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Scalable tuning of building models to hourly data[☆]

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ABSTRACT

Energy models of existing buildings are unreliable unless calibrated so that they correlate well with actual energy usage. Manual tuning requires a skilled professional and is prohibitively expensive for small projects, imperfect, non-repeatable, and not scalable to the dozens of sensor channels that smart meters, smart appliances, and sensors are making available. A scalable, automated methodology is needed to quickly, intelligently calibrate building energy models to all available data, increase the usefulness of those models, and facilitate speed-and-scale penetration of simulation-based capabilities into the marketplace for actualized energy savings. The "Autotune" project is a novel, model-agnostic methodology that leverages supercomputing, large simulation ensembles, and big data mining with multiple machine learning algorithms to allow automatic calibration of simulations that match measured experimental data in a way that is deployable on commodity hardware. This paper shares several methodologies employed to reduce the combinatorial complexity to a computationally tractable search problem for hundreds of input parameters. Accuracy metrics are provided that quantify model error to measured data for either monthly or hourly electrical usage from a highly instrumented, emulated-occupancy research home.

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1. Introduction

Sustainability is perhaps the defining challenge of our time. With only 4.4% of the world's population, the US (United States) consumes 19% of the world's primary energy production. Buildings account for the largest fraction of energy consumption in the US, accounting for 41% of the primary energy used in 2010 [1]. Building energy model creation and simulation have many uses, but they are often fiscally infeasible for all but the largest projects because of the time required to create a model of an existing building and calibrate it to measured data. The US DOE (Department of Energy's) Building Technologies Office is assisting the development of several Emerging Technology applications to significantly reduce costs and drive simulation-informed actualized energy savings into existing light commercial and residential buildings to meet the US goal of reducing building energy use by 50% by 2030 compared with a 2010 baseline.

Many simulation-based analysis tools are available [2] to project how specific policies or energy retrofit measures [3] would maximize return-on-investment for government and utility subsidies. These tools can help resolve issues such as principle-agent, first cost, and cost/performance trade-offs, as well as maximizing financial metrics such as net present value and simple payback. As with all software tools, their analysis suffers from "garbage in, garbage out." This is complicated by the fact that, unlike cars or planes built to a strict engineering specification, buildings are currently based on one-off designs and constructed in the field. They can last decades or hundreds of years, and rarely do any energy use data exist beyond utility bills. For older buildings, optimal retrofit packages and similar analyses are calculated for a fictitious building and necessarily yield suboptimal results. A central challenge in building energy efficiency is being able to realistically and cost-effectively model existing buildings. Even coarse models are useful to determine how incremental energy conservation measures affect whole-building energy consumption. Their usefulness is dramatically greater for existing buildings, for which existing

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data can be used to calibrate the energy model. However, differences between models and actual monthly utility bills on the order of 24–97% [4,5] are common. Many M&V (measurement and verification) protocols specify a required accuracy for a model to be legally useful. Most large organizations use ASHRAE Guideline 14, 5.3.2.4.f requirements, which specify a coefficient of variance for RMSE (root mean squared error) of <15% or 30% and a normalized mean bias error of <5% or 10% for calibrating to monthly or hourly data, respectively [6].

Several simulation engines, and tools that leverage them, are actively supported by DOE [2]. DOEs flagship simulation engine is EnergyPlus [7], which has been supported with over $65 million since 1995. OpenStudio [8] now serves as the primary middleware between simulation engines and analysis tool applications. High-level graphical interfaces and low-level, text-based files allow a user to provide information that fully describes a given building and from which EnergyPlus can calculate detailed heat flow and energy usage information for the building. The number and instances of these input parameters are extensive and highly variable in their combinatorial effects, and their sensitivities are not yet fully explored. This relegates simulation calibration to an “art,” and only a few hundred people have qualified for ASHRAE's building energy modeling professional certification. It is unrealistic to expect even an advanced user to be able to provide accurate values for each of the approximately 3000 parameters expected by EnergyPlus for the average building. To mitigate such issues, a reference or template building already in the preferred tool, which is similar to the user's own building, is used as a default point for parameter values. These values are then “corrected” to more closely match the actual building under consideration, depending on the level of information available (e.g., the data specified by an ASHRAE level 1, 2, or 3 audit). In addition, average material properties are typically used from the *ASHRAE Handbook of Fundamentals* (HoF) which is beginning to include significant variances in material properties identified from controlled laboratory tests [9].

