Annualization of Results of Residential Lighting Meter Data

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ABSTRACT

It is well understood that the use of lighting in residences is affected by the timing of nightfall and changes in the number of hours of darkness across the seasons. In estimating residential lighting hours of use (HOU) for calculating program savings, it is rarely possible to meter homes for a full 12 months. This is due to the cost of having meters occupied for so long, issues with meter failure and interference, the mobility of some proportion of households in a study, and not least, reporting cycles for program evaluations. The uniform methods project recommends six months of metering to capture at least half of the annual solar cycle. Here, we present a method for annualizing residential lighting HOU from a shorter measurement period and demonstrate the accuracy of the method on one set of annual data. The method demonstrates the viability of extrapolating results from metering studies of as few as twelve weeks and shows the sensitivity of the findings to the period of time during which metering is done. The method uses the observed effect of changes in the hours of daylight on the use of lighting in the home.

Introduction

Residential lighting programs have, in many jurisdictions, provided a large share of residential portfolio energy savings. A critical parameter in the estimation of savings is the length of time during the day that lights are turned on. This value is usually a direct multiplier with the difference of wattage between baseline and efficient lighting. In other words, a difference in 10% in the HOU results in a difference in 10% in program savings. It is, thus, critical to obtain an accurate value. Variance in lighting between households makes the accurate estimation of HOU a significant challenge. One approach to dealing with this problem is to conduct a light logging study. Based on a careful sample plan, a set of photo-sensitive meters are attached to residential lighting to obtain a direct estimate of HOU.

It is well understood that residential light usage changes over the course of a solar year, with the earlier daily onset of darkness in the autumn increasing use and the opposite tendency in spring. To capture these changes in use during the year, a light logger study must either leave the loggers in place for an entire year to measure the entire cycle or, if it can be assumed the year is symmetrical around the two solstices, loggers can be left in place for six months. This shorter period is the recommendation of the Uniform Methods Protocol for residential lighting evaluation.¹

For several evaluations of residential lighting programs conducted by Cadmus, however, we have found it not possible to leave loggers in place for as long as six months. In these cases we have left loggers in place for as few as 12 weeks and used regression to fit the logger data to a sine curve. This approach has met with some skepticism as to the accuracy of the generalization. In an effort to confirm

¹ Dimetrosky, Scott. 2013. "Chapter 6: Residential Lighting Evaluation Protocol." The Uniform Methods Project: Methods for Determining Energy Efficiency Methods for Specific Measures. NREL/SR-7A30-53827.

our approach, we compared results from four different studies conducted by Cadmus for Midwestern or East-coast IOUs using this method. Most importantly, we reviewed the methodology using the one instance where we had actually collected data over a full year. We report those findings here.

What we have found is that estimating an accurate and defensible HOU across one year based on partial-year data is contingent on the timing of meter data collection. Our recent research shows that collecting as little as three weeks of lighting usage data before and after one of the two annual solar equinoxes yields a good estimate of annual HOU. In addition to better precision around the HOU estimate, our metering approach is cost-effective and more practical than metering from solstice to solstice. Metering for long periods is expensive, and, especially for winter solstice meter removals, evaluation report deadlines often preclude sufficient time for analytical work.

In this paper we show evidence that estimating HOU from a significantly shorter metering period around either the vernal or autumnal equinox yields acceptably accurate results, and that using summeronly or winter-only meter data tends to over-predict or under-predict annual HOU

Meter Data Analysis

In our effort to support our approach, we developed regression models using meter data collected from a sample of a Midwest Utility's residential customers. We collected these data in 2009 and 2010, during a full year of lighting usage.

We metered up to five CFL fixtures in 44 randomly selected customer homes throughout the utility's service area. After conducting lighting audits in customer homes, field technicians used a project-specific random selection method to determine which CFLs to meter. For a given home, field technicians first determined the total number of CFL fixtures and identified the appropriate range of CFL fixtures (see Table 1). Prior to each site visit, technicians assigned a random fixture start number for each range. This random fixture start number is the starting point from which to identify CFL fixtures to meter. Field technicians then counted a predetermined number of fixture groups from the random start number, and installed a logger on every nth CFL fixture group from the random start number until up to five CFL fixtures received a meter. The purpose in employing this CFL fixture selection process is to eliminate any potential bias that may have occurred if technicians were free to arbitrarily choose CFL fixtures to meter.

Range of CFL Fixture Groups	Random CFL Fixture Group Start Number	Meter Every n th CFL
1-5	4	1st
6-10	2	2nd
11-15	12	3rd
16-20	9	4th
21-25	18	5th
26-30	5	6th
> 30	24	7th

Table 1. Random	CFL	Fixture	Selection	Table
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To calculate average daily HOU from the meter data, we averaged daily use across all loggers, homes, and room types. As expected, we have found differences in HOU by room type. To account for the, we weighted the usage data by the distribution of CFL sockets as a percentage of total CFL sockets for each room type. In weighting for CFLs per fixture, if a logger was installed on a fixture with only

one associated CFL, it would have half the weight of a logger installed on a fixture with two CFLs. Even though a logger collected lighting data from a single lamp, all other CFL lamps in common with that fixture were assumed to have the same HOU.

