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Statistical modeling of the building energy balance variable for screening of metered energy use in large commercial buildings

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ABSTRACT

Whole building energy data are the fundamental metric of building energy performance and used for evaluation of investments in energy efficiency, utility billing, and calibration of building energy simulations. Metered energy use data contain anomalies and bias, and those must be flagged and investigated to reach useful conclusions from the data. The energy balance load E_{BL} representing the aggregate building thermal load is a variable calculated from the metered energy use, and the constancy of E_{BL} as a function of influential variables such as outside air temperature can be used to check the validity of metered whole building energy use. This paper proposes regression models to statistically identify the building-specific daily E_{BL} pattern without prior knowledge of building systems and operations. The proposed models are designed based on simplified load calculation principles, so that the regression parameters have physical significance. The models were applied to the E_{BL} data for 56 buildings on the Texas A&M University campus to examine the applicability. The mean CV-RMSEs of the four-parameter change-point (4P-CP) models, multiple linear regression (MLR) models, and the MLR models incorporating AR(1) error structure ranged from 6.9% to 10.4%. Overall, the MLR models with the outside air temperature and humidity load variables presented the most balanced performance taking account of the availability of variables and the ease of estimation and parameter interpretation.

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1. Introduction

Growing environmental concern and increasing energy cost have been driving investments in building energy efficiency. Whole building energy use is the fundamental metric of energy performance monitoring and plays an important role to determining and reporting the impact of these investments. Metered energy use data often contain anomalies and biases resulting from metering problems such as degradation of sensor elements, undesirable sensor locations, scaling factor errors and sensor labeling errors. Accuracy of measurement is one of the major sources of the financial and performance risks in energy savings projects [1], and the International Performance Measurement & Verification Protocol (IPMVP) [2] and ASHRAE Guideline 14, Measurement of Energy and Demand Savings [3] provide standard measurement and verification (M&V) methods. Both call for appropriate quality control and quality assurance for data collected.

Abnormal energy use can be detected by the distance from the predicted values based on models. The methods used to model the building energy use can be broadly characterized as using the forward or the inverse approach [4]. The forward approach is based on a physical description of the building and requires prior knowledge of the building parameters including the geometry, construction materials, occupancy levels, and the types and controls of the HVAC systems. Accurate information for these parameters is not readily available for existing buildings and it is not cost-effective to collect the information when one analyzes the quality of energy data from hundreds of buildings. The inverse approach is suitable in such a case because it estimates unknown parameters based on the relationship between the known variables using statistical solutions.

This paper proposes several statistical modeling methods for a variable called the energy balance load E_{BL} [5,6] for detecting anomalies and biases in the metered energy data using the inverse approach without prior knowledge of the building parameters. The E_{BL} variable is formulated based on the first law of thermodynamics or energy balance of the building and calculated from separately metered whole building daily electricity, cooling, and heating energy consumption. Shao and Claridge [5] proved that the E_{BL} variable is independent of the type(s) of air handling units used in the building at constant control parameters and exhibits a

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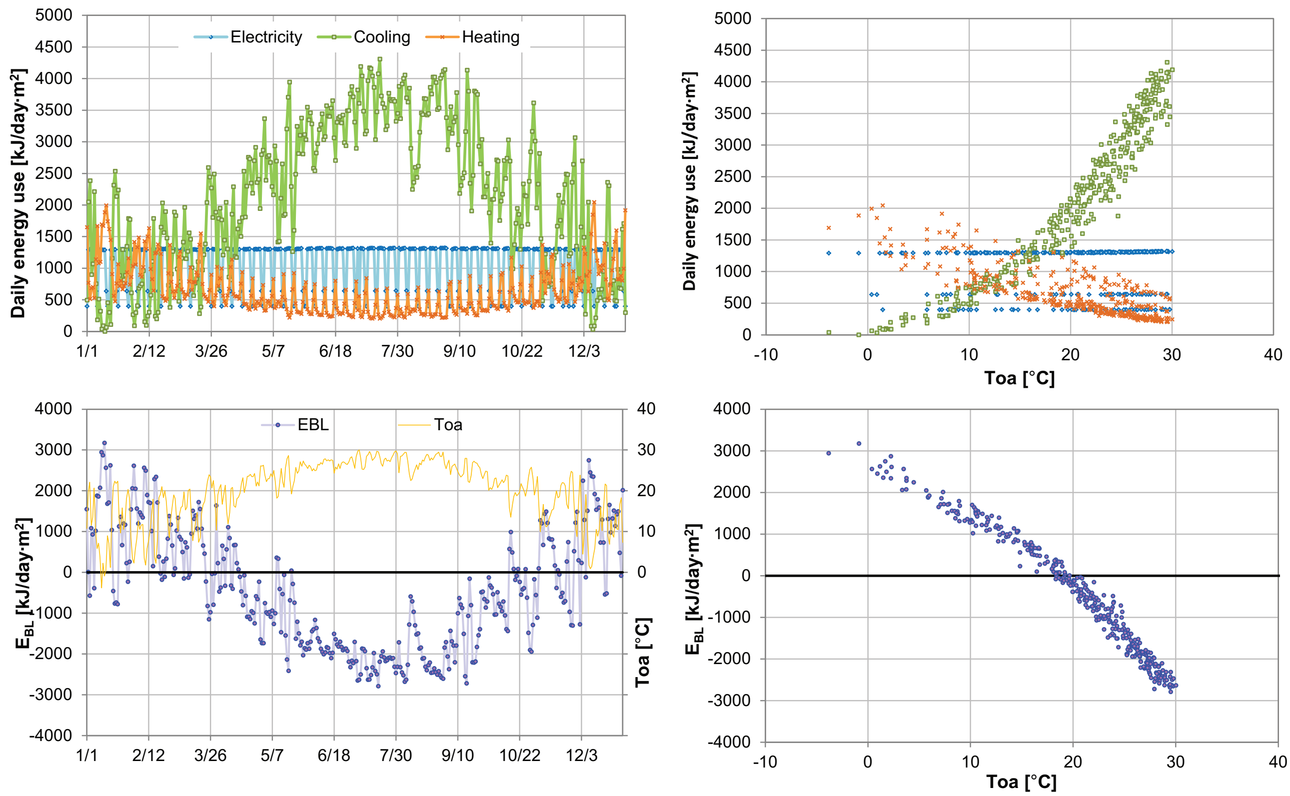

