# The Transition to Remote Energy Efficiency Programs; Proper Evaluation Methods for Small and Midsize Business' No- to Low-Cost Programs

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## ABSTRACT

Over the past decade, we have seen several Northeast and Midwest utilities deliver energy efficiency programs that target no- to low-cost operational changes for small and midsize businesses (SMB) and public institutions. These programs use Advanced Metering Infrastructure (AMI) data to identify customers with significant energy savings potential and assist participants to optimize their energy usage through modifications to their operational schedules, ultimately achieving energy savings.

For these programs to effectively scale, they must demonstrate cost-effective energy savings. However, an industry-accepted, detailed evaluation protocol for these types of programs does not exist and has resulted in discourse among regulators, utilities, evaluators, and program implementers. We believe no- to low-cost SMB programs are similar enough to Strategic Energy Management (SEM) programs to rely on the Department of Energy's Uniform Methods Project (UMP) Chapter 24, SEM Evaluation Protocol as a starting point. In this paper, we share our findings from an analysis in which we test various modeling approaches with a focus on their similarities and comparative practical limitations.

Our goal is to identify an approach capable of producing an unbiased, weather normalized savings estimate with the flexibility of extrapolation while still operating within program data and budget limitations. Based on our findings, we recommend evaluators start by using the *Savings as a Function of Weather Model* described below that is similar to the *Pre-Post Model* in the UMP Chapter 24. This model produces weather normalized annual energy savings, while adding simple modifications to the model specification based on site-specific details.

## Introduction

No- to low-cost programs aim to provide maximum energy savings with limited to no financial expenditure on behalf of the participant. Often these programs are targeted at low-income customers, but utilities have recently begun delivering these programs to SMBs, including programs that specifically target operational enhancements. These programs provide qualified business customers with energy management information services to identify low- and no-cost energy-saving operational changes. These types of changes often include heating, ventilation, and air conditioning (HVAC) cooling and heating adjustments as well as lighting schedule adjustments for buildings such as retail stores, commercial office buildings, schools, and government buildings.

In addition, these programs make recommendations solely on the customer's energy usage data. Rather than program implementers conducting on-site visits or in-person audits, they remotely analyze data for each participant and provide personalized low- or no-cost, easy-to-implement recommendations. The program implementer also monitors energy usage and measures energy savings for each participant.

These types of programs are intriguing to SMBs because they require minimal financial investment (if any) and time commitment, they do not require implementation of the recommendations, and they provide an opportunity to reduce operating costs by reducing the customer's energy usage. For these programs to scale, they must demonstrate cost-effective energy savings. However, an industry-accepted, detailed evaluation protocol for these types of programs does not exist and has resulted in discourse among regulators, utilities, evaluators, and program implementers.

Typically, these programs aim to report weather normalized annual savings. We believe the evaluation approach to estimate savings for these programs should have the ability to achieve four key items:

1. Produce an unbiased estimate of savings[1]
2. Produce weather normalized savings
3. Flexibility to extrapolate savings from a partial year of post implementation data while accounting for weather differences expected in a full calendar year
4. Apply a generalized approach across multiple project types (i.e., a limited amount of custom modeling tailored to each project)

Unfortunately, there is not currently an established protocol to generate evaluated savings based on the four core items above for no-to low-cost programs focused on SMBs. One approach for Measurement and Verification (M&V) of these programs to estimate weather normalized annual savings follows the International Performance Measurement and Verification Protocol (IPMVP) Option C, where energy savings are estimated using site-specific, whole building regression models (Guidehouse 2022; Opinion Dynamics 2023). Low- to no-cost SMB operational programs typically do not produce project level savings large enough to justify fully custom models, site visits, or special metering for every project. This makes IPMVP Option C appealing as it can produce savings estimates using AMI data already collected through the program. Additionally, this allows for an automated approach by applying a standard model specification to all projects. Given the types of buildings typically included in these programs, one could reasonably assume that a linear regression including AMI and weather data can produce unbiased estimates of energy savings for most projects.

While IPMVP Option C provides a framework for estimating weather normalized annual savings, it is very broad and leaves many of the details up to the modeler's discretion. For example, while it does not provide an example of a specific regression equation to estimate project-level savings, it does provide types of explanatory variables to include in a regression model, such as degree days, occupancy information, or operating mode (IPMVP 2022).

The Department of Energy's UMP protocols were designed to provide industry standard approaches for estimating energy savings for different types of energy efficiency measures. Specifically, the UMP SEM protocol was produced based on the IPMVP Option C methodological approach, "but provides greater guidance on how to address the specific challenge of determining and evaluating energy savings achieved through SEM" (Stewart 2017).

