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Uncertainty quantification for combined building performance and cost-benefit analyses

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ABSTRACT

Building performance simulation is most often used to improve the design and at times the operation of buildings. Within a building model, the thermal characteristics of the envelope and the HVAC (heating, ventilation, and air conditioning) equipment are described by parameters that often cannot be estimated with high accuracy (e.g., occupant behavior, building envelope and HVAC equipment performance). Another common part of the design process of a building is a cost-benefit analysis to compare design options and different scenarios. The results are also heavily dependent on assumptions about uncertain economic parameters (e.g., future inflation rates and energy costs). In this paper a Monte Carlo based methodology for uncertainty quantification that combines the building simulation and the cost-benefit calculation is developed and demonstrated. Furthermore, Monte Carlo filtering is applied to determine the model inputs (e.g., design specifications and boundary conditions) that lead to the desired model output (e.g., a positive net present value of the investment). The aim is to propose a methodology that helps to enhance the design process or building operation and supports related decision-making.

1. Introduction

Uncertainty analysis (UA), or alternatively uncertainty quantification (UQ), when applied to building performance simulation (BPS) can improve the design process by considering the uncertainty in important design parameters that impact decision making. Several studies have revealed this very fact. Lomas and Eppel [1] conducted one of the first studies involving sensitivity analysis (SA) using Monte Carlo (MC) techniques for building simulations in 1992. They compared different SA methods and analyzed over 70 uncertain inputs. Macdonald et al. compared different techniques for uncertainty quantification and implemented some methods in a simulation program [2–4]. De Wit et al. [5,6] state, that it is essential to communicate uncertainties to decision makers. But in building simulation practice, an explicit assessment of uncertainty is more the exception than the rule. Therefore, most of the decisions are based on point estimates. If a building simulation is considered as a decision support instrument, it seems to be necessary to assess and communicate the problem of uncertainties properly. Otherwise decisions might be made, which are based on faulty assumptions. This can lead to disappointments when the actual building does not perform as communicated through the design process. With a classical building simulation the answer to design questions is often either *yes* or *no* depending on the assumptions. An example for such a design question could be: *Will the renewable energy system supply 20% of the total yearly energy demand?* With a UA it is possible to answer design questions with probabilities, e.g.: *The probability of more than 20% energy supplied by renewable energies is 80%.* Furthermore, it is possible to compare design options and choose the option with the highest probability of reaching a specific goal.

De Wit and Augenbroe [6] analyzed uncertainties in building design mainly related to thermal comfort. They identified uncertainties in ventilation rates and indoor air temperature distribution as highly influential on the simulation result. Furthermore, they proposed a method for decision making in building design.

Mara and Tarantola [7] performed a sensitivity analysis for a test cell model and focused on SA to aid the model development. They

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calculated the sensitivity indices of simulation inputs using a variance-based method. Burhenne et al. [8–10] performed UA and SA for BPS applied to the design as well as to the operational stage of a building. Furthermore, different ways of generating random numbers were analyzed with respect to their performance (i.e., convergence and robustness). Eisenhower et al. [11] performed an UA and SA investigating the influence of about 1000 parameters using quasi random sampling and a meta-model (response surface). Hopfe and Hensen [12] distinguish between three types of uncertainties (physical, design and scenario uncertainties). They report results of a MC based UA and SA implemented with Latin hypercube sampling (LHS). In their work, the physical UA was conducted by varying physical properties of materials, while the design UA was accomplished by adjusting geometry and glass surfaces. The scenario uncertainty was implemented by varying the infiltration rate and internal loads. Booth et al. [13] performed an UA of housing stock models using Bayesian techniques. Their aim is to analyze different retrofit options at an urban scale.

In practice many decisions are based on their monetary value. It seems to be a natural way to talk about different options in the design phase in terms of money. Particularly, for people without engineering background it is appealing to make a decision on the basis of a monetary value. Cost-benefit analysis (CBA) is a common approach to making economic decisions. The main idea underlying CBA is that total expected costs are compared with the total expected benefits of a project in order to choose the most profitable of the compared options. Benefits and costs are usually expressed in terms of money [14]. The duration of the project considered plays an important role. Usually the cash flow of costs and benefits occur at different times and the analyzed time frame for buildings is usually 5–50 years long. The longer the time frame, the greater the difference in monetary value becomes. Due to this fact, costs and benefits need to be adjusted for the time value of money. All cost and benefit flows in the course of the project (which usually take place at different points in time) are expressed in a common term, their present discounted value (*PDV*) [15]. Rysanek and Choudhary [16] conducted an analysis where they combined building simulation and economic calculations. The economic uncertainties were implemented with a best and a worst-case scenario and different refurbishment options were analyzed by changing the technical system in the building simulation.

