Benchmarking Energy Use in Schools

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ABSTRACT

Local governments across the United States spent approximately $5 billion, an average of $100 million per state, on energy for their public schools in 1992. This represents a tremendous drain on education dollars of which part (captured through building system and operational efficiency improvements) could be directed toward more important educational needs. States and local governments know there are sizeable opportunities, but are challenged by how and where to start. Identifying the worst energy performers, with the most potential, easily and at low cost is a key in motivating local governments into action. Energy benchmarking is an excellent tool for this purpose.

The 1992 US Energy Information Administration's Commercial Buildings Energy Consumption Survey (CBECS) database is investigated as a source for energy benchmarks for local-government-owned schools. Average energy use values derived from CBECS are shown to be poor energy benchmarks. Simple distributions of building energy use values derived from CBECS, however, are shown to be reliable energy benchmarks for local schools. These can be used to gauge the energy performance of your local public school.

Using a stepwise, linear-regression analysis, the primary determinants of electric use in local schools were found to be gross floor area, year of construction, use of walk-in coolers, electric cooling, non-electric energy use, roof construction, and HVAC operational responsibility. The determinants vary depending on the school's location. While benchmarking based on simple distributions is a good method, an improved benchmarking method which can account for these additional drivers of energy use is detailed.

Introduction

The expenditures by local governments for energy in their public schools represent a tremendous drain on education dollars. A sizeable portion of these costs, which averaged $100 million per state in 1992 (EIA 1995), can be captured through building system and operational efficiency improvements and perhaps redirected toward more important educational needs. States and local governments know there are sizeable opportunities, and many are very interested in seizing them, but are challenged by how and where to start.

One method of identifying marginal and poor performers, without rigorous evaluation, is to benchmark or compare a school's energy performance to other similar schools. Learning that 80% of similar schools use less energy can be a key motivator for owner action. This paper discusses methods for benchmarking the energy performance of local schools. The work was performed to support the commercial building research efforts of the US Department of Energy's Office of Building Technology, State and Community Programs. The development of simplified tools for comparing the energy performance of existing buildings is of interest to national, state, and local building owners.

Background

Energy use intensity (EUI) reflects a rate of energy use. Often referred to as the energy use index, average power level, or power density, it is an index that is widely used in building energy analysis.

Expressed as kWh/sf/yr, it is a preferred unit of analysis for commercial building energy use (Eto 1990, Haberl and Komor 1989, Landman 1998, MacDonald 1988). For buildings, the EUI is also commonly expressed in Btu/sf/yr. EUIs are an attempt to normalize energy use relative to it's primary determinant, building floor area, such that the energy use of many buildings are comparable. By normalizing, it is hoped that wide differences between building EUIs will be reliable indicators of inefficient buildings or systems where improvements can be made.

The development of EUIs has been approached using localized sampling by utilities, prototype analysis, performance modeling, load shape estimation, consensus estimates, and wide-scale national sampling (Akbari 1994, Crawley 1987, Eto 1990, Fireovid 1990, EIA 1995). EUIs have also been studied for use as whole-buildings energy design targets (Crawley 1987). Although normalized for the primary determinant of building energy use, floor area, EUIs continue to vary widely and thus, are uncertain benchmarks as indicators of the performance of an individual building.

Because an annual, whole-building EUI (a single EUI representing all energy used in a building) masks much of the information that can be learned from a more detailed investigation of energy use data, EUIs have been studied for each fuel used and for monthly, daily, and hourly time steps (Haberl and Komor 1989, Landman 1998, MacDonald 1988). These efforts have been aimed at determining what can be learned about an individual building from more detailed analysis of energy use data. Limited results are presented in past literature, however, on using whole-building EUIs for building to building comparisons.

Boonyatikarn (1982) performed a statistical analysis on fifty institutional buildings in Michigan to identify building characteristics that induce major variations in building energy use intensity. While there are many issues in Boonyatikarn's work that make in difficult to compare to the work presented here (small sample, mixed building types, detailed building characteristics not found in CBECS, and the use of multiple years of data for a single building as multiple EUIs for analytical purposes), the work demonstrates that regression analysis can successfully identify and quantify the important drivers of energy use in buildings. These abilities offer the opportunity to improve upon annual whole-building EUIs as reliable comparators of energy use between schools. This type of analysis, applied to the much larger CBECS database, is the basis for the improved energy benchmarking method presented in this paper.

