Innovative Lighting Baseline Hours-of-Use Research in Primary and Secondary Schools

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Abstract

Some efficiency programs base their estimates of lighting savings in schools upon hours-of-use that reflect traditional, seasonal occupancy for educational, athletic, and occasional dance functions. But with more communities utilizing school buildings year-round for community events and adult education, some hypothesize that current program savings assumptions do not capture this increased use and hence underestimate measure impacts.

Recently, several electric utilities in Connecticut and Massachusetts sponsored a study to better inform lighting hours *prior to sensor installation* in the interest of more accurately estimating the impact of occupancy sensors on lighting. The utilities sought credible estimates of these "baseline" lighting operating hours in school buildings by a variety of dimensions of interest including school classification, demographics, and room type. In addition to reassessing the value of occupancy sensors in schools, this research also pursued hourly lighting profiles and peak coincidence factors.

The scope of this project proved to be extensive and challenging, employing statistical sampling and data collection techniques in a creative and robust analytical framework. Engineers performed a complete lighting inventory of every room in 80 schools and logged occupancy and lighting hours in 646 rooms across both summer and fall-session periods. In total, analysts processed over one million records of lighting/occupancy data in a complex analysis that combined interview-based and measured hours with room-level detail and school-level characteristics.

This paper highlights some innovative methods while sharing study results. This two-year project offers valuable lessons on how to 1) plan and leverage multi-dimensional data collection and 2) salvage an analysis when assumptions fail.

Introduction

In this study, the term "baseline hours" refers to the number of hours that a given unit of lighting operates across a typical year (i.e. "annual operating hours") prior to the installation of automatic lighting controls. For the purposes of this definition, these controls include, but are not limited to, occupancy sensors, daylight controls, time clocks, and a variety of direct digital controls (DDC).

While ultimately successful, this project encountered some unforeseen obstacles in the planning, sampling, and analysis stages that threatened the analytical framework and risked invalidating results. Perhaps the most valuable lesson of this study is that one occasionally can salvage a disrupted approach with alternative, creative, and even rudimentary techniques. Extensive data and multi-dimensional objectives do not necessarily dictate complex methods. And underlying assumptions can make or break a project.

Analytical Approach

An hours-of-use study employs a different sampling strategy than an impact evaluation. It is well established in the statistical community that stratified sampling is the preferred technique for developing energy-centric results at target precision levels while minimizing sample size requirements. In order to stratify, one seeks a numeric descriptor or "explanatory variable" with which to sort and divide the population. Larger schools generally have more lights in most space types, and thus should have a greater weight and influence on the average hours of use.

Not to be confused with "case weights" which reflect how a sample point (e.g. a school) represents others in the study population, hours-of-use analysis must also weight *within* a given sample point (e.g. individual rooms or fixtures). A single school might represent ten others in a given sample design, but one also needs a framework to quantify the relative influence of the school's hallway, classroom, and storage spaces on the school's overall estimate of hours-of-use.

It turns out that the most appropriate weight for an hours-of-use application is connected demand, based on the fact that energy is the product of demand times hours. So, in order to compute a space-weighted estimate of annual lighting hours for an entire site, one divides the total annual kWh consumption of all lights by their total connected kW lighting load. This ratio – annual kWh over connected kW – is the central interest in an hours-of-use study.

Sample Design Challenges

Since the proposed statistical framework hinged upon quantification of lighting energy and demand, analysts instinctively chose stratified ratio estimation (SRE) techniques to develop the research sample design. Achieving analytical objectives with statistical confidence using SRE requires an accurate and relevant explanatory variable for the entire population of interest. But characterizing the study population proved more challenging than anticipated and posed the first major obstacle.

Load research has taught us that total annual energy consumption is generally a good predictor of lighting energy in non-industrial buildings like schools. Therefore, the sponsoring utilities were asked to provide billing data for all primary and secondary schools in their respective service territories. But utilities had difficulty identifying schools definitively in their customer billing systems. Crosschecks of utility billing data extracts against State and other lists of public and private schools revealed considerable inconsistencies in the expected number of schools.

Analysts were unsuccessful in their attempts to isolate the approximately 1,500 schools in the utilities' customer information systems. Increasingly evident that a valid population dataset of *annual energy consumption* was unattainable within the available project budget, researchers turned attention towards findings alternative data sources for use in developing a viable sample design.

Ultimately, the project team chose data from the National Council for Educational Statistics (NCES) as an accurate, authoritative and reliable resource. With annual energy consumption by school unavailable, analysts settled upon 'total student enrollment' as the next best available characterization of school size for the study population. In essence, the number of students per school was chosen as a proxy for annual energy consumption. Analysts used student population as the explanatory variable to structure the sample design and tailor the sampling fractions to be higher for larger schools.

Salvaging Unexpected Results

A multi-dimensional sample was drawn and field staff visited a total of eighty (80) schools by the end of June 2005, prior to the close of the academic year. Data collection included a complete lighting inventory, verbally-reported hours-of-use, and direct monitoring of both lighting and occupancy hours-of-use with a total of 646 loggers. The monitoring covered a targeted variety of room types and extended from the end of one academic 'year', through the summer, and into the following autumn academic session.

