Draft version June 6, 2017
Preprint typeset using LaTeX style emulateapj v. 01/23/15

SAVINGS ESTIMATION USING THE OpenEEmeter

T. Plagge, P. Ngo, and M. Gee
Open Energy Efficiency Inc.
Draft version June 6, 2017

ABSTRACT

The OpenEEmeter is an open-source library for calculating normalized metered energy savings estimates resulting from building energy efficiency upgrades. This document describes the methods used by the OpenEEmeter to calculate savings, for both billing and AMI (Smart Meter) usage data, and quantifies the accuracy of the models using real and simulated data.

1. INTRODUCTION

The OpenEEmeter is a software library which performs automated savings estimation for building energy efficiency projects. The goal of the OpenEEmeter project and its lead developer, Open Energy Efficiency Inc., is to offer the community a fully transparent and open-source implementation of industry-standard automated Measurement and Verification (M&V) methods which can be used, for example, as part of pay-for-performance efficiency programs.

The types of efficiency projects for which estimates may be computed range from single measures (such as efficient lighting installation or HVAC upgrades) to whole-building upgrades. The Meter focuses on estimating site-level normalized metered savings, not on estimating net savings or on program evaluation; attributing savings to particular measures is beyond the scope of the software at the present time.

In this document, we describe and assess the M&V methodology implemented in the OpenEEmeter. We provide an overview of the key terminology, concepts, and algorithms, and discuss the implementation as applied to billing and AMI usage data. We also provide an assessment of the OpenEEmeter's performance using electricity and natural gas data from 1000 single-family homes in California.

2. TERMINOLOGY AND CONCEPTS

From the perspective of the OpenEEmeter, an energy efficiency project is an intervention undertaken at a single site (at which there may be multiple physical meters) over the course of a known period of time. The time prior to the intervention is referred to as the *baseline period*, the time during the intervention as the *project period*, and the time after the intervention as the *reporting period*. In the case where a single site has a series of multiple interventions, users may choose to combine the interventions into a single project period, or to analyze each intervention separately.

Site energy usage can be usefully broken down into a *base load*, *heating*, and *cooling* component. By definition, the base load is independent of weather conditions, while the heating and cooling components depend on the exterior temperature.

In accordance with industry standards, the heating component is modeled with respect to *heating degree days* (HDD):

$$\mathrm{HDD}_i = \min(T_{H,x} - T_i, 0), \tag{1}$$

where $T_{H,x}$ is the *heating balance point temperature* for the xth period (baseline or reporting), T_i is the average exterior dry bulb temperature over the course of day i.

The cooling component is analogously modeled using *cooling degree days* (CDD):

$$\mathrm{CDD}_i = \min(T_i - T_{C,x}, 0), \tag{2}$$

where $T_{C,x}$ is the *cooling balance point temperature* for the xth period. The cooling balance point, which intuitively can be thought of as the set point of the building's air conditioner thermostat, is required to be greater than or equal to the heating balance point temperature.

The energy usage for each site is broken down into one or more *traces*, i.e., measured energy usages as a function of time from a single source (generally a gas or electric meter). For a hypothetical home with a single electric trace and measurable heating and cooling components, one can model its baseline energy usage on day i as

$$\widetilde{\mathrm{usage}}_{b,i} = \mu_b + \beta_{H,b}\mathrm{HDD}_i + \beta_{C,b}\mathrm{CDD}_i + \epsilon_i \tag{3}$$

where μ_b is the baseline period base load component, $\beta_{H,b}$ and $\beta_{C,b}$ the *heating and cooling coefficients* for the baseline period, and ϵ_i the error term. One can then separately model the reporting period energy usage on day j as

$$\widetilde{\mathrm{usage}}_{r,j} = \mu_r + \beta_{H,r}\mathrm{HDD}_j + \beta_{C,r}\mathrm{CDD}_j + \epsilon_j \tag{4}$$

where the terms are analogously defined.

Once such models have been determined for the baseline and reporting periods, the weather-normalized savings can be estimated over any relevant period. For example, it is common to calculate the *annualized weather normalized savings* as

$$\sum_i \widetilde{\mathrm{usage}}_{b,i} - \widetilde{\mathrm{usage}}_{r,i} \tag{5}$$

where the sum is taken over an entire year, and where the CDD and HDD values for each day are calculated using standard normal year weather data sets such as TMY3. Alternatively, one might choose to calculate the *total gross normalized metered savings* as

$$\sum_i \widetilde{\mathrm{usage}}_{b,i} - \mathrm{usage}_{r,i} \tag{6}$$

tomplagge@openee.io

where the sum is taken over the reporting period (or a subset thereof), CDD and HDD are calculated using the observed site temperatures, and $\text{usage}_{r,i}$ is the observed (rather than modeled) reporting period usage on day i.