We believe SEM programs are similar enough to low- to no-cost SMB operational programs for the UMP SEM protocol when evaluating these programs. The main differences are that no- to low-cost program implementers focus exclusively on facility operations, all contact

[1] Unbiased savings estimates must be linear in parameters, random sampling, sample variation in the explanatory variables, and zero conditional mean (Wooldridge 2019)

between program participants and program staff are remote, and all operational changes are implemented by the participant and their employees or contractors.

In this paper, we examine the pros and cons of three models included in the UMP SEM protocol and conclude that, given its flexibility, the *Savings as Function of Weather Model* is a viable model to produce annual weather normalized savings for these programs. The *Savings as a Function of Weather Model* can produce an unbiased estimate of savings, weather normalized savings, has the potential to extrapolate savings based on a required amount of post implementation data available, and can be applied to multiple project types.

It is important to note that this paper does not assess the accuracy and precision of each UMP SEM protocol model. We believe an assessment of a methodology's ability to produce the correct type of savings should be conducted prior to an assessment of accuracy. Information regarding the testing of accuracy and precision for similar models can be found in (Demand Side Analytics 2022). This paper assumes that all the UMP SEM protocol models have approximately the same level of accuracy and precision. Each of these models used the same input data and the regression specifications do not differ to a large degree. In fact, one can produce exactly equivalent savings estimates across models under certain specifications.[2]

The tested models in this paper primarily differ based on the outputs they can provide. Not every UMP SEM protocol model can produce weather normalized savings for example. Therefore, we compare the regression models within the UMP SEM protocol to assess practicality of which model is the best to evaluate no-to low-cost SMB programs based on the four key items listed above.

## Tested Evaluation Methodologies

There are five regression-based savings methodologies described within the UMP SEM Evaluation Protocol (Stewart 2017), which are described below in Table 1.[3] Within this table, "Avoided Energy" refers to savings estimates that occurred during the observed post-period, whereas Normalized Savings refers to savings estimates that would occur under hypothetical "normal" weather conditions. This study analyzed the *Pre-Post Model*, the *Savings as a Function of Weather Model*, and the *Normalized Operating Conditions Model*, which are shaded in grey in Table 1.

One of our four key items is the ability to produce Normalized Savings. We chose to include the *Savings as a Function of Weather Model* and the *Normal Operating Conditions Model* in the analysis because these two models produce site-specific normalized savings rather than avoided energy. We also included the *Pre-Post Model* because we have seen it commonly used for M&V when evaluating these programs, even though it does not produce normalized savings. We did not include the *Forecast Model*, *Backcast Model*, or *Panel Model* within this study because they do not produce normalized savings based on the methodology described in the UMP SEM protocol. In addition, the *Panel Model* does not produce site-specific savings that are often desired in these types of evaluations. However, if site-specific savings are not important, it may be possible to apply similar regression equations to those we examine here but in a panel context.

[2] For example, the *Savings as a Function of Weather Model* produces the same savings as the *Normalized Operating Conditions* model when all terms are interacted with *Post* and the results are normalized to the same conditions.
[3] The *Savings as a Function of Weather Model* is a variation of the *Pre-Post Model*, and so they are grouped as the same methodology.

Table 1. SEM regression-based savings methodologies

| Methodology Name | Description |
|---|---|
| *Forecast Model* | Uses baseline period to train a model and forecast consumption of the post-period to produce avoided energy savings. Savings equals the difference between forecasted usage and actual. |
| *Pre-Post Model* | Uses baseline and post-period to estimate the effect of the post-period on energy use for each project to produce avoided energy savings. Output units are kWh/day. |
| *Savings as a Function of Weather Model* | Uses baseline and post-period to estimate the effect of the post-period on energy use to produce either avoided or normalized energy savings. Output units are kWh/degree-day. |
| *Normal Operating Conditions Model* | Estimates parameters separately for baseline and post-periods (i.e., two models) and then projects normalized conditions consumption for both models using the estimates to produce normalized energy savings. Savings equals the difference between the projects. |
| *Backcast Model* | The same as the Forecast Model but in reverse to produce avoided energy savings. |
| *Panel Model* | Uses baseline and post-period to estimate the effect of the post-period on energy use across the projects to produce avoided energy savings. Output units are kWh/day. |

*Source*: (Stewart 2017)

For each methodology tested, the analysis utilized a subset of projects from an evaluation Guidehouse completed for a Midwestern utility’s no- to low-cost SMB operational program. The four projects selected for the analysis represented the following common measurement characteristics:

- HVAC measures
- Lighting measures
- Schools
- Short post-periods (i.e., less than a third of a calendar year during the post-period)

These four projects were chosen to collectively cover all the measure characteristics listed above. Beyond these characteristics, these projects were chosen arbitrarily prior to examining any results. Each project, including the post-period start and end dates, building type, and energy efficiency measures conducted for each project, are included in Table 2.

