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Restaurant Energy Use Benchmarking Guideline

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Boulder, Colorado

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Golden, Colorado

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Executive Summary

Architectural Energy Corporation (AEC), an energy and environmental research, development, and design consulting firm in Boulder, Colorado, prepared this document for the Alliance for Sustainable Energy, LLC, the operating entity for the U.S. Department of Energy National Renewable Energy Laboratory. The AEC Project Manager is Judie Porter.

Background

A significant operational challenge for food service operators is defining energy use benchmark metrics to compare against the performance of individual stores. Without metrics, multiunit operators and managers have difficulty identifying which stores in their portfolios require extra attention to bring their energy performance in line with expectations. Energy use per unit of floor area is highly variable across food service facility types; the single energy use intensity as defined for ENERGY STAR® Portfolio Manager would not be adequate to benchmark restaurant performance. Also, the variance in food service facility types was significant enough that developing metrics at the multiunit operator level would likely be more successful than industry-wide metrics.

The size of the floor plate, by itself, is not typically an adequate normalizing factor. Over the past 20 years, the floor plate size has changed (often shrinking); the number of meals served at each store has simultaneously increased. Other variables, such as number of transactions (meals served equivalent), hours of operation, operational practices, and the number and type of appliances, have a discernable influence on energy use. The absence or presence of seating in conditioned space, location and customer traffic patterns, climate zone, absence or presence of automated control systems (time clocks, building energy management systems), facility type (stand-alone building, interior space in a larger building, etc.), type of walk-in refrigeration, and the amount of outside and parking lot lighting included in the utility bill are also energy use factors.

Development Process

This report presents a method whereby multiunit operators may use their own utility data to create suitable metrics for evaluating their operations. It can be used to:

- Provide a high-level view of energy use for all stores.
- Identify stores with high and low energy use.
- Track changes in energy use metrics.

The benchmarking procedure has three major steps. The first two comprise the high-level analysis we propose and will often suffice for a broad characterization of the multiunit operator's portfolio. The third step can be added to conduct a more advanced analysis.

1. Collect data (store locations, annual electricity and gas energy use from utility bills, transactions, operating hours, floor area, store type, etc.).
2. Use histograms and scatter plots to prepare statistical summaries by store type.
3. Prepare multiple regression equations for predicting annual energy use.

The Benchmarking Guideline consists of this report and an example spreadsheet using Microsoft Excel 2003. It shows examples based on data from one multiunit operator. An analyst may use it as the starting point to develop a customized analysis.

Evaluation Approach and Results

The results presented here and in the example spreadsheet are specific to the single dataset analyzed and do not suggest metric targets. Transaction data are usually confidential, so the example spreadsheet includes only normalized transactions.

Tracking energy use metrics over time will provide visibility into system-wide energy performance, identify the top energy users, and enable targeted programs to drive energy use toward programmatic energy targets.

The procedure described here provides a starting point to develop a customized, in-house analysis and tracking system that will help multiunit operators understand how stores use energy. Customized procedures might include analysis of water use (hot water, irrigation, restrooms) and the influence of the number of parking lot lights. In some cases, submetering will have to be installed before the parameters can be extended. The procedure could also be extended to monthly utility use, particularly if automated data acquisition (through a billing service for example) and analyses are implemented. In any case, the procedure should enable multiunit operators to better evaluate restaurants in their portfolios and then prioritize investments in energy saving actions such as retrofits and operational improvements.

Nomenclature

AEC	Architectural Energy Corporation
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
CBEA	Commercial Building Energy Alliance
CDD	cooling degree day
DOE	Department of Energy
HDD	heating degree day
HVAC	heating, ventilation, and air conditioning
IQ	interquartile
NIST	National Institute of Standards and Technology
NREL	National Renewable Energy Laboratory

Contents

Acknowledgments iii
Executive Summary iv
  Background iv
  Development Process iv
  Evaluation Approach and Results v
Nomenclature vi
Figures and Tables viii
  Figures viii
  Tables ix
1.0 Introduction 1
  1.1 Factors Influencing Energy Use 1
  1.2 Limitations of Annual Energy Use Data 1
2.0 Step-by-Step Discussion of Energy Use Benchmarking Procedure 3
  2.1 High-Level Performance Evaluation 6
    2.1.1 Step 1 6
    2.1.2 Step 2 6
    2.1.3 Step 3 6
    2.1.4 Step 4 7
    2.1.5 Step 5 7
    2.1.6 Step 6 16
  2.2 Advanced Performance Evaluation and Prediction 16
    2.2.1 Step 7 16
    2.2.2 Step 8 18
    2.2.3 Step 9 18
    2.2.4 Step 10 18
3.0 Summary and Additional Considerations 22
4.0 References and Bibliography 23
Appendix A Histograms of Electricity and Natural Gas Use 24
Appendix B Scatter Plots of Electricity and Natural Gas Use versus Normalized Transactions 29
Appendix C Discussion of Heating Degree Days and Cooling Degree Days 34
  C.1 Balance Point 34
  C.2 Variable Base Degree Days 34
  C.3 Food Service Facility Balance Points 34

Figures and Tables

Figures

Figure 2-1 Flow chart summary of high-level performance evaluation 4
Figure 2-2 Flow chart summary of advanced performance evaluation and prediction 5
Figure 2-3 Number of stores by annual electricity use 11
Figure 2-4 Number of stores by type by annual electricity use 12
Figure 2-5 Example of annual electricity use scatter plot to show outliers 12
Figure 2-6 Example of annual natural gas use scatter plot to show outliers 13
Figure 2-7 Example annual electricity use box plot with inner fences 14
Figure 2-8 Example annual natural gas use box plot with inner fences 15
Figure A-1 Histogram of electricity use by store type 24
Figure A-2 Histogram of natural gas use by store type 24
Figure A-3 Histogram of electricity use for store type A (197 stores) 25
Figure A-4 Histogram of natural gas use for store type A (197 stores) 25
Figure A-5 Histogram of electricity use for store type B (399 stores) 26
Figure A-6 Histogram of natural gas use for store type B (399 stores) 26
Figure A-7 Histogram of electricity use for store type C (86 stores) 27
Figure A-8 Histogram of natural gas use for store type C (86 stores) 27
Figure A-9 Histogram of electricity use for store type D (206 stores) 28
Figure A-10 Histogram of natural gas use for store type D (206 stores) 28
Figure B-1 Scatter plot of electricity use for all stores 29
Figure B-2 Scatter plot of natural gas use for all stores 29
Figure B-3 Scatter plot of electricity use for store type A 30
Figure B-4 Scatter plot of natural gas use for store type A 30
Figure B-5 Scatter plot of electricity use for store type B 31
Figure B-6 Scatter plot of natural gas use for store type B 31
Figure B-7 Scatter plot of electricity use for store type C 32
Figure B-8 Scatter plot of natural gas use for store type C 32
Figure B-9 Scatter plot of electricity use for store type D 33
Figure B-10 Scatter plot of natural gas use for store type D 33

Tables

Table 2-1 Summary of Statistics by Store Type 9

Table 2-2 Example Annual Kilowatt-Hour Data Range for Use in Histogram Function 11

Table 2-3 Regression Equation Matrix Using Raw Data 19

Table 2-4 Regression Equation Matrix Using Processed Data 20

Table 2-5 Regression Equation Matrix With CDDs and HDDs Added 21

1.0 Introduction

The U.S. Department of Energy National Renewable Energy Laboratory is working with the Restaurant Project Team of the Commercial Building Energy Alliance to identify energy savings technologies, components, products, and operational strategies. A significant operational challenge for food service operators is defining energy use benchmark metrics to compare against the performance of individual stores. Without this, multiunit operators and managers have difficulty identifying which stores require extra attention to bring their energy performance in line with expectations.

Several years ago, a national restaurant subcommittee, working with Fisher-Nickel, Inc., attempted to define metrics that could be used for the ENERGY STAR® Portfolio Manager Program. The program requires energy use intensity defined as Btu/ft^2, which requires combining consumption values for commonly used power sources, such as electricity, natural gas, and propane. The committee found that energy use per unit of floor area was highly variable across food service facility types because of different facility types, differences in menu, number of meals served, cooking and refrigeration appliances, hours of operation, and many other factors (unpublished report). The variance was so wide that the subcommittee members concluded that the energy use intensity as defined for ENERGY STAR would not be adequate to benchmark energy use. In particular, separate metrics need to be used for each energy source. They also found that the variance in food service facility types was significant enough that developing benchmarks for a given multiunit operator would likely be more successful than the national level benchmarks found in ENERGY STAR Portfolio Manager.

This report presents a method for multiunit operators to use their own utility data to create suitable benchmarks for evaluating their operations. It can be used to:

- Provide a high-level view of energy use for all stores.
- Identify stores with high and low energy use.
- Track changes in energy use.

1.1 Factors Influencing Energy Use

The size of the floor plate, by itself, is not usually adequate as a normalizing factor to fully characterize energy consumption. Over the past 20 years, the typical floor plate size has changed (often shrinking), and the number of meals served at each store has increased. Hours of operation, operational practices, and the number and type of appliances also have a discernable influence on energy use. The authors' experience has shown that the absence or presence of seating in conditioned space, location and customer traffic patterns, climate zone, absence or presence of automated control systems (time clocks, building energy management systems), facility type (stand-alone building, interior space in a larger building, etc.), type of walk-in refrigeration, and the amount of outside and parking lot lighting included in the utility bill are also factors.

1.2 Limitations of Annual Energy Use Data

Annual energy use is convenient because it has 1/12 the data points of the monthly data from which it was derived. But convenience, in this case, hides information that could be used to diagnose why the energy use in a particular store is high or low. It also hides data accumulation errors. For example, if one month of electricity use were missing for a particular store, it would not be apparent, and the resulting lower annual energy use would make that store look more energy efficient than its peers. Likewise, apparent high energy use may result from doubling up some monthly energy bills. Our scope of work includes analysis using annual energy numbers only; however, with careful modifications, one could extend it to include analysis of subannual periods.

2.0 Step-by-Step Discussion of Energy Use Benchmarking Procedure

This procedure consists of several distinct steps: Figure 2-1 shows these steps for the basic, high-level analysis; Figure 2-2 shows the additional steps necessary to complete the more advanced analysis. Greater detail follows the figures.

The procedure is divided into these two analysis levels because the operators tasked with identifying restaurants in need of audits, inspections, and retrofits often face tight time constraints. In many instances, a quicker, high-level analysis will help the operator identify retrofit opportunities; however, some may benefit from the potential for greater accuracy in benchmarking and the creation of benchmarking equations that can predict energy consumption under varying operational conditions.

