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Algorithm for automating the selection of a temperature dependent change point model

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ABSTRACT

An algorithm was developed to automate the process of selecting a temperature dependent change point model. Regression models based solely on outdoor air temperature for monitoring and verification purposes are common. The correct change point model shape is determined through a series of three tests. The first test checks whether the coefficients of the model are the correct sign for the shape. The second test checks if the coefficients for the model are significant. The final test checks whether enough data points are present in each temperature region of the model. The algorithm was tested with synthetic EnergyPlus electricity and natural gas data for an outpatient hospital, medium office building, large office building, large hotel, secondary school, and warehouse, with weather data from Chicago, Miami, Seattle, and Fairbanks. The algorithm was able to select the most appropriate temperature dependent change point model for all 48 cases tested. The algorithm can be used in an automated energy modeling routine for monitoring and verification or for checking human decision-making in the energy modeling process.

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1. Introduction

Regression modeling is often used to determine savings from a building energy retrofit. The regression model can predict the baseline, or pre-retrofit, energy use based on influential parameters such as outdoor air temperature. The energy consumption for the building during the post-retrofit period can be predicted from the baseline regression model. This baseline regression model also allows an analyst to determine normalized savings under different building operating conditions.

Two widely used guidelines for the measurement and verification (M&V) process are ASHRAE Guideline 14: Measurement of Energy and Demand Savings, and the International Performance Measurement and Verification Protocol (IPMVP) [1,2]. Both of these guidelines detail three major savings determination approaches in addition to deemed savings. The approaches include retrofit isolation, whole building, and calibrated simulation. The IPMVP breaks up the retrofit isolation approach into two options (A & B), and ASHRAE Guideline 14 breaks up the whole building approach into a performance and prescriptive path. The algorithm presented in this paper would be part of the whole-building performance or prescriptive path under ASHRAE Guideline 14 and part of Option C for the IPMVP.

ASHRAE Guideline 14 and the IPMVP are designed to provide a common set of terms and methods helping people involved in energy efficiency projects such as facility energy managers, energy service companies (ESCOs), and consultants. In particular, both documents provide details for inverse models used to determine energy savings. ASHRAE Guideline 14 presents more specific details regarding inverse modeling for the whole building approach than does the IPMVP.

The IPMVP has detailed the basic approach to savings determination with the following steps [2]. The algorithm presented in this paper relates to the baseline model creation, which is part of step 5 and is necessary for computing and reporting savings in step 8 of the IPMVP process.

1. Select the IPMVP Option consistent with the scope of the project (similar to selecting a path from ASHRAE Guideline 14).
2. Gather relevant energy and operating data from the baseline period.
3. Determine the energy savings program.
4. Prepare the measurement plan, and verification plan if necessary.
5. Design, install, and test any special equipment under the M&V plan.

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6. After the energy savings measures are implemented, follow up with a commissioning process.
7. Gather energy and operating data from the post-retrofit period.
8. Compute and report savings in accordance with the M&V plan.

Change point models, also known as piecewise linear regression models, are often used in predicting heating and cooling energy consumption in residential and commercial buildings, and are specifically discussed in the IPMVP and in ASHRAE Guideline 14. The physical basis of the linear change point methods are well known, and with interpretation, certain parameters such as the balance point temperature can be estimated [3–6]. Degree-day approaches, often used for estimating the heating load for residential buildings, could be considered the first use of change point models for estimating energy use [7]. Fels generalized the degree-day approach and set the stage for using change point models measuring energy savings for other energy components and for commercial buildings [8]. However, other authors have warned against the dangers of assuming degree-day models and the simple physical basis behind them can be accurately applied to all buildings [9,10].

Many additional parameters and methods for data-driven modeling have been suggested to improve upon the single-variate linear approaches. Katipamula et al. [11] suggested adding other variables relating to the dew point at the cooling coil, solar load, and a breakup of internal and external loads. Multiple linear regression models have shown great functionality in terms of evaluating initial designs [12–14], the prediction of energy consumption and demand in several different building sectors [15–17], and predicting indoor temperature and relative humidity [18]. Measurement and verification can use any advanced mathematical technique for building energy prediction including Fourier series [19,20], support vector machines [21–28], neural networks [29–32], among others.

Heo and Zavala [33] and Burkhart et al. [34] have argued for Gaussian process modeling in M&V to capture the complexity and non-linearity of building energy consumption and increase the accuracy of the savings uncertainty estimates. This work focused on linear change point models at the monthly time scale because of the innate simplicity and the relationship to ASHRAE Guideline 14. The physical basis for outdoor air temperature based linear change point models is described in [35].