Table 2. SMB project descriptions

| Project Name | Post-Period Start Date | Post-Period End Date | Building Type* | Savings Description |
|---|---|---|---|---|
| Heating | 01/06/2022 | 12/31/2022 | Commercial | Heating setpoint adjustment |
| School | 02/09/2022 | 12/31/2022 | Grade School | HVAC schedule and heating/cooling setpoint adjustment. |
| Lighting | 02/10/2022 | 12/31/2022 | Retail Store | Lighting schedule adjustment and malfunction correction. |
| Short Post-Period | 09/16/2022 | 12/31/2022 | Public Assembly Building | HVAC schedule and cooling setpoint adjustment. |

** During the evaluation, the only information we received regarding participant information was the building type.*
*Source*: Guidehouse analysis

All methodologies used hourly AMI data that was aggregated to the daily level as well as Typical Meteorological Year (TMY3) weather data. For simplicity, this analysis included TMY3 weather data from the same weather station for the four projects (Wilcox and Marion 2008). While a standard evaluation would use the weather station closest to each participant, this analysis kept the source of historical weather information the same across the projects for consistency purposes. This historical weather information was sourced from the National Ocean and Atmospheric Administration's (NOAA's) Quality Controlled Local Climatological Database.

### ***Pre-Post Model***

*The Pre-Post Model* used the baseline period (i.e., period prior to the energy efficiency intervention) and the post-period (i.e., period after the intervention) to estimate average daily energy savings for each project. Within this model, the post-period term was not interacted with other variables, so the savings were not dependent on additional factors included in the model, producing a "level savings effect" (Stewart 2017). The "level savings effect" equals the effect of energy usage during the post-period, net of the effects accounted for by other variables included in the regression model (e.g., month, weather), which we interpreted as savings. An example of the *Pre-Post Model* equation is shown in Equation 1.

Equation 1. Example pre-post model equation

$$E_d = \sum_{m=1}^{12} \beta_{d,m} Month_{t,m} + \gamma CDD_d + \delta HDD_D + \theta Change_d + \varepsilon_d$$

Where:

- *d* and *m* index the date and month of year, respectively.
- $E_d$ is the customer's energy consumption for date *d*.
- $Month_{t,m}$ comprises a set of 12 month-of-year indicators, each of which equals 1 if *t* falls in month *m*, and 0 otherwise.
- $CDD_d$ are the cooling degree days during date *d*.

- $HDD_d$ are the heating degree days during the date $d$.
- $Change_d$ is a vector of binary variables, each of which equals 1 if $d$ falls within the dates of the confirmed change(s), and 0 otherwise. This includes any changes to the program component and baseline adjustments as applicable.
- The $\beta_{d,m}, \gamma, \delta,$ and $\theta$ coefficients are unknown parameters to be estimated.
- $\varepsilon_d$ is a daily mean-zero disturbance term.

Once this model was estimated for each project, savings equaled the post-period estimate (i.e., $\theta$) multiplied by the number of time intervals, or the number of days within the post-period for each site. Daily avoided energy savings in Table 3 equates to $\theta$ in Equation 1. Total avoided energy savings is calculated by multiplying the number of post-period days by the daily avoided energy savings, whereas total annualized savings is calculated by multiplying the daily avoided energy savings by 365 days. The avoided energy and annualized savings ratios from the *Pre-Post Model* are also included in Table 3.

Table 3. Avoided energy and annualized results for *Pre-Post Model*

| Project Name | # Post-Period Days | Daily Avoided Energy Savings (kWh) | Total Avoided Energy Savings (kWh) | Total Annualized Savings (kWh) | Savings Ratio |
|---|---|---|---|---|---|
| Heating | 358 | 22.7 | 8,128 | 8,287 | 98.1% |
| School | 326 | 798.4 | 260,285 | 291,423 | 89.3% |
| Lighting | 325 | 54.6 | 17,734 | 19,917 | 89.0% |
| Short Post-Period | 106 | 64.3 | 6,814 | 23,463 | 29.0% |

*Source*: Guidehouse analysis

There are two fundamental issues with the *Pre-Post Model*. The first issue is that this model does not produce weather normalized savings. This methodology does not include TMY3 data, or any other normalized weather data set, in any steps. The only calculation step between the model output and the savings was multiplying the post-period parameter by the number of days within the post-period. Therefore, these results could not be considered normalized as there was no mechanism to adjust the savings to a different set of weather conditions.

