Inverse Modeling of Portfolio Energy Data for Effective Use with Energy Managers

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Abstract

Development, features, and use of a tool for inverse energy modeling for a portfolio of municipal buildings is described. The tool is software-automated to enable batch-processing. Statistical fitness is automatically evaluated to provide a baseline for energy retrofit program measurement and verification (M&V). Particular attention is paid to tool outputs that support use by an end user, such as an energy manager, for initial facility diagnostic purposes to guide further investigation.

Objectives and Modeling Approach

The fundamental objective of the work was to provide an industry-standard basis for evaluating NYC's municipal energy retrofit program. This process required a statistically-validated linear regression model for whole facility energy use, per the requirements of the International Performance Monitoring and Verification Protocol (IPMVP) and ASHRAE Guideline 14. The methodology set forth in the ASHRAE Inverse Modeling Toolkit (Kissock, 2003) was applied.

During the course of the work, we realized that, in addition to serving as the basis for M&V, the method could also be used to provide diagnostic insights into building performance and potential systems improvements (Kissock, 2004). This became an important objective of the work as the client agency energy managers are, at present, much more involved in energy efficiency project identification than M&V.

A third, less developed, objective was to be able to use inverse models in conjunction with physics-based forward models. A third, less developed, objective was to be able to use inverse models in conjunction with physics-based forward models. In work with other teams (Eicker, 2016; Schumacher, 2017) we discovered that the partitioning of baseload versus weather-sensitive loads in change-point models can be useful to validation and calibration of forward models.

Methods

After an initial two years of manual processing using industry-standard tools, a semi-automated batch-processing procedure was developed. Visual Basic (VBA) scripts were used to import NYC facility energy consumption data files, and to clean and prepare data for batch processing using Energy Explorer (Kissock, 2000). Output from this process was then used to recreate change-point linear regression models in MS Excel, and a scripted algorithm used a series of three tests – a shape test, a t-test and a data population test – to select the best-fitting model (2-, 3-, 4- or 5-parameter) (Figure 1).

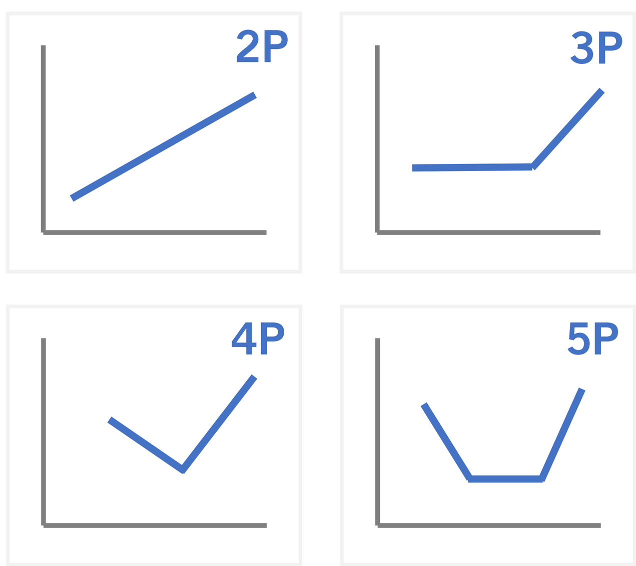

Figure 1. Types of Change-point models

The selected model was then displayed in a simple dashboard format, along with regression coefficients and associated statistical metrics (Figure 2).

Full Process Automation. The modeling process was fully automated using a custom-developed Python application, PyBEMA, linked to a database management system. Change-point models were generated in PyBEMA using piecewise linear regression, and processed data was then pushed to an enhanced MS Excel dashboard (Figure 2).

Timeframes. The number of data points were increased from 12 months to 24 to account for various data fidelity issues, such as estimated meter readings. Models were also improved with normalization to actual billing periods.

Data Visualization and Usability Testing. The enhanced MS Excel dashboard includes additional evaluative visualizations and associated metrics, presented for one facility at a time – though benchmarked against the full dataset. Usability testing is currently underway with NYC client agency energy managers.