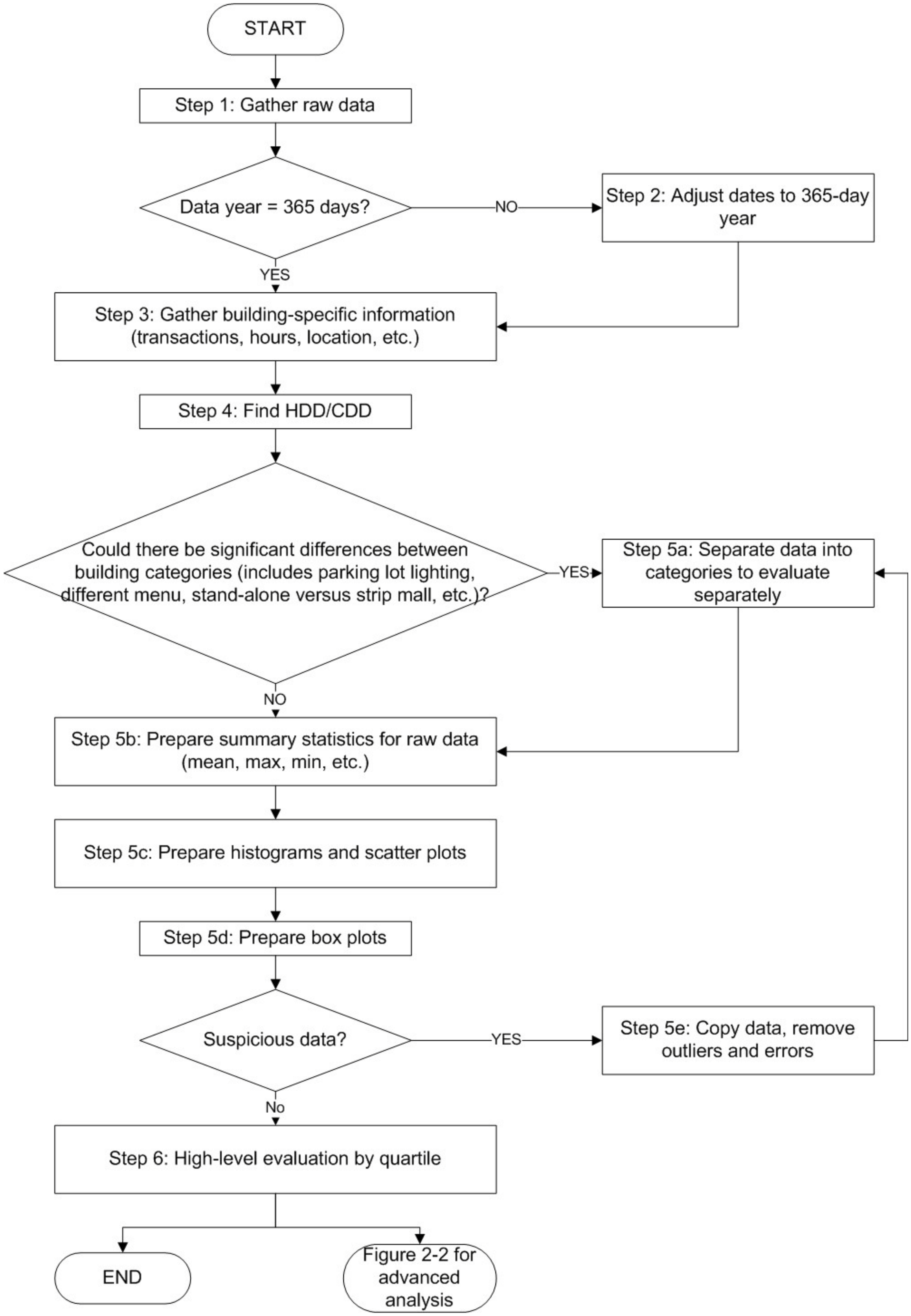

Figure 2-1 **Flow chart summary of high-level performance evaluation**

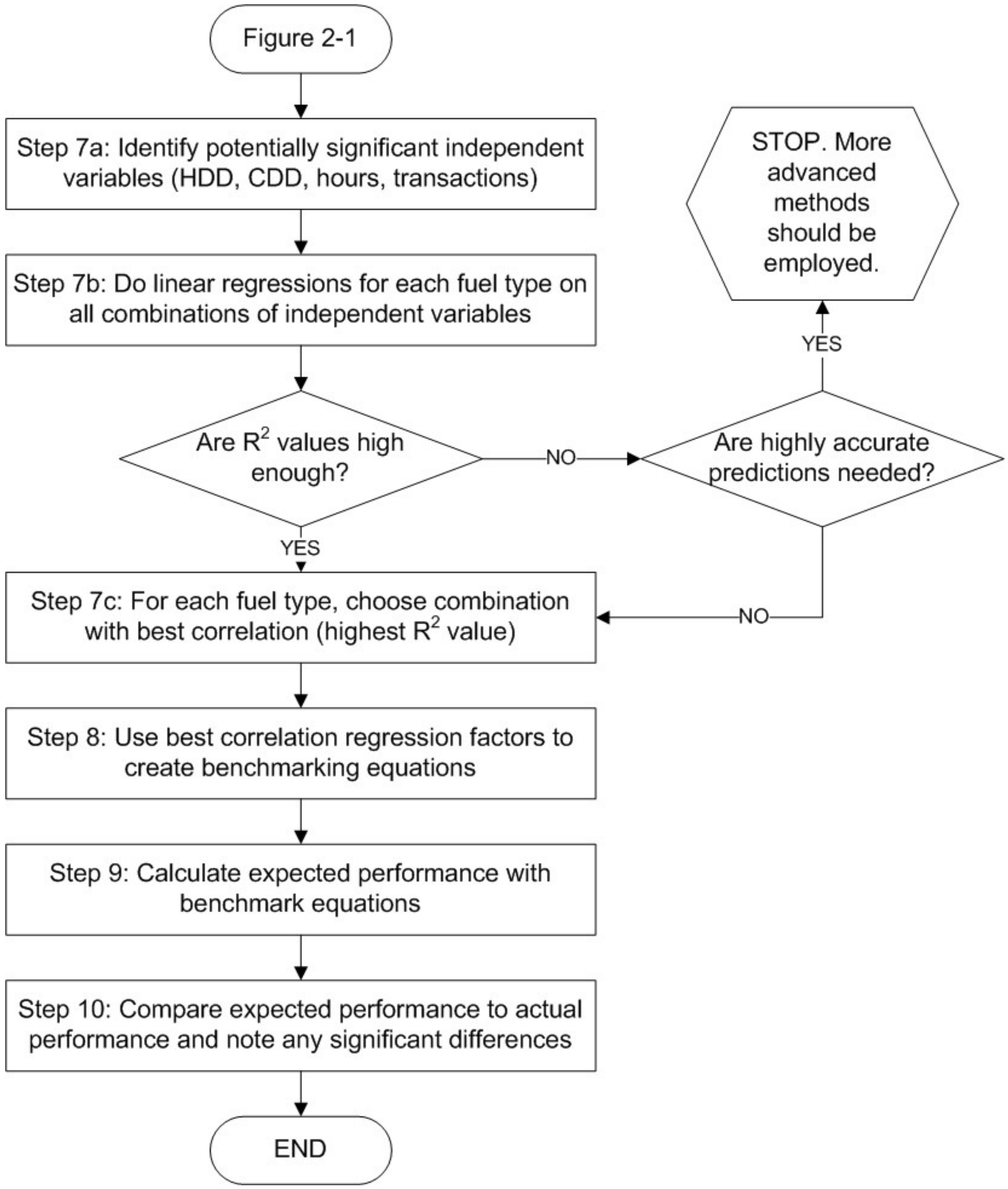

Figure 2-2 Flow chart summary of advanced performance evaluation and prediction

In Figure 2-2, it is important to note that the R^2 value does not represent the only statistical parameter that could be relevant to evaluating the strength of the linear regressions. This statistic is emphasized here because it is more widely known and is included in the example spreadsheet.

Distinguishing which correlation fits the operator's needs might be a function of the difference in R^2 values between two regressions instead of the two absolute values. For example, one hypothetical regression might combine the effects of transactions and weekly hours and result in an R^2 value of 38%. Another regression might add the effects of heating degree day (HDD) to those of transactions and weekly hours and result in an R^2 value of 39%. Including the HDD independent variable increased the R^2 value, and therefore the strength of the regression, but perhaps not enough to justify the extra effort involved in obtaining the HDD values for multiple stores. The analyst might instead choose to focus on regressions based only on transactions and weekly hours. Whether or not the analyst feels confident using benchmarking equations with R^2 values on the order of 38% is another matter; statisticians prefer R^2 values closer to 70%–95%, but such correlation strengths may not be achievable without extra submetering or advanced energy management system efforts.

The following sections provide a discussion for each step in the procedure. The results are specific to the single dataset analyzed and do not suggest metric targets. Transaction data are usually confidential, so the example spreadsheet includes only normalized transactions.

2.1 High-Level Performance Evaluation

Explanation is provided here for the steps illustrated in Figure 2-1.

2.1.1 Step 1

Gather data for electricity (kilowatt-hours and annual peak kilowatts), gas (therms, cubic feet, or hundred cubic feet), propane (therms, cubic feet, or hundred cubic feet), other utility bill information (such as water and sewer use in gallons or hundred cubic feet), and total cost for each utility type summarized annually in a spreadsheet.

2.1.2 Step 2

Identify the analysis year. Determine annual totals by summing 12 consecutive monthly totals and adjusting for the number of included days. An analysis year consists of 365 consecutive days, whether or not the data were collected during a leap year. In the event that the 12 consecutive months amount to slightly more or fewer than 365 days, the total should be adjusted by adding or subtracting average daily values symmetrically for the beginning and end months of the analysis year (Barley et al. 2005).

The available data will likely contain errors and anomalies. At this stage, the data may be termed *raw*; after errors or anomalies are removed from the dataset, the dataset will be called *processed*.

2.1.3 Step 3

Gather the following information about each store:

- Transactions (number of meals served equivalent for the same period as the utility bills)
- Hours of operation
- Building type (stand-alone, embedded, different brands/menu types, etc.)
- Floor plate size (note use of net or gross floor area and whether floor area is conditioned)
- Location (zip code or latitude and longitude)
- Whether parking lot lighting is included in the utility bill.

The most important data are the transactions, followed by hours of operation, location (climate), and building type. Other factors, such as whether parking lot lighting is included in the electric utility bill, also have an observable influence on energy use and help explain the variance in use among stores that are otherwise comparable.

2.1.4 Step 4

Using zip code or latitude/longitude data, add HDDs (Base 50°F) and cooling degree days (CDDs) (Base 65°F) for each store in the database. If degree day data using different bases are available, these may be used to see if a better regression data fit can be obtained. Appendix C includes more information on variable base degree day calculations and why Base 50°F works well for HDD and Base 65°F works well for CDD in this dataset. Ensure that there is a reasonable match between the days of the month represented by degree days and those represented by the utility data.

This may be a time-consuming one-time task, but it is important because climate influences electricity consumption for cooling and natural gas use for heating. The example in the Guideline uses "normal degree day data," which is degree day data based on a historical reference period. A more accurate approach would be to use actual CDD and HDD data for the actual analysis period, but these data may not be readily available for all locations. Furthermore, this step would need to be repeated if the analysis were undertaken each year. Commercial as well as governmental sources are available for summarized data. Some datasets are free; others are available for a fee. Degree day data can be obtained from the National Climatic Data Center (NCDC 2011).

The base temperature (50°F) suggested for the HDD is lower than that typically used for residential or commercial office analysis because food service operations have higher internal loads. (See Appendix C for further discussion of HDDs and CDDs.)

2.1.5 Step 5

Step five involves segregating and processing the data and reviewing basic statistics. For clarity, Step 5 consists of five substeps (5a–5e).

2.1.5.1 Step 5a

Segregate data by categorical variables: store type (stand-alone, etc.), whether or not parking lot lighting is included in the utility bills, etc. These can be labeled as type "A", "B", "C", and "D."

At a minimum, concepts or construction prototypes (differences in menu, food process appliances, floor plate area, etc.) should be grouped into separate datasets. The data subsets should have at least 50 stores each; fewer than 50 stores do not provide an adequate statistical sample (NIST/SEMATECH 2011). Table 2–1 shows differences in energy use and normalized transactions for one multiunit operator's data.

2.1.5.2 Step 5b

Prepare a summary of raw data, including maximum, minimum, mean (average), standard deviation, and count.

This summary will provide some insight into the raw dataset, showing typical energy use and providing information about data extremes that may be incorrect data, or data that are not appropriate to include in the dataset.

2.1.5.3 Step 5c

Prepare histograms and scatter plots of each energy type (see example spreadsheet).

The histograms and scatter plots will provide insight into the distribution of the energy data. This is important because certain statistical tests, to be applied in later steps, assume a normal distribution of the data (a bell shaped or Gaussian curve). Alternative tests may be used if the data distribution is skewed to the right or left.

Excel has a Histogram function under the Data Analysis Subtab of the Data Tab. It requires that each cell within the range have valid numeric data (no missing data – blank cells, and no alpha characters). If data are missing, the record should be copied to another sheet and then the original record eliminated from the analysis range. To use the Histogram function, create a column with bins of data (kWh/yr in this case), at an interval that will provide a good overview of the data spread. Table 2–2 is an example of the data range used to create the charts shown in Figure 2-3 and Figure 2-4. Additionally, the example spreadsheet has equations that create the counts in the bin.

Table 2-1 Summary of Statistics by Store Type

Store Type	Statistic	Annual Electricity Use (kWh)	Annual Gas Use (Therms)	Normalized Weekly Transactions	Area (ft^2)	Weekly Hours	CDD65	HDD50
All	Total	297,709,262	9,716,986	344.967	2,899,767	120,659	1,271,779	800,718
	Max	603,960	29,776	1.000	8,153	168	3,866	3,552
	Min	16,360	426	0.043	1,376	73	121	4
	Mean	335,258	10,943	0.388	3,266	136	1,432	902
	Std. Dev	92,936	3,227	0.116	557	19	554	873
	Median	341,609	10,820	0.378	3,333	128	1,348	671
	Q1	279,484	9,066	0.321	3,000	124	1,158	97
	Q3	401,966	12,936	0.453	3,516	143	1,685	1,409
	Count	888	888	888	888	888	888	888
Type A	Total	52,201,682	2,218,016	82.296	628,235	26,852	250,046	67,174
	Max	406,720	17,248	1.000	4,898	168	3,038	3,552
	Min	18,560	756	0.114	1,376	73	121	4
	Mean	264,983	11,259	0.418	3,189	136	1,269	341
	Std. Dev	55,060	2,466	0.136	623	21	500	657
	Median	266,088	11,244	0.394	3,100	131	1,294	65
	Q1	232,089	10,069	0.319	2,759	126	959	15
	Q3	301,228	12,747	0.495	3,516	168	1,534	331
	Count	197	197	197	197	197	197	197
Type B	Total	148,694,470	3,875,113	143.302	1,293,318	52,513	622,774	508,075
	Max	603,960	29,776	0.777	4,320	168	3,866	3,481
	Min	16,360	440	0.043	1,650	109	450	28
	Mean	372,668	9,712	0.359	3,241	132	1,561	1,273

Store Type	Statistic	Annual Electricity Use (kWh)	Annual Gas Use (Therms)	Normalized Weekly Transactions	Area (ft^2)	Weekly Hours	CDD65	HDD50
	Std. Dev	97,846	3,215	0.104	446	16	533	719
	Median	389,560	9,369	0.358	3,333	127	1,501	1,104
	Q1	348,280	8,383	0.302	3,230	121	1,240	845
	Q3	426,440	11,026	0.416	3,490	132	1,699	1,586
	Count	399	399	399	399	399	399	399
Type C	Total	33,943,348	922,638	33.887	303,244	11,777	141,380	132,639
	Max	544,280	17,748	0.930	8,153	168	3,231	2,790
	Min	99,120	1,870	0.098	1,960	105	845	42
	Mean	394,690	10,728	0.394	3,526	137	1,644	1,542
	Std. Dev	85,538	2,770	0.109	809	16	636	905
	Median	406,739	10,836	0.381	3,490	132	1,378	1,957
	Q1	363,120	9,157	0.345	3,333	127	1,252	568
	Q3	454,020	12,222	0.443	3,550	141	2,041	2,285
	Count	86	86	86	86	86	86	86
Type D	Total	62,869,762	2,701,219	85.482	674,970	29,516	257,579	92,830
	Max	466,144	20,149	0.832	5,662	168	2,566	3,020
	Min	26,120	426	0.045	2,026	108	121	4
	Mean	305,193	13,113	0.415	3,277	143	1,250	451
	Std. Dev	54,063	2,844	0.104	520	19	504	767
	Median	304,727	13,294	0.412	3,200	138	1,223	98
	Q1	276,883	11,806	0.342	2,882	128	922	27
	Q3	336,973	14,663	0.478	3,563	168	1,597	424
	Count	206	206	206	206	206	206	206

Table 2-2 Example Annual Kilowatt-Hour Data Range for Use in Histogram Function

Range
0
25,000
50,000
75,000
100,000
125,000
(continue adding 25,000 for each subsequent row until…)
625,000

Figure 2-3 shows a histogram for one multiunit operator with about 900 stores in the database. There is a dip in the center of the data (at 350,000 kWh/yr) and a small bump at 125,000 kWh/yr. These indicate that the distribution represents more than one subdataset, or factor. This operator has four brand concepts that influence the overall energy use distribution.