But subsequent analysis revealed disappointing statistical precision from the analytical models. As it turned out, the weak linkage between 'student enrollment' and lighting energy/demand, compounded by high variability within the sample data itself, yielded estimates of relative precision that did not permit differentiation across all dimensions of interest. In other words, the resultant error bound on lighting hours was so large that subsequent testing concluded no statistically significant difference between most school types.

In an effort to salvage the study, analysts retrenched and examined the data under various alternative post-stratifications, weighting schemes, and statistical models. Dr. Roger L. Wright was brought in to help develop a method to recover the study, leveraging unprecedented amounts of data on operating and occupancy patterns in schools to yield conclusive and meaningful results. As will be shown, sometimes we fail to "see the forest for the trees" and basic, simpler methods prevail.

Multi-Dimensional Objectives

The utility sponsors sought results for school baseline lighting hours-of-use across many dimensions of interest, including:

- **Classification**: Elementary, Middle, and High
- **Funding**: Public, Private
- **Special**: Vocational, Technical, Charter, Magnet
- **Location**: Rural, Suburban, Urban
- **Room Type**: Auditorium, cafeteria, classroom, gymnasium, hallway, kitchen, library, locker room, mechanical room, office, restroom, storage closet, teacher's lounge, and 'other' spaces.
- **Classroom Usage**: Kindergarten, computer lab, music education, chemistry lab, lecture hall, etc.
- **Vintage**: Less than 5 years old, 5 to 15 years old, over 15 years old

RLW ran numerous iterations in order to optimize coverage and expected relative precision across analysis segments. It was necessary to consolidate and prioritize this list, as it would be unlikely to attain statistically significant results in all of these dimensions within available budget resources. Table 1 presents the expected precision for a sample of 80 schools by the five 'primary' analysis sectors. Preliminary expectations were for ±10.9% relative precision on the overall estimate of annual operating hours.

Table 1. Expected Precision by Primary Analysis Sector

	Population		Sample	Expected
School Type	**Size (N)**	**% of Total**	**Size (n)**	**Precision**
Public 'Standard' School	1088	74%	42	12.5%
Public Vo/Tech School	18	1%	5	24.2%
Public Magnet School	23	2%	6	30.9%
Public Charter School	20	1%	6	27.4%
Private School	312	21%	21	20.6%
Grand Total	**1461**		**80**	**10.9%**

As seen in Table 2, we also investigated the expected precision across a number of additional but 'secondary' analysis sectors. These dimensions were of considerable interest to the study team, and analysts worked to prioritize them accordingly. The sample allocation and resultant precision were steered towards focusing precision upon more important sectors (like public vs. private schools) and relaxing precision in less important sectors (such as by school type classification). In addition to ±10% overall, RLW targeted ±20% by public/private class and no worse than ±30% in any of the following sectors.

Table 2. Expected Precision by Secondary Analysis Sector

School Type	Population Size (N)	Population % of Total	Sample Size (n)	Expected Precision
By Funding Source				
Public	1149	79%	59	11.8%
Private	312	21%	21	20.6%
By School Locale				
Urban	401	27%	30	20.5%
Suburban	756	52%	35	16.7%
Rural	304	21%	15	25.4%
By Type Classification				
'Standard' School	1399	96%	63	11.3%
Vo/Tech	19	1%	5	31.8%
Magnet	23	2%	6	29.1%
Charter	20	1%	6	27.3%
By Educational Level				
Primary	932	64%	38	16.6%
Middle	250	17%	17	23.7%
High	279	19%	25	19.3%

Data Collection

Data collection began in May 2005. Field staff recruited and visited the full sample of eighty (80) schools by the end of June, prior to the close of the academic year. A total of 646 lighting and occupancy loggers monitored a sample of room types in these schools throughout the summer and into the autumn academic year. Loggers were retrieved in October 2005, and the data were downloaded, extracted and prepared for analysis.

The fundamental data collection activity associated with this project was the on-site visit. Structured data collection forms helped assure quality and completeness of data collection while at a customer site. A concise but detailed survey instrument was used to interview those who customarily occupy the various room types of interest (classrooms, corridors, offices, etc.) and assess the effects of behavioral factors and after-school activity schedules on the hours of use for each room type.

School management, administrators, maintenance personnel, and educational staff were all interviewed to develop an informed estimate of overall annual operating hours. Researchers intentionally monitored across both in-session and summer academic seasons and captured school-specific calendars in order to accurately annualize all of the data. RLW interviewed all persons who regularly use or control the lighting in specific buildings, areas, and rooms in the sample. These interviews were used to probe for behavioral influences and activities that may affect the specific patterns of use for each schoolroom, including evening or other non-school hour activities for the community.

The interviews also gathered information on the behavioral factors impacting the lighting use within each school area. In addition, the auditors sought to identify any changes that were expected to take place in the school's foreseeable future that might affect the operating hours of the lighting that were being assessed. Auditors remained vigilant for potential anomalies in the data collection that could skew results, such as atypical schools closings, budgetary constraints, major renovations or upgrades, sale of buildings, addition of modular classrooms, board of education mandates, etc.

