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A model-based decision support tool for building portfolios under uncertainty

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ABSTRACT

Despite abundant energy use data, few facilities managers have a good benchmark for tracking energy performance in commercial buildings. Building energy self-benchmarking is an effective means of comparing performance to expectations. This paper presents an improved theory for a decision support tool that can self-benchmark building energy performance, identify energy faults, and quantify their severity. Detailed building energy simulation modeling of a big-box retail store with open source software is accessible and economical to industry for generating performance benchmarks. Methods of parametric sampling and uncertainty analysis are enhanced with detailed parameter uncertainty characterization. Uncertainty and sensitivity analysis are used to adjust risk tolerance thresholds for each unique monitored end-use. A dynamic cost function allows utility theory to compute expected costs covering multiple criteria. Improved theory for decision support tool is tested on ten faulted model scenarios placed in three climate zones. Finally, we demonstrate fault response prioritization.

1. Introduction

Standards such as LEED® guide energy efficient design, but the energy savings predicted by the design models often deviate significantly from actual building usage data [1]. The root causes of this gap include: (1) inaccurate assumptions in the design energy model relating to design, occupant behavior, or control strategies, (2) improper execution of intended construction, (3) unintended control strategies in the operation of building systems, and (4) poor assumptions in design [2]. Building energy performance benchmarking can reveal the presence of "faulted" operational states, as well as quantify the severity of these faults. There are two primary classes of building performance benchmarking: *peer comparison* of performance among other similar buildings, and *self-benchmarking* compared to an ideal baseline. This paper is focused on a tool for performing building self-benchmarking; one which requires a relatively high level of expertise to utilize.

Installing sub-metering infrastructure that monitors and records building energy end-uses can provide rich data for building energy self-benchmarking and is a prevailing trend for commercial buildings [3]. There is growing potential to utilize sub-metered data from categorical building systems' end-uses as a feedback mechanism that can help bridge the gap between intended and actual operation [4]. There are vast amounts of building energy data available to facilities managers (FM), however FM lack the resources to analyze it. Thus, the FM typically does not know if their buildings perform as they were intended.

Henze et al. [5] developed the concept of an Energy Signal Tool for operational performance decision support, which is made more credible and accurate with uncertainty analysis (UA) and probabilistic model predictions. The tool alerts facilities managers of building consumption anomalies across a variety of monitored end-use categories. Henze et al. [5] used utility theory to merge measured consumption data, probabilistic predictions, and a scalar cost function to provide easily interpreted visual results in the form of a five-level traffic light. In their work, user-defined risk tolerance thresholds give the user decision support for addressing and prioritizing energy-related faults in reference to measurements taken over a rolling retrospective period. The authors based their investigation on reduced order models developed in the

Abbreviations: AMY, Actual Meteorological Year (weather data); BMS, building management system; CDD, cooling degree days; CDF, cumulative distribution function; ESTool, Energy Signal Tool; EUI, energy use intensity; FAR, false alarm ratio; FDD, fault detection and diagnostics; FM, facilities manager(s); HDD, heating degree days; HVAC, heating ventilation and air conditioning; LHS, Latin Hypercube sampling; NGAS, natural gas; NREL, National Renewable Energy Laboratory; OAT, one at a time (local sensitivity analysis method of parameter screening); PDF, probability distribution function; REFR, refrigeration; SA, sensitivity analysis; SR, signal priority ratio; UA, uncertainty analysis; WBE, whole building energy.

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Matlab technical computing environment for ease of data processing and maximum theoretical development.

This paper builds upon the concepts for an Energy Signal Tool (ESTool) as proposed by Henze et al. [5] with a more detailed modeling platform and alterations to the foundational theory. Here we use open-source detailed building energy simulation software common to engineering practitioners to create probabilistic predictions of performance. This paper also explores the use of UA and sensitivity analysis (SA) in the context of setting risk tolerance thresholds, for which there is little previous research. We also show that risk-tolerance thresholds can be defined in a more sophisticated manner than arbitrary levels, involving a combination of probabilistic state masses and straightforward user input. The application of utility theory is enhanced by a novel approach of accepting input to the cost function from an ordinary user with several organizational objectives in mind.

2. Review of energy performance benchmarking practices

The US Environmental Protection Agency (EPA) offers information on building performance assessment and benchmarking through its Energy Star Portfolio Manager program [6]. This system has participation from 40% of the US commercial building stock, which belies the simplicity of its use [6]. Individual building performance is compared to a peer group from the most recent Commercial Buildings Energy Consumption Survey (CBECS) data set, yielding a score that is a product of "*a statistical regression model that correlates the energy data to the property use details*" [6,7]. This rating system is the most rigorous peer benchmarking system of its kind in the United States [8]. Portfolio manager is an excellent starting point, and can help cities track goals toward progress such as Architecture 2030, but falls short of offering a benchmark that supports energy management activities. For example, Hinge et al. [9] found that Portfolio Manager scores for primary education facilities in the Northeast depended heavily on the amenities of the building (e.g., ventilation levels, technology), and the experience level of the facilities management personnel. Peer groups are static; an upgrade to the functions that a building provides will result in a reduced Portfolio Manager score [9]. Peer benchmarking in general also does not show efficiency gains when improvements in one end-use have been offset by changing operations that affect another.