Scope

This work was performed to present different approaches for benchmarking the energy use of local-government-owned schools. The methods presented consist of 1) using regional building performance data from the CBECS database for benchmarking at a macro level, 2) using state-level building performance data for more localized and accurate benchmarking, and 3) a method for further improving accuracy by accounting for energy use drivers in schools beyond building size.

Approach

Building energy performance data for local-government-owned school buildings were extracted from the CBECS database. Summary statistics were produced that characterize how the electricity use per square foot in schools is distributed for the nine census divisions identified in the CBECS database. The reliability of the CBECS regional distribution for Census Division 3 is confirmed by comparison to a state-level distribution. Finally, stepwise, least-squares linear regression modeling was performed on the energy use and building characteristics data for 449 local-government-owned schools in CBECS to identify the important secondary determinants of electric use intensity in school buildings. Models relating school electric use intensities to these determinants are then presented. The results have been used to develop a spreadsheet-based, energy-benchmarking tool for schools that is more accurate than comparisons to average EUIs and simple EUI distributions.

The CBECS Database

The 1992 Commercial Buildings Energy Consumption Survey (CBECS) contains energy consumption, energy expenditure, and extensive energy-related building characteristics for 6,751 commercial buildings. All fifty states and the District of Columbia are represented. Locally-owned-government school buildings comprise 449 buildings in this database. These 449 buildings represent approximately 163,000 local-government-owned schools across the U.S.[1] The smallest geographical region identified for each school is one of nine U.S. census divisions as shown in Figure 1.

All school buildings in the database have over 1,000 square feet of floor area. Floor area has been rounded off for all buildings. This rounding can produce errors in energy use intensity between 5 and 10% in most cases. For the smallest buildings, 1001 to 1750 square feet, this rounding can lead to sizeable EUI errors between 14 and 25%. These small buildings can easily be creating problems in the tails of statistical EUI distributions as discussed in this paper. Fortunately, these smaller buildings represent only about 10% of the sample. In addition, these errors can be positive or negative so there is some balancing of errors within the sample of buildings.

Results

The CBECS database contains 719 educational buildings that fall under the ownership categories shown in Table 1. This analysis focuses on the 449 schools in the CBECS database that are owned by local governments. This subset was chosen because public schools comprise most of the schools in the U.S., are most abundant in the CBECS database, and were found to have significantly different energy performance than the other two most popular ownership categories (state government and religious). The local schools were divided into their respective census divisions for analysis.

Benchmarking Using CBECS Averages

A simple approach often used to benchmark building energy use is to compare to the average energy performance of a group of similar buildings. The possibility of benchmarking an individual building against an average created from the CBECS database was investigated. Analyses were completed by census division, the smallest geographical division available. The 449 local-government-owned schools are distributed across the nine US census divisions as shown in Table 2.

A frequency chart showing the distribution of electric energy use intensities in Census Division 3 is shown in Figure 2. In this figure, the CBECS weighting factors have been applied to the 69 buildings sampled such that the distribution should be representative of the approximately 17,750 local-government-owned schools in Census Division 3. The average and median (the value on the distribution where half are larger and half are smaller) EUIs for the group are also shown. Electric EUIs have a wide range but more

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[1] Sampling for the CBECS database was designed such that each building in it represents a specific number of the total buildings in the U.S. (referred to as the weight). To accurately reflect all U.S. buildings, it is necessary to weight each building appropriately when conducting analyses.

importantly, the distribution is skewed well below the average. Similar skewed distributions occur in all census divisions. This is important because skewed distributions shift averages away from the middle of the distribution. Depending on the extent of the skewness, a building could be an average performer among a group but could still be a very poor performer when compared to others.