While hours-of-use information was collected verbally for all spaces in all schools, it was measured (i.e. logged) for a carefully-selected logger sub-sample of spaces in each school. RLW employed both statistics and reason when selecting spaces for monitoring. Without knowing anything about the school in advance, it was impractical to specify the required number and placement of loggers before the visit. Interviews were conducted across the entire sample, because they were the most cost-effective means of characterizing operating hours across a multitude of space types. The lighting and occupancy loggers were used to refine and calibrate these interview results. The loggers were installed across a sample of room types and focused on spaces with significant square footage and connected lighting load.

For this study, the team chose combination lighting/occupancy loggers made by Sensor Switch, a manufacturer of occupancy sensors. These loggers are designed specifically for estimation of occupancy sensor savings potential and are proven in this study environment. This logger records change-of-state timestamps for both lighting and room occupancy, enabling researchers to estimate the savings potential for a given space, as indicated by the amount of time that the space is lit but unoccupied.

Analysis

As depicted in Figure 1, RLW employed a multi-stage analysis to expand the data from room-level detail to a building-level overview to a market-level summary. Comprehensive inventory data were collected for each room in the school, regardless of whether a lighting/occupancy logger was installed. This room-level inventory was associated with both verbally-reported and direct-monitored occupancy and lighting hours in order to 'build up' the room-level audit data to a characterization of the entire school. Thus, even without logger data, evaluators were able to compute room-level estimates of lighting annual energy usage (kWh) and connected demand (kW).

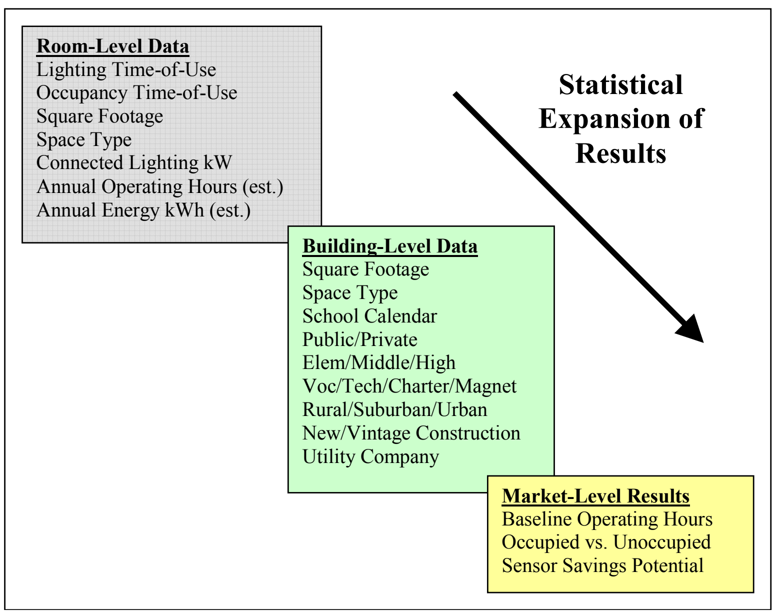


Figure 1. Study Analysis Flow

A critical aspect of this study was the collection of operating schedules as provided verbally by school personnel. An annual calendar was constructed for each school in order to categorize each day on one of five schedule types: Half-Day, Normal Day, Weekend, Summer School, and Vacation. In this manner, analysts leveraged all available data towards developing an aggregate, annual estimate.

The strength of this method is that it embraces the unique day types of the school sector instead of employing general assumptions or adjustments to annualize operation. Table 3 illustrates an example of one school's lighting energy, demand, and hours-of-use based upon 'verbal only' and 'verbal and monitoring' operating schedules. Similar analysis was conducted for all schools in the sample.

Table 3. Example School Results by Room Type

Room Code	Room Type	Verbal Only			Verbal and Monitoring		
		Energy kWh	Connected kW	Annual Hours	Energy kWh	Connected kW	Annual Hours
AUD	Auditorium	11,366	14.800	768	11,366	14.800	768
C	Cafeteria	6,261	3.112	2,012	7,867	3.112	2,528
CR	Classroom	53,742	30.736	1,749	53,221	30.736	1,732
G	Gymnasium	11,930	6.825	1,748	22,748	6.825	3,333
H	Hallway	33,272	10.200	3,262	33,229	10.200	3,258
K	Kitchen	3,230	2.276	1,419	3,230	2.276	1,419
LIB	Library	1,812	1.200	1,510	3,176	1.200	2,647
LR	Locker Room	2,475	1.416	1,748	2,475	1.416	1,748
MR	Mechanical Room	50	0.852	58	50	0.852	58
O	Office	8,189	3.300	2,482	8,740	3.300	2,649
OTH	Other	281	0.176	1,599	281	0.176	1,599
RR	Restroom	5,576	1.740	3,205	5,576	1.740	3,205
SC	Storage Closet	190	3.270	58	406	3.270	124
TL	Teacher's Lounge	713	0.792	900	826	0.792	1,042
TOTAL		**139,089**	**80.695**	**1,724**	**153,191**	**80.695**	**1,898**

A total of nine (9) loggers were installed at this particular school in the underlined room types, using monitored data to refine the verbally-reported results. In a typical school, auditors would install several loggers in classrooms and at least one in a hallway and another in the gymnasium, as these are the room types that usually have the highest energy consumption. Beyond this 'first priority' sample, auditors chose spaces with operating hours of the greatest uncertainty, i.e. where loggers were expected to improve the verbal estimate of operating hours. In the table above, the monitoring yielded kWh and hence operating hours that were 10% higher than verbally reported. Gymnasium hours in particular were significantly underestimated by interviewees at this school.

