Shedding Light on Winter Lighting

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ABSTRACT

Summer peak demand has historically been the focus of utility electric energy efficiency programs; thus, evaluators have developed a well-documented understanding of summer coincidence factors for most commercial and industrial (C&I) buildings and space types. Recently utilities have expanded the focus of their energy efficiency programs to include tracking winter demand savings in response to new opportunities and requirements of the PJM capacity performance product. Technical reference manuals do not yet contain winter coincidence factors and so it is hard to do a parameter-based program evaluation with the currently available data.

One solution is for evaluators to simply collect a large amount of data for C&I lighting use during the winter peak demand period to calculate winter coincidence factors. This paper explores a more economical approach of collecting a more modest amount of data and leveraging past summer metering data for C&I buildings to calculate winter peak demand coincidence factors. It also explores using Bayesian methods to better quantify uncertainty within and between sites.

To determine if past summer data of C&I lighting usage could be used to calculate winter coincidence factors, this team installed over 600 lighting loggers at 79 sites covering six major C&I building types as well as a mix of other building types for a nine-month period that covered both the winter and summer PJM peak demand periods. The team was able to determine a statistically significant relationship between summer and winter metered hours and bring in data from nearly 500 loggers from previous studies. This allowed the team to calculated statistically significant winter coincidence factors for 46 space types.

Introduction

Lighting coincidence factors (CF) and annual hours of use (HOU) are important inputs for estimating energy savings and peak demand impacts from lighting efficiency programs. Historically, commercial lighting metering studies have sought to establish estimates for these parameters by deploying loggers only for about a month during the summer months (designed to capture the summer peak period). However, with the recent emphasis on the possibilities for a winter peak capacity market in PJM territory, the lack of winter-logged lighting data presented challenges in accurately characterizing the lighting demand savings during this time. This study seeks to improve the body of knowledge on the subject.

In late 2015 the EmPOWER Maryland utilities worked with Navigant to design a C&I lighting metering study in their territories with the aim of determining winter PJM coincidence factors. Navigant developed a plan to meter 79 different sites from six prominent building types[1] and a mix of the remaining building types for a continuous period covering both the PJM winter and summer peak demand periods.

[1] Health, Grocery, Offices, Retail, Warehouses and K-12 Education

Terminology

The peak periods used in this study are defined as:

- PJM Summer Peak - Non-holiday weekdays from 1 June through 31 August, 2pm to 6pm
- PJM Winter Peak – Non-holiday weekdays from 1 January through 28 February, 7 am to 9am and 6pm to 8pm
- PJM Winter Hours Summer Season Peak – Non-holiday weekdays from June 1 through August 31, 7am to 9am and 6pm to 8pm.

"Non-holiday weekdays" means the analysis excludes the four federal holidays that fall during the winter and summer peaks: New Year's Day, Martin Luther King, Jr. Day, Presidents' Day, and Independence Day.

Throughout this paper, certain terminology is used to describe the original source of metered data. The term "current study" refers to the logger deployments Navigant carried out between December 2015 and September 2016. The loggers were deployed for an average of 8 months during this current study to cover both the PJM summer and winter peak periods. In contrast, "historic data" refers to logger data gathered once per year from 2010 – 2013 through short-term studies covering approximately two to four weeks during the PJM summer peak period.

Study Objective

The primary goal of this study was to produce a table of PJM Winter Coincidence Factors by:

- building type[2]
- space type[3]
- building type-space type combinations[4]

The metering study was designed to accomplish the primary goal through two main avenues. The first was primary metered data of C&I lighting which could be used to directly determined PJM winter coincidence factors. The second avenue that Navigant pursued was to leverage the data from historical studies. To leverage this historical data Navigant's examined the relationship between the:

- PJM Winter Coincidence Factor (calculated from metered data taken over the PJM winter period,
- PJM Winter Hours Summer Season Coincidence Factor (i.e., the winter coincidence factor calculated using summer period data).

Methodology

Current Sample

Navigant sampled 79 facilities across the six building types with the most significant energy and demand savings from the past 18 months of participant data for the EmPOWER C&I lighting programs.

[2] E.g., office building, warehouse, etc.
[3] E.g., private office, hallway, restroom, conference room ,etc.
[4] E.g. office building hallways

The sample for this study was drawn from program participants in 2014 Q3 through 2015 Q3. Each facility in the sample was mapped into one of the seven groups shown in Table 1.