The second issue is the potential bias in savings results when calculating annualized savings. When taking a deeper look into the "Short Post-Period" project, Table 3 shows that this project's total avoided energy savings was 29% smaller than the total annualized savings. This project raised the cooling setpoints at the site, but the post-period goes from mid-September 2022 through December 2022. If it is assumed that the cooling season goes from June through September each calendar year, then the impact of the cooling setpoint change for this project was based on 14 days of cooling season, which was around 14% of the total post-period days. Therefore, the average daily savings for this project was based on a proportion of around 14% for the cooling season and 86% for the non-cooling season during the post-period.

When this proportion of cooling and non-cooling savings during the post-period was extrapolated to 365 days, the annualized savings value represented a year with these uneven proportions. Figure 1 examines the uneven seasonal proportions between the baseline and post-periods for the "Short Pre-Period" project.[4]

[4] Within this paper, "post-period" and "reporting period" refer to the period after a customer makes operational energy changes through this type of program.

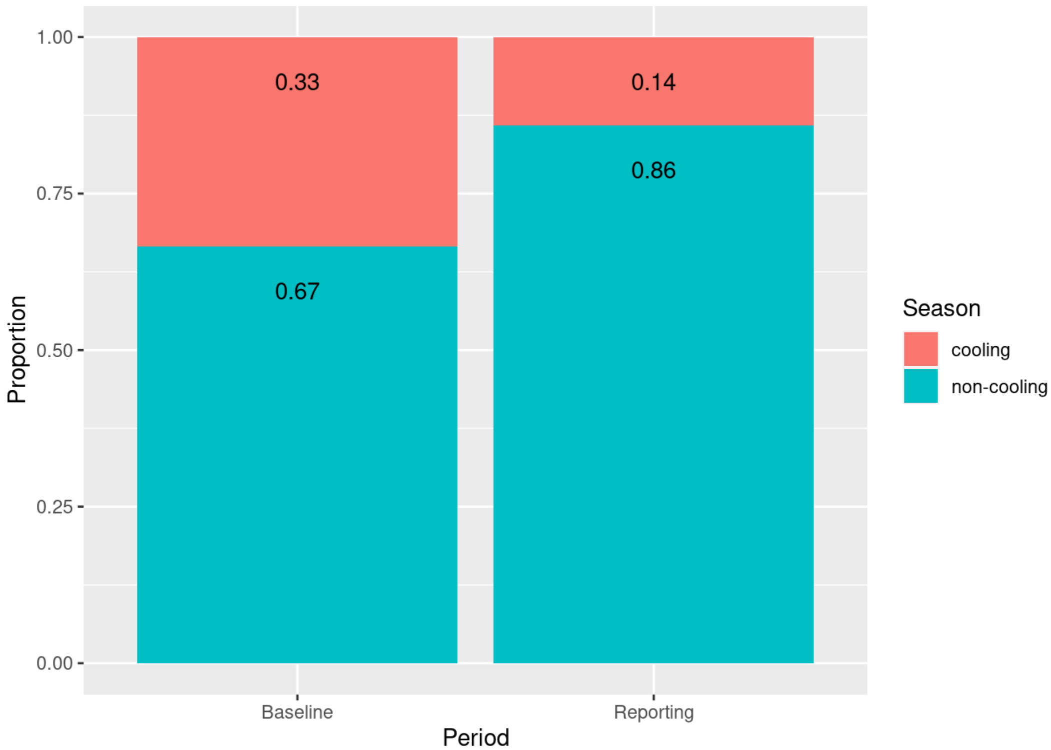


Figure 1. Cooling and non-cooling proportions of data during the baseline and post-periods for the "Short Pre-Post" project. *Source:* Guidehouse analysis.

Since the extrapolation for this methodology had no mechanism to adjust to different seasonality than what was observed during the post-period, the extrapolation of savings for this project was likely causing a bias towards zero by not fully capturing the effect of the increased cooling setpoint that would be expected over the course of a full year.

Figure 2 summarizes the *Pre-Post Model's* ability to achieve our key items. When this model is properly specified, it can produce an unbiased estimate of avoided energy savings. This model can be easily applied across project types and can accommodate minor adjustments, such as non-routine events. However, the *Pre-Post Model* has no direct mechanism to produce normalized savings. In addition, without incorporating an entirely new methodology, extrapolating savings from this model would mean extending the estimated avoided energy savings to a full year. This can introduce bias given it does not account for seasonal differences between the post-implementation period and a calendar year. While the *Pre-Post Model* is beneficial for producing unbiased avoided energy savings, we do not recommend using this model to produce annual normalized energy savings.