The monitored data enabled additional analyses that were not feasible using non-monitored information. Table 4 presents a tabulation of the data from the lighting and occupancy loggers that show the percentage of time by status by room type.

Table 4. Example Occupancy/Lighting Status by Room Type

Room Type	Lit		Unlit
	Occupied	Unoccupied	
Cafeteria	16%	13%	71%
Classroom	11%	3%	85%
Gym	17%	21%	62%
Hall	25%	12%	63%
Library	16%	15%	70%
Office	26%	12%	62%
Storage Closet	7%	35%	58%
Teacher's Lounge	8%	4%	88%

Table 4 suggests high savings potential (a significant proportion of time unoccupied but lit) for gym and storage spaces, whereas classrooms appear to have the lowest relative potential. Ironically, classrooms are the most popular occupancy sensor locations in schools.

Statistical Expansion

As it is the population aggregate estimate that proves the most meaningful, the next step was to expand the sample results to the school population. Thus, the final stage required analysts to combine the fixture-level loggers, room-level information, and building-level characteristics to compute market-level results in all dimensions of interest.

The critical ratio in this analysis is between lighting consumption (kWh) and connected load (kW). This particular ratio uses connected lighting load (kW) to serve as the weight and unifying term throughout the hours-of-use analysis. RLW's analysis was performed using industry-proven model-based statistical sampling (MBSS®) techniques and facilitated through the processing capabilities of SAS® analysis software.

The indicator 'total student enrollment' was not as good a predictor of school energy usage as had been anticipated. No better explanatory variable was found, however. RLW's initial statistical expansions showed that the relationship failed to support the traditional stratified ratio estimation approach that one would typically apply to this effort.

Normally, stratifying the population serves to greatly improve statistical results. Generally speaking, maintaining homogeneous analysis groups helps to mitigate and minimize variability. In simplest terms, it has been shown that 'large' sample points with high energy consumption (or savings) perform differently than 'small' points with lower estimates. The preferred RLW approach is thus to stratify them by size and to sample them independently.

However, when the initial statistical analysis yielded considerably worse statistical precision than expected, the logical course of action was to pursue alternate statistical designs via re-sectoring and post-stratification of the study sample. But after many unsuccessful attempts to remodel this school data, analysts discovered, quite by accident, that the results improved as the number of strata were reduced. The descriptive variable of student enrollment failed to support stratified ratio estimation (SRE) models, i.e. it was not an appropriate indicator of size for this study. Although this finding eliminated SRE methods, usually the most effective statistical technique for energy impacts, it redirected attention back to basic statistical methods.

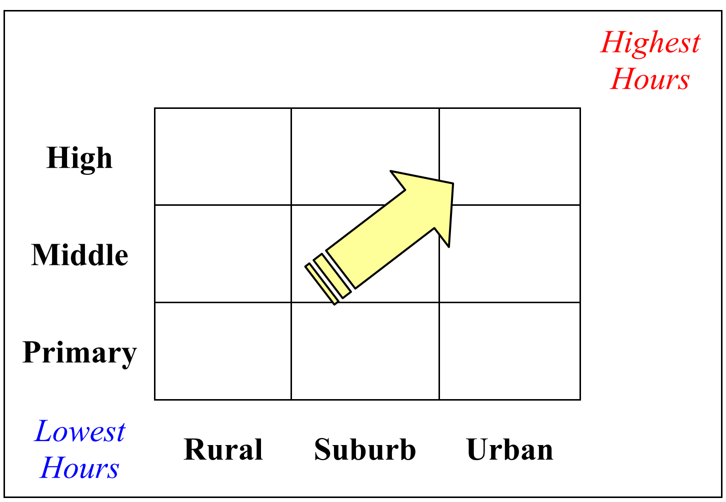


Figure 2. Optimal Sector Design for Schools

While achieving unfavorable statistical precision, the SRE did suggest that school level (primary, middle, high) and locale (rural, suburban, urban) were the two analysis sectors that consistently yielded the best statistical precision. Furthermore, as depicted conceptually in Figure 2, the lighting hours-of-use were notably different and increasing across both independent dimensions.