Table 1. Final Sample

Building Type	Number of Buildings	Number of Site-Spaces
Schools[5]	20	92
Warehouses	7	71
Retail	9	57
Health	7	23
Grocery	5	23
Offices	4	58
Other	27	205
Total	79	437

Logger Weighting

Following the logger deployments, Navigant retrieved, reviewed and analyzed the logger data. For each of the parameters of interest, Navigant calculated weighted averages for each:

- building type
- space type
- building type-space type combination

Figure 1 shows how parameters determined from a single logger are weighted from an individual circuit up to the building type – space type level.

[5] Only K – 12 education facilities where available within the sample. From this point forward the "Schools" building type will be referred to as Education

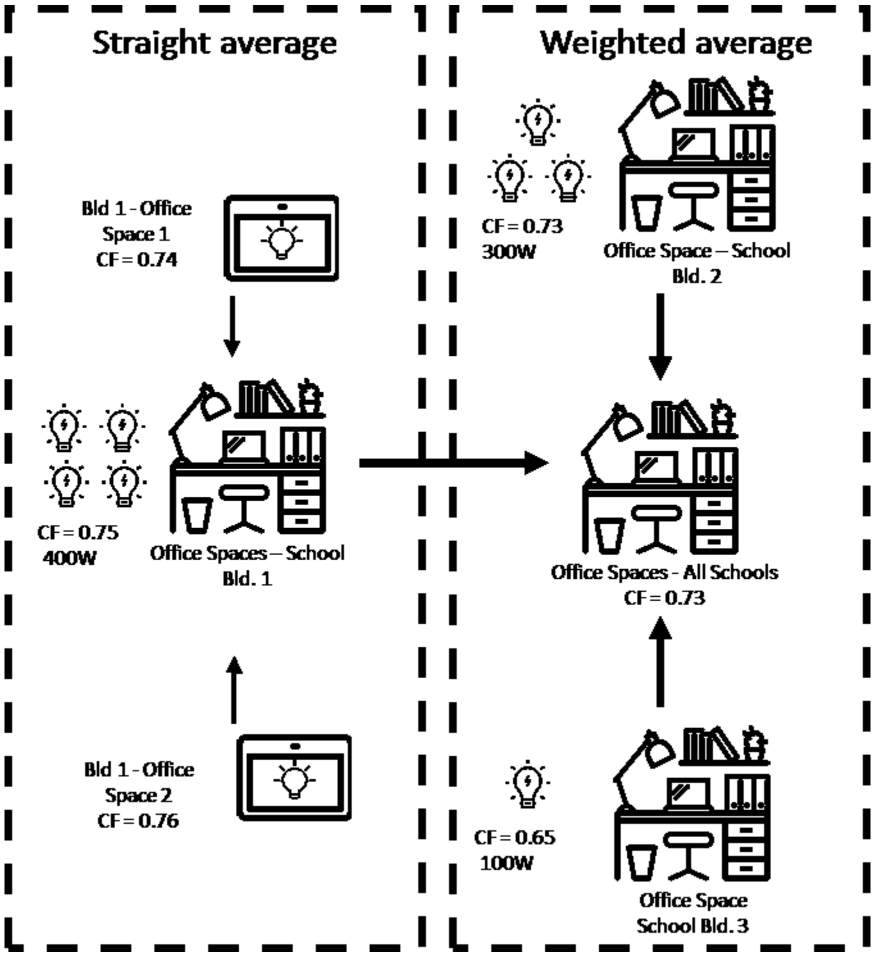

Figure 1. Logger weighting

To report savings at the space type level across all building types, it was also necessary to weight the building level results by the distribution of building types for program participants. Navigant used census level tracking data from the prior two years, weighted by energy savings, to determine the distribution of building types.

To simplify the process for calculating the space type weighted means (independent of the building type), Navigant by grouped each of the original data points for each building type into a new building type designated "All". As such, the roll-up method yields results at the unique building type-space type level, but also at the space type level across all building types, without having to use a separate approach.

Leveraging data from past studies

For the current study, this team calculated PJM Winter CFs using logger data collected within the PJM Winter Peak Period. However, this team had data from nearly 1,000 additional loggers that could add statistical significance to the PJM Winter CFs.

Figure 2 shows a comparison of the lighting load profiles for the six major building types. The dark band indicates the PJM Winter Peak hours. This figure helps to give a sense of how consistent the seasonal hours are at the building level.