As the variance in material properties increases; as building systems, equipment, and materials become more complicated and diverse; and as energy simulation modeling algorithms evolve to more thoroughly model existing systems and capture new equipment technologies, there is a need to mitigate this complexity by relying on cost-effective, intelligent algorithms to calibrate building energy models to use as many data as are available. The Autotune project [10] aims to solve this need with an automated process and has previously demonstrated calibration results for envelope parameters using monthly utility data [11]. This paper extends that work by discussing the scalable methodologies used to tune a building energy model's 100+ envelope parameters to whole-building hourly electrical usage data.

2. Background

2.1. Autotune background

The Autotune project has used 269+ channels of 15-minute sensor data from a robotically-emulated-occupancy ZEBRAlliance [12,13] 2800 ft^2 research home. Parametric ensemble models of this building were simulated using HPC (high performance computing). The Titan supercomputer at ORNL (Oak Ridge National Laboratory) allowed the use of 131,072 cores to calculate 524,288 simulations and write 44 TB of data to disk in 68 min [14]. Some of the latest advances in web-oriented database storage were used to allow queryable simulations generated from varying 156 inputs and reporting 96 outputs at 15-minute resolution (35 MB per simulation) for 8 million EnergyPlus simulations [15]. Measured data often are corrupt because of uncalibrated sensors or missing data, so statistical techniques have been refined for autonomous quality assurance and gap-filling [16]. Extensive big data mining was conducted through the creation of an HPC-enabled suite of machine learning algorithms (MLSuite [17]) to generate agent-based encapsulation of knowledge for Autotune deployment on mobile devices. EnergyPlus was approximated with machine learning algorithms to reduce simulation runtime from 3 min to 4 s with a minimal trade-off in accuracy for the processed building types [17]. The Autotune project, to promote open science, is making a portion of the 267 TB (26.9 trillion data points) of EnergyPlus simulation data freely available online.[1]

2.2. Simulation accuracy

Despite the proliferating use of building energy tools, there remain many concerns and shortcomings applicable to all simulation engines. The primary concern is typically the accuracy of the simulation engines for realistically modeling (via inputs) a virtual building so that it matches a real-world building. A HERS (Home Energy Rating System) study in 1999 [18] using the REM/Rate simulation engine for 2300 homes in Wisconsin found that the median home's heating use—40% of the average annual Wisconsin energy bill—was overestimated by 22%, with the worst 15% median being off by 62%. Another study in 2000 [19] covering 500 homes in 4 states found no relationship between asset ratings and energy consumption. A 2008 pilot study [4] found 190 Home Energy Saver, REM/Rate, and SIMPLE residential simulation models had a 25.1–96.6% error rate compared with actual monthly electrical energy usage. A 2012 study [5] found that 859 residential models across Home Energy Saver, REM/Rate, and SIMPLE had a mean absolute percentage difference of 24% compared with actual monthly electrical energy use and of 24–37% compared with actual natural gas use for a sample size of 500 houses. All of these studies use comparisons with monthly utility bill data; the challenge of accurately matching hourly or 15-minute data for dozens of sub-metered data channels is significantly more difficult.

The challenge for simulation accuracy can be reduced to two primary issues: (1) a gap between the as-modeled and as-built structure, and (2) limitations of the modeling engine's capabilities.

2.3. Common errors with simulation inputs

Gaps between as-modeled and as-built structures have many sources, with the fault being traceable to an inaccurate input file rather than the simulation engine itself. We have worked with building scientists and conducted a sensitivity analysis to identify the most important input parameters.

Infiltration—the rate at which air and energy flow through the building envelope (typically measured in cubic feet per minute per square foot)—cannot be cheaply tested. Blower-door tests can determine the infiltration rate at a given pressure (usually 50 Pa), but these are one-time measurements that vary significantly as a function of other variables such as temperature, wind speed, and wind direction. Therefore, infiltration is often one of the first variables energy modeling experts use to manually align a simulation model with actual data.

A second issue is the schedule of building usage, which includes the number of occupants; times of occupancy; HVAC (heating, ventilation, and air-conditioning) set points; operation schedule; and other factors. These also constitute inputs to the simulation engine but are often specified in a separate EnergyPlus file for convenience. For many of these, cost-effective sensors do not exist

[1] http://autotune.roofcalc.com.