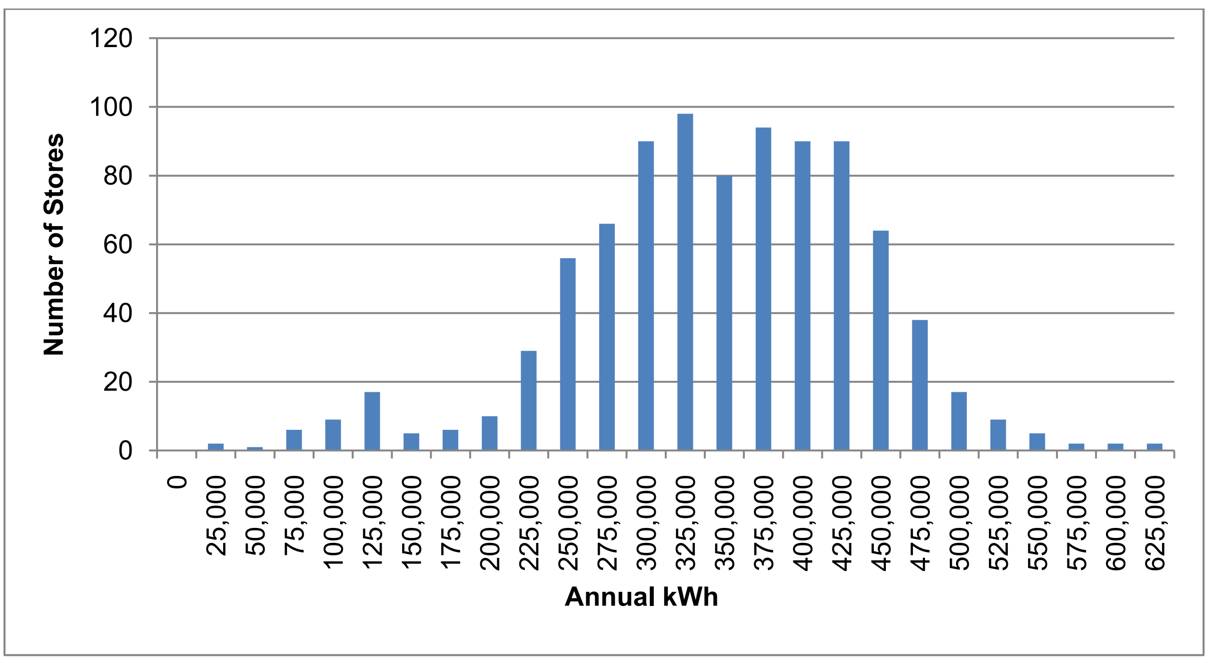

Figure 2-3 Number of stores by annual electricity use

Figure 2-4 shows that two of the four concepts use more electric energy than the other two. It also shows that the bump at 125,000 kWh/yr appears to be associated with the "B" concept, which has the most stores using more than 350,000 kWh/yr. This may be a case of missing monthly utility bills or a misclassification as part of the "B" set. A full set of histograms for each concept is included in Appendix A.

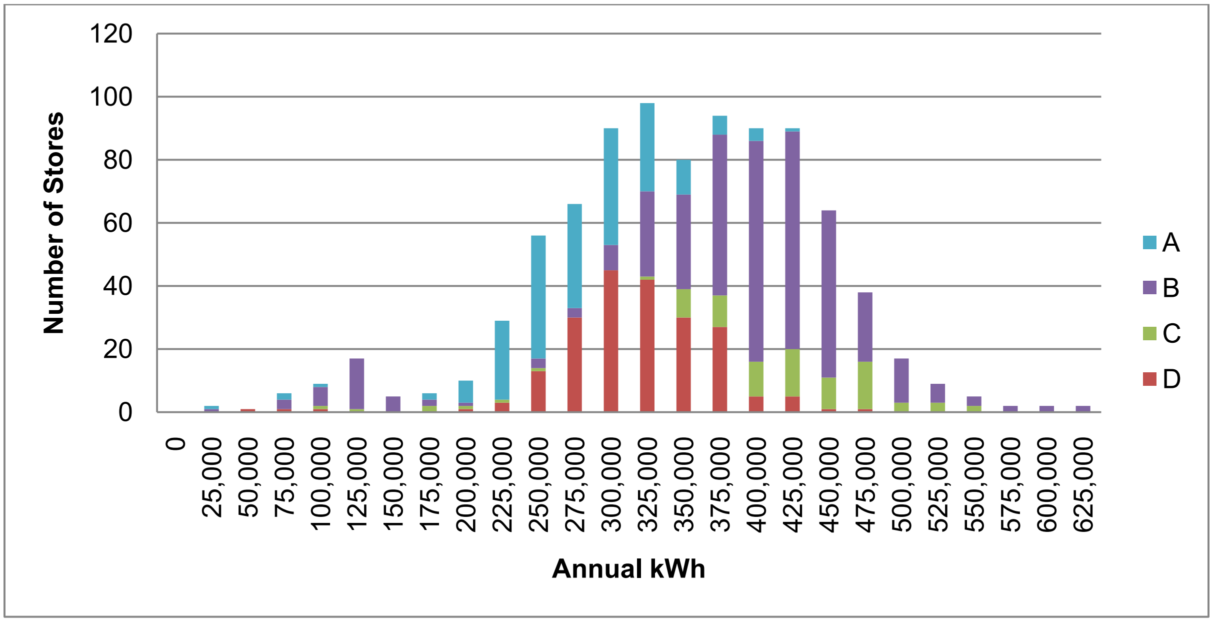

Figure 2-4 Number of stores by type by annual electricity use

Scatter plots, such as those in Figure 2-5 and Figure 2-6, show more detail about distribution of electricity and gas use versus normalized transactions. Appendix B includes the scatter plots for all four store types examined for an example multiunit operator, as well as scatter plots for all of the operator's 900 stores combined.

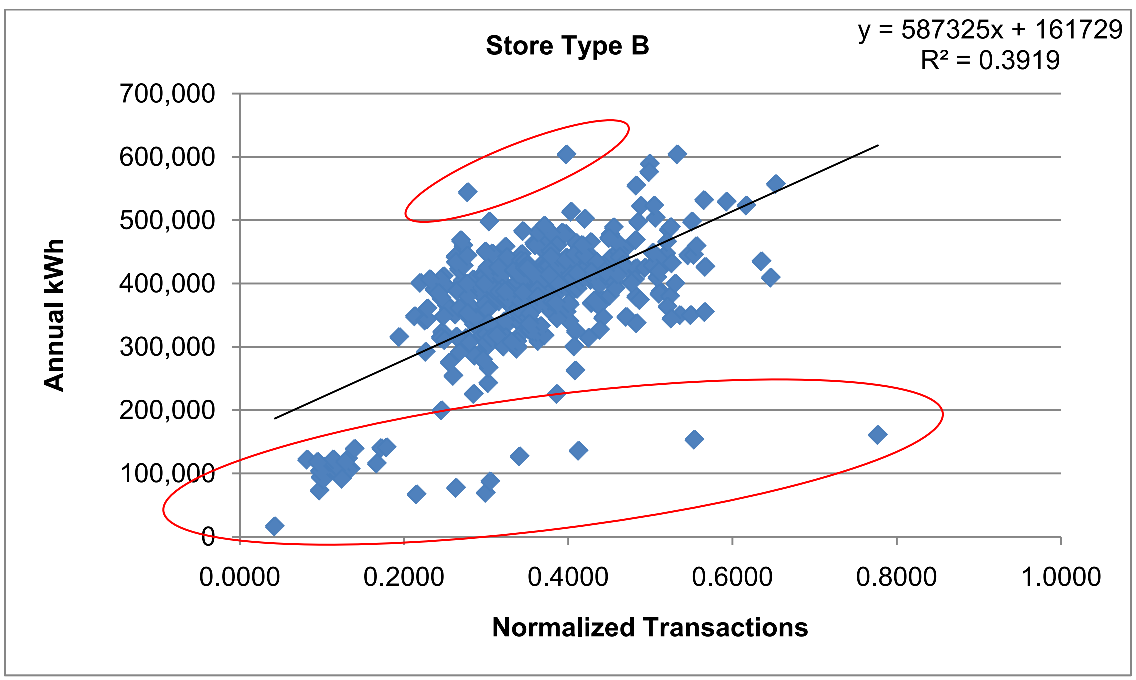

Figure 2-5 Example of annual electricity use scatter plot to show outliers

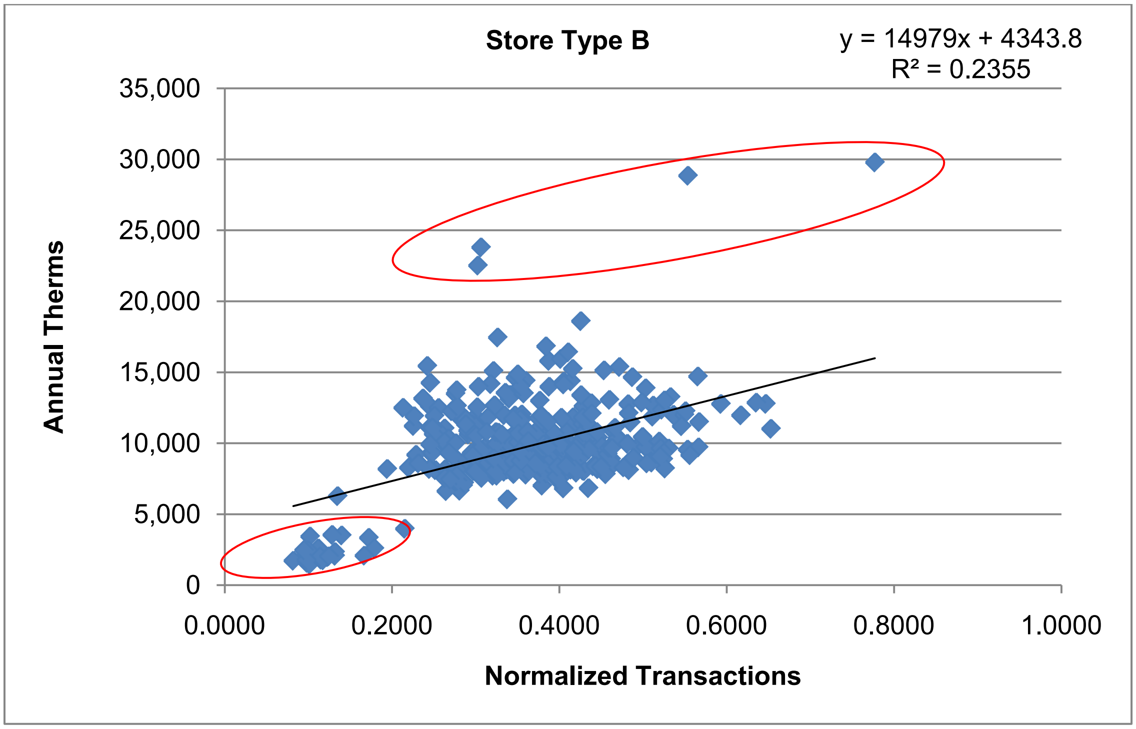

Figure 2-6 Example of annual natural gas use scatter plot to show outliers

2.1.5.4 Step 5d

The National Institute for Standards and Technology (NIST) has an online Engineering Statistics Handbook that describes several methods for identifying outliers (NIST/SEMATECH 2011). (Excel uses Q1 as the lower quartile and Q3 as the upper quartile, while the NIST Handbook refers to the upper quartile as Q2.) The following abstract lays out one of the methods, based on the box plot:

> The box plot is a useful graphical display for describing the behavior of the data in the middle as well as at the ends of the distributions. The box plot uses the median and the lower and upper quartiles (defined as the 25th and 75th percentiles). If the lower quartile is Q1 and the upper quartile is Q2, then the difference (Q2 - Q1) is called the interquartile range or IQ.
>
> <u>Box plots with fences</u>
>
> A box plot is constructed by drawing a box between the upper and lower quartiles with a solid line drawn across the box to locate the median. The following quantities (called fences) are needed to identify extreme values in the distribution tails:
>
> Lower inner fence: Q1 - 1.5*IQ
>
> Upper inner fence: Q2 + 1.5*IQ
>
> Lower outer fence: Q1 - 3*IQ
>
> Upper outer fence: Q2 + 3*IQ

Outlier detection criteria:
A point beyond an inner fence on either side but within the outer fences is considered a mild outlier.
A point beyond an outer fence is considered an extreme outlier.

Figure 2-7 and Figure 2-8 show example box plots for the example multiunit concepts in Figure 2-4. The light blue bars represent the range of the data (maximum to minimum). The green boxes represent the IQ range, which means that 50% of the stores have kWh/yr within that range. In this case, the dark green boxes are relatively small compared to the maximum-minimum range, and they are located above the midpoint of the max-min range. This suggests that investigating the energy use of stores below the lower inner fence (below the bottom red dashed line) may identify data anomalies that could be either corrected or eliminated from the dataset. If so, the changes would reduce the standard deviation and likely improve the regression model predictive accuracy.

The energy use of stores above the upper inner fence is likely higher than required. These stores are candidates for review. The first action item is to ensure that no double monthly entries were made. The second is an energy audit, including review of operational practices, equipment in use, hours of operation, and set points. For example, exterior lighting, including building lighting and parking lot lights, may be left on longer than needed.

Excel does not have a box plot template, although the stock charts have a similar format. Figure 2-7 and Figure 2-8 are custom charts that will be provided in the example spreadsheet with instructions.

