), production, and even weather data to generate linear regression models to represent the relationship between the energy consumption, the production rate, and the weather condition. Using an automotive assembly plant as an example, Wenning [17] showed that the one-variable (production only) linear regression model (1VLR) can represent the relationship between electricity and production significantly better than CEI (Figure 1). The advantage of the 1VLR can be also quantitatively demonstrated by the much greater value of R^2 (Coefficient of Determination) and much smaller value of SE (Standard Error).

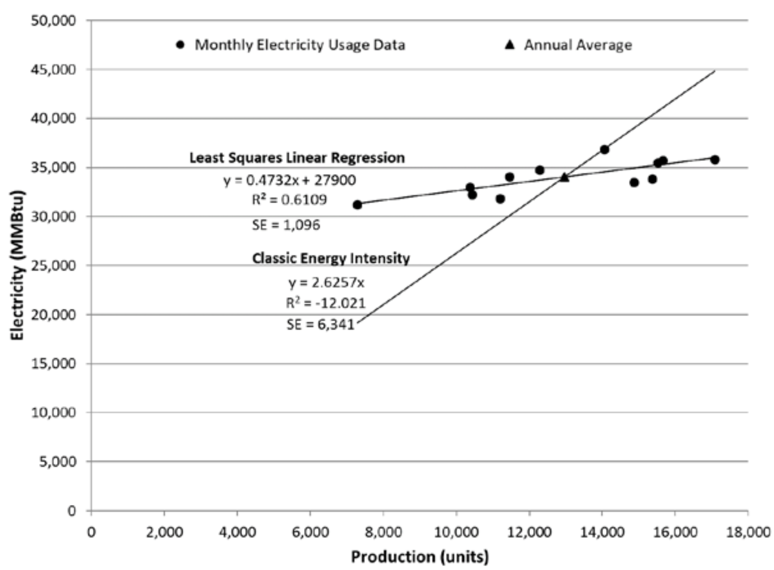

Figure 1. 1VLR vs. CEI [17].

However, because the regression models approach requires more data and statistical analysis expertise, it has only been adopted by a number of facilities and many doubt it is worth the effort to collect more data and generate linear regression models. This study presents quantitative results showing the improvement in accuracy that can be achieved using 1VLR compared with CEI and two-variable (production and weather) regression models (2VLR) compared with 1VLR by analyzing 477 monthly data sets over 11 years for two major manufacturing sectors, primary metal and transportation equipment manufacturing.

2. Methodology

2.1 Data Characteristics

To study the accuracy advantages of 1VLR over CEI and 2VLR over 1VLR, 477 sets of electricity usage, natural gas usage, cooling degree days (CDD), heating degree days (HDD), and production data for two manufacturing sectors (primary metal manufacturing and transportation equipment manufacturing) were analyzed (Table 1).

Because the characteristics of electricity and natural gas consumptions are typically different, they were studied separately, using their own CEI and 1VLR and 2VLR models. The 2VLRs for both electricity and natural gas include production; however, because electricity use is more governed by process cooling and natural gas by process heating, the second independent variables were CDD and HDD, respectively.

Table 1: Studied two manufacturing sectors

NAICS Code	NAICS Sector	Number of Data Sets	Data Time Range	# of Plants
331	Primary Metal Manufacturing	310	2005–2015	39
336	Transportation Equipment Manufacturing	167	2005–2015	40

2.2 Standard Error Ratio (SER)

Statistically, standard error (SE) of the estimates represents the average difference between the actual values and the regressions outputs [19], intuitively describing the fit of the regression models to the sample values. To compare these three approaches, ratios (SER) of the SE (CEI/1VLR and 1VLR/2VLR) were evaluated. If the SER is greater than unity, then the alternate method (the denominator) has less standard error than the original.

Many major measurement and verification protocols (e.g., ASHRAE 2014) have uncertainty requirements equal to or less than 10% and use 10% savings as an approach selection threshold. Therefore, this study selected an SER threshold of 1.1 to illustrate significant improvement over the original analysis method. The SER threshold of a given facility could be different from 1.1, depending on the accuracy requirements of energy performance tracking and the M&V protocols of the facility. However, selecting a different SER threshold might affect the conclusions presented here. In this study, when the SER was greater than 1.1, it was interpreted to mean that the accuracy had been significantly improved.