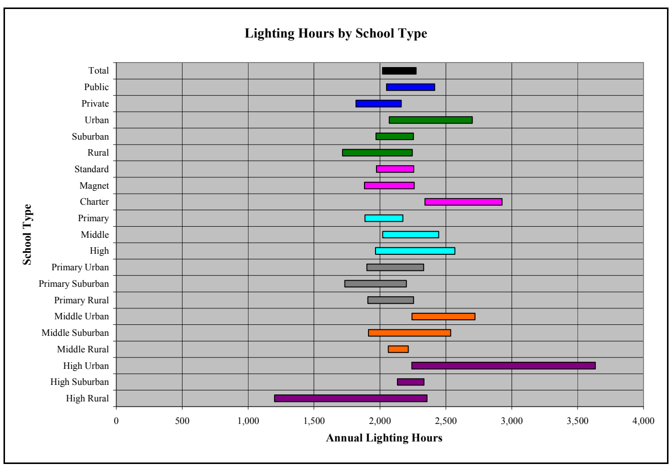
Another important finding was that one of the sample sites was a significant outlier. Subsequent investigation revealed that this was a massive vocational/technical school with many very large and densely lit 'shop' spaces. This school was a major statistical anomaly, with different energy characteristics from the other schools. While analysts were disappointed to have collected its data for naught, this school disrupted the homogeneity of the sample and justified the decision to drop it from the research sample.

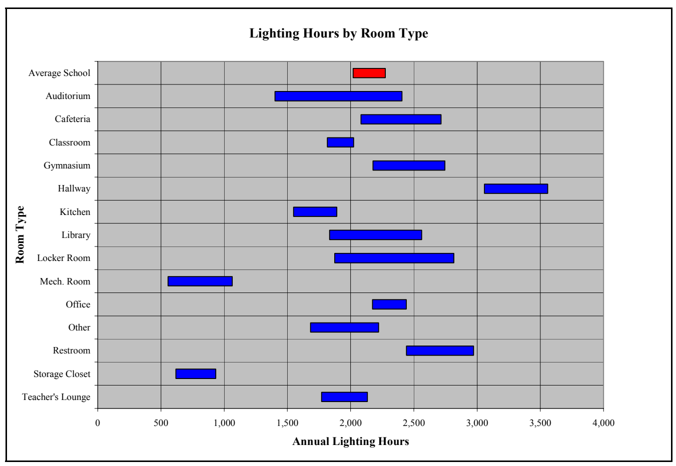
In the end, analysts abandoned the SRE approach and re-weighted the sample based upon simple random sampling in these nine sectors (three Levels, each with three Locales). Fortunately, all seventy-nine (79) schools were distributed fairly randomly across these nine cells, providing reasonable representation and coverage.

Results

Figure 3 presents the final, weighted analysis results by school type. This chart plots the region between the upper and lower error bound of the estimate as a horizontal bar representing the 90% confidence interval centered upon the mean estimate of lighting hours. Color coding the different sector groupings reveals significant overlap in the estimates. The overall estimate of 2,147 hours achieved very good relative precision of ±5.9%.

Challenges arose when attempting to differentiate between school types, however. For example, while public and private schools realized seemingly distinct annual lighting hours of 2,233 and 1,990, respectively, closer examination shows that the error bounds overlap. This is the case for all but one of the analysis sectors: only Charter schools possessed distinct confidence intervals. As evidenced below in magenta, Standard and Magnet schools have consistent lighting hours, while Charter schools have statistically higher usage.





Figures 3 and 4. Baseline Lighting Hours by School Type and Room Type

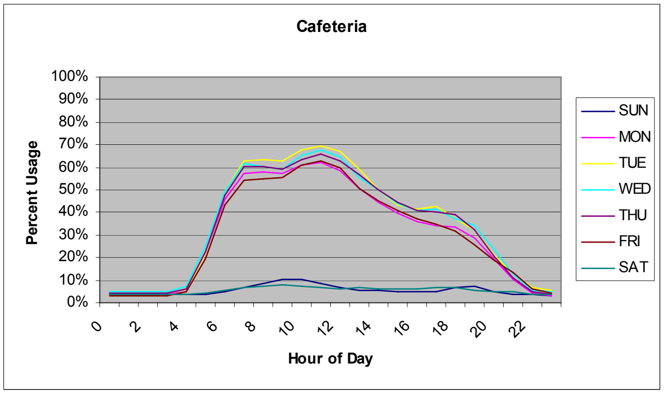
Figure 4 presents similar results by room type. In contrast to results by school type, these results are more statistically significant, in that most spaces are differentiated by exclusive, non-overlapping error bounds. Baseline hours range from 800 hours for storage closets to a high of 3,129 hours for hallways and corridors. Restrooms were found to be lit 2,380 hours per year, second only to hallways.

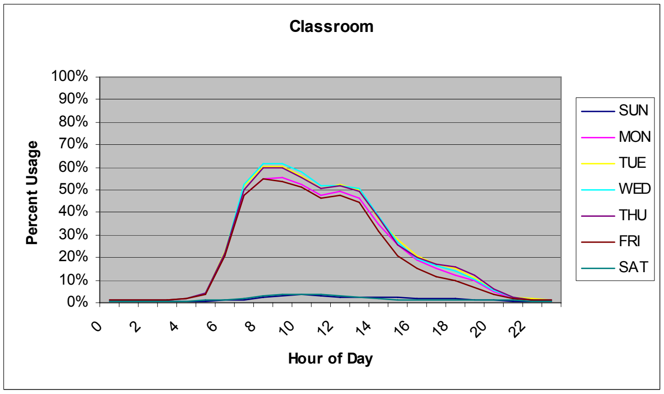
Figure 4 also is quite revealing when viewed for clustering. For instance, mechanical rooms and storage closets are distinct outliers below 1,000 hours, as are hallways at 3,100 hours. Teacher's lounges and "other" spaces (e.g. stage, nursing, and test rooms) are lit in overall hours similar to classrooms. Restrooms are fairly distinct from classrooms and hallways, but the remaining room types such as cafeteria, library, and offices are notably similar.