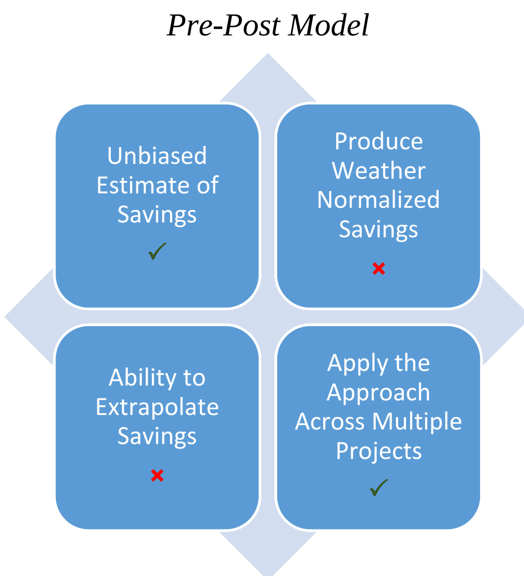


Figure 2. *Pre-Post Model* Key Items

### *Normal Operating Conditions Model*

The *Normal Operating Conditions Model* estimated savings under normal operating conditions. This is the most fundamental way to produce weather normalized savings among the five regression-based methodologies for evaluating SEM programs (Stewart 2017). This method required separate estimation of parameters for the baseline and post-periods rather than a single model that includes both periods.

This method used the values from both models to predict outcomes using normalized weather conditions as inputs. The *Normal Operating Conditions Model* equation was the same as Equation 1, except the baseline and post-periods were estimated separately. This produced an estimate of consumption under normal conditions separately for the baseline and post-periods. The post-period results were subtracted from the baseline period results to produce normalized savings.

Unfortunately, this method runs into limitations given our example regression equation when there are months missing from the post-period. For example, the "Short Post-Period" project was missing January through August from the post-period, and so the post-period model could not produce estimates for any of those binary indicator parameters and therefore could not directly produce a full year of savings. Instead, this analysis produced normalized savings for the duration of the post-period for the sake of comparison to the other methodologies.

Table 4 shows the savings ratios in savings comparing the *Pre-Post Model* results to the *Normal Operating Conditions Model* results. This provides an idea of how weather-normalizing affects the results for these projects. The weather normalized savings of the *Normal Operating Conditions Model* ranged from 96% to 104% of the *Pre-Post Model* results. Similar to the *Pre-Post Model*, the *Normal Operating Conditions Model* may not have adequately captured the relationship between savings and weather for the "Short Post-Period" project.

Table 4. Comparison of *Pre-Post Model* and *Normal Operating Conditions Model*

| Project Name | *Pre-Post Model* Savings (kWh) | *Normal Operating Conditions Model* Savings (kWh) | Savings Ratio |
|---|---|---|---|
| Heating | 8,128 | 7,974 | 98.1% |
| School | 260,285 | 271,246 | 104.2% |
| Lighting | 17,734 | 17,444 | 98.4% |
| Short Post-Period | 6,814 | 6,602 | 96.9% |

*Source*: Guidehouse analysis

Figure 3 summarizes the *Normalized Operating Conditions Model's* ability to achieve our key items. Properly specified, this model can be expected to produce an unbiased estimate of normalized savings. This model can also easily be applied across project types and can accommodate minor adjustments such as non-routine event binary variables. Unfortunately, extrapolation of savings with the *Normal Operating Conditions Model* is not straightforward with certain model specifications. Therefore, the *Normal Operating Conditions Model* is not the preferred model to use when estimating annual normalized savings for these programs.

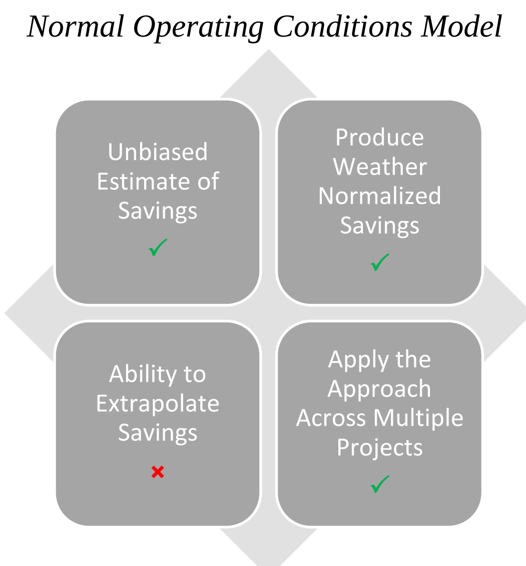


Figure 3. *Normalized Operating Conditions Model* Key Items

### *Savings as a Function of Weather Model*

The *Pre-Post Model* can be slightly adjusted to produce weather normalized results. The *Savings as a Function of Weather Model* allows for the estimation of both a "level savings effect" and a "slope-shift savings effect," which allows the model to produce savings that vary with weather (Stewart 2017).