2.3 P-values of Intercept, CDD and HDD

CEI fundamentally uses a straight line through origin (i.e., intercept is zero) with the slope equal to the ratio of annual total energy over total production to represent the relationship between energy consumption and production. Conversely, the intercepts and slopes of regression models are determined by minimizing the sum of the squares of the differences between predicted and actual sample values, and thus experts consider linear regression models to be a more accurate representation of the plants' energy characteristics.

For a linear regression, the p-value of intercept tests the null hypothesis that the intercept equals to zero [20]. This study used it to evaluate the validity of CEI's zero intercept assumption. The smaller the p-value is, the more likely the above hypothesis is false, meaning that the intercept is non-zero and that more likely the assumption of zero intercept in CEI is flawed. While the inaccuracy of CEI may not just be due to faulty assumptions about the intercept but also the definition of the model's slope, this study only explores the intercept as the source of accuracy improvement by 1VLR over CEI.

In 2VLR, similarly, the p-values were used to test the null hypothesis that regression coefficients of the additional independent variables (CDD and HDD) were equal to zero (meaning CDD and HDD had no effect on the energy consumption). Like the intercept analysis, the smaller the p-value is, the more likely the above hypothesis is false, meaning that the coefficient is non-zero and the assumption of a zero coefficient in 1VLR is flawed. The minimum level of significance (minimum p-value) was set to 0.1, to be consistent with common manufacturing facilities' energy performance analysis methodologies [6, 21]. Because a p-value of 0.05 is also commonly used in general statistical fields, both significant levels are illustrated in the results.

Table 2 Summary of Statistical Tests

Test	**Accuracy Improvement of 1VLR over CEI**	**Accuracy Improvement of 2VLR over 1VLR**
Standard Error Ratio	CEI/1VLR >1.1	1VLR/2VLR>1.1
p-Values	Intercept p-Value < 0.1	CDD p-value < 0.1 (for electricity) HDD p-value < 0.1 (for natural gas)

3. Results and Discussions

3.1 1VLR vs. CEI

Primary Metal Manufacturing

Figures 2 and 3 show the SER (CEI/1VLR) distribution for various annual electricity and natural gas consumptions, respectively. For electricity and natural gas, the SER was greater than 1.0 for all plants, suggesting 1VLR was more accurate than CEI for all studied plants and production years. Figures 2 and 3 also show that SER for electricity was in general much greater than for natural gas. However, there was no clear relationship between SER and energy consumption.

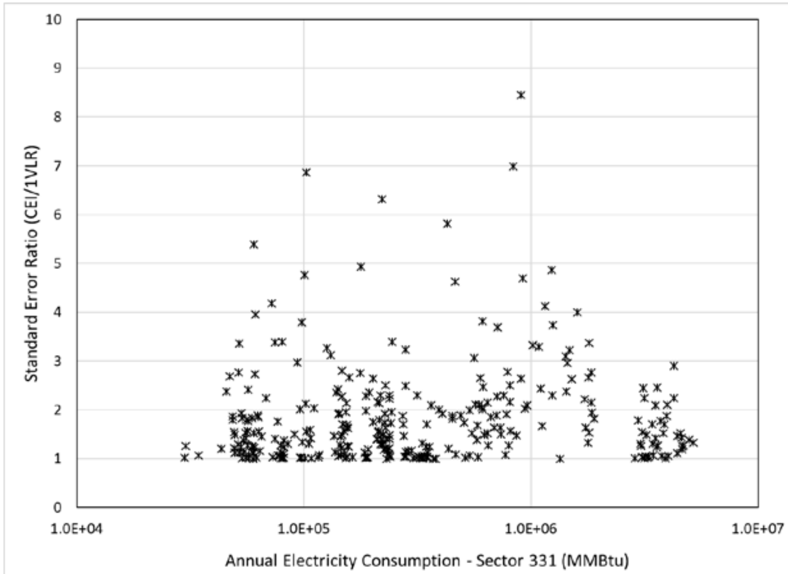

Figure 2. SER (CEI/1VLR) vs Plant Annual Electricity Consumption – Sector 331.