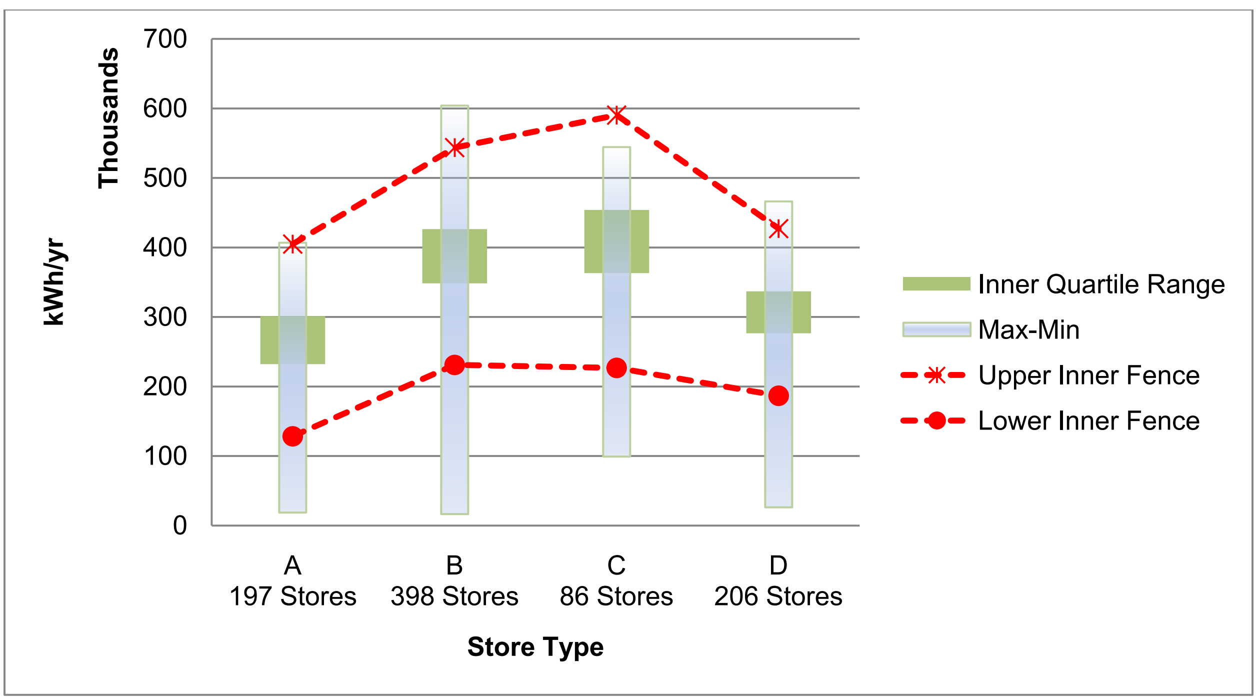

Figure 2-7 Example annual electricity use box plot with inner fences

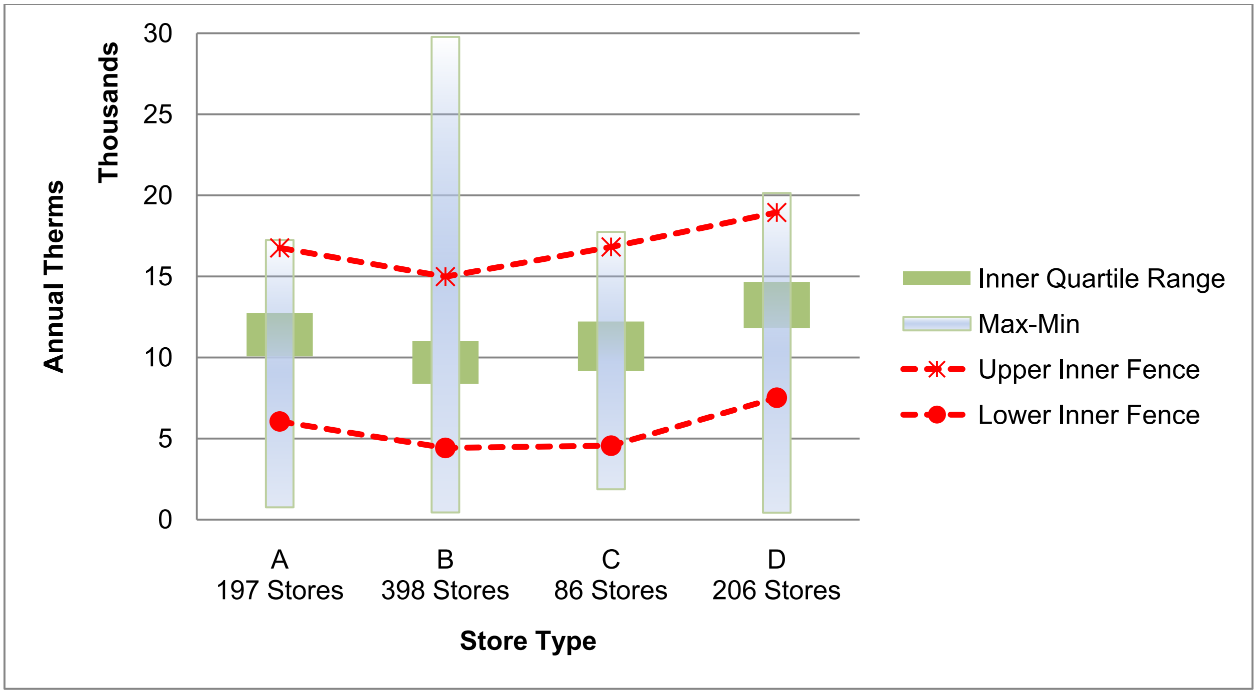

Figure 2-8 Example annual natural gas use box plot with inner fences

2.1.5.5 Step 5e

Use the summaries prepared in Steps 5b, 5c, and 5d to look for data anomalies, including partial year data, missing data, and billing errors.

Several standard statistical tests can be used to characterize outlier data points. The data may show unusually low energy use values because a month or several months are missing. Unusually high values may be due to double counting or a store that has unusually high transactions or longer operating hours than others. This is where normalizing values against transactions, operating hours, and other independent variables can provide guidance about whether to keep the outlier in the data or remove it as being unrepresentative.

Decide whether to remove data anomalies.

An extreme outlier is likely to be a data error and should be rejected. A mild outlier may be due to unusual conditions, but is nonetheless likely to be valid and should be retained. Some mild outliers in utility bill data will be due to missing months of data. In any event, extreme and mild outliers should be investigated to determine what caused the underlying high or low energy use. Stores with partial annual utility or transaction data (one or more months missing) should not be included in the analysis.

Figure 2-7 and Figure 2-8 depict outliers in data for an example multiunit operator. Figure 2-7 shows that every store type has lower mild outliers and that Type A and Type C have higher mild outliers. The lower outliers are likely cases of missing monthly data that should be investigated. Figure 2-8 shows lower mild outliers for each store type, but Type C has one or more very high gas users compared to the other stores.

2.1.6 Step 6

After completing Steps 1 through 5, the operator has enough information to do a high-level data evaluation. The work to this point answers the following fundamental questions:

- Are there significant differences in store type that should be evaluated separately (types A, B, C, and D in the example data)? Recall that each dataset should include at least 20 stores for valid statistical parameters.
- What is the performance range? The maximum and minimum statistics show the range.
- How much energy does the average store consume? The mean statistic will show the average consumption. The median is also a useful statistic, as it represents the 50^{th} percentile in the distribution. If the mean and median values are close, the distribution does not likely exhibit much skew.
- What do the distributions of energy consumption look like? Is there a lot of scatter, or are data points clustered tightly together? If there is skew, is it toward high or low consumption? Do there appear to be many or few outliers? The histograms and scatter plots help identify these characteristics. Box plots are also helpful in identifying outliers.
- How many stores exhibit higher-than-expected consumption, but not so high that a data anomaly is suspected? These are retrofit candidates and should be evaluated more closely by site visits, evaluation of finer-grained data (through an energy information system or sub-metering, or both), energy audits, or some combination of all three. Higher-than-expected, but not suspicious, consumption numbers lie above the third quartile and below the upper inner fence in a box plot. The example spreadsheet identifies these values with a yellow highlight on the "Complete Inputs" worksheet.

If the operator does not wish to perform the advanced performance evaluation (see Section 2.2), the final action should be to investigate stores identified as potential retrofit candidates. If several data anomalies appear, they should be corrected and the previous steps redone.

2.2 Advanced Performance Evaluation and Prediction

Explanation is provided here for the steps illustrated in Figure 2-2.

2.2.1 Step 7

Step 7 involves finding the best correlation factors for the linear regression equations that will predict performance. For clarity, Step 7 consists of three substeps (7a–7c).

2.2.1.1 Step 7a

Identify potentially significant independent variables.

The regressions performed in this analysis will use electric or natural gas consumption as dependent variables and factors affecting consumption as independent variables. The independent variables used in the example analysis are:

- Normalized transactions
- Weekly hours of operation
- Floor area
- HDD
- CDD.

The list of independent variables to consider is unique to an operator. The five variables mentioned provide a helpful starting point.

2.2.1.2 Step 7b

For each subgroup (Store Type A, Store Type B, etc.), use the Excel LINEST function to develop a regression model. This model provides factors to be applied to continuous variables to compute a reference point for energy consumption. For example, if the significant independent variables are floor area, HDD50, weekly operating hours, and annual transactions, the annual reference energy will be calculated using an equation such as:

$$\boldsymbol{kWh = a + b \times Transactions + c \times WeeklyOperatingHours + d \times HDD50 + e \times FloorArea} \quad (2\text{-}1)$$

Where:

a	=	constant
b	=	transactions slope
c	=	weekly operating hours slope
d	=	HDD50 slope
e	=	floor area slope

The LINEST function requires the independent variables (in this case, transactions, weekly operating hours, floor area, and HDDs) to be in one contiguous data range within a spreadsheet tab. (See the “Regression Analysis” tab of the example spreadsheet for more details.)

2.2.1.3 Step 7c

Prepare tables or plots of predicted versus actual energy consumption to evaluate the performance of the regression model.

Table 2-3 depicts first pass results for an example multiunit operator. The first pass at creating a regression equation did not remove outliers, but six records with no electricity data were removed. Table 2-3 shows the results of the regression analysis (the R^2 is quite low and varies considerably by store type and mix of independent variables).

Table 2-4 is based on the same data as Table 2-3, except that five records with no gas use were removed, as were two records for Store Type B, each with reported annual electricity use in excess of 2 million kWh/yr. Note the improvement in the R^2 for Store Type B electricity use; however, each had gas use, and removing those records slightly decreased the R^2 for Store Type B gas use.

Overall, Table 2-4 shows that the data fit using normalized transactions, weekly hours, and floor area provides the best fit compared to combinations of two variables or a single variable. Normalized transactions have the largest influence on the data fit for electricity. No single independent variable has a similar influence on the data fit for gas.

Table 2-5 is based on the analysis in Table 2-4 with the addition of CDDs and HDDs. The R^2 values are improved, but generally the selected variables appear to account for 60% or less of the actual energy use by store type. The R^2 values would likely improve with further investigation and removal of outliers. Closer matching of dependent to independent variables, such as using only sub-metered HVAC energy as the dependent variable and weather parameters (HDD and CDD) as the independent variables, should also improve the R^2 correlations. In general, the resulting equations based on the LINEST function will not provide useful results unless the R^2 is greater than 70%-80%. Commercial statistical software packages are available, usually for a fee, and can provide additional parameters to help determine the quality of a linear regression.

2.2.2 Step 8

Use the combination of independent variables with the best correlation factors to create benchmarking equations. These will contain a constant term and one slope term (rate of change of dependent variable with respect to independent variable) per independent variable. The equations will take the form of Equation (2-1).

The example spreadsheet shows the R^2 statistic to guide the analyst toward the best correlation. A higher R^2 value indicates a better correlation. Statistics such as P-factors and F-test could also be used to help determine the strength of these linear regressions. Statistical software is commercially available, usually for a fee.

2.2.3 Step 9

Use the benchmarking equations created in Section 1.1.1 to calculate the expected performance of each store. Insert the values of the known operational characteristics (transactions and weekly hours), for example, for each store into the benchmarking equations to predict electricity and natural gas consumption for each store.

2.2.4 Step 10

Compare the expected performance (see Section 2.2.3) to the actual performance reported in utility or metered data, and note any significant differences. Examining differences by percentage will be more helpful than looking at absolute differences in kilowatt-hours or therms.

Stores with percent changes less than zero use less energy than predicted by their operational characteristics. Conversely, stores with positive percent changes use more energy than expected. Among such stores, slight variations may indicate noise in the data or inaccuracy in the prediction. Changes greater than 5%, however, should be noted; changes greater than 10% may indicate a candidate for a site visit or energy audit. Any changes greater than 25% should be considered a data error (see Section 2.1.5.5).

Table 2-3 Regression Equation Matrix Using Raw Data
(excluding six records with no electricity data and including 45 records with no gas data)

Independent Variables	Store Type	Electricity					Natural Gas				
		Constant (y-intercept)	Floor Area Slope	Trans-actions Slope	Weekly Hours Slope	R^2	Constant (y-intercept)	Floor Area Slope	Trans-actions Slope	Weekly Hours Slope	R^2
Transactions, Weekly Hours, Floor Area	A	–18,229	18.2	15.5	1,155.7	0.57	810	0.4	0.4	54.4	0.38
	B	71,873	–6.2	70.4	518.3	0.26	–4,741	0.0	1.4	71.1	0.38
	C	383,019	–19.5	48.8	–862.9	0.29	–4,408	0.9	0.3	78.2	0.44
	D	32,013	21.3	25.9	642.0	0.45	3,719	0.9	0.7	24.2	0.15
Transactions, Floor Area	A	109,989	13.7	25.7	0	0.45	6,840	0.2	0.9	0	0.25
	B	124,687	–3.9	72.5	0	0.26	2,504	0.3	1.7	0	0.28
	C	287,514	–22.3	45.7	0	0.27	4,243	1.1	0.6	0	0.26
	D	111,276	17.8	31.5	0	0.42	6,704	0.8	0.9	0	0.13
Transactions	A	151,358	0	26.2	0	0.43	7,305	0	0.9	0	0.25
	B	111,498	0	72.7	0	0.26	3,477	0	1.7	0	0.28
	C	243,464	0	37.2	0	0.24	6,439	0	1.1	0	0.18
	D	166,122	0	32.3	0	0.39	9,158	0	0.9	0	0.12
Weekly Hours, Floor Area	A	–48,365	22.8	0	1,759.3	0.47	–13	0.5	0	70.8	0.34
	B	227,089	–28.4	0	1,858.3	0.04	–1,629	–0.5	0	98.0	0.20
	C	377,643	12.6	0	–200.1	0.01	–4,446	1.1	0	82.9	0.43
	D	2,961	29.5	0	1,426.8	0.27	2,973	1.1	0	44.3	0.11
Weekly Hours	A	29,639	0	0	1,719.6	0.41	1,666	0	0	70.0	0.33
	B	144,668	0	0	1,784.0	0.03	–3,011	0	0	96.7	0.20
	C	396,596	0	0	–13.9	0.00	–2,815	0	0	98.9	0.34
	D	110,877	0	0	1,347.6	0.20	7,139	0	0	41.3	0.07
Floor Area	A	202,767	19.2	0	0	0.04	10,099	0.3	0	0	0.01
	B	450,797	–22.0	0	0	0.00	10,163	–0.1	0	0	0.00
	C	354,445	11.4	0	0	0.01	5,164	1.6	0	0	0.21
	D	223,710	24.5	0	0	0.05	9,832	1.0	0	0	0.03
Transactions, Weekly Hours	A	45,724	0	17.0	1,065.1	0.53	2,095	0	0.5	52.5	0.37
	B	53,453	0	70.7	495.9	0.26	–4,833	0	1.4	71.0	0.38
	C	359,699	0	42.0	–992.0	0.27	–3,384	0	0.6	83.8	0.40
	D	109,767	0	27.8	527.0	0.41	7,109	0	0.7	19.2	0.13

Table 2-4 Regression Equation Matrix Using Processed Data
(excluding five records with no gas data and two records with extremely high electricity data)