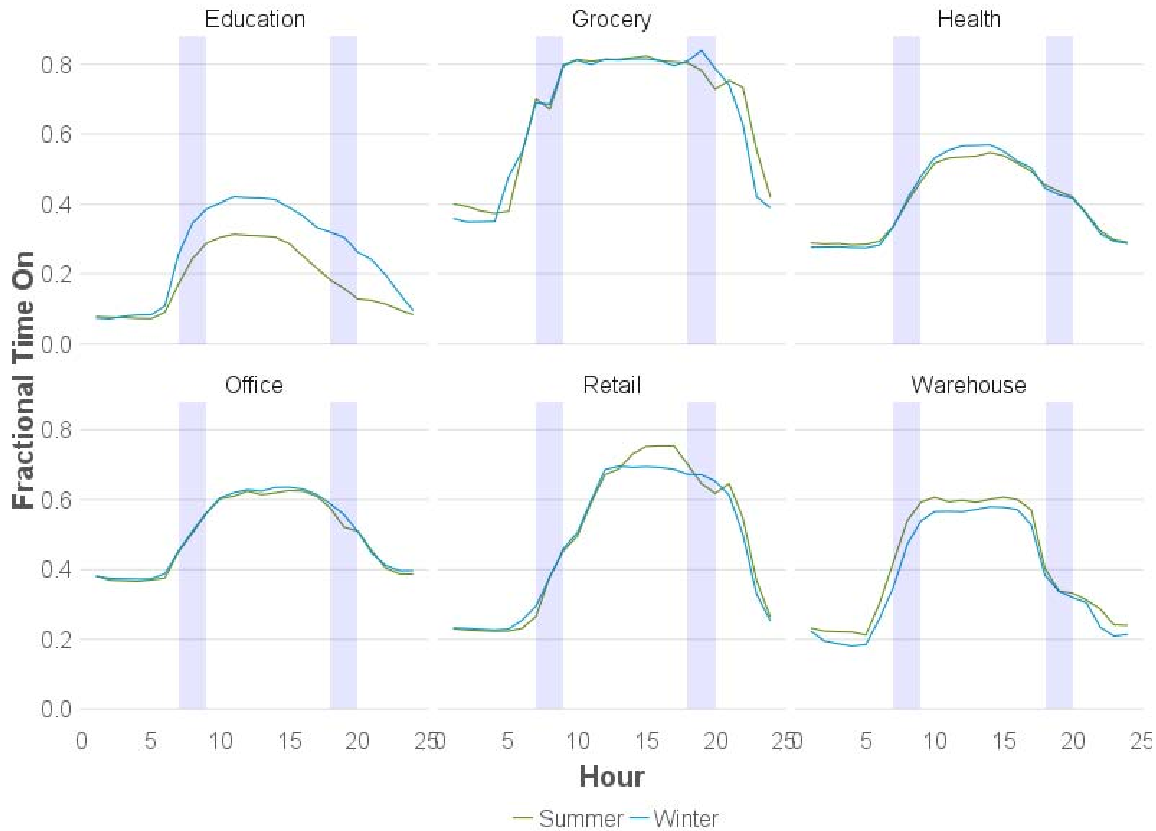

Figure 2. Comparison of Summer and Winter Lighting Load Profiles (With PJM Winter Peak Hours Highlighted)

Figure 3 shows a comparison of the PJM Winter Peak CFs and the PJM Winter Hours Summer Season Peak CFs[6]. The less variable the hours were between the winter and summer periods the closer a point will fell to the reference line.

[6] A coincidence factor calculated using the winter peak hours (7 – 9 am, 6 – 8 pm) using data from the PJM summer days (non-holiday, non-weekend days in June through August).