Averages and medians were checked for the impact of skewness. Table 2 shows these results and confirms that all distributions are skewed (averages are higher than medians in all cases, and much higher in many). The skewness is sizeable in 6 of 9 census divisions where the average falls at 72% or higher on the EUI distributions. This means that 72% of buildings in Census Division 1 and an extreme 86% of buildings in Census Division 8 use less than the average energy use per square foot in their respective census divisions. For these census divisions, benchmarking to an average would likely lead the owner to no action in most cases (excessive energy use intensities are not apparent). Distributional benchmarking (determining the percent of similar buildings using less energy), however, eliminates this masking of high energy use and would hopefully motivate the owner toward further investigation.

Benchmarking Using CBECS Distributions

Because of the skewness of EUI distributions, the distributions themselves offer improved benchmarking over averages. The CBECS database can be used to generate cumulative EUI distributions for local-government-owned schools in each census division. The school EUIs presented in Figure 2 are presented as a cumulative distribution in Figure 3. With knowledge of their building's energy use and size, an owner or manager can calculate their school EUI and find the percent of similar schools using less energy per square foot from this type of distribution. The reliability of these cumulative distributions created from CBECS regional data was investigated for use in localized benchmarking.

One weakness of the CBECS database for benchmarking is small sample size. Four of the census divisions have sample sizes between 21 and 29 buildings (identified in Table 2). The electric EUIs of the 22 schools sampled in Census Division 8 are presented in ascending order in Figure 4. In this census division, there is one extreme building at 61 kWh/sf/yr and one building represents approximately 5% of the sample. When the appropriate weights are applied to each building to make the resulting distribution representative of all buildings in the census division, the building now represents 9% (it's weight is 602 and there are approximately 6600 local-government-owned schools in Census Division 8). An extreme value such as this representing a sizeable portion of a sample has a dramatic effect on a group average. This situation should be of major concern to anyone benchmarking against averages.

Smaller sample size and extreme values are of less significance in distributional benchmarking. In this approach, small sample sizes provide few observations at the extreme ends of a distribution. Thus, there is uncertainty as to where the true tails (ends) of the distribution lie. This is not that big of a concern for distributional benchmarking, however. It is not that important to know that a building that benchmarks at 85% would actually benchmark at 75% if the sample size were larger. This is because buildings that fall at either of these levels, unless they have features that cause their energy use to be high, are both excessive energy users. Where accuracy is needed most is in the middle portions of the distribution where most observations are found. Here, a small change in electric EUI can shift the percentile ranking on a cumulative distribution substantially.

A second concern of using the CBECS data for benchmarking is whether the regional CBECS school energy use data accurately represents the performance of a local school. The CBECS database consists of a very small sampling of all buildings within each census division. As a result, the database provides weighting factors to apply to each observation so that analysis results will be representative of all buildings within the census divisions. Due to the small sample sizes, the ability of CBECS analyses to represent an entire census division is an issue of debate. This concern was examined by comparing an EUI distribution for schools in the state of Ohio with the CBECS EUI distribution for Census Division 3 (consists of Ohio, Michigan, Wisconsin, Illinois, and Indiana). Figure 5 shows this comparison. The weighted CBECS distribution tracks very closely the distribution developed from data on the 158 local-government-owned schools in Ohio.

If the CBECS weighting factors are not applied to each observation, the resulting distribution is considerably different. If the 69 buildings in Census Division 3 are taken and simply ordered by increasing electric EUI, the unweighted distribution results. Figure 6 shows that this unweighted distribution is much lower than the Ohio distribution at most EUI bins.

Improving Benchmarks Beyond Simplified Distributions

There are common characteristics that consistently cause a building's energy use to be higher than in other similar buildings. Typical examples for office buildings are a high occupant density (the number of people per square foot), large amounts of electronic equipment such as computers, and long operating hours. A large database of individual buildings containing both energy use and characteristics data, such as the CBECS, can be used to identify the building characteristics that are the most common and significant drivers of building energy use (Boonyatikahn 1982). This has recently been done for office buildings using the CBECS database (Sharp 1996). This work performed a similar analysis for schools. In simple distributional benchmarking, energy use is normalized for floor area to get energy use per square foot and then the ranking (ordering by increasing EUI) is performed. By identifying the most important secondary drivers through analysis of energy performance data from existing buildings, it is possible to normalize for additional energy use drivers and improve upon our benchmarking ability.