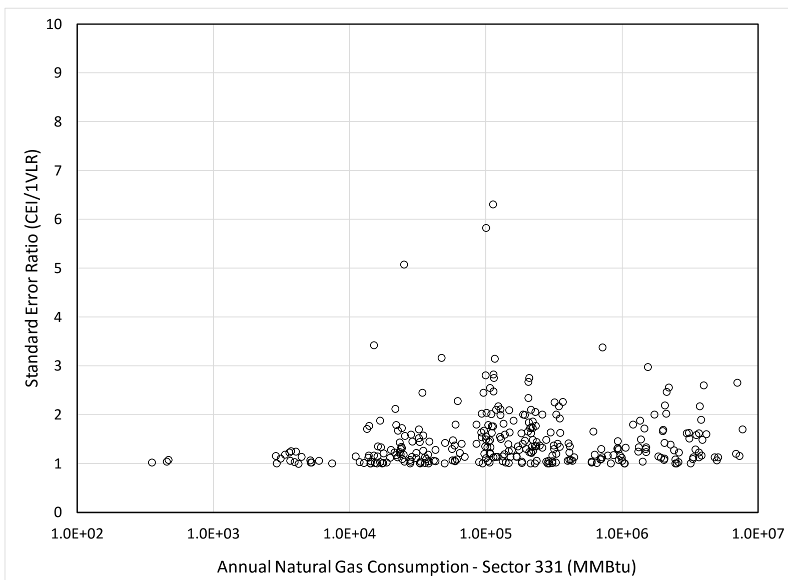

Figure 3. SER (CEI/1VLR) vs Plant Annual Natural Gas Consumption – Sector 331.

For electricity (Figure 4), 1VLR demonstrated significant accuracy improvement (i.e., SER was greater than 1.1) for 79% (244) of total data sets. For the other 21% (66) of total data sets, the SEs caused by CEI and 1VLR were close (SER was less than 1.1). Similarly, for natural gas, 73% (225) of total data sets showed significant accuracy improvement by 1VLR.

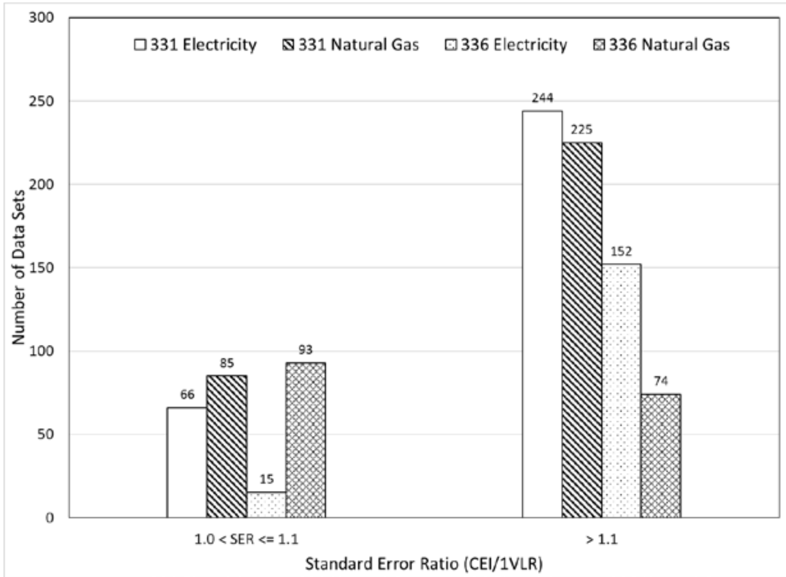

Figure 4. SER (CEI/1VLR) Bin Distribution.