The OpenEEmeter, therefore, must perform several steps for each site:

- Load usage data and account for estimated readings.
- Load project start and end dates, and split usage data accordingly; using information about the project site (generally its postal code), select and load the appropriate weather observations.
- Check for data sufficiency to ensure that valid models can be derived for the baseline and reporting periods.
- For the project baseline period, determine the appropriate usage model, which may include μ_b, $\beta_{H,b}$, $\beta_{C,b}$, $T_{H,b}$, and $T_{C,b}$.
- For the project reporting period, determine the appropriate usage model, which may include μ_r, $\beta_{H,r}$, $\beta_{C,r}$, $T_{H,r}$, and $T_{C,r}$.
- Calculate the relevant aggregate savings estimates.

In the next section, we discuss these steps in specific detail.

3. METHODOLOGY

The OpenEEmeter uses an energy trace as its fundamental unit of analysis. It accepts as inputs the trace's usage data, the site's temperature data over the relevant time period, and project data such as project start and end dates. Multiple models are fit using ordinary least squares, and are tested for qualification against the trace's baseline and reporting periods; the qualifying model with the highest R^2 is then identified. These baseline and reporting models are then used to generate savings estimates.

Billing period data and AMI data are handled by two separate but similar models (`CaltrackMonthlyModel` and `CaltrackDailyModel`, respectively). Differences between the two will be noted below.

3.1. *Data*

Usage data is accepted by the OpenEEmeter models in the following form:

Timestamp: The beginning of the measurement period.

Usage: The metered usage for the measurement period.

Temperature: The mean temperature in degrees Fahrenheit during the measurement period.

The measurement periods for a trace are assumed to be complete–i.e., the first measurement period ends at the beginning of the second measurement period. If the measurement periods are not of consistent periodicity (for example if they represent monthly billing cycles as opposed to daily, hourly, or 15-minutely AMI data), the trace should be terminated using a timestamp with NULL usage that represents the end of the last measurement period; if this entry is not included, then the last measurement period in the trace will be discarded.

Note that the OpenEEmeter provides optional `formatter` helper classes to handle both AMI and billing data, and to deal with estimated readings; see the ReadTheDocs documentation for further information. The monthly model accepts properly-formatted AMI or billing data, while the daily model accepts AMI data only.

3.2. *Project data*

If the OpenEEmeter is to estimate savings for a given trace, it is required that project start and end dates be provided. The baseline period is then defined as all data prior to the start date, and the reporting period as all data subsequent to the end date, exclusive. Site location information in the form of a ZIP code is also required in order to identify the appropriate weather station and normal year weather.

3.3. *Data sufficiency*

Data sufficiency requirements are imposed on both the baseline and reporting period before the model is fit. First, the trace length is required to be greater than or equal to `min_contiguous_months`, which by default is set to 12. Therefore, by default, traces of less than a year in length result in an error. For baseline periods, the contiguous months must end immediately before the project start date; for reporting periods, they must begin immediately after the project start date. The sum of the entire trace is also required to be greater than 0.01 in its unit of measure.

Additional sufficiency requirements are imposed by the monthly model. For each billing period, it is required that there be 15 or more days of valid usage and temperature data. If billing data is provided, only the latter requirement is operative.

3.4. *Modeling*

For each billing and reporting period, up to four models are tested for qualification. All models are fit using ordinary least squares. The first is an *intercept-only* model,

$$\widetilde{\text{usage}}_i = \mu + \epsilon_i, \tag{7}$$

which by construction has an R^2 value of 0.0.

The second model tested is the *HDD-only* model:

$$\widetilde{\text{usage}}_i = \mu + \beta_H \text{HDD}_i + \epsilon_i. \tag{8}$$

The balance point temperature for computing HDD is optionally determined by a grid search between 55 and 65 degrees Fahrenheit, inclusive. If the grid search is enabled, the model is fit for each qualifying candidate balance point, and the balance point with the best R^2 is selected. To qualify as a candidate balance point, there must be at least 10 days with non-zero HDD and a total HDD of at least 20 over the full baseline or reporting period, and the resulting μ and β_H must be nonnegative.

If the option fit_cdd is set equal to True, as it is by default for electric (but not natural gas) traces, then two additional models are tested:

$$\widetilde{\text{usage}}_i = \mu + \beta_C \text{CDD}_i + \epsilon_i \tag{9}$$

and

$$\widetilde{\text{usage}}_i = \mu + \beta_H \text{HDD}_i + \beta_C \text{CDD}_i + \epsilon_i. \quad (10)$$

As with the heating degree day balance point, the cooling degree day balance point can optionally be chosen using a grid search, where here the allowed range is from 65 to 75 degrees Fahrenheit, inclusive. The same qualifications are applied to candidate cooling degree day balance points as for heating degree day balance points.

Of the two or four candidate models which are fit for a given modeling period, each is tested for qualification. A model qualifies if the intercept and heating/cooling coefficients are nonnegative, and if the p-values for all parameters are less than 0.1. The qualifying model with the highest value of R^2 is chosen as the *best-fit qualifying model*.