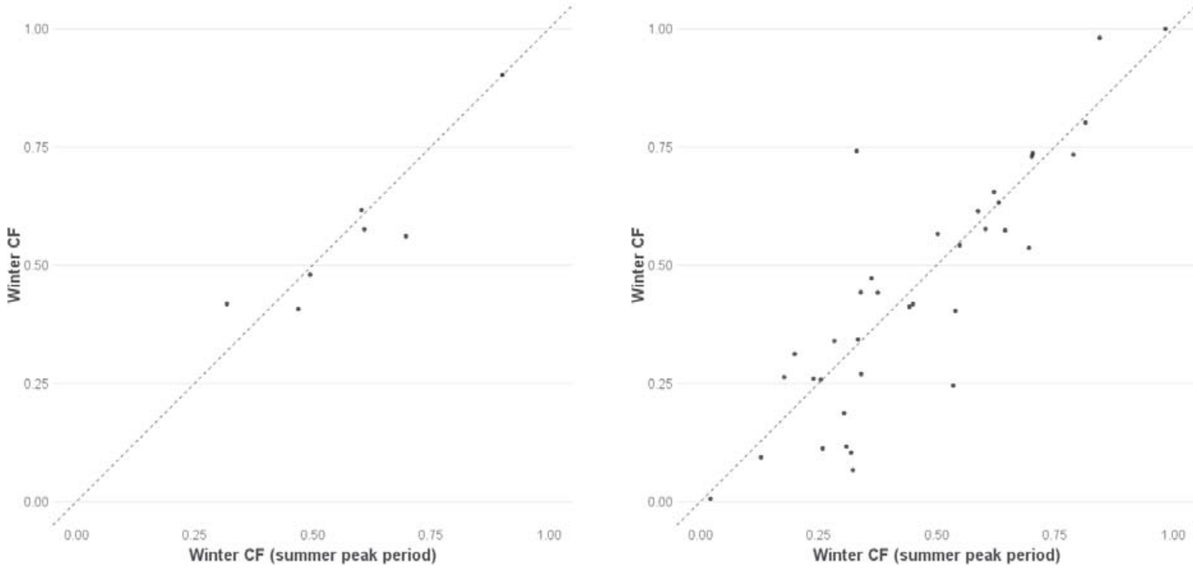

Figure 3. Comparison of PJM Winter Peak and PJM Winter Hours Summer Season Peak

In order to determine values for the winter peak CFs with historic data, Navigant used the current study to fit a regression model that established the relationship between winter CFs calculated with actual metered winter data and a PJM Winter Hours Summer Season Peak CFs (calculated using winter peak hours with summer peak period data from the same logger).

Uncertainty

Navigant considered three sources of error in this analysis:

1. Within-site uncertainty
2. Between-site uncertainty
3. Winter CF extrapolation modeling error

The three sources of uncertainty were considered at each of the three different levels in the analysis hierarchy – building type only, space type only, and building type-space type combination. Navigant combined the uncertainties and used a relative precision cutoff of 35 percent or an absolute precision cutoff of 0.20. Parameters with precisions above these cutoffs were not included in the space type results or were combined with other categories form a more generic space type that could meet the cutoffs.

Within-Site Uncertainty

The first source of uncertainty Navigant considered was the “within-site” uncertainty. This is the sampling error associated with variance in a parameter between samples of the same space type within a given site. Error in parameter measurement from this source would result, for example, if only one room of a space type was measured at a site, while other rooms of the same space type at that site behaved differently.

For this source of uncertainty, Navigant used a Bayesian statistical modeling approach. For a given building type, space type, or building type-space type combination, Navigant first recognized that all other spaces with the same building type and all other buildings with the same space type may offer some information about the within-site variance of a parameter. For example, the hours of use in office buildings may be similar, regardless of the individual building, or whether you are looking at a hallway or conference room, because office buildings share a use-pattern. Similarly, the hours of use in conference rooms may be similar, regardless of whether the conference room is in an office or a hospital. If the measurements from one office conference room are statistically similar to other measurements across offices, or conference rooms, this allows a more accurate estimate to be made. Thus, these data could supplement the low count of within-site variances Navigant could establish from each combination alone (more than one room of a certain space type *within* a site needs to be measured to determine this source of uncertainty). This data comprised *a prior* belief about what the within-site variance should look like for a certain building type or space type. Navigant could then weight the uncertainty based how closely the parameter tracked the prior distribution of the same parameter for the relevant building type, space type, and building-space type.

Figure 4 shows the hours of use variances of classroom spaces within one education facility compared to the variance within education buildings and within classroom spaces (across all buildings). One can see that the distribution of variances at this site (the current observation) matches the distribution of variances across classroom space-types closer than is does the distribution of variances across spaces within educational buildings. Therefore the combined variance distribution for this site will be weighted towards the space-type distribution over the building distribution.