Hourly Lighting Profiles

One of the advantages of monitoring was that it permitted development of detailed hourly lighting profiles. These baseline profiles are derived from actual metered data, representative of lighting usage prior to the installation of occupancy controls. These results are fully-weighted, adjusted by connected lighting kW at the room-level and expanded using the final case weights.

Some interesting observations can be drawn by the following figures. For instance, one can see the signs of non-traditional space usage (weekend, after school, and evening hours) in several of these profiles. While an important component of these annualize profiles, increased summertime usage is apparent not in the shape itself but in the amplitude or upwards shift of the profile.

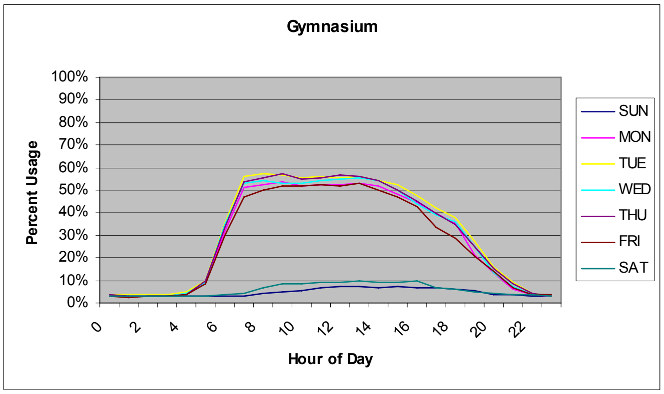


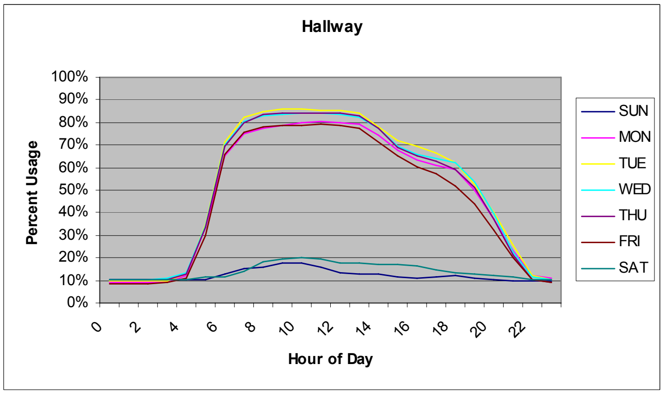


Figures 5 and 6. Baseline Lighting Profiles – Cafeteria and Classroom

The cafeteria profile in Figure 5 is very consistent by day-of-week with a notable early morning startup, lunchtime peak, and moderate afternoon decline. The late afternoon and evening plateau is a combination of two major influences: 1) use of cafeterias for afternoon activities and social groups, and 2) a small proportion of schools that provide dinner service.

Like most of these load shapes, the average classroom profile in Figure 6 shows little variation by day-of-week. Lighting usage ramps up quickly in the morning, levels off midday, and drops off steeply after dismissal. This profile in particular appears to exhibit evidence of summertime classroom usage. Both verbal and monitored research indicated that summer school lighting had a morning emphasis with half-day schedules such as 8AM to 1PM.