This concept of secondary drivers and their associated distributions is illustrated in Figure 7. This figure shows that a simple EUI distribution actually consists of multiple smaller, secondary distributions that can be created by grouping buildings by additional building characteristics beyond floor area. A building that may benchmark high in the primary distribution may actually be energy efficient if it happens to have a characteristic that increases energy use when present. By normalizing for the most important secondary characteristics, potential errors are further reduced and there is more confidence in the benchmarking results. The example benchmark shown in Figure 7 represents a building benchmarking at approximately 75% on the primary (floor area normalization) distribution. In this case, the buildings appears to be an excessive energy user. Thus, an owner or manager of a large number of properties trying to reduce a multi-million dollar energy budget would want to make this building a higher priority in their efforts. If it turned out, however, that this building was operated 168 hours per week, the answer could be completely different. Moving horizontally onto the secondary distribution for buildings with 168-hour operating weeks, the building is found to benchmark at around 30%. As a result, this building would likely no longer even be a priority for the owner's or manager's initial efforts.

As buildings in the CBECS database are grouped by secondary characteristics, sample sizes can decrease rapidly. To overcome the problems of small sample size, as opposed to analyzing only the few buildings with 168-hour operating weeks, all school buildings in the census division were used to determine the relationship between operating hours and EUI. The sample size remained large, allowing a reliable relationship between a key building characteristic and building energy use to be determined. The relationship can then be used to normalize for a secondary effect if found important. This was the approach used to establish relationships between secondary building characteristics and energy use.

A stepwise, multi-variate linear regression analysis was used to identify the relationships between school electric EUIs and secondary building characteristics. One-hundred fifteen of the over 600 building characteristics reported for buildings in the CBECS database were selected for analysis. These characteristics were selected based on the author's knowledge of building characteristics that would be most likely to have significant impacts on building energy use. Of the 115 starting characteristics, most were found to have a statistically significant relationship to electric EUI in at least one census division, even though correlations were very small (this occurs in part due to very large sample sizes that are created when the CBECS weights are applied). These were refined down to 32 characteristics each of which had two properties 1) the characteristic had a statistically significant relationship to EUI in two or more census divisions, and 2) the characteristic provided a partial R**2 of at least 0.05 when correlated to electric EUI. These 32 characteristics are summarized in Table 3. The characteristics are related to climate, the type of fuels used for heating and cooling, how the building is used, how it is operated and controlled, and what types of systems are utilized (heating, cooling, lighting, water heating, refrigeration).

The set of 32 characteristics were refined in an iterative process by removing those characteristics that were the least common and weakest predictors for the nine census divisions. This was an iterative process because the removal of one variable can affect the predictive ability of another and its statistical significance. The process produced 6 variables which were found to be the most common and correlated determinants of school electric use intensity in the nine census divisions. The two most common characteristics correspond to year of construction and the presence of walk-in coolers. The other four characteristics correspond to the use of electric cooling, the amount of natural gas used, the person responsible for the HVAC equipment, and roof construction.

Standard linear regression was performed on the final six variables to determine model coefficients for each census division. Models based on a small number of the strongest characteristics are simpler and are close approximations of estimates that an expanded model based on all significant variables would produce.

The resulting predictive model for electric energy use intensity (kWh/sf/yr) in local-government-owned schools is:

$$\ln(kwhsf) = a + b * YRCON + c * RFGWI + d * ELCOOL + e * NGBTUSF + f * OPHVAC1 + g * RFCNS3.$$

CBECS definitions for the variables in the model are defined in Table 3. RFGWI, ELCOOL, OPHVAC1, and RFCNS3 have a value of 1 when they are either true for or present within the building, and 0 otherwise. Coefficients and associated statistics for each census division model are given in Table 4. Note that individual census division EUI models are modeled on only two or three building characteristics. Yet, model R**2s, which are statistics related to how well a model can predict variations in the dependent variable, EUI, range from between 0.35 and 0.89. Expanding models to include other building characteristics did little to improve these R**2s. These results indicate that these simple 2- and 3-parameter models can explain most of the variation in electric EUIs that can be explained by all CBECS variables investigated.