Independent Variables	Store Type	Electricity					Natural Gas				
		Constant (y-intercept)	Floor Area Slope	Trans-actions Slope	Weekly Hours Slope	R^2	Constant (y-intercept)	Floor Area Slope	Trans-actions Slope	Weekly Hours Slope	R^2
Transactions, Weekly Hours, Floor Area	A	–19,262	19.0	142,059	1,205.7	0.58	744	0.4	3,237	57.5	0.39
	B	180,031	16.6	606,116	–595.9	0.39	–3,400	0.1	12,485	62.3	0.33
	C	383,019	–19.5	503,967	–862.9	0.29	–4,408	0.9	3,587	78.2	0.44
	D	38,137	21.5	235,902	690.0	0.43	4,096	0.9	4,953	27.1	0.13
Transactions, Floor Area	A	113,795	14.2	253,542	0	0.44	7,093	0.2	8,556	0	0.23
	B	119,427	13.9	580,567	0	0.38	2,939	0.4	15,157	0	0.24
	C	287,514	–22.3	471,909	0	0.27	4,243	1.1	6,491	0	0.26
	D	122,565	17.8	299,890	0	0.38	7,414	0.8	7,468	0	0.10
Transactions	A	156,417	0	259,884	0	0.41	7,650	0	8,639	0	0.23
	B	166,748	0	574,570	0	0.38	4,344	0	14,979	0	0.24
	C	243,464	0	383,790	0	0.24	6,439	0	10,884	0	0.18
	D	177,243	0	308,343	0	0.35	9,857	0	7,845	0	0.08
Weekly Hours, Floor Area	A	–45,420	23.1	0	1,737.4	0.50	148	0.5	0	69.6	0.37
	B	316,101	–1.0	0	461.9	0.01	-597	-0.2	0	84.1	0.18
	C	377,643	12.6	0	–200.1	0.01	–4,446	1.1	0	82.9	0.43
	D	16,503	28.4	0	1,365.4	0.27	3,642	1.1	0	41.3	0.10
Weekly Hours	A	33,610	0	0	1,697.5	0.43	1,886	0	0	68.8	0.35
	B	313,126	0	0	459.1	0.01	–1,256	0	0	83.5	0.18
	C	396,596	0	0	–13.9	0.00	–2,815	0	0	98.9	0.34
	D	120,705	0	0	1,287.6	0.20	7,621	0	0	38.3	0.06
Floor Area	A	202,573	19.6	0	0	0.05	10,089	0.4	0	0	0.01
	B	371,681	0.6	0	0	0.00	9,524	0.1	0	0	0.00
	C	354,445	11.4	0	0	0.01	5,164	1.6	0	0	0.21
	D	228,168	23.5	0	0	0.05	10,044	0.9	0	0	0.03
Transactions, Weekly Hours	A	47,258	0	159,300	1,109.1	0.53	2,196	0	3,614	55.4	0.38
	B	229,374	0	596,510	–535.8	0.39	–2,998	0	12,407	62.8	0.33
	C	359,699	0	433,541	–992.0	0.27	–3,384	0	6,680	83.8	0.40
	D	116,531	0	256,619	573.5	0.38	7,526	0	5,859	22.0	0.10

Table 2-5 Regression Equation Matrix With CDDs and HDDs Added

Independent Variables	Store Type	Electricity							Natural Gas						
		Constant (y-intercept)	Floor Area Slope	Trans-actions Slope	Weekly Hours Slope	CDD Slope	HDD Slope	R^2	Constant (y-intercept)	Floor Area Slope	Trans-actions Slope	Weekly Hours Slope	CDD Slope	HDD Slope	R^2
Transactions, Weekly Hours, Floor Area, HDD, CDD	A	–37,425	12.0	1.2	1,210	18.8	148,333	0.59	826	0.0	1.8	49.7	0.1	6,544	0.59
	B	195,377	–10.6	–22.5	–381	18.0	597,142	0.41	–6,507	2.0	3.2	32.3	–0.1	14,011	0.56
	C	517,680	–66.7	–59.1	–329	–11.5	414,951	0.34	–4,772	0.8	1.8	55.5	0.4	6,306	0.59
	D	906	24.3	–0.2	757	22.9	217,807	0.48	2,226	–0.1	1.5	31.2	0.6	9,712	0.25

3.0 Summary and Additional Considerations

Tracking energy use metrics over time will provide visibility into system-wide energy performance, identify the top energy users, and enable targeted programs to drive energy use toward the typical metrics.

The procedure described here provides a starting point to develop a customized in-house analysis and tracking system that will help multiunit operators understand how stores use energy. Customized procedures might include analysis of water use (hot water, irrigation, restrooms, etc.) and the influence of the number of parking lot lights. In some cases, submetering will have to be installed before the parameters can be extended. The procedure could also be extended to monthly, weekly, or even daily utility use, if automated data acquisition (through a billing service, for example) and analyses are implemented. Looking at utility subdaily data is not recommended, as hourly scatter can be large enough to obscure broader seasonal trends. Such data could provide useful information, however, for investigating component performance or behavioral contributions. Any extension of the analysis to subannual periods would require careful modifications to the example spreadsheet.

As new stores are built, or periodic renovations are undertaken, performance metrics will also change, and hopefully energy use will decrease over time. But certain actions that increase revenue (adding new equipment to support new menu items or extending operations from 18 to 24 hours per day, for example) may also increase energy use. If the transactions also increase, the revenue metrics may improve even though total energy use increases.

Another factor influencing year-to-year energy use is weather. Actual HDDs and CDDs are preferred, but manually obtaining these values for the whole data system may be time consuming and costly. Third-party services available via the Internet can help automate this process.

Data for an example multiunit operator are used in this Guideline and the accompanying spreadsheet to illustrate the performance evaluation process. The example results underscore the challenges that restaurant operators face when trying to benchmark performance. Even when data from only one multiunit operator are analyzed, with four concepts (A, B, C, and D) analyzed separately to increase correlation strength, the highest correlation strength found in the example corresponds to an R^2 value less than 60%. Obtaining meaningful cross-sectional benchmarking correlations across the entire restaurant sector would present even greater challenges.

In spite of such challenges, the process in this Guideline and accompanying spreadsheet provides a step-by-step starting resource that restaurant owners, energy managers, and operators can use to investigate their stores and refine performance metrics. This should enable them to better evaluate restaurants in their portfolios and then prioritize investments in energy-saving actions such as retrofits and operational improvements.

4.0 References and Bibliography

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Appendix A Histograms of Electricity and Natural Gas Use

This appendix includes histograms of electricity and natural gas use by store type. Figure A-1 and Figure A-2 show the entire dataset; Figure A-3 through Figure A-10 show separate histograms for each store type.

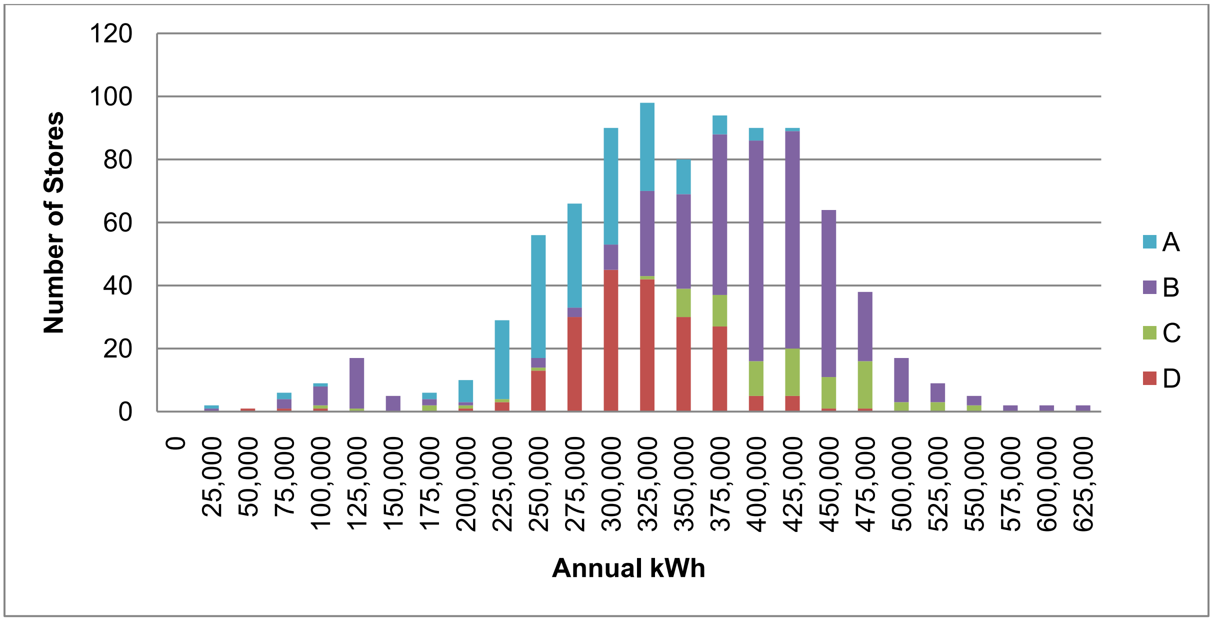

Figure A-1 Histogram of electricity use by store type

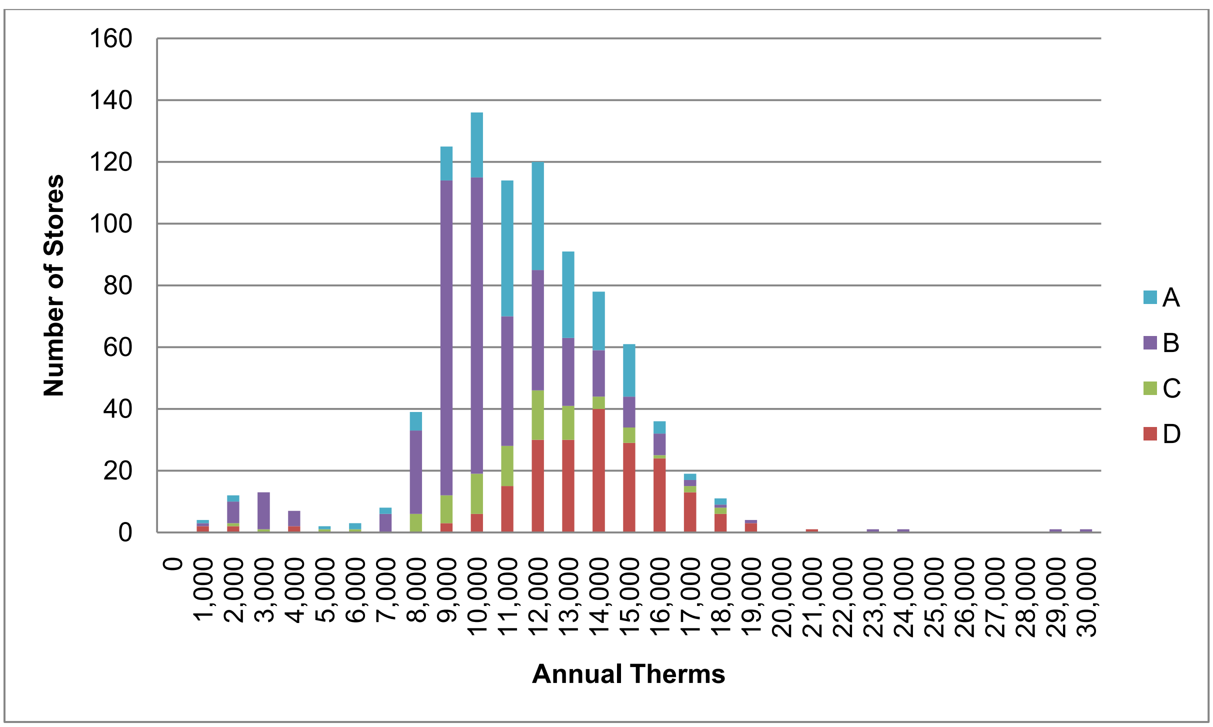

Figure A-2 Histogram of natural gas use by store type

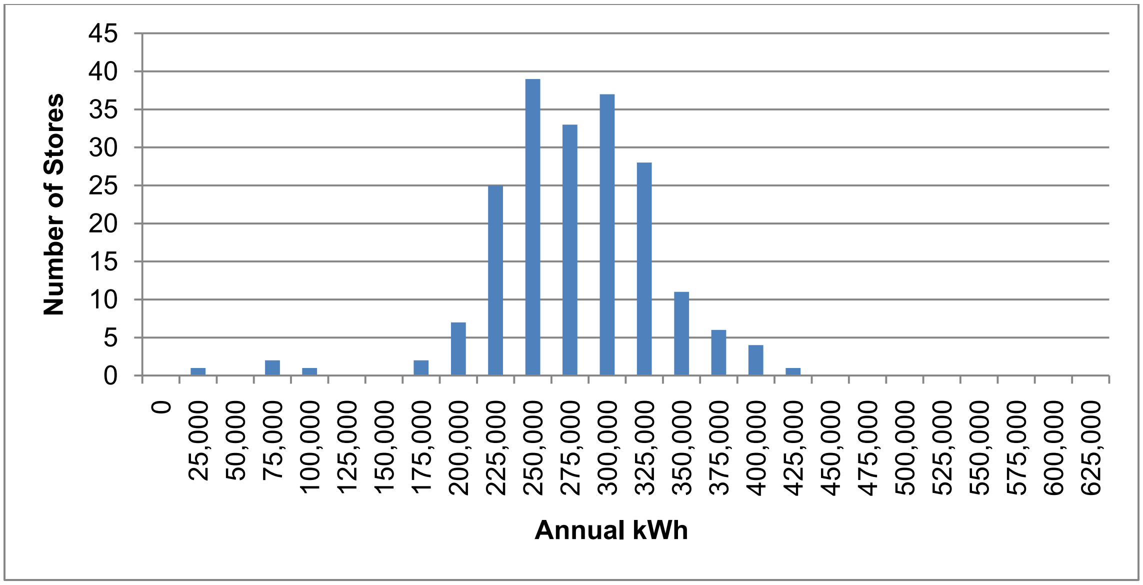

Figure A-3 Histogram of electricity use for store type A (197 stores)

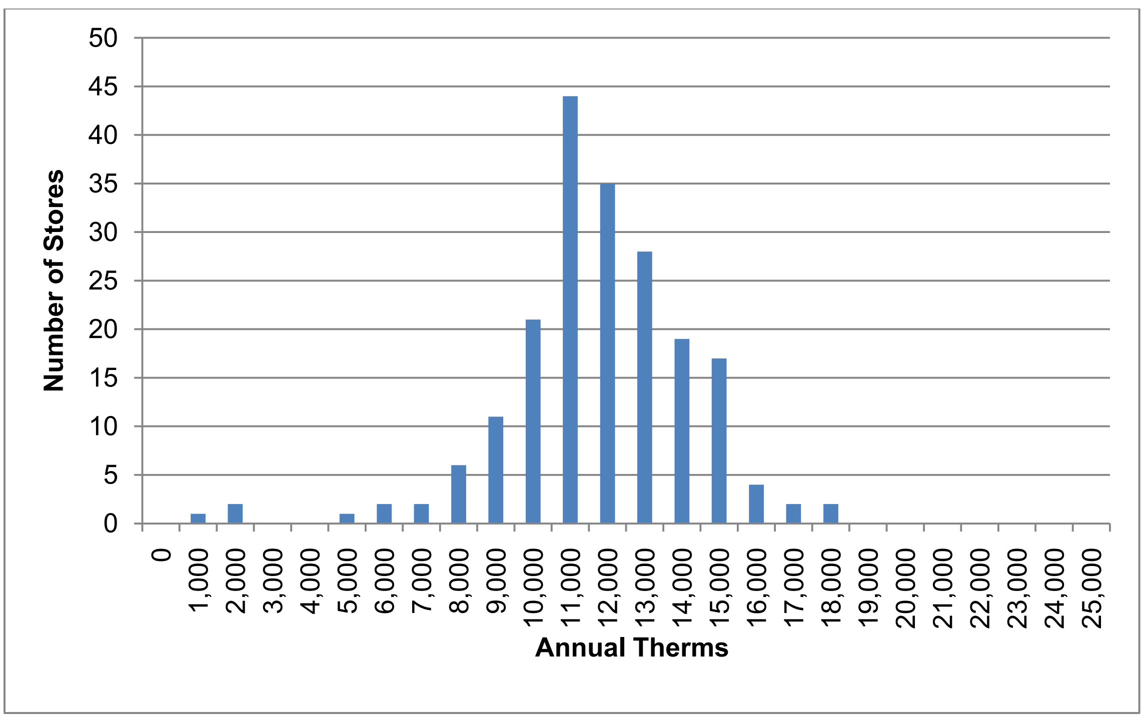

Figure A-4 Histogram of natural gas use for store type A (197 stores)