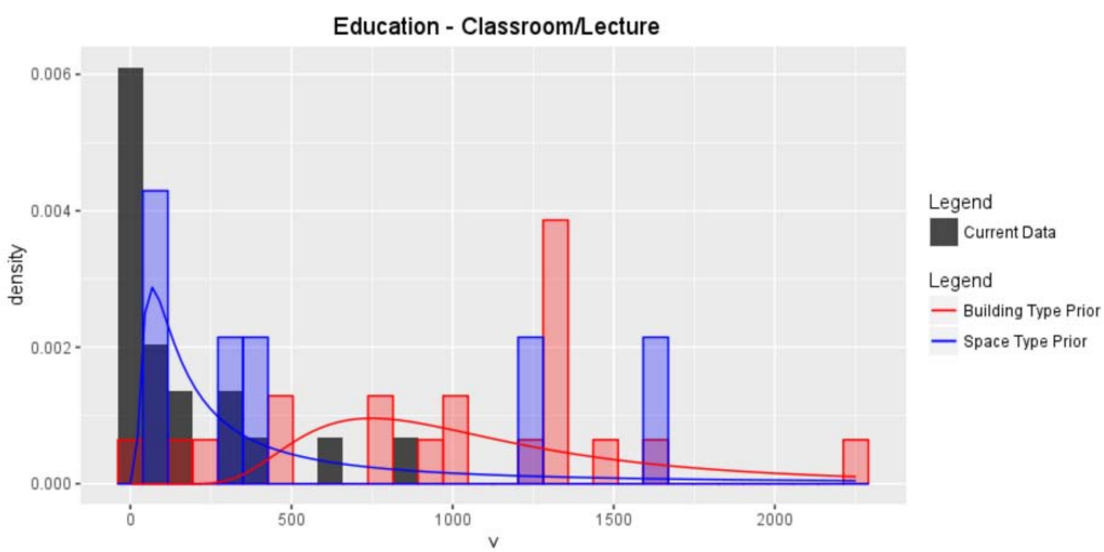

Figure 4. Bayesian analysis of an educational building – classroom space type

Between-Site Uncertainty

The second source of uncertainty Navigant considered was between sites. This is the uncertainty that arises from the variance between sites having the same building type and space type. Error in parameter measurement from this source would result, for example, if only one site for a particular building / space-type combination was measured, while other sites with the same building type-space type combination behaved differently.

For this source of uncertainty, a much simpler approach was taken. The mean of each parameter was calculated for each site, and the variance between those parameter means gives the between-site variance.

Winter CF Regression Uncertainty

Since the historic data did not include winter measurements of CFs. Navigant used a linear regression model to establish the relationship between winter CFs calculated using PJM Winter Peak CFs and PJM Winter Hours Summer Season Peak CFs. The regression was used to predict the winter CF for each logger in the historic studies for which the winter CF was not measured, and error is thus introduced by virtue of using modeled estimates.

To capture this source of uncertainty, errors from the linear regression model were grouped by building type, by space type, and by building type-space type combination and relative precision was calculated for each group.

Results

Table 2 shows the building-level PJM Winter coincidence factors and their associated relative precision at a 90 percent confidence level while tables 3 and 4 show similar results for the building / space-type and all building / space-type levels.

Table 1. PJM winter CF Values and Precisions at the Building Type Level

Building Type	No of Site-Spaces	PJM Winter CF	PJM Winter CF RP
Education	92	0.33	18%
Grocery	23	0.93	8%
Health	23	0.51	18%
Office	58	0.48	11%
Other	205	0.54	8%
Retail	57	0.65	11%
Warehouse/Industrial	71	0.50	10%

Table 3. PJM winter CF Values and Precisions at the Building Type-Space Type Level