3.5. *Savings estimation*

Savings may be estimated over any period of time where temperatures are available. Two common choices are the normal year savings, and the reporting period savings. Both involve out-of-sample predictions for at least one model; to estimate the error for each point in the out-of-sample predictions, we first define the mean squared error as

$$s^2 = \sum \frac{(\text{usage}_i - \widetilde{\text{usage}}_i)^2}{(N-k)} \quad (11)$$

where k is the number of degrees of freedom (1 for intercept-only, 2 for HDD-only, etc.). Then the prediction variance for out-of-sample data x_0 is given by

$$\hat{V}_s = x_0(X'X)^{-1}x_0' + s^2 \quad (12)$$

where $(X'X)^{-1}$ is the parameter variance-covariance matrix estimated from the OLS fit.

Normal year savings— To compute normal year savings, both the baseline and reporting best-fit qualifying models must be determined. Each model is then used to predict usage given the normal year temperatures, and the difference between the sums of the predictions then represents the savings estimate, and the variances of the sums and differences are computed in the usual way. Days without a defined normal year temperature are ignored.

Reporting period savings— To compute reporting period savings, only the baseline period best-fit qualifying model must be determined. The model is then used to predict usage during the reporting period, and the sum of the actual measured usage is subtracted from the sum of the predicted usage to determine the savings. The actual measured usage is assumed to have a variance of zero. Days without a reporting period temperature or usage estimate are ignored.

4. VALIDATION

In order to assess the performance of the OpenEEmeter model, we obtained a set of 1000 anonymized electric and natural gas traces from single-family homes in California. At least two years of baseline period data were provided for each home in the validation data set, as well as at least one year of reporting period data. Since the true savings from each project is unknown, we perform our assessment by selecting, for each home, the baseline data from the year prior to the project start date as the testing data, and the baseline data from two years prior to the project start date through one year prior to the project start date as the training data.

Table 1
Validation results for 1000-home samples

Fuel	CV(RMSE)			NMBE		
	25%	50%	75%	25%	50%	75%
Electric	0.28	0.37	0.53	-0.12	-0.02	0.07
Gas	0.53	0.69	0.90	-0.20	-0.05	0.05

Each home in the validation data set was analyzed using the algorithms described in Section 3, with the training data as the "baseline" and the testing data as the "reporting" period. The reporting period savings was calculated for each home, and the CV(RMSE) and NMBE were calculated as a measure of model performance. CV(RMSE) is defined as

$$\text{CV(RMSE)} = \frac{\sqrt{\frac{1}{N}\sum_i^N (\text{usage}_i - \widetilde{\text{usage}}_i)^2}}{\text{mean(usage)}} \quad (13)$$

and NMBE as

$$\text{NMBE} = \frac{\frac{1}{N}\sum_i^N (\text{usage}_i - \widetilde{\text{usage}}_i)}{\text{mean(usage)}} \quad (14)$$

where usage is the observed usage in the testing period and $\widetilde{\text{usage}}$ is the predicted usage in the testing period using the training period model. See Granderson (2015) for further details and justification.

The results are presented in Table 1. The median, 25th, and 75th percentile CV(RMSE) and NMBE are shown across the 1000-home sample. For these homes, both the NMBE and the total portfolio savings suggest a general downward trend in energy usage, slightly more pronounced for natural gas. However, the NMBE and CV(RMS) values compare favorably with similar analyses (see for example Granderson (2015)).

The Open Energy Efficiency team has tested several variations on the model presented in this work, for example by including calendar effects and using alternative regression techniques. Using a robust regression algorithm that minimizes the Huber-t statistic rather than the mean-square error produced an NMBE value slightly nearer zero (-0.006 rather than -0.02 for the electric validation data set), but had little effect on CV(RMSE) and increased computational cost by a factor of approximately three; calendar effects produced marginal improvements at best, and resulted in over-fitting in some cases where regularization was not applied. None of the variations we tested were deemed compelling enough to include at the present time, though the option to use robust regression in place of ordinary least-squares may be offered in future versions of the software.

5. CONCLUSIONS

The OpenEEmeter is intended to serve as an open, validated, industry-standard set of methods to be incorporated into business models, analyses, and program design and operation. The metered savings estimates can be used in a variety of commercial applications, such as pay-for-performance programs; and can also be used as the basis for further analysis, such as EM&V. For example, metered savings estimates may be used as dependent variables in regression analyses to attribute savings to individual measures, or computed for appropriately-constructed comparison groups for program evaluation.

The methods described in this document are used by the OpenEEmeter to produce weather-normalized metered savings estimates for energy efficiency interventions in single-family residential homes. These methods can be readily extended to apply to multifamily properties, which the Open Energy Efficiency team has tested in cooperation with NYSERDA. With additional extensions to account for business days, estimations may also be produced for small and medium businesses; the team expects to implement these extensions as validation data becomes available.

REFERENCES

Granderson, J., et al 2015, LBNL-187225