A customized portfolio benchmarking method for restaurants was explored by Hedrick et al. [10]. The authors demonstrated that a benchmarking system tailored to each restaurant is the best way to evaluate performance. They took a statistical approach to benchmarking by deriving regression models for expected performance from best correlation of independent variables such as hours of operation, facility type, and observations in weather. This type of benchmark reveals whether or not one particular store is an outlier in the data set on a qualitative basis. It has the advantage of simplicity to the user, but may not be accurate independent variables that are hard to measure, such as local heating degree days (HDD) and cooling degree days (CDD), are missing or inaccurate.

With the increasing amount of sub-metered energy data available, it is a trend in industry to have more interest in advanced energy self-benchmarking. This has created the opportunity for a number of software as a service (SaaS) platforms being offered by companies such as Building IQ and Ecova-Verisae that are in high industry demand. These SaaS platforms offer features such as machine learning algorithms that use building management system (BMS) data to filter out faulted conditions from normal anomalies to develop unique fit mathematical models capable of predictive optimization [11]. They also offer proactive optimization analysis in real time with expert staff available to guide customers to energy savings priorities [12]. This is excellent for managing opportunities in a building portfolio, but SaaS platforms are driven by reduced order models that use a select few observed environmental variables to predict normal energy consumption patterns. Mathematical algorithms cannot handle simple inputs such as operational schedules and HVAC controls logic that a detailed energy model can. This type of benchmarking solution does not offer combined decision support with energy benchmarks as well as other organizational priorities as inputs. Incorporating other goals, such as human comfort and sales, into the picture will be especially as businesses increase energy efficiency and thus decrease the cost share that energy has on their overall plan.

3. Literature review

Uncertainty analysis (UA) quantifies the uncertainty in model outcome due to the uncertainty that exists in the set of model input parameters [13]. Detailed energy simulation models have thousands of input parameters characterizing the usage patterns, operational strategy, and physical properties of a building and its systems. Even for existing buildings with extensive construction and operational documentation, there are uncertainties in some parameters such as outdoor air infiltration rate, occupancy schedules, and equipment performance curves. When using a detailed energy simulation model as a performance benchmark, it is a sure thing that a point estimate of energy use during any given period produced by the model will differ from the measured value. Various combinations of parameter values in the model will result in a range of model outcomes. UA is an important component of simulation models used for decision-making, as it acknowledges the unknowns that go into establishing a baseline [14]. Hopfe and Hensen [15] have demonstrated robust methods in which UA can be used in conjunction with sensitivity analysis to improve the decision making process in building design.

Booth and Choudhary [16] propose a framework of UA for assessing the potential impact of energy efficiency policy in UK housing. Their goal was to minimize the financial risk of program implementation to the UK government by providing a range of expected outcomes that result from retrofit measures that allows for spending prioritization. Wang et al. [17] used Monte Carlo analysis (MCA) to examine the uncertainties in building performance due to model accuracy, modeling assumptions, climatic data, and actual operational practices. These authors found a spread of up to 100% in energy consumption between a building operating in the worst and best possible manner, which is far greater than contributions most design features could make. Bucking et al. [18] used probability distributions of parameters extracted from solutions to a Net Zero Energy (NZE) building optimization algorithm to characterize uncertainty in energy performance. They generated probable ranges of energy performance by using random MCA sampling with batch sizes of 1000 models to sample from 26 uncertain model parameters. These authors were able to extract probability distribution functions of parameters that showed which values were most likely to result in a NZE-compliant design. Several other authors have worked with UA for building design optimization purposes [18–21].

Calibration of a benchmark model is crucial for the success of self-benchmarking methods. Statistical calibration of a model is very challenging, as there are thousands of knobs to turn that could all potentially have an impact on helping the model match the measured data. This issue of over-parameterization is compounded by limitations in computational power. Saltelli et al. [22] show how model parameter space can be reduced with a combination of local pre-screening and global sensitivity analysis. There are many examples of studies in the literature where the dozens of parameters that are contained in building simulation models are reduced to fewer than ten that have high significance to the model outcome [15,18,21].

In Heo et al. [23] a scalable, probabilistic methodology is presented that is based on Bayesian calibration of normative energy models. Based on CEN-ISO building standards, normative energy models are light-weight, quasi-steady state formulations of heat balance equations, which makes them appropriate for modeling large sets of buildings