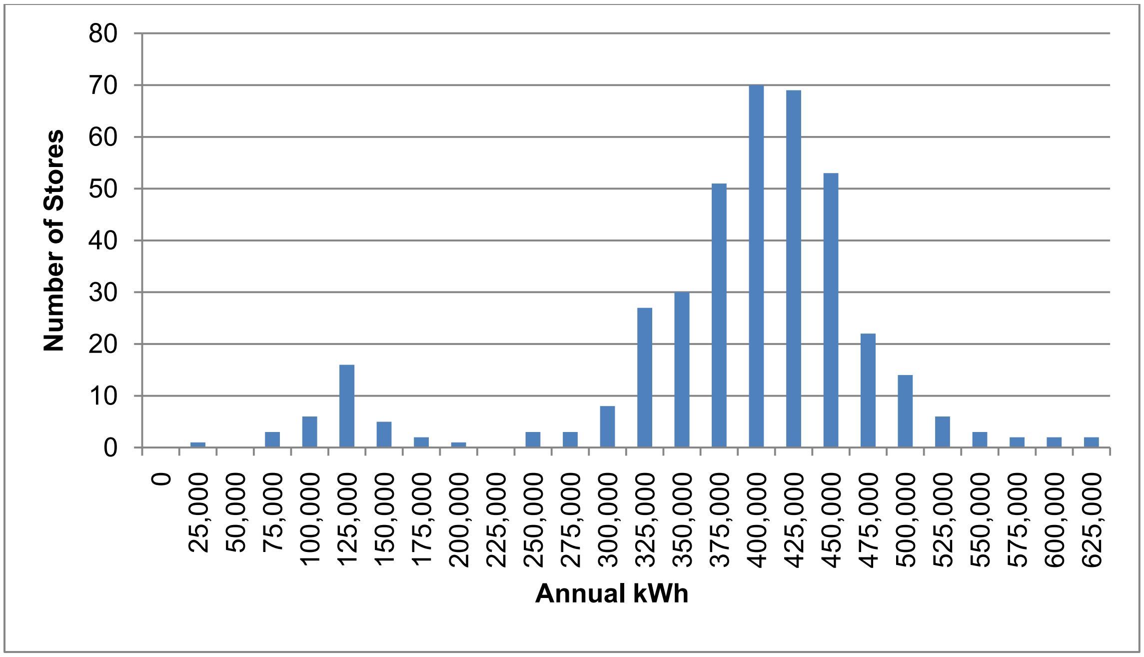

Figure A-5 **Histogram of electricity use for store type B (399 stores)**

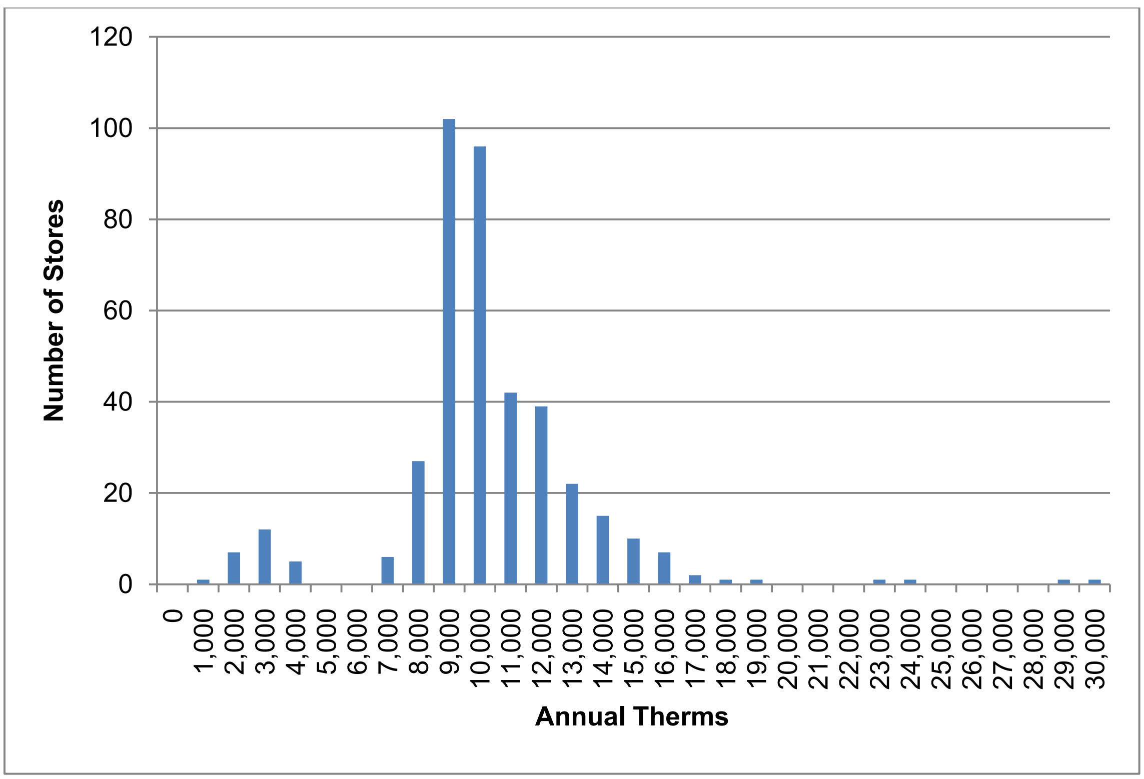

Figure A-6 **Histogram of natural gas use for store type B (399 stores)**

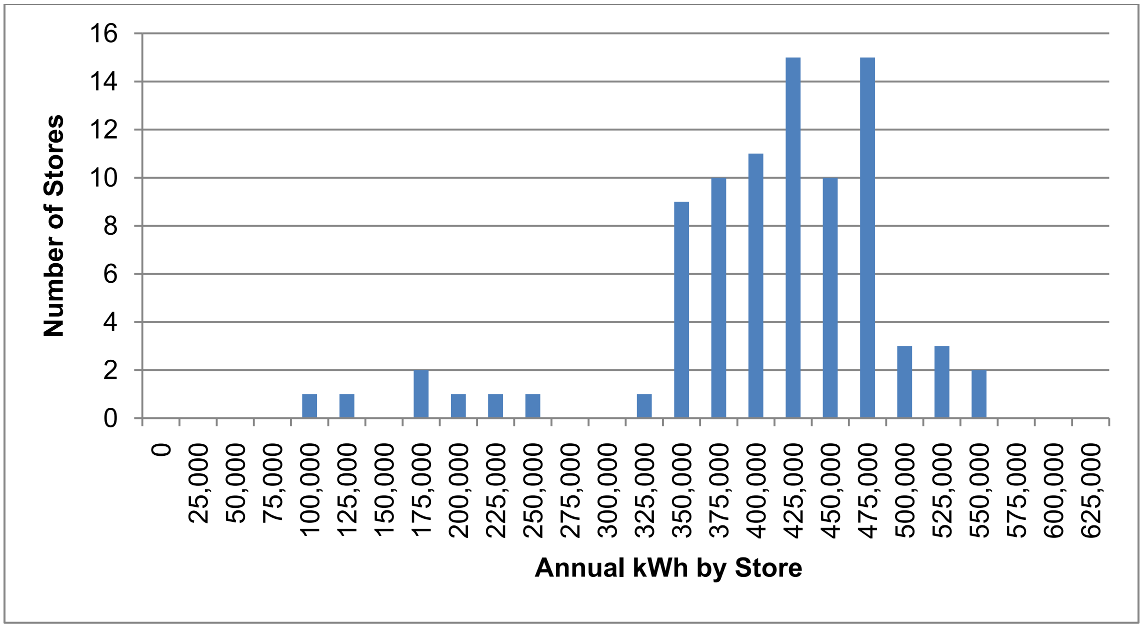

Figure A-7 Histogram of electricity use for store type C (86 stores)

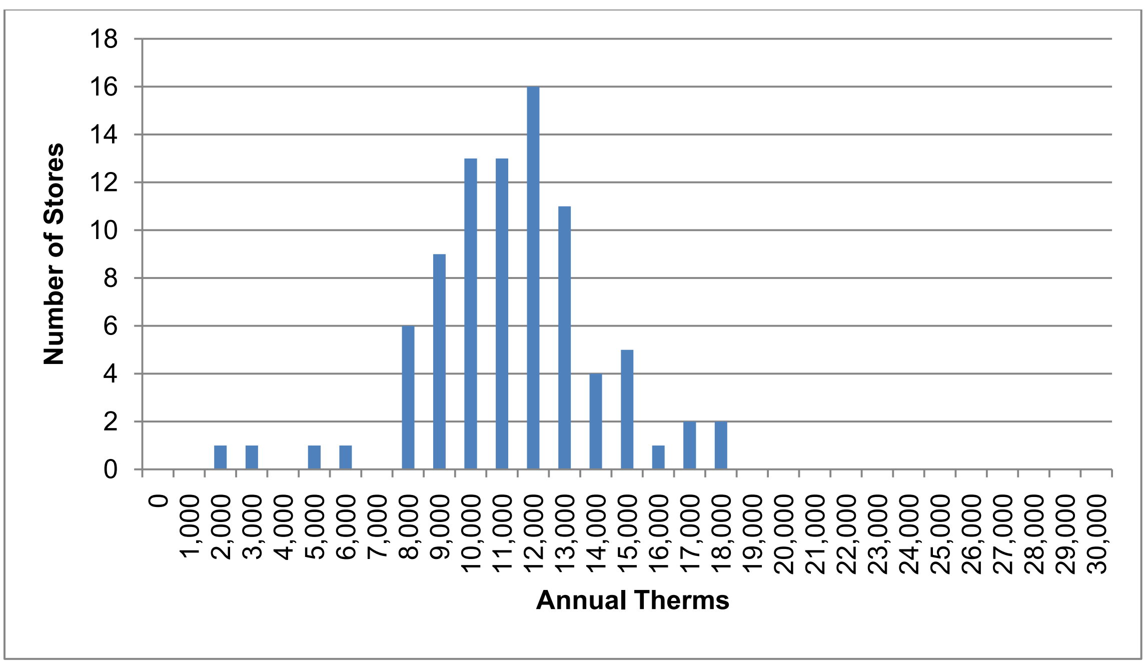

Figure A-8 Histogram of natural gas use for store type C (86 stores)

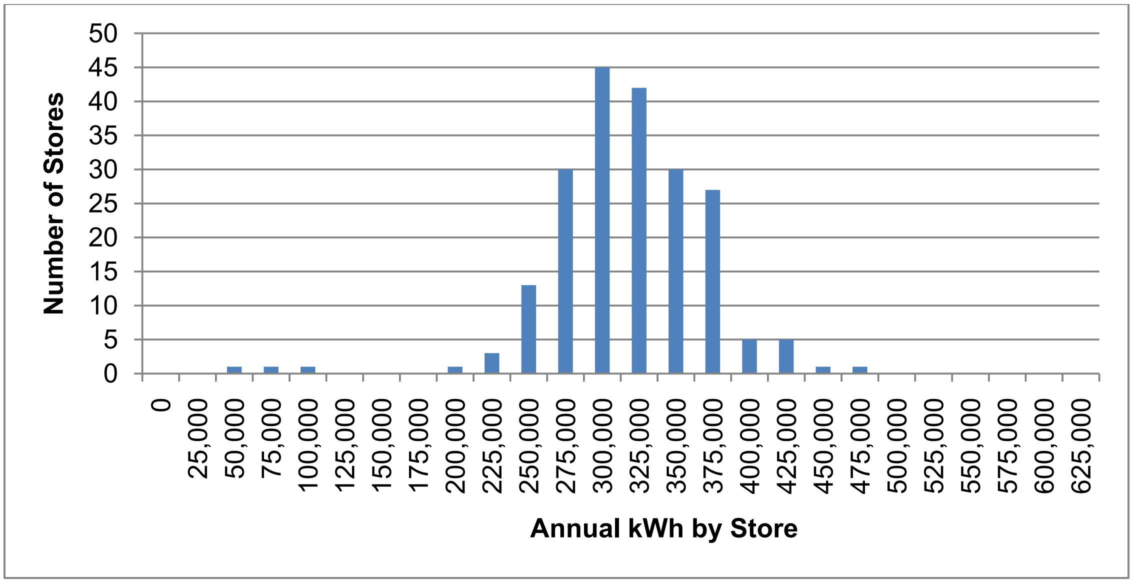

Figure A-9 Histogram of electricity use for store type D (206 stores)

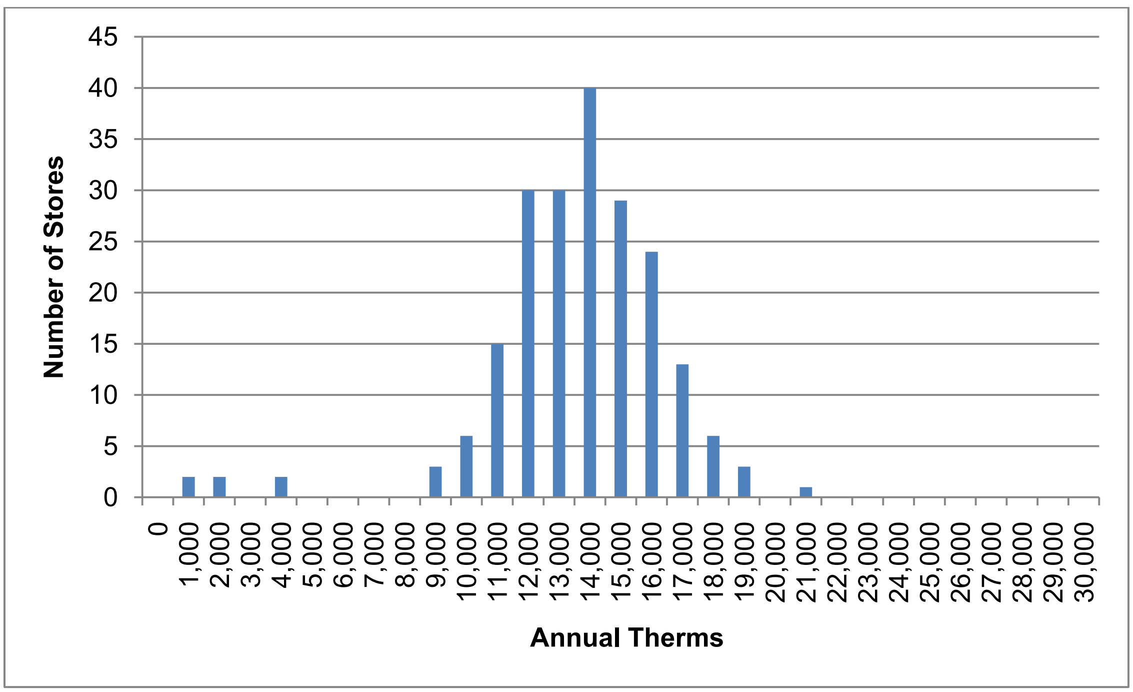

Figure A-10 Histogram of natural gas use for store type D (206 stores)

Appendix B Scatter Plots of Electricity and Natural Gas Use versus Normalized Transactions

This appendix includes scatter plots of electricity and natural gas use data. Figure B-1 and Figure B-2 show the entire dataset; Figure B-3 through Figure B-10 show separate plots for each store type.