Building Type[7]	Space Type	PJM Winter CF	Relative Precision	Absolute Precision
Education	Classroom/Lecture	0.20	40%	0.08
Education	Corridor/Hallways	0.75	10%	0.07
Education	Office (Executive/Private)	0.26	80%	0.21
Education	Office (General)	0.46	32%	0.15
Education	Office(Open Plan)	0.54	29%	0.15
Education	Other	0.35	21%	0.07
Grocery	Other	0.82	22%	0.18
Grocery	Retail Sales/Showroom	0.93	5%	0.05
Grocery	Storage (Conditioned & Walk-In Refrigerator/Freezer)	0.98	10%	0.10
Health	Corridor/Hallways	0.77	22%	0.17
Health	Other	0.41	27%	0.11
Office	Corridor/Hallways	0.71	21%	0.15
Office	Lobby (Main Entry and Assembly)	0.80	26%	0.21
Office	Office (General)	0.48	16%	0.08
Office	Other	0.48	22%	0.10
Retail	Lobby (Main Entry and Assembly)	0.63	24%	0.15
Retail	Office (General)	0.40	39%	0.15
Retail	Other	0.51	20%	0.10
Retail	Restrooms	0.70	29%	0.20
Retail	Retail Sales/Showroom	0.64	13%	0.08
Warehouse/Industrial	Auto Repair Workshop	0.49	34%	0.17
Warehouse/Industrial	Comm/Ind Work (General High Bay)	0.86	27%	0.23
Warehouse/Industrial	Comm/Ind Work (General Low Bay)	0.78	25%	0.19
Warehouse/Industrial	Office (General)	0.36	37%	0.13
Warehouse/Industrial	Other	0.44	16%	0.07
Warehouse/Industrial	Restrooms	0.47	26%	0.12
Warehouse/Industrial	Storage (Conditioned & Walk-In Refrigerator/Freezer)	0.40	27%	0.11

[7] There is a catch-all “Other” building type that was used in the analysis. However, to avoid confusion, the parameters for the “Other” building type is not shown. Instead, for building type-space-type combinations not appearing in

, refer to the All building type in

Table .

Table 4. PJM Winter CF Values and Precisions - All Building Types

Space Type	PJM Winter CF	Relative Precision	Absolute Precision
Auto Repair Workshop	0.61	32%	0.19
Classroom/Lecture	0.20	32%	0.06
Comm/Ind Work (General High Bay)	0.82	14%	0.11
Comm/Ind Work (General Low Bay)	0.77	21%	0.16
Conference Room	0.16	39%	0.06
Corridor/Hallways	0.73	7%	0.05
Dining Area	0.51	16%	0.08
Exercise Centers/Gymnasium	0.60	21%	0.13
Kitchen/Break room & Food Prep	0.42	21%	0.09
Library	0.31	27%	0.08
Loading Dock	0.62	22%	0.14
Lobby (Main Entry and Assembly)	0.71	12%	0.08
Lobby (Office Reception/Waiting)	0.49	21%	0.10
Mechanical/Electrical Room	0.46	21%	0.10
Office (Executive/Private)	0.20	37%	0.07
Office (General)	0.43	13%	0.06
Office(Open Plan)	0.49	15%	0.07
Other	0.40	19%	0.08
Outside/Outdoor Area	0.58	11%	0.06
Parking Garage	0.78	17%	0.13
Restrooms	0.30	23%	0.07
Retail Sales/Showroom	0.78	10%	0.08
Storage (Conditioned & Walk-In Refrigerator/Freezer)	0.44	20%	0.09
Storage (Unconditioned)	0.40	24%	0.10

Table 5 shows the distribution of loggers between the current study and past studies. It should be noted that not all loggers from past studies could be used due to various issues with data quality. Because this study began during the school year (as opposed to historical studies conducted during the summer) this team nearly quadrupled the number of logger data points from education facilities.

Table 5. Comparison of logger distributions between current and past studies

Building Type	Number of loggers from past studies	Number of loggers from current study
Education	64	183
Grocery	39	39
Health	23	64
Office	87	81
Retail	86	74
Warehouse/Industrial	161	90
Total	460	528

Figure 5 shows a comparison of current and past winter PJM CFs[8]. One can see that most parameters received minimal adjustments although there were some larger shifts in a few space types.