Two important ASHRAE research projects investigated inverse modeling, ASHRAE RP-1050 and RP-1404. ASHRAE RP-1050 produced the Inverse Modeling Toolkit (IMT), which was a Fortran 90 application for developing regression models specifically for building energy use [36]. A user of the Inverse Modeling Toolkit needs to select the type of regression model from experience. ASHRAE RP-1404 presented modeling techniques using a year of monthly utility bill data combined with a shorter span of sub-metered hourly or daily data necessary for generating change point M&V models [37–39]. Reducing the necessary time span of baseline data is more important for daily and hourly modeling where sub-metering is often required. Monthly utility bills are more often available.

A goal of this work is to reduce the amount of necessary experience or to eliminate the human decision-making in selecting a proper change point baseline regression model. Automating the selection of a temperature dependent change point regression model is dependent on the selection of a proper model shape. Some information regarding selection procedures can be found in [40,41]. In this paper, the term model shape, or the model type, refers to the models as shown in Fig. 1. The model shapes considered for this algorithm include 2P, 3P-Heating, 3P-Cooling, 4P, and 5P. The “NP” nomenclature stands for the number of parameters determined by the regression, which are the B’s in Fig. 1.

Although 7 models are shown in Fig. 1, computationally there are only 5 different models. The 5 different models are 2P, 3P-Heating, 3P-Cooling, 4P, and 5P. The differences between the models are in the calculation procedures, particularly in how the transformed temperature variables are calculated. In fact, after the temperature transformations, the 2P, 3P-C, and 3P-H models are all simple linear regressions, and the 5P and 4P are multiple linear regressions of the same form. Some consider the 4P model to have a “cooling” and “heating” shape similar to the 3P models, but the differences lie in the signs of the coefficients instead of the calculation procedure for the 3P-C and 3P-H models.

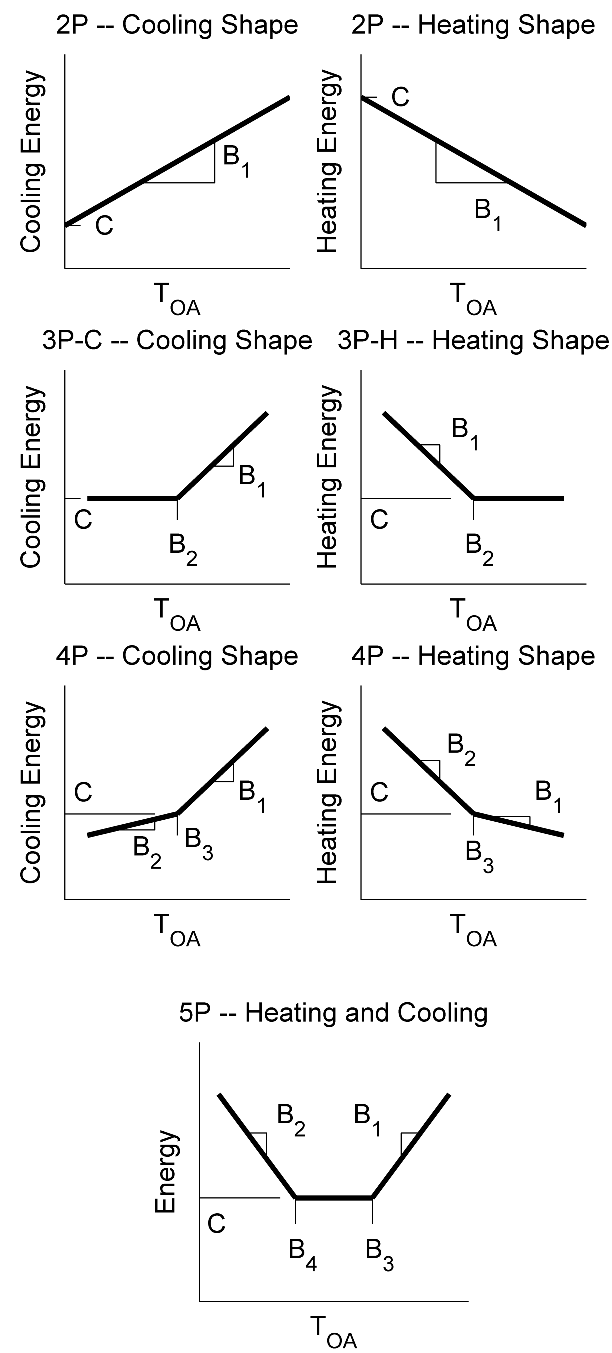

Fig. 1. IMT change point models. Top row: 2P cooling and heating models. Second row from top: 3P cooling and heating models. Third row from top: 4P models in the “cooling” and “heating” shape. Bottom row: 5P heating and cooling model.

Mathematically, the forms of the models are (using the nomenclature from ASHRAE Guideline 14)

$$2\text{P}: \quad E = C + B_1(T) \tag{1}$$

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