As mentioned earlier, one of the two fundamental differences between CEI and 1VLR is that CEI assumes the intercepts of the linear equations to be zero and the p-value of intercept tests the null hypothesis that the intercept equals to zero. Figure 5 presents a histogram of the intercept p-value of for both electricity and gas in which both p-value cut-offs, 0.05 and 0.1, are shown. To follow the current general practice in this field, the cut significance of 0.1 was used for discussion here. For electricity, the p-value of intercept was significant for 75% (231) of the data sets. For natural gas, 63% (196) of the total data sets fell into this category. These observations from intercept p-values analysis were consistent with the ones from the SER analysis (Fig. 4).

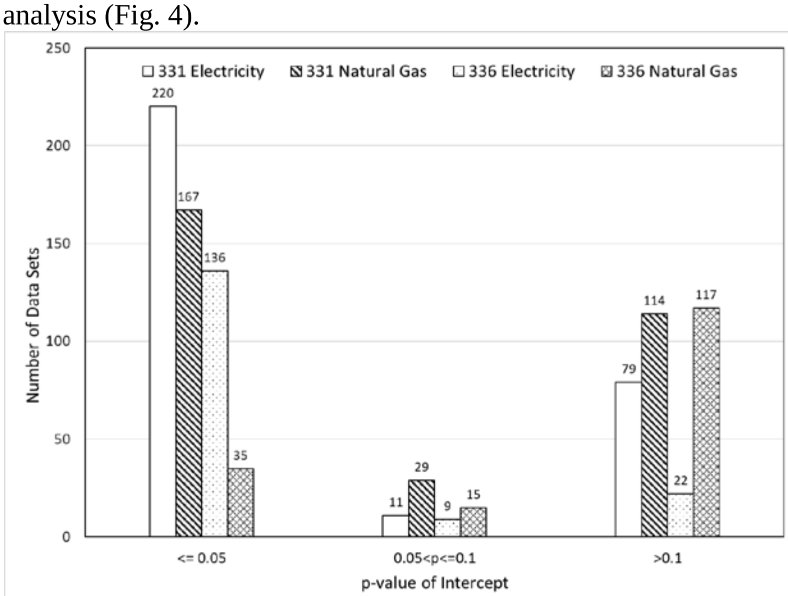

Figure 5. Intercept p-Value Bin Distribution.

Transportation Equipment Manufacturing

Figures 6 and 7 show 1VLR was more accurate than CEI for all studied plants and production years. Like Primary Metal Manufacturing, Figures 6 and 7 also show that SER for electricity was in general much greater than for natural gas. However, there was no clear relationship between SER and energy consumption.

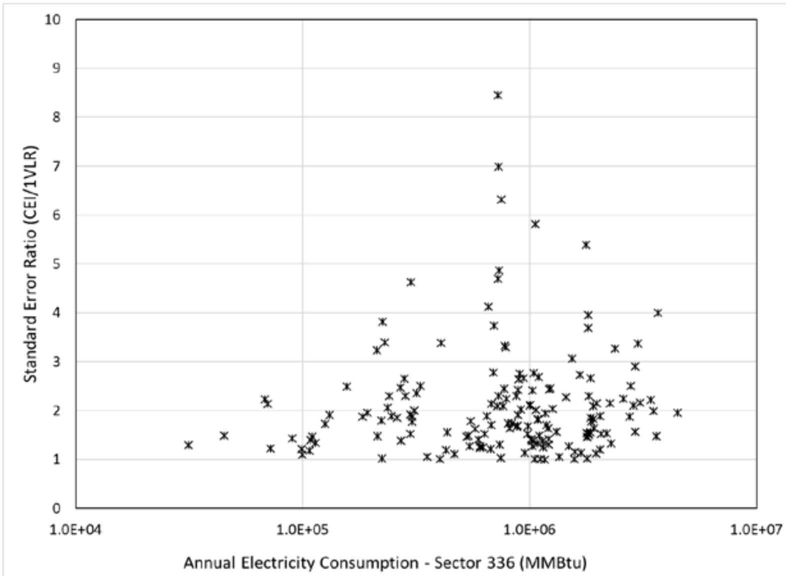

Figure 6. SER (CEI/1VLR) vs Plant Annual Electricity Consumption – Sector 336.