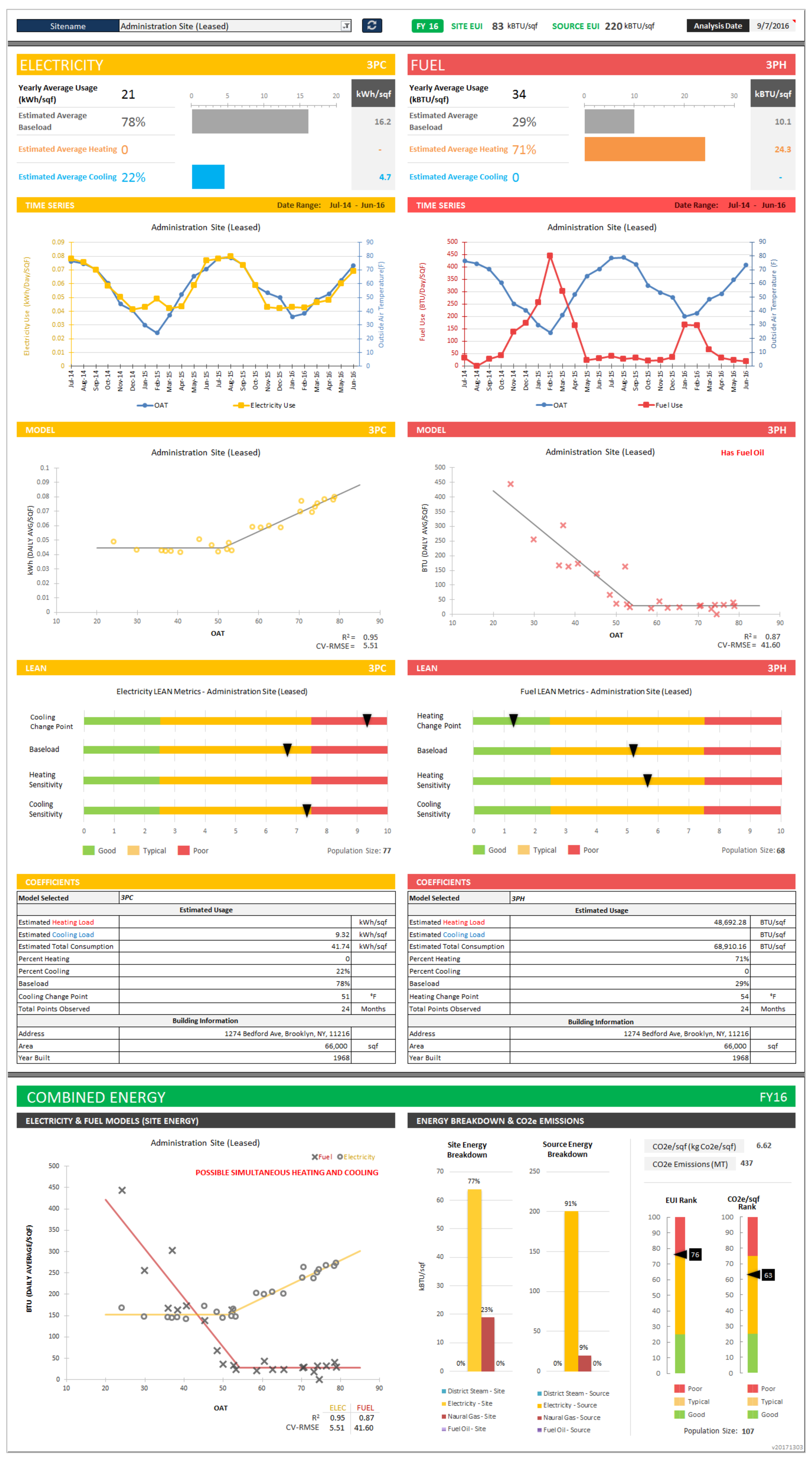

Figure 2. Dashboard user interface

Results

PyBEMA readily processes hundreds of facilities at a time, producing graphed linear change-point regression (CP) models and associated metrics that are accessed via the MS Excel dashboard. The dashboard is designed to present the information that is most relevant for a high-level assessment of facility energy consumption, for both electricity and available thermal fuel data.