In this paper we combine UA, BPS and CBA. An uncertainty quantification for the uncertain BPS and CBA inputs is performed. Sampling based on Sobol' sequences is used because quasi random sampling proved to be more effective in terms of convergence and robustness compared to pseudo-random sampling, stratified sampling and Latin hypercube sampling [10,11]. A method for quantifying the uncertain inputs of the CBA is outlined. This paper employs a methodology for performing the analysis that is scalable depending on individual project requirements and can be applied to answer several questions common in building design and operation. The methodology consists of the characterization of the uncertain input, employing an effective sampling method, i.e. sampling based on Sobol' sequences, and recommendations concerning the coupling of the BPS and the CBA. Practical advice on how to implement the methodology is given and appropriate ways of displaying the results of the analysis are shown.

MC filtering is applied to determine which input parameter drives the result into a certain region (e.g., efficient design, positive net present value). This application is of high value to supplement the typical building design process. It can lead to more efficient systems and an improved design. The ultimate goal is to support decision makers and implicitly take salient uncertainties into account in the decision making process. Furthermore, insights are gained how technical systems can be improved in order to reach performance goals or requirements.

The proposed methodology is applied to an example case. Main results are that the probability of more than 20% of the total energy demand supplied by renewable energies is 60%, whereas the probability that the investment in the solar thermal equipment is profitable is 9%. The most influential parameters, which lead to these results, are identified and it is analyzed under which conditions higher probabilities can be reached.

This article is organized as follows: the methodology section covers the theoretical aspects of the work, i.e. modeling approach, CBA, ways of quantifying input uncertainties, sampling related issues and MC filtering. The simulation section describes the BPS model used in the case study, the CBA of the case study and the used tools. The results and discussion section presents the results obtained in the case study: BPS results, CBA results and MC filtering results. Finally, the conclusion and outlook section outlines the conclusions of the work carried out and suggests further directions for research.

2. Methodology

2.1. Modeling approach

The literature introduced in the introduction shows that the most commonly applied approach for UA in BPS is based on MC techniques. However, it is also possible to reformulate models in a way that they can take probability density functions (PDF) as input and compute a PDF as output rather than producing point estimates of the simulation output. A study conducted by Jacob et al. [17] showed that this method requires extensive mathematical modeling efforts and more computational resources than MC techniques for a given accuracy and building problem.

The analysis described in this paper is conducted using a 2-step-procedure. The first part is the MC simulation of the performance of the building and its HVAC equipment. The output of the BPS (e.g., the amount of energy supplied by a solar thermal system) is used as input for the cost-benefit MC-analysis. Fig. 1 shows an overview of the simulation process. All CBA inputs, which are considered uncertain, are sampled except for one input of the CBA that is the result of the BPS. The histograms represent the inputs that are considered as uncertain and the uncertain output, respectively. Besides the uncertain inputs there are many parameters and variables that are considered as known. Hence, point estimates are used for these inputs. The decision if a parameter or variable is considered as known or as uncertain can be based on several criteria. These are the project scope and associated questions to be answered, the available information, the resources and time that can be spend to conduct the analysis and the specific method that is applied. In most cases it is desirable to consider the most uncertain and the potentially most influential parameters as uncertain. A good example for such a variable is the air change rate of a natural ventilated building since it is known to be influential on the energy demand and highly uncertain because it depends on the occupant's behavior. Furthermore, the inputs that can be easily changed in the design or operation phase of a building are of great interest. The mass flow rate of the solar thermal collector is an example for such a variable.

2.2. Building performance simulation model

One part of the proposed methodology is a dynamic BPS. The level of detail might vary depending on the analyzed case. However, the computational cost of the model plays an important role in the MC setting. The possibility for parallelization can help