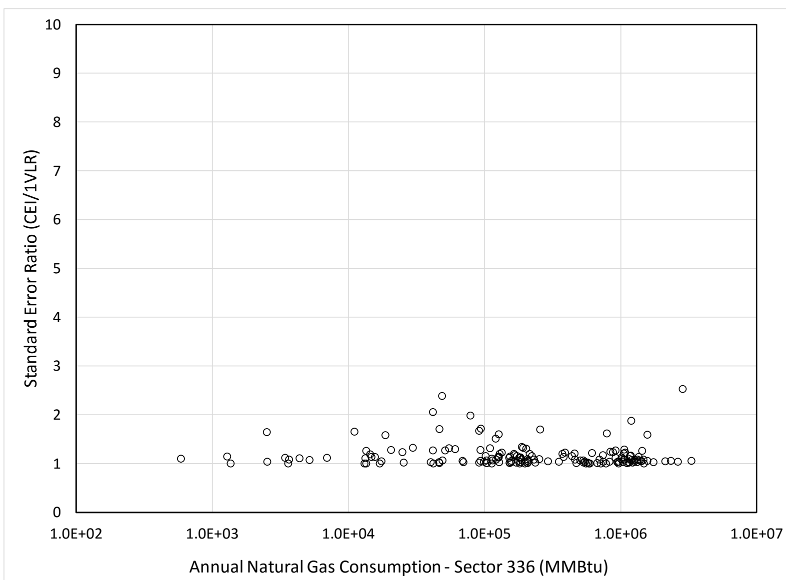

Figure 7. SER (CEI/1VLR) vs Plant Annual Natural Gas Consumption – Sector 336.

A similar analysis was performed for the Transportation Equipment Manufacturing sector (Figure 4). For electricity, 91% (152) of total data sets showed significant accuracy improvement by 1VLR, which was more than the Primary Metal Manufacturing sector. Additionally, the intercept p-value was less than 0.1 for 86% (145) of total data sets (Figure 5).

For natural gas, 1VLR demonstrated significant accuracy improvements for 44% (74) of total data sets, fewer than the Primary Metal Manufacturing sector (Figure 4). The intercept p-value was less than 0.1 for 30% (50) of total data sets (Figure 5). It was worth noting that the number of data sets that showed accuracy improvements via SER was higher than the ones with significant intercept p-values. One possible reason is that the accuracy improvement for these data sets by 1VLR, in addition to the different intercepts, could also be due to the different slope calculations between CEI and 1VLR.

3.2 2VLR vs. 1VLR

Primary Metal Manufacturing

To include the impact of weather conditions on energy consumption, CDD and HDD were also incorporated to the electricity and natural gas regression models, respectively. Weather conditions are known to affect space and manufacturing processes' cooling and heating, and thus energy consumption. Experts often recommend the inclusion of these variables, based on the assumption that they improve model accuracy. This section explores that assumption.

The standard errors caused by 1VLR (production is the only independent variable) and 2VLR (production and CDD for electricity; production and HDD for natural gas) are compared in Figure 8. For electricity, adding CDD improved 42% (130) of total data sets, showing that CDD significantly improved the regression models' accuracy. This can be explained by the significance of the CDD coefficient (p-value of CDD was less than 0.1) for 42% (130) of total data sets (Figure 9).

For natural gas, significant accuracy improvement after adding HDD to the regression models was demonstrated for 76% (235) of total data sets. Additionally, the p-value of HDD was less than 0.1 for 73% (229) of total data sets.

Transportation Equipment Manufacturing

For electricity, 59% (98) of total data sets showed significant accuracy improvement [SER (1VLR/2VLR) is greater than 1.1] (Figure 8). This aligned very well with 59% (97) of total data sets, which had significant CDD p-values (Figure 9).

For natural gas, 95% (158) of total data sets showed significant accuracy improvement [SER (1VLR/2VLR) is greater than 1.1] and the HDD p-values were significant for 95% (158) of total data sets.