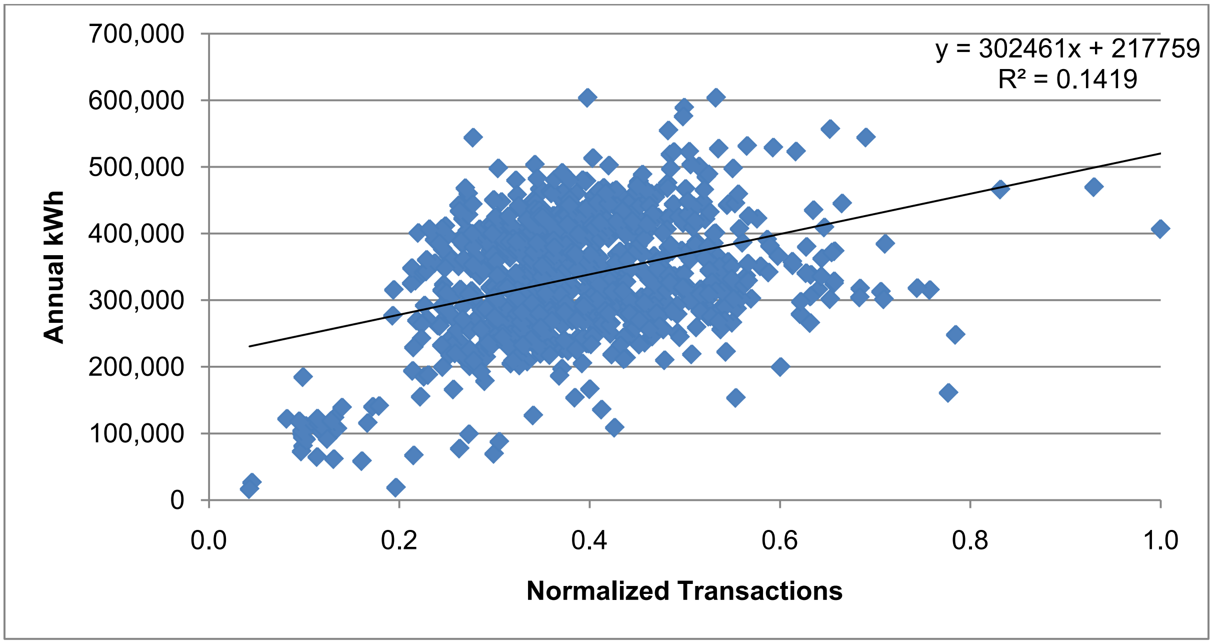

Figure B-1 Scatter plot of electricity use for all stores

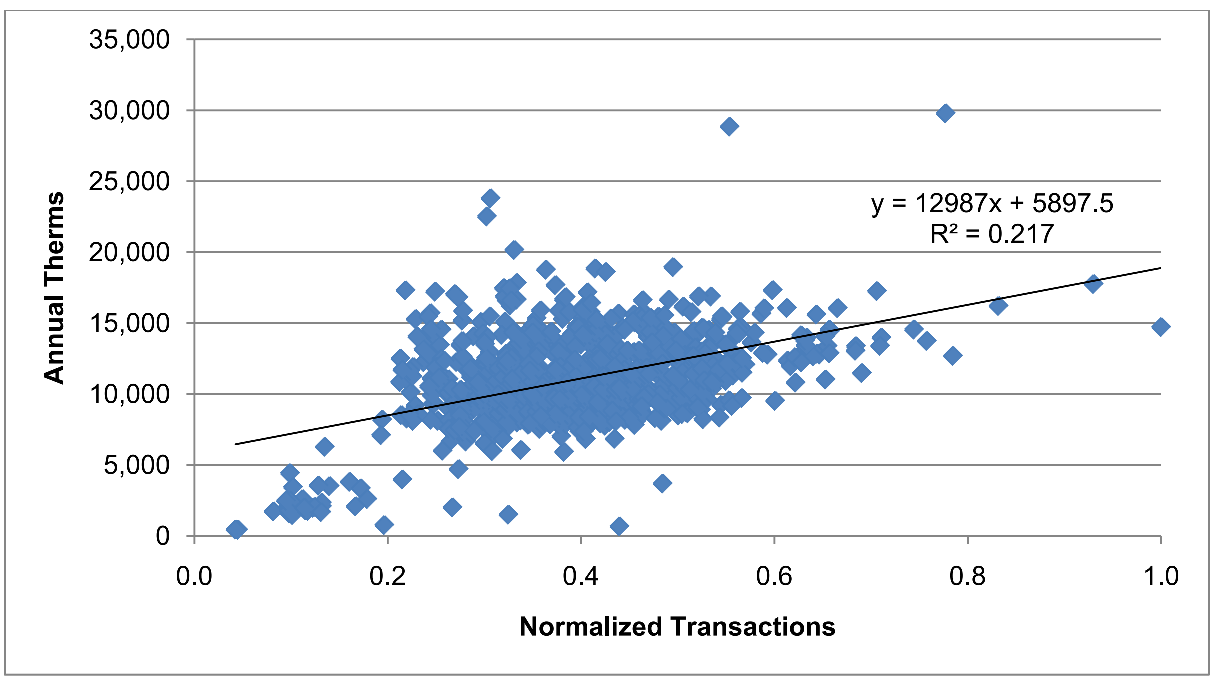

Figure B-2 Scatter plot of natural gas use for all stores

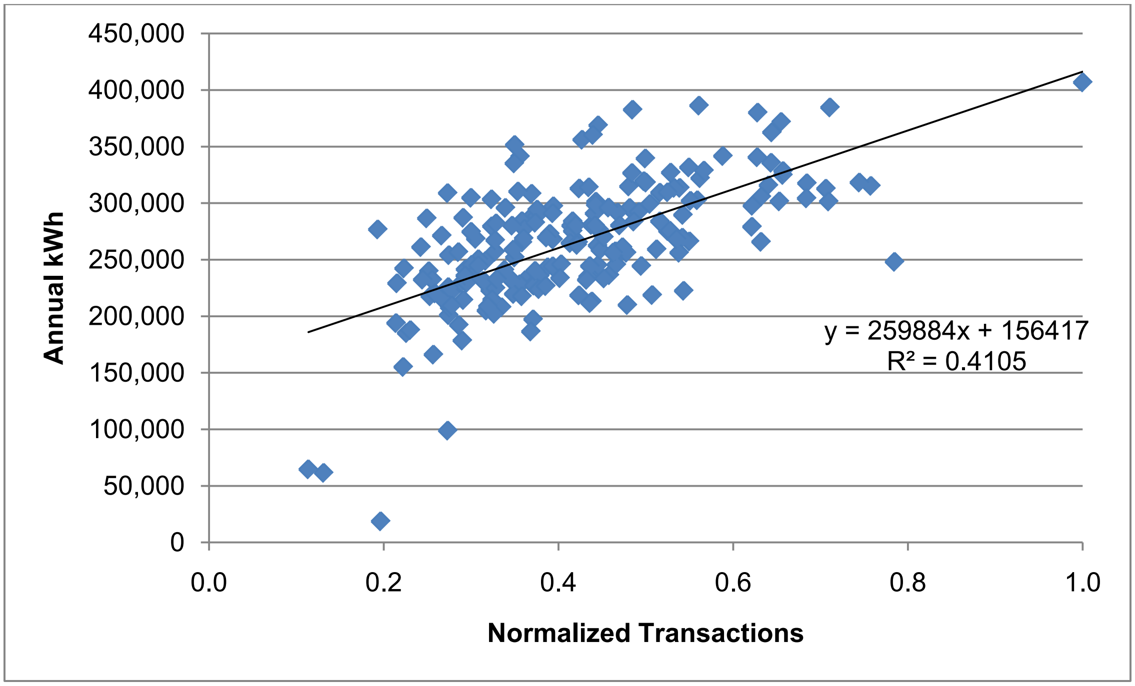

Figure B-3 Scatter plot of electricity use for store type A

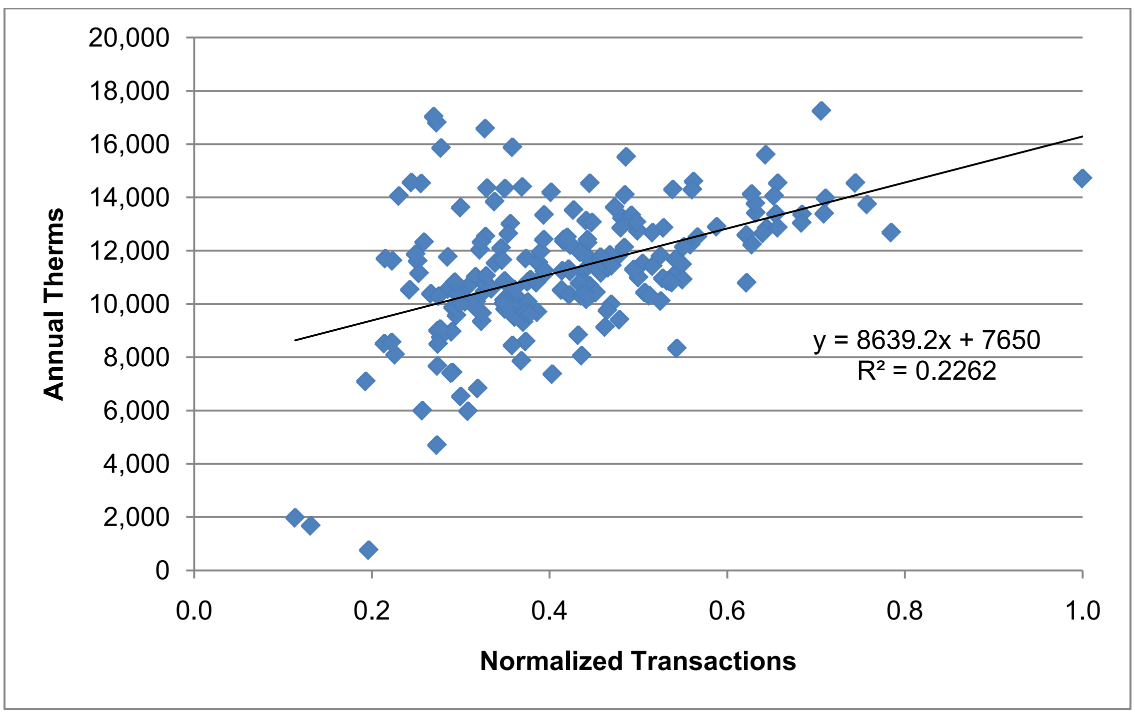

Figure B-4 Scatter plot of natural gas use for store type A

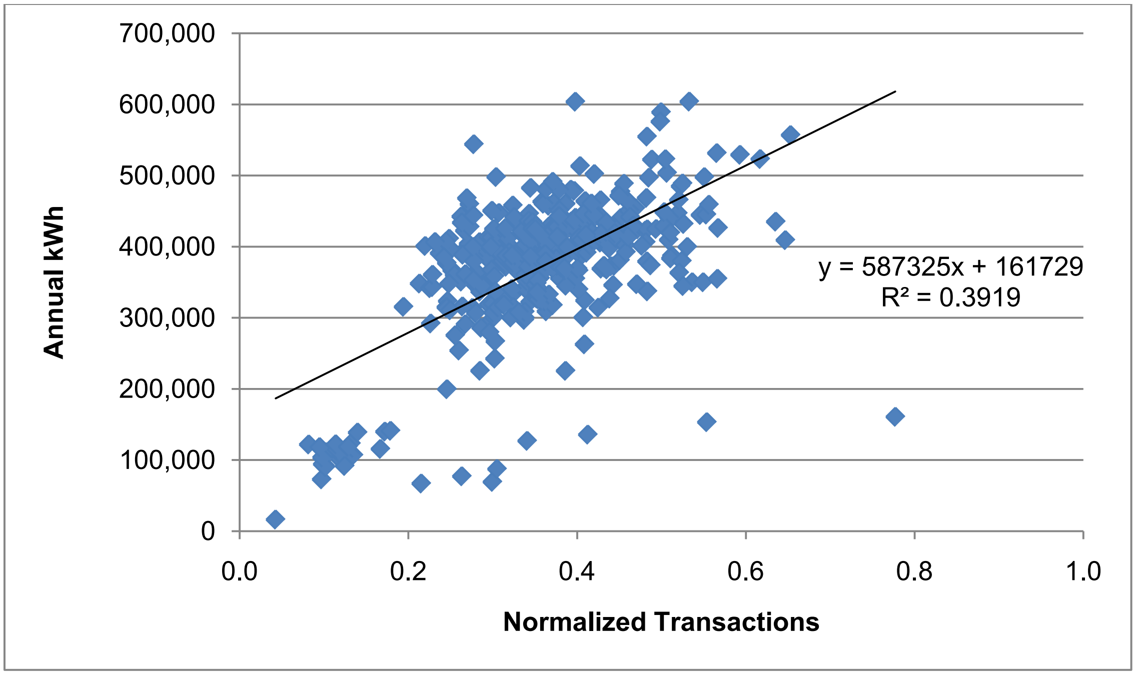

Figure B-5 Scatter plot of electricity use for store type B

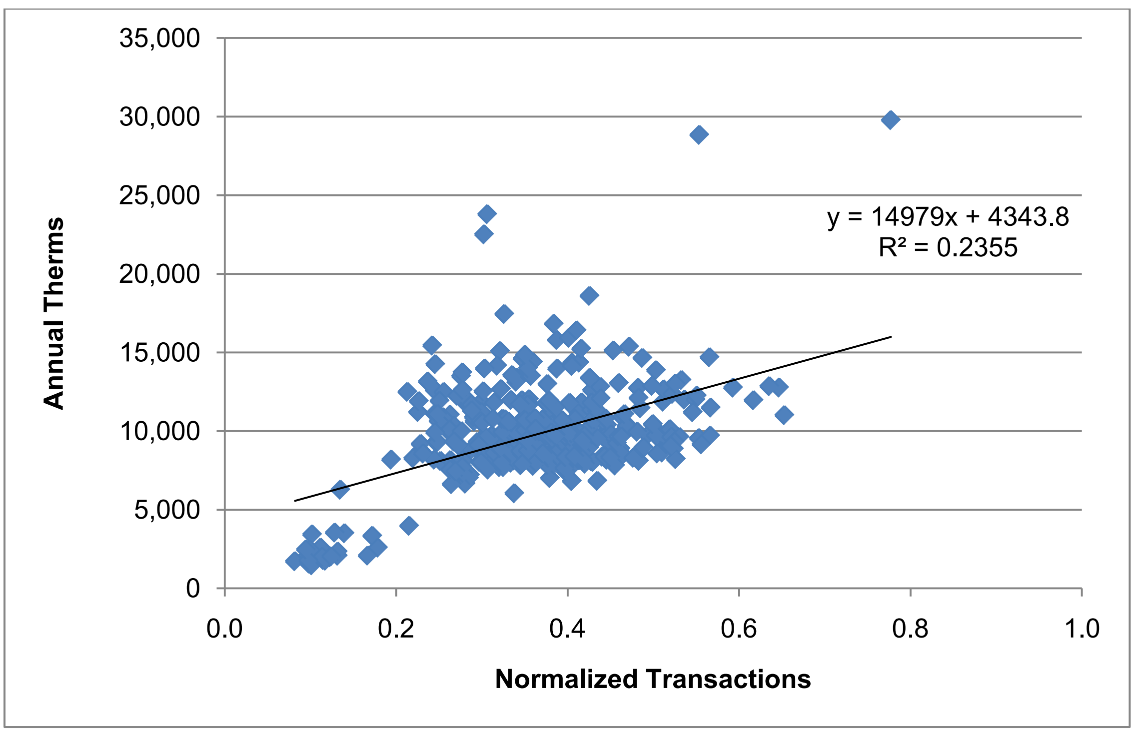

Figure B-6 Scatter plot of natural gas use for store type B

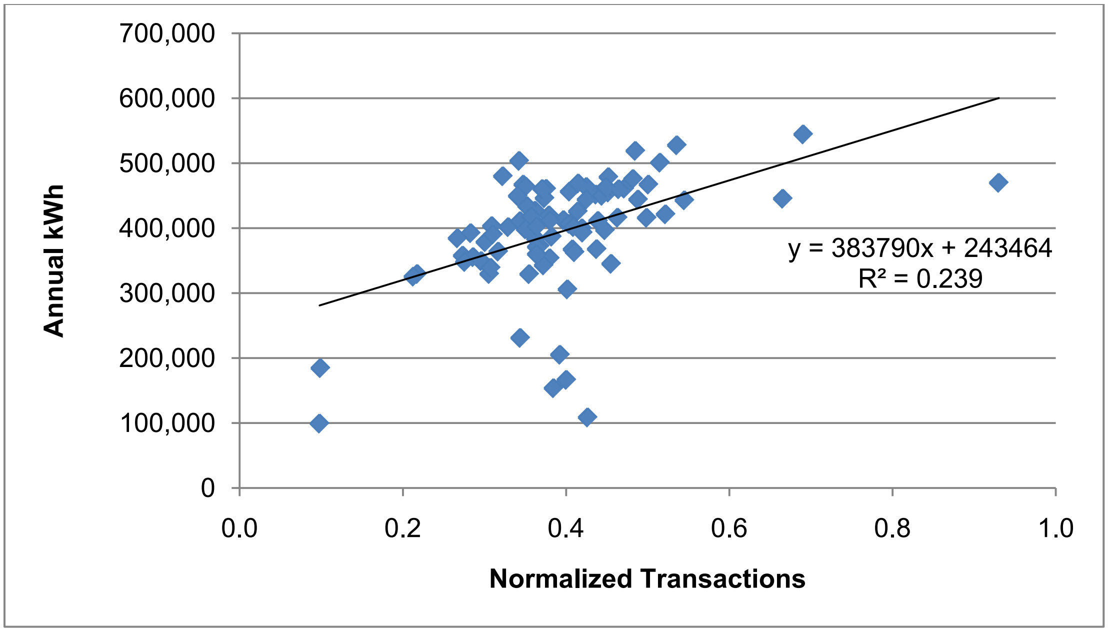

Figure B-7 Scatter plot of electricity use for store type C

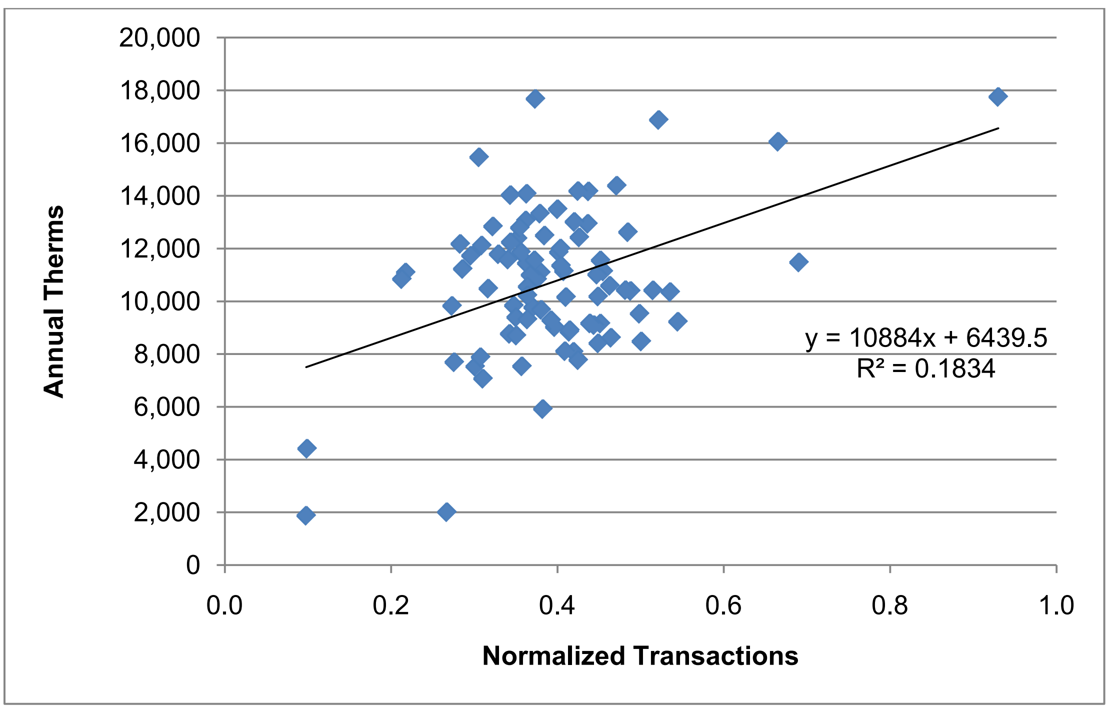

Figure B-8 Scatter plot of natural gas use for store type C

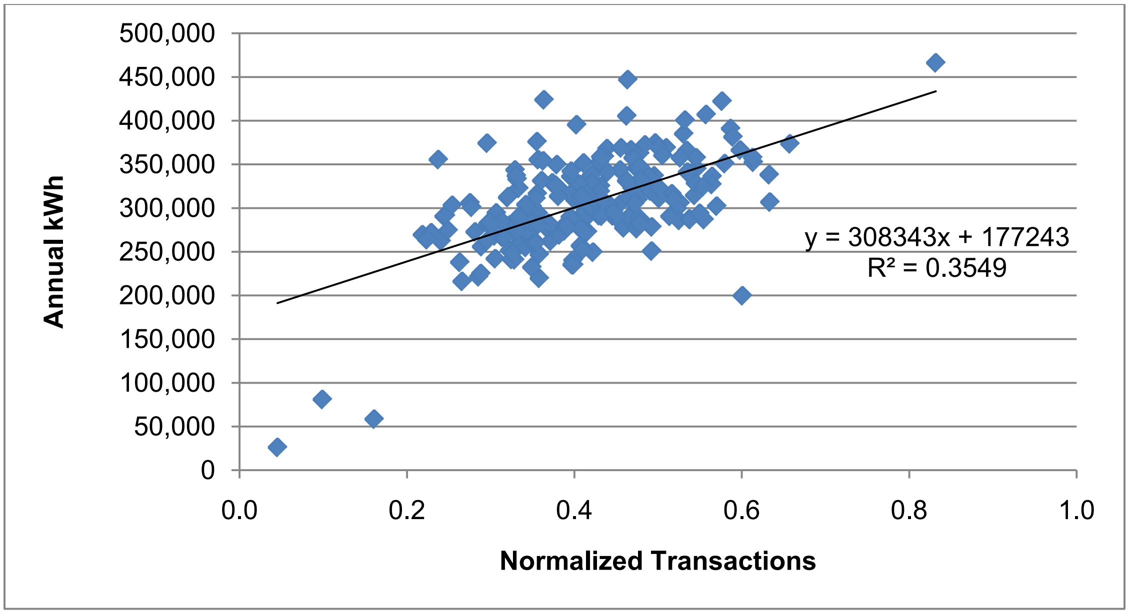

Figure B-9 Scatter plot of electricity use for store type D

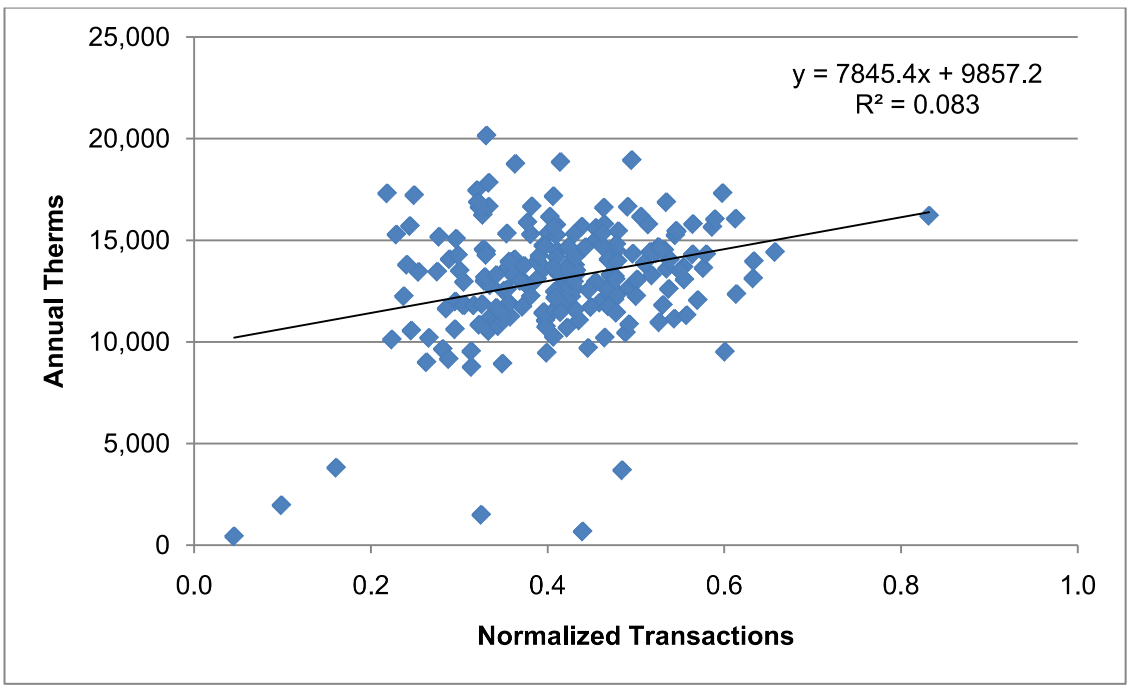

Figure B-10 Scatter plot of natural gas use for store type D

Appendix C Discussion of Heating Degree Days and Cooling Degree Days

This appendix presents the concepts of building balance points and degree days in detail.

C.1 Balance Point

Heating and cooling requirements vary for each building depending on multiple variables, including the amount of glazing, level of insulation, occupancy and process load outdoor air ventilation, wind conditions, thermostat set points, amount and control of natural ventilation, door openings and closings, and internally generated heat. In general there is an average outdoor temperature at which a building requires no mechanical heating or cooling. This is called the *balance point*. In reality, the balance point changes constantly, based on how external weather and internal heat-generating loads change throughout the day. Thus, it is typically a temperature range, but for convenience in estimating required annual heating or cooling energy, a single temperature is selected. The heating balance point may differ from the cooling balance point.

