Energy and Buildings 110 (2016) 1–12

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

A method of probabilistic risk assessment for energy performance and cost using building energy simulation

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ARTICLE INFO

Article history:
Received 16 July 2015
Received in revised form
28 September 2015
Accepted 29 September 2015
Available online 8 October 2015

Keywords:
Building energy modeling (BEM)
Building information modeling (BIM)
Energy efficiency
Energy use intensity (EUI)
Sensitivity analysis
Risk assessment
Monte Carlo method
Latin hypercube sampling

ABSTRACT

Energy efficient buildings rely on simulation to predict energy performance. However, problems associated with simulation tools can lead to surprises when discrepancies are found between actual and predicted building energy performance; this frustrates building owners, investors, and designers.

A probabilistic method of risk assessment for the calculation of energy use intensity and total utility cost in energy performance has been developed. Sensitive and uncertain parameters were selected and given a probability distribution instead of one fixed value for the simulations. Latin hypercube sampling was used to generate input combinations with parameter values picked stochastically from distributions based on the Monte Carlo method. With these input combinations, 10,000 simulations on seven distributed parameters were run using a cloud processing service. The output data, energy use intensity and energy cost, were analyzed using curve-fitting techniques to find a best-fit distribution, which could be used for risk analysis of energy performance and cost. The results illustrate the probability and reliability of prediction within a specific range. Instead of relying on a single value, these curves would help designers better evaluate design alternatives, and the probability distribution of energy performance and cost would be useful in making decisions about investments for energy efficient projects.

1. Introduction

The rapidly growing global energy consumption by buildings has exceeded the other major sectors of industrial and transportation in the past 20 years, and the upward trend continues with growth in population, increasing demand for building services, and comfort levels [1]. As a necessity instead of a matter of choice or luxury, energy efficient buildings ushered in an era of development including the updating of technology, new materials, design ideas, and advanced equipment. Although there is a burst of growing popularity in energy efficient buildings, the growth of this industry does not seem as strong as expected. In the United States in 2008, non-residential energy efficient construction starts were only 10% [2]. Among multiple difficulties like financial feasibility and public awareness of environment and policy, the performance risk in energy efficient building projects is a significant issue hindering the development of this industry.

Performance risk is the possibility of occurrence of discrepancy between expected energy performance during the design stage and real energy performance after project completion. In a major review of the US Energy Service Company (ESCO) market, 40% of projects had savings that deviated by more than 15% from projections, and in 30% of the cases, predicted savings were greater than actual [3]. Among 120 LEED certified projects, 25% of the buildings show savings in excess of 50%, well above any predicted outcomes, while 21% show unanticipated measured losses [4]. Other studies also show performance uncertainty in LEED certified buildings; in one study, the results show that although collectively, the LEED buildings use the same amount of source energy as do other NYC office buildings, LEED Gold buildings show a 20% reduction while Certified and Silver level actually use more energy [5]. ESCOs can also benefit from a financial risk analysis to assess the probability of the payback period of their investment for making a profit. An analysis of residential construction by Soratana and Marriott showed a likely payback period between 16 and 55 years (mean 35 years), which is longer than the typical contract lengths (7–20 years). The auditor's experience (in the parameter "offered savings") had a major impact. This study showed that overall the residential market is risky for ESCOs [6].

Risks in energy efficient building projects lie in uncertainties and volatilities of many aspects including conceptual design, engineering simulation, construction, operation, maintenance, and verification and other extrinsic factors like energy cost, policy, and

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http://dx.doi.org/10.1016/j.enbuild.2015.09.070
0378-7788/

so on. Computer simulation is the key step of predicting building energy performance; however, despite preconceptions that it is accurate and precise, it has many uncertainties that lead to an unreliable prediction since most of the inputs are estimates from experience or code requirements instead of real or measured data. Even if a very high quality simulation has been accomplished, risk is still introduced in the building construction [7,8] and operation phase. No construction can be done 100% as the design team expected [9]. In operation, occupants' behaviors also have significant influence on energy performance, 4.2% in one study [10]. A 3 year study of a multifamily residential complex in Switzerland, had what was they thought to be a not unusual difference of 50% between expected and real thermal energy consumption that they attributed to conditions of occupancy use, performance of new energy technologies, and the weather [11]. Other researchers have determined that occupant behavior in setting the thermostat and ventilation flow rates over-rule building considerations such as window g and U values, wall conductivity, and orientation for heating loads, which are important parameters when their behavior is not taken into account [12]. Research in ongoing to create methods of predicting occupant behavior [13,14], but currently these methods are often not included in popular energy software, and they are difficult to include because of the paucity of experimental data or models that include simulated occupant behavior [15].