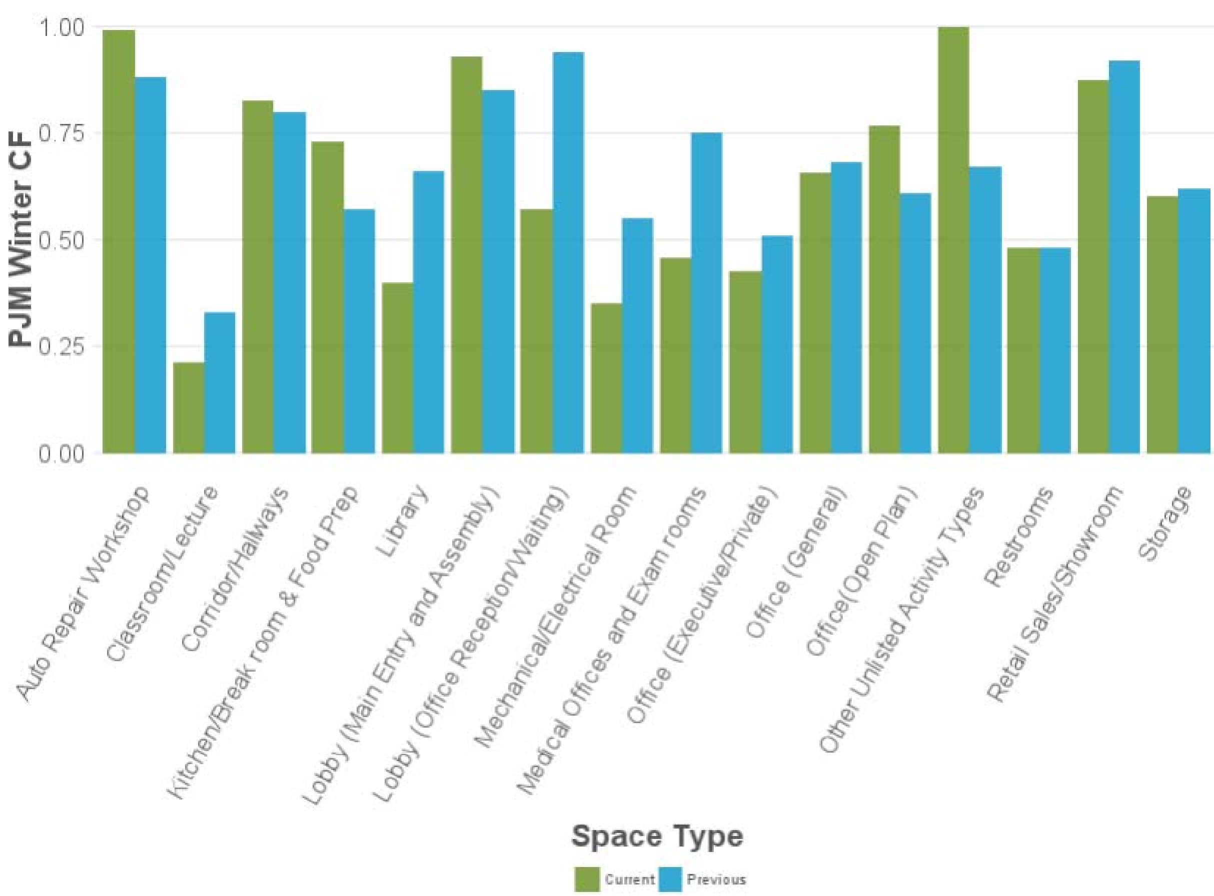

Figure 5. Selected comparisons of PJM Winter CFs between past studies and current study

[8] where the winter PJM CFs being calculated using the linear regression technique described above

However, even for the parameters that showed larger shifts (relative to most parameters) the statistical precisions improved from previous studies and additional space types were added. Table 6 shows how the methods outlined above allowed this team to generate additional building / space-type combinations that met the statistical thresholds outlined in the uncertainty section.

Table 6. Quantity of Statistically valid space-types

Building Type	Previous Study[9]	Current Study[10]
All	17	23
Grocery	1	3
Health	2	2
Office	2	5
Retail	3	5
School	3	6
Warehouse / Industrial	3	7
Total	31	46

Summary and Conclusions

By conducting a long-term lighting metering study that captures both winter and summer months, this team has established a methodology for using summer logged data to estimate winter peak coincidence factors. Additionally, using a Bayesian approach to examining within site and between site uncertainty can provide a better understanding of the statistical significance of the results. Future research could examine if similar studies with a Bayesian analysis of uncertainty between different regions could allow this data to be leveraged to efficiently and economically produce winter CF parameters for other regional TRMs.

References

Northeast Energy Efficiency Partnership. 2017. "Mid-Atlantic Technical Reference Manual v6." *NEEP Website.* Feb. 23. http://www.neep.org/mid-atlantic-technical-reference-manual-v6.

PJM Forward Market Operations. 2016. *PJM Manual 18B: Energy Efficiency Measurement & Verification.* Valley Forge, PA: PMJ.

[9] EmPOWER Maryland Final Impact Evaluation Report Evaluation Year 4 (June 1, 2012 – May 31, 2013). Navigant, June, 2014.
[10] Includes numbers from previous study. I.e., for the “All” building type there are six additional statistically valid space types