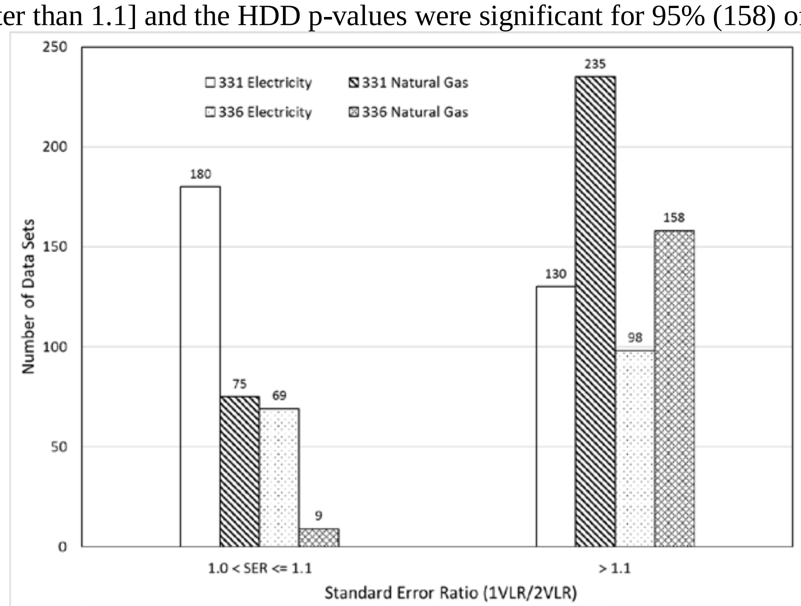

Figure 8. SER (1VLR/2VLR).

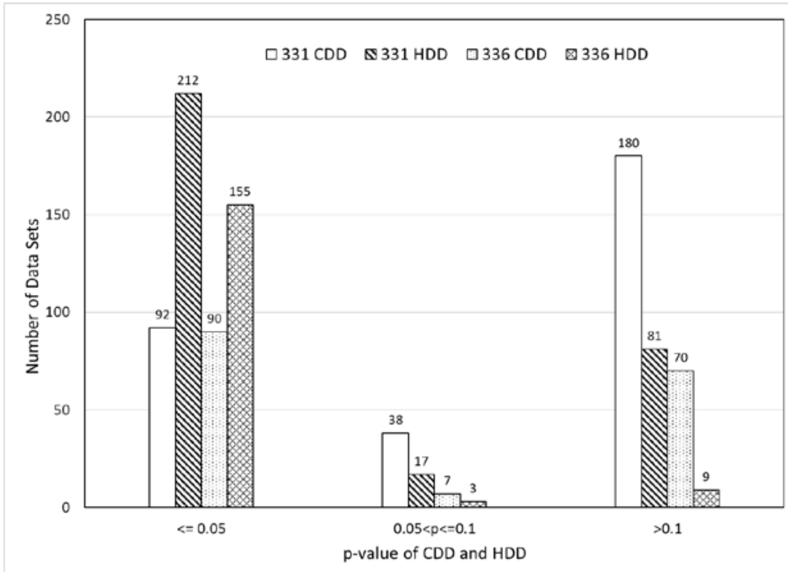

Figure 9. p-values of CDD and HDD.

3.3 2VLR vs. CEI

Primary Metal Manufacturing

Compared to CEI, 2VLR showed significant accuracy improvement for 90% (280) of total data sets for electricity and 92% (286) of total data sets for natural gas (Figure 10).