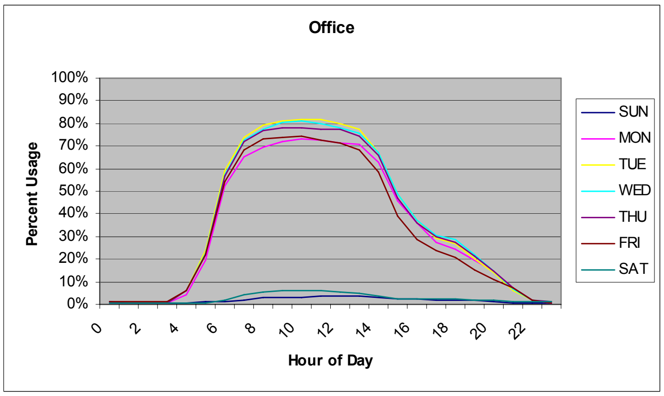


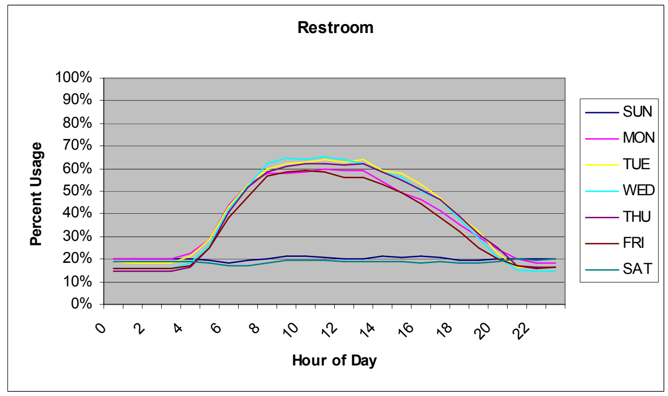


Figures 7 and 8. Baseline Lighting Profile – Gymnasium & Hallway

One of the reasons why gymnasiums have such high operating hours is because traditional high-bay, metal-halide fixtures have a significant startup delay, so 'lights off' vigilance is actually discouraged. Also, most gymnasiums do not have publicly-accessible light switches but breakers or keyed relays with restricted access. This gym profile in Figure 7 shows steady afternoon usage with a gradual evening taper, again suggesting an increase in non-academic space usage. The low usage on Saturday is a little surprising, but engineers cite some interview and observational evidence that much weekend gym usage is unlit. Athletic leagues often rent school gymnasiums on weekends, and they are encouraged to keep the lights off whenever ambient lighting conditions permit.

Figure 8 presents the baseline hallway profile. This load shape is both elevated and consistent, with a stable plateau between 7AM and 3PM and a gradual decline until 10PM. The base load of 10% represents the amount of security lighting as well as the proportion of schools that maintain 24-hour lighting in certain corridors.

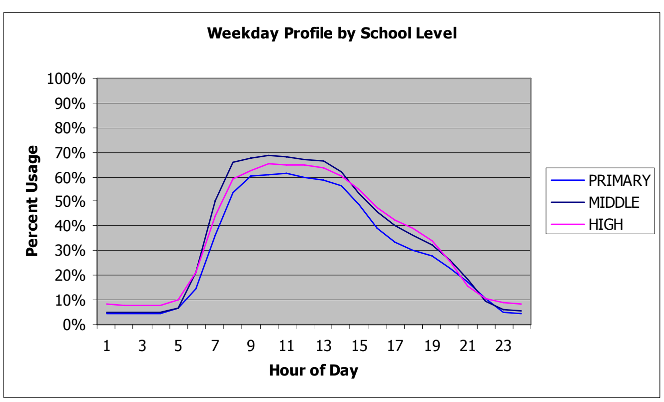


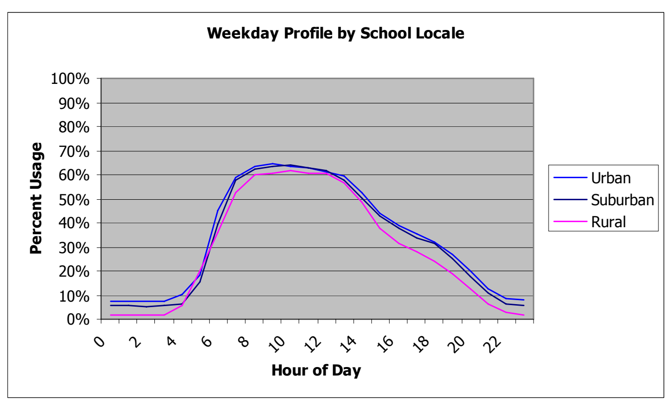


Figures 9 and 10. Baseline Lighting Profile – Office and Restroom

As non-community spaces, the classroom and office profiles are the only lighting shapes that truly approach zero usage on nights and weekends. This baseline office profile in Figure 9 is very smooth and consistent with a slight evening tail due to extended hours and/or cleaning schedules. It is interesting that offices exhibit a 6-7% dip in lighting usage on Monday and Friday.

The restroom profile in Figure 10 offers some good insight. In RLW's evaluation experience, some implementation contractors suggest that restrooms are lit 24 hours per day as the baseline of an occupancy control measure. With a sample of 41 loggers, these data indicate that restroom users are reasonably vigilant in managing restroom lighting. The profiles show that 24 hour lighting persists for about 18% of the restrooms, however.





Figures 11 and 12. Baseline Weekday Lighting Profile by School Level and Locale

Analysts also examined hourly profiles by school level. As seen in Figure 11, the weekday profile shape doesn't vary greatly by school level, e.g. primary, middle, or high school. However, the operating hours by school type do increase slightly in that sequence, and this figure illustrates some of the differences. The earlier day start of middle and high schools is evident in the figure, as is the more extended duration of the day at high schools. The weekend profiles differed very little and are not presented here for that reason.

The profiles by school locale were not as distinct as the study team had anticipated. Figure 12 presents the difference between urban, suburban, and rural schools. Rural schools show reduced after-school usage, but other than that, the three lighting load shapes are virtually identical.

Occupancy Sensor Savings Potential by Room Type

In addition to providing estimates of baseline operating hours separately by room and school type, this study also reported on the relationship between lighting usage and room occupancy. Up to this point, analysts estimated baseline lighting hours using logger data on the number of lit hours. In this analysis stage, researchers were interested in ascertaining an estimate of savings potential by considering both lighting *and occupancy* status.