This model has the same limitations as the *Pre-Post Model* in that the parameter estimates on the "post" variable(s) are reflective of post-period conditions. However, one of the main benefits of the *Savings as a Function of Weather Model* is that savings are decomposed into level savings and savings per degree day. In addition, this method can achieve weather-normalization in much the same way as the *Normal Operating Conditions Model*. We also believe it enables potential extrapolation of savings to a full year from a partial year of post-period data using a more reasonable assumption that the relationship between savings and weather is fully captured in the post-period.[5] This contrasts with the *Pre-Post Model* extrapolation that requires the assumption that the post-period conditions are reflective of an entire year. This assumption is often untrue for projects with HVAC measures and short post-periods.

Equation 2 lays out an example equation for the *Savings as a Function of Weather Model*. It is very similar to the *Pre-Post Model* (Equation 1), except it includes interactions between the intervention and weather. This equation produces a level effect as well as an effect dependent on weather.

Equation 2. Example savings as a function of weather model equation

$$E_d = \sum_{m=1}^{12} \beta_{d,m} Month_{t,m} + \gamma CDD_d + \delta HDD_d + \theta Change_d + \varphi_L Change_d * CDD_d + \varphi_Q Change_d * HDD_d + \varepsilon_d$$

Where:

- *d* and *m* index the date and month of year, respectively.
- $E_d$ is the customer's energy consumption for date *d*.
- $Month_{t,m}$ comprises a set of 12 month-of-year indicators, each of which equals 1 if *t* falls in month *m*, and 0 otherwise.
- $CDD_d$ are the cooling degree days during date *d*.
- $HDD_d$ are the heating degree days during the date *d*.
- $Change_d$ is a vector of binary variables, each of which equals 1 if *d* falls within the dates of the confirmed change(s), and 0 otherwise. This includes any changes to the program component and baseline adjustments as applicable.
- The $\beta_{d,m}, \gamma, \delta, \theta, \varphi_L$ and $\varphi_Q$ coefficients are unknown parameters to be estimated.
- $\varepsilon_d$ is a daily mean-zero disturbance term.

When applying observed post-period weather to the *Savings as a Function of Weather Model*, the results, shown in Table 5 were nearly the same as the *Pre-Post Model*. This was expected given the only difference between these two models was the inclusion of the intervention and weather interaction terms within the *Savings as a Function of Weather Model*.

[5] To date, Guidehouse has not encountered any research to determine the minimum amount of post-period data required to generate accurate extrapolation results.

Table 5. Comparison of non-annualized *Pre-Post Model* results and non-weather normalized *Savings as a Function of Weather Model* results

| Project Name | *Pre-Post Model* Savings (kWh) | *Savings as a Function of Weather Model* (Non-Weather normalized) Savings (kWh) | Savings Ratio |
|---|---|---|---|
| Heating | 8,128 | 8,071 | 100.7% |
| School | 260,285 | 256,406 | 101.5% |
| Lighting | 17,734 | 17,398 | 101.9% |
| Short Post-Period | 6,814 | 6,835 | 99.7% |

*Source*: Guidehouse analysis

Next, in Table 6, after producing weather normalized from the *Savings as a Function of Weather Model*, the results of this model were compared to the *Normal Operating Conditions Model*. The most notable difference was in the "Lighting" project, which was not expected to have weather-sensitive savings. In this case, we recommend using the *Pre-Post Model* results rather than forcing the model to estimate an effect that does not exist.

Table 6. Comparison of *Normal Operating Conditions Model* results and weather normalized *Savings as a Function of Weather Model* results

| Project Name | *Normal Operating Conditions Model* Savings (kWh) | *Savings as Function of Weather Model* (Weather normalized) Savings (kWh) | Savings Ratio |
|---|---|---|---|
| Heating | 7,974 | 8,329 | 95.7% |
| School | 271,246 | 282,387 | 96.1% |
| Lighting | 17,444 | 19,404 | 89.9% |
| Short Post-Period | 6,602 | 6,781 | 97.4% |

*Source*: Guidehouse analysis

The final comparison was to extrapolate the savings for the *Savings as a Function of Weather Model* to a full typical weather year and compare it to the *Pre-Post Model* savings that were also extrapolated to a year. The main difference between these results was attempting to weather-normalize and account for seasonality through the weather dependent terms within the *Savings as a Function of Weather Model*.

The savings ratios in Table 7 are very close, ranging from 98.2% to 101.5%. The small difference in results is based on a couple of items:

- The difference between the normal, annual weather and the observed post-period weather
- The model accuracy in capturing the relationship between savings and weather

If the model cannot capture the relationship between savings and weather, then the non-interacted "post" term represents a non-weather sensitive savings estimate. In that case, the *Savings as a Function of Weather Model* ends up not performing much differently compared to the *Pre-Post Model*.