Along with a statistical model, regression analysis produces equations that describe the confidence levels for predicted values that would resulting from applying the regression model. These equations can be used to determine the distribution of predicted EUIs that would result from applying the model. For a specific building, distributions of predicted EUIs will differ based on the model used (which census division) and the values of the building characteristics. Because of the wide variation in values of the important building characteristics identified, many different predictive distributions will result from applying the electric energy use models, and thus computational ability is needed. A spreadsheet-based benchmarking tool was developed for this purpose. The spreadsheet provides school districts an easy-to-use tool for evaluating the energy performance of an individual school using the more accurate, higher order benchmarking scheme that accounts for these important secondary building characteristics. Similar work for office buildings demonstrated that this approach provides considerable improvement for building-to-building comparisons (Sharp 1996).

Conclusions

Most distributions of energy use intensities for buildings are skewed. As a result, using the average performance of a group as an energy benchmark is often a poor energy performance indicator. Distributional benchmarking is much better. CBECS-based, census division (regional) distributions, when weighted, appear to be good approximations for distributions at the state level. At a minimum, these CBECS distributions can serve as an effective benchmarking tool for owners and managers until such time as they may be able to assimilate their own local energy bills for developing localized results or the accuracy of their regional CBECS distribution for local application is confirmed.

Simple distributional benchmarking can be improved by normalizing for the important secondary drivers (building characteristics) of school building energy use. Regression analysis can be used to determine reliable relationships between these secondary drivers and energy use for this normalization when sample sizes are of adequate size. A spreadsheet-based benchmarking tool has been developed based on these results to provide local school districts a simple tool for using improved, distributional benchmarking to compare their school's energy performance to others. The tool is downloadable from the website for Oak Ridge National Laboratory's Buildings Technology Center (http://eber.ed.ornl.gov/products.htm) .

Either of these approaches will allow local-government-owned school systems to begin to identify their schools having excessive energy use. This can be of value to school systems in many ways including: 1) identifying schools with the most severe operational, control, and system problems, 2) helping to prioritize buildings for improvements, 3) assessing energy cost reduction opportunities in schools targeted for renovation, 4) determining the best schools for energy performance contracts, and 5) establishing what is an acceptable energy performance for new schools.

Acknowledgments

This work was supported by the Commercial Buildings Research Program of the U.S. Department of Energy Office of Building Technology, State and Community Programs under contract No. DE-AC05-96OR22464.

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Table 1. Ownership of the 719 educational buildings in CBECS.

Owner	No. of buildings	Owner	No. of buildings
Federal government	6	Private utility	2
State government	110	Religious	66
Local government	449	Other	86

Table 2. Electric use statistics for local-government-owned schools in the CBECS (medians and averages are weighted values).

Census division	1	2	3	4	5	6	7	8	9
Number of buildings in CBECS database	21	55	69	21	74	29	75	22	83
Number of buildings in census division	5792	11907	17777	9777	22377	12012	29524	6613	46722
Median EUI (kWh/sf/yr)	4.8	4.9	4.7	4.4	7.5	8.7	7.4	7.7	7.3
Average EUI (kWh/sf/yr)	5.3	5.1	6.8	6.0	11.0	9.7	10.5	12.8	8.8
Location on distribution where average occurs, %	72	66	73	79	66	75	83	86	60

Table 3. CBECS and related defined variables with statistically significant relationships providing partial R**2s of 0.05 or greater when correlated to electric use intensity (EUI).

Variable	Definition	Variable	Definition
CLIMATE5	Climate zone	NGHT15	Natural gas used for main heating
YRCON5	Year construction was completed	NGHT25	Natural gas used for secondary heating
HT25	Secondary energy used for heating	HWWATR5	District hot water for water heating
COOLP5	Percent cooled in 1992	RFGWI5	Refrig./freezer walk-in units in bldg.
WKHRS5	Total weekly hours open	FLUORP5	Percent lit by fluorescent lights
RFCNS3	Roof is shingles (not wood) [defined]	WIN5	Exterior wall insulation
NGBTUSF	Annual natural gas use-mBtu/sf [defined]	RDOTNF5	Reduction in other equipment off-hours
FDRMP5	Pct. floorspace commercial food prep.	EMCSCL5	EMCS controls cooling
CMPRMP5	Pct. floorspace computer rooms	EMCSLT5	EMCS controls lighting
PORVAC5	Space vacant for at least 3 months	DAYCTL5	Daylighting controls
LTHRS5	No. extra hours lighting equip. used	DEMMTR5	Electricity demand-metering
CDD655	Cooling Degree-Days (Base 65 F)	FKSUPL5	Fuel oil supplied
HTPHP5	Pct. heated by the heat pump	NWKER5	Number of workers
SLFCNP5	Pct. heated by individual space heaters	LTOHRP5	Percent lit during operating hours
BOILP5	Pct. heated by boilers	OPHVAC1	Person responsible for HVAC equipment is owner/manager [defined]
ELCOOL5	Electricity used for cooling		
ELWATR5	Electricity used for water heating		