As shown in Figure 1, visual inspection of the meter data appears to support the assumption that lighting usage varies inversely with daylight hours. Also apparent, however, is the significant variation in average HOU from one day to the next. We would expect a larger study to smooth out some of this variation.



Figure 1. Metered Daily HOU

Model Specification

We assume that daily lighting usage varies inversely with the hours of daylight for a given geographical area. This relationship is best represented as a sinusoidal curve. The data were transformed to the curve specified below, for which the α term, i.e., the intercept, represents the average HOU and the β term represents the amplitude of the curve. Our team used ordinary least squares (OLS) regression to develop an initial model. After discovering appreciable autocorrelation in the data, the team used the Yule-Walker estimation method to develop final parameter estimates.

The model we estimated is as follows:

Hours of
$$Use_d = \alpha + \beta * Sin\left(-2\pi \left(\frac{284 + Day_d}{365}\right)\right) + \varepsilon$$

Where:

Hours of Use_d = Hours of use for given day of year (d = 1 to 365) α = Annual average HOU (intercept) β = Amplitude of sinusoid function (slope the intercept) Day

- = Day of the year where January 1 has a value of 1 and December 31 has a value of 365
- = Error term of the regression

Model Results

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Estimation Using Annual Data

Table 2 shows the model fit statistics and Table 3 shows the estimated parameter values for a model that fits data from the entire sampling period (one year). After detecting severe autocorrelation in the OLS model, we re-estimated the annual model using the Yule-Walker method which corrects for autocorrelation.²

Table 2. Yule-Walker Model Statistics for entire sample period

Statistic	Value	P-Value
F-Value	54.32	< 0.0001
R^2	0.5778	
Durban-Watson	2.2628	0.9933

Table 3. Model Parameter Estimates and Statistics (Annual Model)

Variable	Estimate	Standard Error	t Value	P-Value
Annual Average HOU	2.98	0.04	73.88	< 0.0001
Amplitude	0.42	0.06	7.37	< 0.0001

The overall fit statistics of the Yule-Walker estimation show a highly significant model. The R^2 of the corrected model is 0.5778; the model explains about 58% of the variation in hours of use. The intercept, 2.98, is the estimated average annual hours of use. The estimated mean using the full year data is the same value as the measured mean. The beta coefficient of 0.422 is the amplitude of the sine curve for the entire year, representing the proportion of an hour above and below the mean HOU that lighting use varies over the course of the year. This suggests the average HOU deviates by about 0.422 x 2 x 60 = 50 minutes per day between the summer and winter solstices.

Estimation Using Partial Year Data

To test our thesis that collecting data before and after either the spring or fall equinox results in a more accurate HOU estimate, we modeled HOU using different intervals of data around the spring and fall equinoxes and around the summer and winter solstices, to provide the greatest contrast in data. We selected intervals of $\pm 2, \pm 3, \pm 4, \pm 6, \pm 9$, and ± 12 weeks around each of the four periods, resulting in 4, 6, 8, 12, 18 and 24 weeks of data, respectively, to predict hours of use. Note that the 24 week model is close to the number of weeks recommended by the UMP.

² The Yule-Walker correction method uses an iterative process to correct for serially correlated disturbance. Once the procedure converges around a value for the disturbance, the data are transformed and parameter estimates are developed by the generalized least squares. The resulting parameter estimates are both best and unbiased.

Equinox Models. Table 4 and Table 5, below, show the regression fit statistics and parameter estimates for a very good model, the \pm 3-week spring equinox model.

Statistic	Value	P-Value
F-Statistic	5.29	0.0266
R ²	0.11	
Durban		
Watson	2.04	0.4893

Table 4. Regression Statistics for ± 3-week Spring Equinox Model

Table 5. Model Parameter Estimates a	nd Statistics (H	± 3-week Sr	oring Eq	minox Model)	
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Variable	Estimate	Standard Error	t Value	P-Value
Average Annual HOU	2.94	0.0383	76.67	< 0.0001
Amplitude	0.44	0.1813	2.3	0.0266

The beta coefficient (amplitude) from the \pm 3-week spring equinox regression model is significant, with a p-value of 0.0266. The R² of the model, 0.11, which indicates that the day of the year explains 11% of the variation in HOU during the 6-week analysis period. The Durban-Watson statistic in the OLS model does not indicate the presence of autocorrelation; therefore no correction method was undertaken.

The annual average HOU estimate from the \pm 3-week spring equinox model (2.94) is 0.04 hours less than the measured average and full-year estimate HOU of 2.98. The amplitude estimate of the \pm 3week spring equinox model is 0.02 more than the beta coefficient of the annual model (0.42). In other words, the \pm 3-week spring equinox model differs from the annual model by only 2 minutes and 24 seconds per day. This is an error of only 1.3%.