C.2 Variable Base Degree Days

A degree day unit represents the difference between the actual average daily outdoor temperature compared to a selected base temperature (the balance point temperature). For example, if the average outdoor temperature for a day is 35°F and heating is required for a particular building when the outdoor temperature is below 60°F, the HDDs for that day total 25. CDDs are similarly calculated: if the average daily temperature is 75°F and the building requires cooling when the average outdoor temperature exceeds 65°F, the total CDDs for that day are 10.

C.3 Food Service Facility Balance Points

Zones in a building, especially in a food service facility, may have different balance points. The energy used by food service appliances is typically 30%–50% of total building energy (Claar et al. 1985; Smith et al. 1999; Smith and Fisher 2001; Zhang et al. 2010). Some of this energy leaves the building through kitchen exhaust, exfiltration through drive-through windows, and with take-out orders. Heat gain from appliances typically causes kitchens to be warm to hot; thus, they may have longer cooling hours and seasons than the dining room, which may have high heat gains from lighting, customers, solar gains through glazing, soup and salad bars, and drink machines. Thermostat set points for the kitchen and dining areas may be different as well. These differences in loads on the mechanical heating and cooling systems result in different balance points for these zones. There are likely to be many hours when the dining room requires heating and the kitchen requires cooling simultaneously.

Field experience and measured data indicate that kitchen balance points are 40°–55°F; dining rooms are 55°–65°F.