Table 4. Regression models and associated statistics by census division.

Model: ln(kWhsf) = a + b*YRCON + c* RFGWI + d*ELCOOL + e*NGBTUSF + f*OPHVAC1 + g*RFCNS3

Census division	Model R**2	Model f stat.	Coeff. a	t stat.	Coeff. b	t stat.	Coeff. c	t stat.	Coeff. d	t stat.
1	0.47	2586	-8.714	-46.4	0.0106	53.7	0.271	28.3	0	
2	0.35	3234	-4.952	-39.3	0.0067	50.4	0.344	65.0	0	
3	0.42	4303	-7.027	-43.6	0.0088	51.8	0		0.318	46.9
4	0.76	10253	0.325	33.2	0		1.120	86.2	0.955	87.3
5	0.89	85590	0.000		0		0		2.433	402.94
6	0.35	3219	-11.684	-58.7	0.0143	68.7	0.206	21.5	0	
7	0.45	12211	-5.296	-35.7	0.0074	48.3			0	
8	0.64	3867	40.648	92.2	-0.0390	-86.9	-1.241	-70.2	0	
9	0.36	8362	1.757	351.2	0		0		0	

Census division	Coeff. e	t stat.	Coeff. f	t stat.	Coeff. g	t stat.
1-2	0		0		0	
3	0.00176	88.0	0		0	
4	0		0		1.52	117.4
5	-0.01422	-119.6	0		0	
6	0		0		0	
7	0		1.15	140.4	0	
8	0		-2.11	-97.4	0	
9	0.00543	71.3	0.44	50.1	-1.22	-120.9

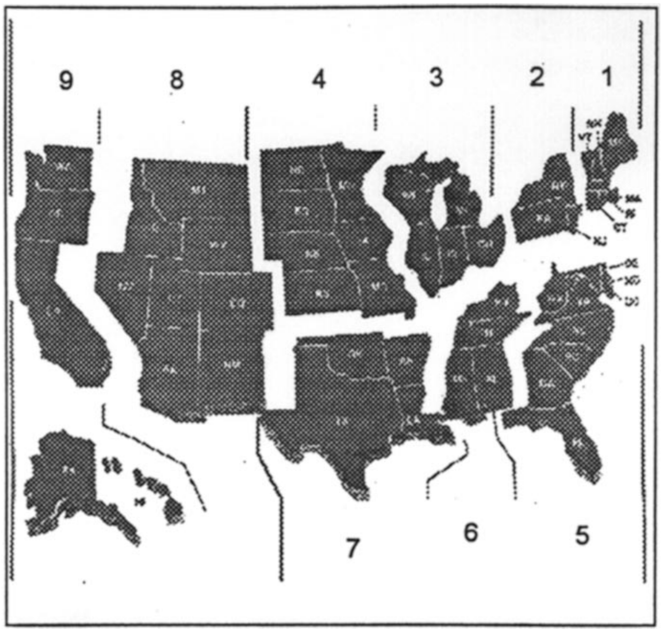

Figure 1. The nine US census divisions as defined in CBECS.