Table 7. Comparison of annualized *Pre-Post model* results and weather normalized *Savings as a Function of Weather Model* results

| Project Name | *Pre-Post Model* (Annualized) (kWh) | *Savings as Function of Weather Model* (Weather Normalized) Savings (kWh) | Savings Ratio |
|---|---|---|---|
| Heating | 8,287 | 8,442 | 98.2% |
| School | 291,423 | 294,249 | 99.0% |
| Lighting | 19,917 | 19,959 | 99.8% |
| Short Post-Period | 23,463 | 23,122 | 101.5% |

*Source*: Guidehouse analysis

Figure 4 summarizes the *Savings as a Function of Weather Model's* ability to achieve our key items. This model can produce an unbiased estimate of normalized savings and can easily be applied across project types as well as accommodate minor adjustments, such as non-routine events. This model can also be adjusted to extrapolate savings while accounting for estimated weather differences. However, it is important to note that extrapolation may still introduce bias in some cases if the model cannot correctly capture all relevant relationships. For example, projects related to cooling-dependent measures should not extrapolate savings if the post-implementation period does not include any information during the cooling period.

*Savings as a Function of Weather Model*


Figure 4. *Savings as a Function of Weather Model* Key Items

## Potential Model Adjustments

Based on the testing of various SEM methodologies above, a one-size-fits-all approach may not work for all projects. Rather, it could be beneficial to consider more site and measure characteristics for each project when evaluating these types of programs in the future. We recommend adjusting the *Savings as a Function of Weather Model* based on site-specific characteristics (i.e., *Alternative Model).*

For each project, we use the *Savings as a Function of Weather Model* as the core model and then make modifications based on project-specific details. These were not, necessarily, the best models for each project. Rather, these adjustments were made to demonstrate the flexibility with this methodology when evaluating no- to low-cost SMB operational projects. In addition to these examples, binary indicators may be added to the model to account for non-routine events.

**“Heating” Project**

For the “Heating” project, the evaluators knew that the heating setpoints were lowered. Therefore, this project should not produce any savings related to cooling, and so the interaction between cooling degree days (CDD) and the intervention term were removed from the model. Table 8 shows no statistical significance at the 90% confidence level on the interaction term between HDD and the intervention (i.e., “HDD*Post”) for either model. The heating-dependent effect would be difficult to detect if this site had non-electric heating. Therefore, it is important to confirm the site’s heating fuel type and clarify how this measure was producing electric savings.

Table 8. Comparison of *Savings as a Function of Weather Model* and *Alternative Model* results for “heating” project

| Model Term | *Savings as a Function of Weather Model* | | | *Alternative Model* | | |
|---|---|---|---|---|---|---|
| | Estimate | Standard Error | P-Value | Estimate | Standard Error | P-Value |
| Post | -34.160 | 8.194 | <0.001 | -25.909 | 4.083 | <0.001 |
| HDD*Post | 0.014 | 0.009 | 1.585 | 0.007 | 0.006 | 0.237 |

*Source*: Guidehouse analysis

**“School” Project**

The “School” project included heating and cooling schedule and setpoint adjustments. Because schools normally have seasonal, non-weather dependent usage, the *Alternative Model* can replace the monthly fixed effects with an indicator variable determining summer vacation. When replacing the monthly fixed effects with a summer vacation indicator, the model results in Table 9 show a stronger cooling-dependent effect (i.e., “CDD*Post”), but the heating-dependent effect (i.e., “HDD*Post”) is no longer statistically significant at the 90% confidence level. This aligns with a non-electric heating site. The monthly fixed effects may have created difficulties for the model to separate weather effects compared to separating the heating- and cooling-dependent effects.

Table 9. Comparison of *Savings as a Function of Weather Model* and *Alternative Model* results for “school” project

| Model Term | *Savings as a Function of Weather Model* | | | *Alternative Model* | | |
|---|---|---|---|---|---|---|
| | Estimate | Standard Error | P-Value | Estimate | Standard Error | P-Value |
| Post | -935.990 | 380.504 | 0.014 | -619.929 | 365.733 | 0.091 |
| CDD*Post | -1.050 | 1.077 | 0.330 | -1.873 | 1.046 | 0.074 |
| HDD*Post | 0.590 | 0.452 | 0.192 | 0.199 | 0.418 | 0.635 |

*Source*: Guidehouse analysis

**“Lighting” Project**

The “Lighting” project only adjusted the lighting schedule, making this intervention insensitive to weather. Therefore, the *Pre-Post model* was sufficient to use for this project because savings were not expected to vary seasonally or with weather.