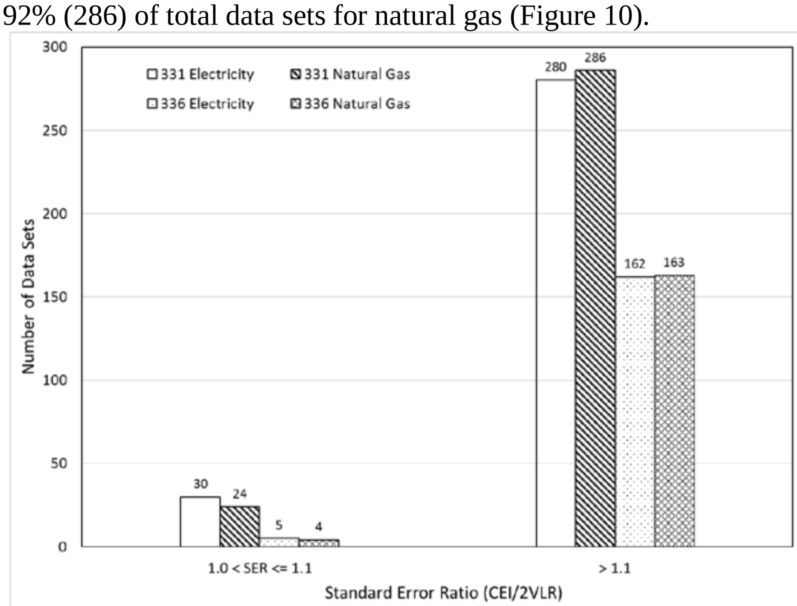

Figure 10. SER (CEI/2VLR).

Transportation Equipment Manufacturing

Compared to CEI, 2VLR showed significant accuracy improvement for 97% (162) of total data sets for electricity and 98% (163) of total data sets for natural gas (Figure 10).

3.4 Approaches Selection

Based on these results, it can be concluded, if not limited by data availability and analysis resources, 2VLRs are typically more accurate for modeling the energy performance of primary metal and transportation equipment manufacturing facilities. This approach almost always had lower standard errors than 1VLR and CEI, although the accuracy improvements might not be substantial (i.e., SERs were less than 1.1) for some cases.

1VLR demonstrated significant accuracy improvement in electricity consumption tracking for 79% of the Sector 331 data sets and 91% of the Sector 336 data sets. Developing electricity 1VLRs is highly recommended for both sectors.

For natural gas, accuracy improvement by 1VLR was shown for 73% of the Sector 331 data sets and 44% of the Sector 336 data sets. Hence, developing natural gas 1VLRs for the Sector 331 is logical. 1VLR is still recommended over CEI for natural gas; however, for the Sector 336, as shown in Figure 8, HDD had a great impact on reducing model error. Because production rate is of paramount importance to manufacturing facilities, production is almost always included before adding new independent variables.

Adding CDD to electricity linear regression models significantly improved model accuracy for just about 50% of facilities (42% of the Sector 331 data sets and 59% of the Sector 336 data sets). If limited by data availability and analysis resources, facilities in these two sectors may choose to use 1VLRs, instead of two-variable (production and CDD) linear regression models for electricity. However, adding HDD to natural gas linear regression models significantly improved accuracy for 76% of the Sector 331 data sets and 95% of the Sector 336 data sets. Therefore, developing two-variable (production and HDD) linear regression models is recommended for natural gas for both sectors.

4. Conclusions

Because it can be easily understood and calculated, the classic energy intensity method (CEI) is widely used to track manufacturing facilities' energy performance. However, CEI is based on a fundamental assumption about the relationship between energy consumption and production that is very rarely valid. Therefore, a one- or multiple-variable linear regression models approach is generally recommended. However, due to limited data availability and analysis resources, only some facilities use the regression models approach, and many suspect it is not worth the effort in their specific cases.

In this study, the accuracy of CEI, one-variable (production only) linear regression models (1VLRs), and two-variable (production and weather) linear regression models (2VLRs) were compared for primary metal and transportation equipment manufacturing sectors. By analyzing 477 data sets covering 79 plants and 11 production years, the following major conclusions were reached.

1. For both primary metal and transportation equipment manufacturing sectors, the errors caused by CEI were in general greater for electricity than for natural gas.
2. For primary metal manufacturing, compared to CEI, 1VLR showed significantly improved accuracy for 79% of electricity consumption data sets and 73% of natural gas consumption data sets. For transportation equipment manufacturing, 1VLR showed significant accuracy improvement for 91% of electricity consumption data sets and 44% of natural gas consumption data sets. These results are well supported by the distribution of the intercept's p-value.
3. For primary metal manufacturing, compared to 1VLRs, 2VLRs showed significant accuracy improvement for 42% of electricity consumption data sets and 76% of natural gas consumption data sets. For transportation equipment manufacturing, 2VLRs showed significant accuracy improvement for 59% of electricity consumption data sets and 95% of

natural gas consumption data sets. This can be explained by the distribution of CDD's and HDD's p-values.