Change-point Models. Figure 3 shows typical CP model output, in this case a 3-parameter cooling (3PC) model for electricity, with data points, best-fit line and model quality metrics. Figure 4 shows a sample of visualizations that are based on combined electricity and thermal energy, including site and source energy breakdown, EUI and CO_2e ranking.

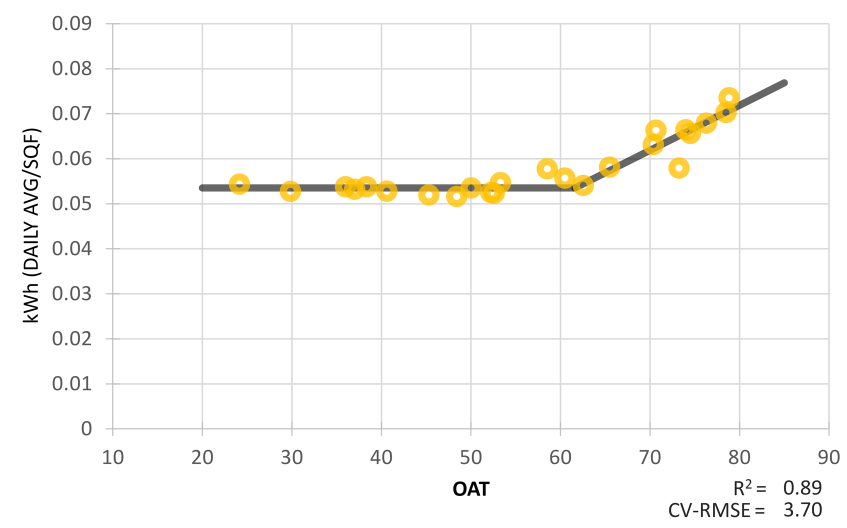

Figure 3. Electricity change-point model for a NYC municipal office building

Diagnostics. CP models can be used for diagnostic purposes, to identify areas of performance deficiencies that likely merit further investigation. As an example, a high electricity baseload can indicate excessive ventilation or systems that are left running 24/7.

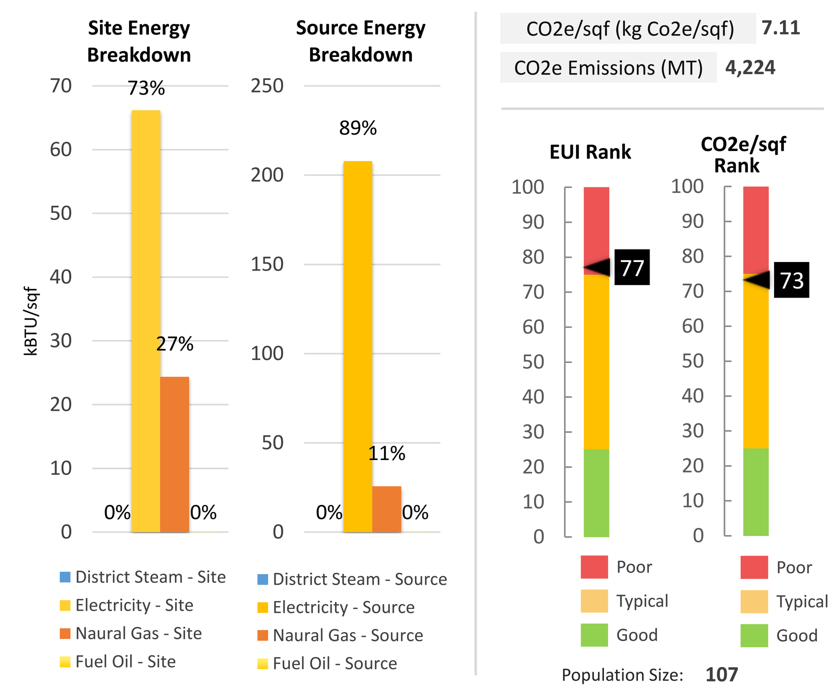

Figure 4. Combined energy metrics for a NYC municipal office building

Lean Energy Analysis. The Lean Energy Analysis (LEA) technique (Kissock, 2004; Abels, 2011) uses CP model regression coefficients to benchmark performance across portfolios based upon CBECS building type; quartiles are used to identify the best, worst and typical performers. In addition to the rating scale included in the dashboard (Figure 5a), LEA data is used to generate quad charts that identify best and worst performing facilities based on comparisons of multiple metrics (e.g., cooling change-point vs. cooling sensitivity) (Figure 5b).