Sensor savings potential was estimated using data from three sources. First, analysts computed baseline hours using verbal and observational estimates of operating hours. Next, these baseline estimates were refined by data collected with a sample of 646 lighting loggers. Finally, analysts examined the relationship between lit hours and occupied hours to derive an estimate of operating hours under occupancy sensor control. The difference between the baseline (pre-sensor) hours and the occupancy sensor hours are the savings potential in terms of annual hours during which lights could be turned off through the use of occupancy sensors.

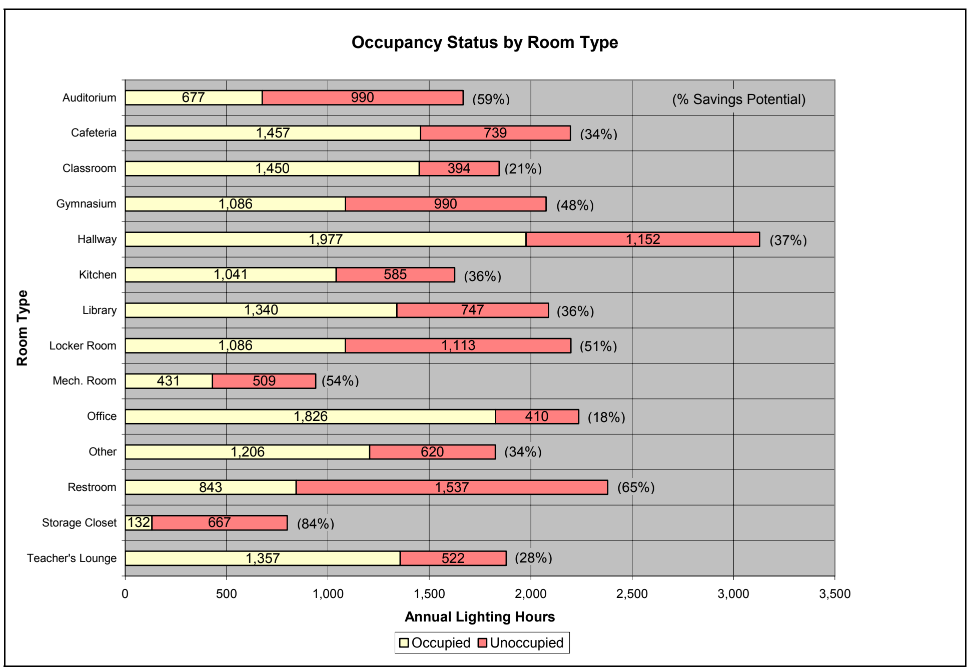


Figure 13. Occupancy Sensor Status by Room Type

Figure 13 presents the results of this analysis for baseline and sensor-controlled lighting. The large unoccupied periods in pink highlight the dramatic savings potential by installing occupancy sensors. These data are annualized estimates of lit/occupancy percentage and account for the effects of occupancy sensor lag. The values for percent savings potential are expressed as the ratio of the unoccupied hours to total (occupied plus unoccupied) hours. Occupancy sensors are typically set to shut off lights when a room has been unoccupied for a pre-determined duration. In schools, occupancy sensors are usually set for a 30-minute delay. The final analysis in this study passed the raw metered data through 'sensor lag' routines to estimate the number of hours the lights would have operated under sensor control. This sensor lag effect served to increase the annual sensor-controlled hours by 30-minutes at the end of each operating cycle.

Conclusions

In short, this project confirmed the hypothesis that traditional expressions of school operating hours do not fully reflect current school utilization for non-academic and community events. Annual lighting operation of 1,600 to 1,800 hours is commonly employed in lighting contractor and utility savings calculations, while this study concluded a weighted-average of 2,147 annual lighting hours.

Many existing efficiency programs estimate occupancy sensor savings as 30% or 33% of the baseline hours. It is noteworthy that the savings potential for classrooms (21%) and offices (18%) – the most popular sensor locations in schools – fall short of current assumptions. On the other hand, mass assembly areas such as auditoriums (59%) and gymnasiums (48%) rank amongst the highest savings potential in schools. In terms of absolute "hours saved", the greatest potential exists in restrooms (1,537 hours) and hallways (1,152 hours).

This project combined extensive data collection with multi-stage, multi-dimensional analyses in pursuit of study objectives. A team of engineers performed a complete lighting inventory of every room in 80 schools and logged occupancy and lighting hours in 646 rooms across both summer and fall-session periods. In total, analysts processed over one million records of lighting/occupancy data in a complex analysis that combined interview-based and measured hours with room-level detail and school-level characteristics.

While ultimately successful, this project encountered some unforeseen obstacles in the planning, sampling, and analysis stages that threatened the analytical framework and risked invalidating results. It is hoped that readers find value in some of the following lessons:

- Fundamental assumptions can make or break a project.
- Sometimes, one of the boldest assumptions is that sought data is attainable.
- Persist and retrench to overcome methodological setbacks. Roadblocks may be bypassed, and solutions can present themselves in mysterious ways.
- Vast amounts of data and multi-dimensional objectives do not dictate complicated techniques. Never rule out rudimentary methods; simpler is often better.