4. For primary metal manufacturing, compared to CEI, 2VLRs showed significant accuracy improvement for 90% of total data sets for electricity and 92% of total data sets for natural gas. For transportation equipment manufacturing, compared to CEI, 2VLRs showed significant accuracy improvement for 97% of total data sets for electricity and 98% of total data sets for natural gas.
5. For both primary metal and transportation equipment manufacturing, provided resources are available, two-variable (production and weather) linear regression models for both electricity and natural gas consumption are recommended. To achieve a good balance between accuracy improvements and resources requirements, one-variable (production only) linear regression models for electricity consumption and two-variable (production and HDD) linear regression models for natural gas consumption are recommended for both sectors in the case of limited resources.

5. Acknowledgments

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6. References

[1] EIA (2017). Monthly Energy Review, July 2017.

[2] Sandberg, P. and M. Söderström (2003). "Industrial energy efficiency: the need for investment decision support from a manager perspective." Energy Policy 31(15): 1623–1634.

[3] Kissock, J. K. and C. Eger (2008). "Measuring industrial energy savings." Applied Energy 85(5): 347–361.

[4] EVO (2012). International Performance Measurement and Verification Protocol (IPMVP), Vol 1.

[5] ASHRAE (2014). ASHRAE Guideline 14 Measurement of Energy, Demand, and Water Savings.

[6] USDOE (2013). Superior Energy Performance Measurement and Verification Protocol for Industry.

[7] Boyd, G. A. (2005). "A method for measuring the efficiency gap between average and best practice energy use: the ENERGY STAR industrial energy performance indicator." Journal of Industrial Ecology 9(3): 51–65.

[8] Boyd, G. A. (2009). Development of a Performance-based Industrial Energy Efficiency Indicator for Pharmaceutical Manufacturing Plants, Duke University.

[9] Liu, Y., et al. (2016). "Toyota Motor Energy Analysis and Modeling," Duke University.

[10] Lammers, N., et al. (2011). "Measuring progress with normalized energy intensity." Society of Automotive Engineers World Congress Conference. Detroit, MI, USA.

[11] Anstett, M. and J. F. Kreider (1993). "Application of neural networking models to predict energy use." ASHRAE Transactions 99(1): 505–517.

[12] Kissock, J. K. (1994). "Modeling commercial building energy use with artificial neural networks." Intersociety Energy Conversion Engineering Conference 3: 1290–1295.

[13] Kalogirou, S. A. (2000). "Applications of artificial neural-networks for energy systems." Applied Energy 67(1): 17–35.

[14] Rossi, F., et al. (2014). "Artificial neural networks and physical modeling for determination of baseline consumption of CHP plants." Expert Systems with Applications 41(10): 4658–4669.

[15] Carpenter, K. and J. K. Kissock (2005). "Quantifying Savings from Improved Boiler Operation." Industrial Energy Technology Conference, New Orleans, LA, USA.

[16] Xia, X. and J. Zhang (2013). "Mathematical description for the measurement and verification of energy efficiency improvement." Applied Energy 111: 247–256.

[17] Wenning, T., et al. (2017). Quantifying the statistical importance of utilizing regression over classic energy intensity calculations for tracking efficiency improvements in industry. ACEEE Summer Study on Energy Efficiency in Industry. Denver, CO, USA.

[18] USDOE (2015). Quadrennial Technology Review 2015.

[19] Draper, N. R. and H. Smith (1998). Applied Regression Analysis. New York, NY, Wiley-Interscience.

[20] Kutner, M. H., et al. (2004). Applied Linear Regression Models. New York City, NY, McGraw-Hill Education.

[21] US DOE (2015). Energy Intensity Baselining and Tracking Guidance.