Overall, the \pm 3-week spring equinox model most closely resembles the full sample regression, both in terms of predicted HOU and modeled amplitude. Figure 2 shows the predicted values of the \pm 3-week Spring Equinox model compared to the annual model. The figure shows the portion of meter data that goes into the prediction.



Figure 2. Spring Equinox ± 3-week Model and Annual Model Compared to Observed Data

As noted above, we also estimated HOU using different numbers of weeks around spring and fall equinoxes and summer and winter solstices. The results from these models are presented in Table 6.

Model	Predicted Annual Average HOU	Amplitude	R ²
Full Year	2.98	0.42	0.58
Equinox			
Spring ± 2 Week	2.94	0.78	0.17
Spring ± 3 Week	2.94	0.44	0.11
Spring ± 4 Week	2.90	0.58	0.28
Spring ± 6 Week	2.96	0.72	0.57
Spring ± 9 Week	3.01	0.45	0.52
Spring ± 12 Week	3.02	0.38	0.48
Fall ± 2 Week	3.19	-1.50	0.33
Fall \pm 3 Week	3.12	-0.57	0.16
Fall ± 4 Week	3.12	-0.59	0.24
Fall \pm 6 Week	2.96	0.72	0.57
Fall \pm 9 Week	3.01	0.45	0.52
Fall \pm 12 Week	3.02	0.38	0.48

Table 6. Summary of Full and Partial-Year HOU Regression Models

Looking at the predicted HOU in Table 6, the spring models produced annual average HOU estimates that were more consistent with one another than the fall equinox models and closer to the annual model. The 2, 3, and 4 week fall models significantly overestimated annual HOU; the 6, 9, and 12 week models, however, performed as well as the spring models. We note that not all of the models that performed well in predicting HOU captured the amplitude of the annual cycle accurately. Several of the briefer fall models actually reversed the slope of the curve. The better-performing models on HOU tended to do better in predicting amplitude; however both the spring and fall 6-week models over-estimated amplitude.

Solstice Models. We also estimated HOU using periods of $\pm 2, \pm 3, \pm 4, \pm 6, \pm 9$, and ± 12 weeks around the summer and winter solstices. As expected, these models performed less well than the equinox models. For instance, while the ± 3 -week winter solstice model is statistically significant, the predicted average annual HOU is negative and therefore not realistic. Additionally, the predicted amplitude is more than 6 times larger than the annual model's amplitude of 0.42. The regression results were not statistically significant for the remaining 5 models. Winter and summer solstice model results are shown in Table 7. Winter models substantially under-estimated HOU; summer solstice models substantially over-estimated HOU. Even the ± 12 week (6 month) models do not perform well.

Model	Predicted Annual Average HOU	Amplitude	R ²
Full Year	2.98	0.42	0.58
Solstice			
Winter ± 6 Week	1.55	1.98	0.25
Winter ± 9 Week	2.88	0.54	0.24
Winter ± 12 Week	2.85	0.57	0.30
Summer ± 6 Week	5.78	3.54	0.63
Summer \pm 9 Week	3.54	1.12	0.59
Summer ± 12 Week	3.28	0.82	0.6

Table 7. Summary of Full and Partial-Year HOU Regression Models

Figure 3 compares the modeled average HOU using three \pm 6 week time periods. Only the spring model fists the meter data well.



Figure 3. Six-Week HOU Models

Conclusion and Implications

When Cadmus began using regression analysis to generalize annual HOU from a few weeks of meter data, we typically had data from late August through early October. This was not out of design but flowed from the planning, plan approval, and fieldwork cycle that occurs for several clients. Late summer was the earliest we were getting into the field and January reporting schedules dictated when we came out of the field. Fortunately, this is a nearly optimal time to do metering for annual projection, based on our review of metering data and the underlying concepts.

Because the period of the sinusoidal curve that forms the basis of our model is known (it is the length of the solar year), knowing the slope of the curve at the equinox provides all of the additional information needed to define the shape of curve. Indeed, except for the significant variation in day-to-day lighting use, the model suggests that a single measurement on the solar equinox would provide a good estimate of the average HOU. Because of the variation in lighting use from day-to-day, however, measurements around the equinox that are sufficient to estimate a trend can be used to provide the information needed.

We noted that the amplitude of our estimated curve was not always accurate even when the mean value was close to being correct. For data evenly distributed around the equinox, the trouble of fitting a sine curve may be unnecessary. A straight average of the data—which is essentially what the intercept produces—could suffice.

It seems to us that the reason meter data collected around the solstice does not produce an accurate estimate of annual HOU is that the random variance in the data is very large relative to the trend at these times. Depending on the weeks that are metered, random dips and peaks in the measured values distort the shape of the curve. Around the equinoxes, the ratio of signal-to-noise is higher and

thus a more accurate estimate is achieved.

The study we used for this report was somewhat smaller than a typical logger study we conduct and the amount of random variance was high. At Cadmus, we are moving toward larger samples with more loggers at each location, to smooth out some of this noise. We are also shifting our metering activity—that which is not already so timed—to the periods surrounding the spring and fall equinoxes.