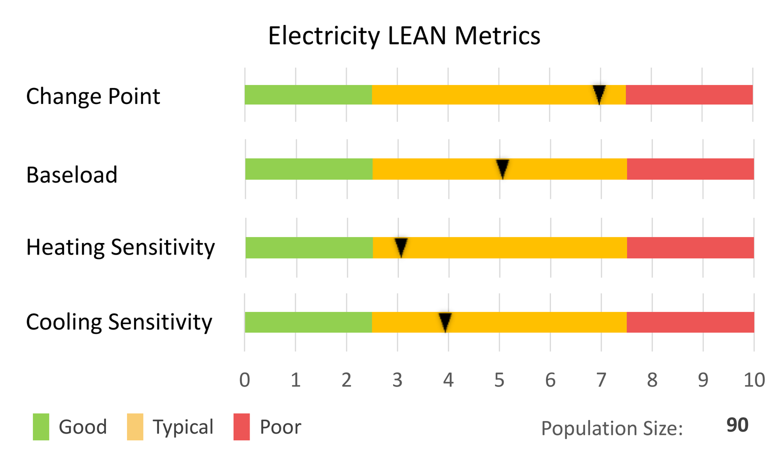

Figure 5a. Electricity graphic rating scale used to display facility rankings

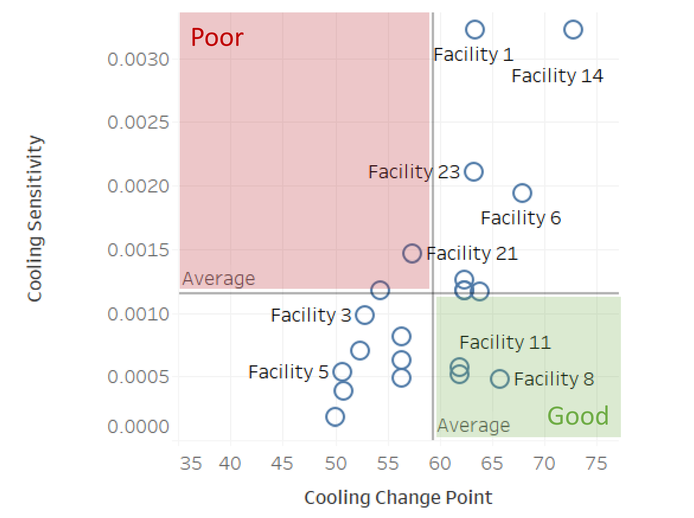

Figure 5b. Cooling sensitivity (slope) vs. cooling change-point

Discussion and Analysis

Interpreting Poor Fit. Estimated utility meter readings, lack of fuel oil consumption data contribute to poor model fit. Operational issues related to occupancy/operating hours require multivariate analysis to improve model fit.

Interpreting Baseload. Baseload is identified as a corollary of change-point, and is quantified as the value of that point at the y-axis (i.e., y-intercept).

Interpreting Change-point. Change-point is analogous to a facility's thermal balance point, above which energy is used for heating and below which energy is used for cooling.

Interpreting Slopes. The slope indicates seasonal energy use per degree of outdoor air temperature, and degree of steepness of the slope can therefore provide an indication of a facility's overall heating or cooling efficiency (with caveats).

Initial User Experience Testing Results. Users tend to focus strongly on the value of heating/cooling change-points and the degree of heating/cooling slopes. However, there is a tendency to misinterpret these metrics; for example, change-points are often assumed to be heating/cooling thermostat setpoints. This primary focus on change-point and slopes often causes users to overlook the magnitude of the baseload, and therefore not as strongly consider no- or low-cost operational measures that could potentially reduce consumption.

Future Work. MS Excel is being phased out as the dashboard is ported to a web-based environment.

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