All these factors affect the energy performance of buildings and unfortunately are all difficult to predict. Mills and Weiss identified the risks associated with energy efficiency projects into two categories: intrinsic and extrinsic volatilities and the risk into five categories: economic, contextual, technology, operation, and measurement and verification [16]. Van Gelder et al. propose a methodology that includes pre-processing for selection of parameters, screening and updating, and then probabilistic design. The authors' intent was to use effectiveness and robustness indicators that are used in the manufacturing industry to also enable evaluation of the results: "effectiveness is defined as the ability of the design option to optimize the performance, while robustness is defined as the ability to stabilize this performance for the entire range of input uncertainties" [17].

Uncertainty in building performance must be taken into account [18]. Less has been done for incorporating overall risk assessment into energy simulations that takes multiple factors into consideration. Macdonald and Strachan reviewed the sources of uncertainty in the predictions from simulation with techniques of differential sensitivity analysis and Monte Carlo analysis and then incorporated uncertainty analysis into ESP-r [19]. Hopfe and Hensen from investigated the potential design support by applying uncertainty analysis in building performance simulation [20]. Heo et el. also cast concern on certain assumptions in energy modeling even for building retrofits where more is known than for new construction, specifically that the values used to create the "good fit between monitored and computed energy consumption" does not mean that those values are actually the ones that represent reality and concludes that "the current methods are not capable to support retrofit decision-makings at large scale with adequate risk management" [21]. They propose their own probabilistic methodology based on Bayesian calibration of normative energy models. Tian provides an overall review of sensitivity analysis methods including how to deal with correlated inputs and the difference between global and local techniques [22]. Spitz et al. used three sensitivity analysis methods: local sensitivity, correlation, and global sensitivity. They used EnergyPlus for simulations and validated their results against measured values in an experimental house that is a full scale test facility. Their metric was indoor air temperature. Because they used both real data and simulations, they were able to evaluate the uncertainties of the sensor readings and simulation uncertainty and discuss which type was most prevalent in different parts of their case study [23].

2. Methodology

In order to assess uncertainty and risk in energy efficient building projects, a probabilistic based simulation method has been proposed. This section documents the overall methodology and workflow used to pursue this goal and details each step of the research process (Fig. 2.1).

2.1. Risk analysis

There are numerous possible sources of risk that can cause the variation in building energy performance. Risk analysis is the main step to transform risk in practice to simulations. Also this is the step to identify sources of risk and quantify their possibility of occurring. This step is based on the input parameters of a certain simulation program (EnergyPlus in this case) by identifying and generating possibility distributions. It is possible to derive the possibility distributions mathematically based on the range of values for the parameters or from specific information, manufacturer specifications for instance, directly from practice. Although it is better to include all uncertain parameters to get accurate results, this is difficult to realize due to the limitation of explicit data and time. Therefore a sensitivity analysis was performed to eliminate the less important parameters and keep the most uncertain and influential ones. Preliminary selection was conducted to eliminate some ignorable parameters by professional experience, followed by a differential sensitivity analysis (DSA) for a detailed selection of key parameters. After the identification of key parameters, probabilistic analysis of each parameter was performed to present small pieces of risk in practice situations. This step was completed by curve fitting techniques with historical data, standard and guidelines, and judgment from professionals.

2.1.1. Sensitivity analysis

Before proceeding to sensitivity analysis, a preliminary selection of input parameters is necessary due to the limitation of time and software capability. Others have used sensitivity testing for a large range of parameters reduced to a smaller number (eight) of parameters that represent properties of the building's thermal performance with good matching of results [24]. Considering the final target of assessing risk, the parameters selected should have two attributes: sensitive to energy performance and uncertainty in practice. After collecting all the input parameters from model, preliminary selection can be processed based on the parameters' sensitivity and uncertainty. Program settings (such as output file format) and geometry related parameters (such as building footprint) were eliminated with the assumption that simulation will be run correctly, and there will be no discrepancy in building geometry. Then non-sensitive parameters were eliminated, and finally parameters without uncertainty were eliminated. This preliminary selection was done by literature review and interviews of experienced professionals in related areas.

Differential sensitivity analysis is widely used because it enables to explore the sensitivity of the outputs to inputs directly [25,26]. In addition, sensitivity analysis is relatively easy to implement in energy simulation programs. DSA involves varying just one input for each simulation while the remaining inputs stay fixed at their most likely base-case values. The changes in the output are therefore a direct measure of the effect of the change made in the single input parameter. Repeating simulations with variation of one input parameter each time enable the individual effects of all input changes and allows users to understanding potential priorities (for example, in building design of geometry versus material) [27]. This