Fig. 1. An example of the carpet plot using the simulated energy consumption for a large office building with conditioned area of 46,320 m^2 (498,600 ft^2). The indoor air temperature set point is 24 °C (75 °F) and the building total air exchange rate is constant at 35.9 kg/s (79.1 lb/s) throughout the year. The daily consumption values for individual energy types are plotted in the top and the daily energy balance loads are plotted in the bottom. The left plots are time series and the right plots are functions of the daily average outside air temperature.

largely linear pattern as a function of outside air temperature T_{oa}. The use of the E_{BL} variable in addition to the energy data provides an intra-experimental comparison [7] involving measured cooling and heating energy and electricity use based on the energy balance. This is valuable especially for commercial buildings which have simultaneous cooling and heating.

A graphical tool developed by Baltazar et al. [8,9] visualizes questionable E_{BL} points as outliers or ill-behaved patterns in the plot of E_{BL} versus T_{oa} as in Fig. 1. This tool has been used to monthly validation of metered energy use for over 100 commercial buildings on the Texas A&M University campus and successfully detected faulty energy use data due to sensor assignment errors and scaling errors in energy metering. Proposed statistical modeling reveals the relationships between E_{BL} and influential factors that are difficult to find by visual examination of E_{BL} versus T_{oa} plots and assists energy analysts judging data. The developed E_{BL} models can be used to detect anomalies and level shifts in the whole building energy use data in two different cases: (1) newly obtained data are compared to the model prediction based on the past data; (2) data in a certain span are filtered retrospectively using the fitted model based on the same span of data. Continuous monitoring and assessment of metered energy use for utility billing, performance tracking and reporting are categorized as (1), and verification of energy data for energy savings baselines and for calibration of building energy simulations are categorized as (2). In either case, the validity of data is checked in terms of the constancy of E_{BL} models.

The E_{BL} model structure is derived based on simplified engineering principles so physical interpretation of the model parameters is possible. The parameters obtained from inverse building energy modeling are usually interpreted in terms of the heat loss coefficient including ventilation, base temperature, and for dynamic models, thermal capacitance [10–15]. Hammarsten [16] and Rabl [12] note that there can be considerable uncertainties in the estimated parameters due to non-linearity and non-constancy in actual building systems, measurement errors, and estimation bias from violation of statistical assumptions. However, several applications of the inverse method to large numbers of buildings [17–19] show the usefulness of these parameters in building performance benchmarking. Careful interpretation of the parameter estimates may be used for a causal analysis of changes in the E_{BL} patterns and for a peer-comparison of building load characteristics. Our main focus in the present work is the prediction of E_{BL}, and the interpretation of estimated parameters is not discussed quantitatively. Quantitative analysis of E_{BL} model parameter estimates is found in [20].

The paper is organized as follows. Section 2 gives a derivation of a functional expression of the E_{BL} variable and the basic structure that will be the foundation of regression models. Section 3 describes the data collected from 56 buildings and analyzes the correlations between E_{BL} and explanatory variables. Section 4 proposes four regression models of E_{BL}, and Section 5 applies these regression models to the data and discusses the results and the applicability of these regression models. Finally, remarks about the proposed methods and further challenges for future study are given in Section 6.

2. Model structure for the energy balance load E_{BL}

2.1. Definition of E_{BL}

The net change of the total energy in a building ΔE_{CV} is equal to the difference between the total energy entering $\Delta E_{entering}$ and leaving $\Delta E_{leaving}$ the building. That is,

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