**“Short Post-Period” Project**

For the “Short Post-Period” project, the best attempt to adjusting the *Savings as a Function of Weather Model* was to remove the interaction between heating degree days (HDD) and the intervention term as well as the monthly fixed effects since most of the heating season was not included in the post-period. Unfortunately, neither model could detect a statistically significant weather dependent effect at the 90% confidence level separate from the level effect. This project likely had too short of a post-period to estimate unbiased annualized results.

Table 10. Comparison of *Savings as a Function of Weather Model* and *Alternative Model* results for “short post-period” project

| Model Term | *Savings as a Function of Weather Model* | | | *Alternative Model* | | |
|---|---|---|---|---|---|---|
| | Estimate | Standard Error | P-Value | Estimate | Standard Error | P-Value |
| Post | -62.270 | 15.873 | <0.001 | -52.054 | 6.414 | <0.001 |
| CDD*Post | 0.009 | 0.213 | 0.967 | 0.018 | 0.191 | 0.927 |

*Source*: Guidehouse analysis

## Project Summaries

This exercise provided more information about each site, but also raised questions about an automated process using a standard *Pre-Post Model* for every project when evaluating these types of programs. Below we summarize the results across the methodologies for each project:

- “Heating”: There was not any information for this project related to heating type, the amount the setpoint was lowered, or an explanation for how this project achieved electric savings if it did not have electric heat. However, this analysis suggested that if this site did have electric heat, then the *Savings as a Function of Weather Model* should have picked up this effect. Unfortunately, none of the models were able to clearly define the heating type for this site, but the results provided more information about the site’s heating usage compared to what was originally included in the site description in Table *2*.
- “School”: This project did not display anything unusual, although it could be worth examining a modified model that allows separate extrapolation between in-session and out-of-session periods.
- “Lighting”: This project was likely fine using the *Pre-Post Model*, but it was included in the analysis for comparison purposes. An important finding from this project was that it is not beneficial to force a model to estimate weather dependent savings when none are expected.
- “Short Post-Period”: This project likely did not include enough post-period data to properly capture the effect of a cooling setpoint adjustment. The *Savings as a Function of Weather Model* demonstrated this by failing to show a relationship between savings and cooling degrees.

## Conclusion

This analysis has shown that the *Savings as a Function of Weather Model* adapted from the *Pre-Post Model* within the UMP SEM Evaluation Protocol is a viable model for evaluating energy savings from no- to low-cost operational programs. This model can be used as a base model to produce weather normalized annual energy savings for each program participant, but also has the flexibility to consider site-specific characteristics, such as the heating type, the seasonality of energy usage (e.g., summer break period for schools), and the amount of days during the post-period. These adjustments to the model may include, but are not limited to, indicator variables for significant schedule changes (e.g., summer break) and removing the interaction terms between the intervention term and weather term when savings are not expected for a particular season (e.g., a project with only the heating setpoints lowered).

This modeling approach can produce normalized savings extrapolated to a full year in cases when the post-period is shorter than a year. It also allows the extrapolation to account for expected seasonality for weather dependent projects. However, the ability to estimate these types of savings in a defensible manner requires additional considerations for each project, especially when it comes to data availability. There is limited certainty when extrapolating savings based on a partial year of data for measures that are not weather dependent, such as lighting, because energy usage for these measures does not fluctuate greatly depending on the weather. However, the risk for accurately extrapolating savings based on limited data for weather dependent measures, such as adjusting HVAC schedules, increases dramatically. This is demonstrated with the inability to detect statistically significant weather dependent effect for the “Short Post-Period” project.

Using the *Savings as a Function of Weather Model* from the UMP SEM protocol as a base model with small adjustments to consider site-specific characteristics creates a streamlined M&V approach. Application of a standard model to all projects can allow for automation, so long as the modeler builds in the appropriate quality control checks and understands when the standard model does not work.

The analysis in this paper only included four SMB projects as the intent was to examine the practical functionality of multiple approaches. To better understand how the *Savings as a Function of Weather Model* performs and what additional site-specific adjustments can be made to the model, we recommend replicating this analysis with additional projects. Including more sites with a partial year of post-period data could help to develop an approach for extrapolating weather dependent savings to a full year based off a partial year of data. The accuracy of extrapolation across a larger sample could be tested by extrapolating savings for a site with a partial year of post-period data and then comparing that value to the estimated normalized savings for those same sites after they have a full year of post-period data.

In addition, to date, Guidehouse has not seen any research that investigates the minimum amount of post-period data required to support accurate extrapolation results. For subsequent research to this paper, Guidehouse is developing an analysis to investigate the declination of extrapolation accuracy based on the amount of post-period data available. We plan to analyze extrapolation accuracy based on the project type (e.g., lighting measures versus HVAC control), the amount of energy savings, and other project-specific factors that may contribute to extrapolation accuracy.

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