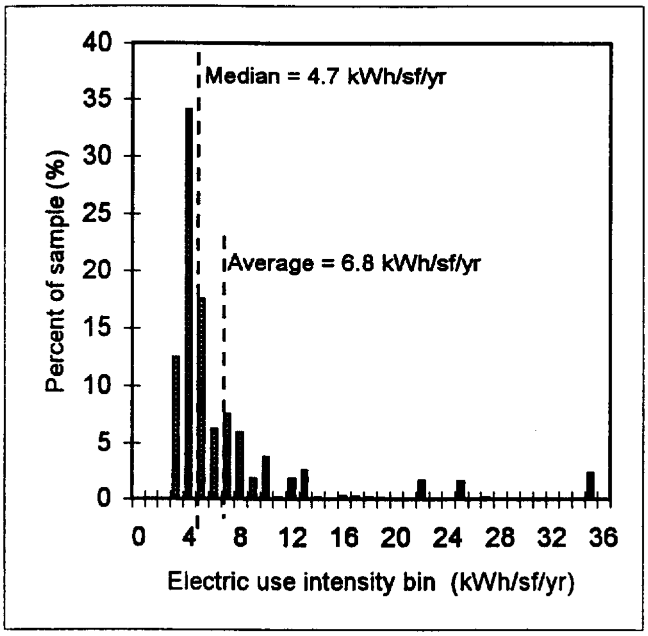

Figure 2. Frequency distribution of EUIs for local-government-owned schools in Census Division 3 (CBECS weightings applied).

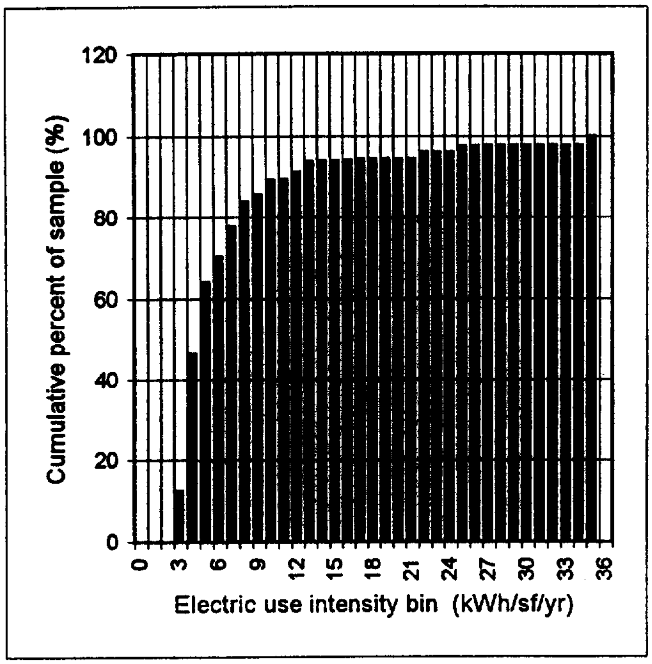

Figure 3. Cumulative frequency distribution of EUIs for local-government-owned schools in Census Division 3 (CBECS weightings applied).

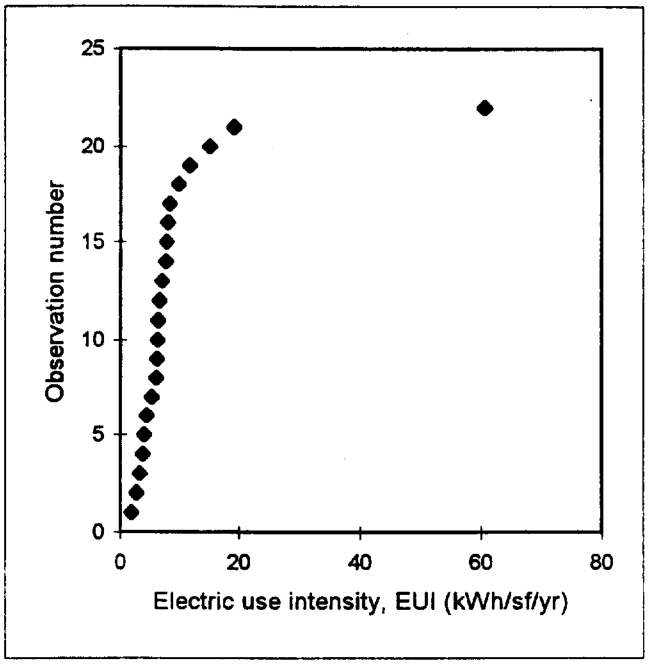

Figure 4. EUIs for the 22 schools in Census Division 8 arranged in ascending order.

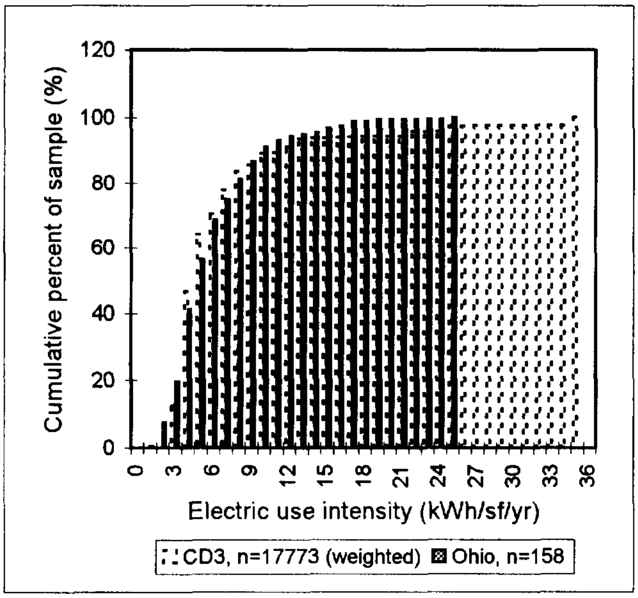

Figure 5. Cumulative frequency distribution of CBECS observations for school EUIs in Census Division 3 versus Ohio observations.

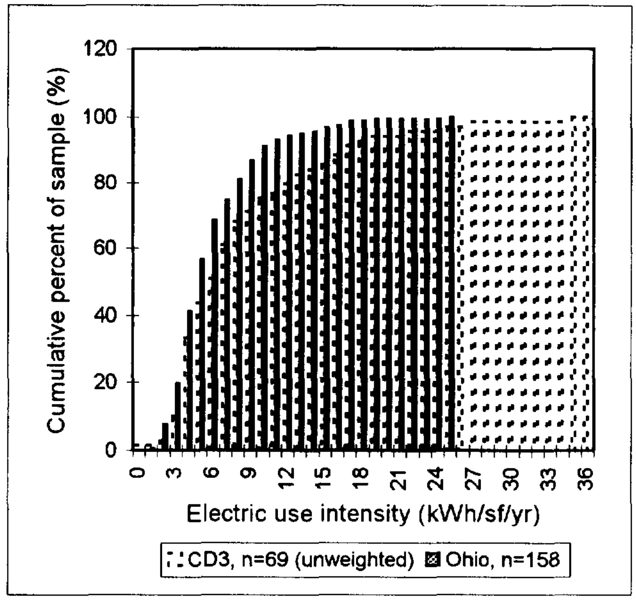

Figure 6. Cumulative frequency distribution of unweighted CBECS observations for school EUIs in Census Division 3 versus Ohio observations.

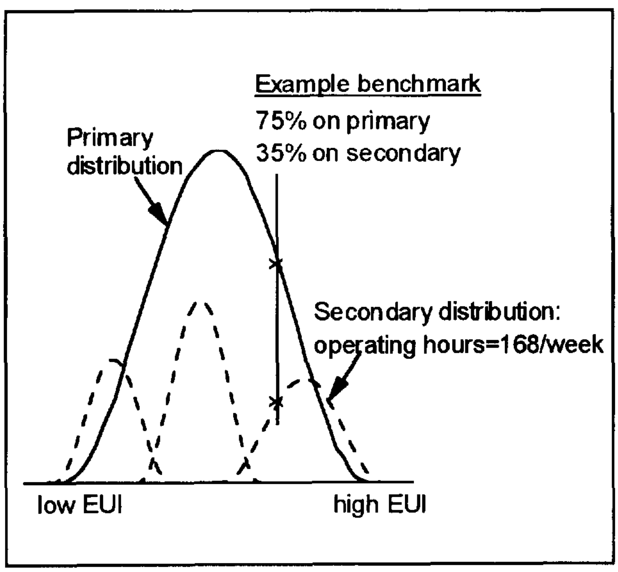

Figure 7. A distribution of building EUIs is made up of multiple secondary distributions.