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Decision making of HVAC system using Bayesian Markov chain Monte Carlo method

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ABSTRACT

Building simulation has become an indispensable decision making tool since it is capable of capturing dynamic behavior of building systems and predicting impact of energy saving components. However, it has been well acknowledged that simulation prediction is often significantly influenced by treatment of uncertain inputs. This paper presents multi-criteria (construction cost, total energy consumption) decision making of HVAC systems under uncertainty. In this study, a library building was selected and modeled using EnergyPlus 6.0. There were two HVAC candidates: (1) variable air volume (VAV) for interior zone + fan coil unit (FCU) for perimeter zone + gas boiler + electric chiller, (2) VAV + FCU + gas boiler + electric chiller + ice thermal storage system. For uncertainty analysis, unknown inputs were identified based on the literature and the Latin hypercube sampling (LHS) method was employed. Then, Bayesian decision theory was applied to solve stochastic decision making. In particular, the paper includes preferences of building stakeholders (three architects, four simulation experts, three HVAC experts) by using Markov chain Monte Carlo (MCMC). It is shown that such quantitative stochastic appraisal yields more meaningful information than the traditional deterministic approach, and helps to improve confidence in simulation results.

1. Introduction

With advances in numerical methods, computing power, and quantitative/qualitative growth of simulation knowledge, building energy simulation has been recognized as a practicable approach during building design process since it provides meaningful information and better design support such as answering what-if scenarios, system dimensioning, fine-tuning, etc. However, decision making involves the following unresolved issues: (1) so far, decision making studies have employed the deterministic approach without taking into account stochastic nature of the building and its subsystems [1–6], (2) classical optimal design problem has been focused on a single criterion even though the decision making involves multi-criteria [7–12], (3) most of the design alternatives are assessed based on subjective judgment and engineering intuition [13–16]. In other words, decision making process must deal with performance assessment of design alternatives under uncertainty as well as multiple criteria (e.g., cost, energy efficiency, thermal comfort, indoor air quality, daylighting, etc.,) based on preferences from various building stakeholders.

With this in mind, stochastic multi criteria decision making (MCDM) enhanced by Bayesian inference would be a potential recipe, which is the theme of this study. Bayesian inference employs an MCDM method based on the subjective utility function of decision makers (DM). The utility function presents an attitude and preference of the DM towards risk. The previous studies [1,17] presented a decision making addressing the following criteria (investment cost, thermal comfort, and energy efficiency) using a joint utility function. But those studies assumed a linear marginal utility function regardless of the subjective utility of diverse DMs (e.g., designer, engineer, simulation expert, occupants etc.). To solve for such limitation, the authors employed a multi-attribute utility function (MAUF) with the best trade-offs, and Bayesian inference for obtaining a posterior distribution of unknown quantities (expected utilities and weighting factors). Bayesian inference is a statistical approach based on Bayes' rule to estimate posterior distributions of the unknown quantities over distributions of observed data. In area of building simulation, Bayesian inference has been successfully used to calibrate uncertain inputs in either normative calculation or transient simulation [18–20].

For energy modeling of a given building and its HVAC systems, EnergyPlus 6.0 was selected. A screening method was then applied to identify dominant inputs on simulation outputs. The Monte Carlo

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a_1, a_2 (dimensionless) design alternative
U(dimensionless) utility function
E(dimensionless) expected value
x_1 (KRW) construction cost
x_2 (kW h) total energy consumption
$P(\theta|y)$ (dimensionless) posterior distribution
$P(y|\theta)$ (dimensionless) likelihood function
$\pi(\theta)$ (dimensionless) prior distribution
θ (dimensionless) unknown inputs
y (dimensionless) observation value
μ (dimensionless) mean value
σ (dimensionless) standard deviation
t (dimensionless) the number of uncertain inputs
g (dimensionless) the number of sampling grid
r (dimensionless) the number of trajectories
k_i (dimensionless) weighting factor
p_i (dimensionless) regression coefficient
a, β (dimensionless) shape parameters
Γ (dimensionless) gamma function

technique was used for uncertainty propagation of the dominant inputs. The MCDM problem in this paper was then introduced to determine an optimal alternative of HVAC system with the best trade-offs between construction cost and total energy consumption.

2. Stochastic multi-criteria decision making

2.1. Monte Carlo simulation for uncertainty analysis

Over the last several decades, building simulation tools have been developed enormously. However, simulationists often find it difficult to determine accurate simulation inputs. In addition, the simulation task includes several model biases (numerical uncertainty, simplifications of the reality, subjective judgment, and modeling assumptions etc.). Fig. 1 shows the problems and issues in the building performance simulation and assessment. It is highly probable that 10 different simulationists will present 10 different outputs for a given single building. In other words, to improve the confidence of the simulation model under strong stochastic nature, it is rational to adopt not a deterministic approach but a stochastic approach.

The Monte Carlo simulation has been widely used to account for such stochastic nature [22]. de Wit [1] and Macdonald [2] presented remarkable results for ascertaining importance of uncertainty and sensitivity analysis in area of building simulation. de Wit [1] conducted uncertainty and sensitivity analysis of indoor thermal comfort with natural ventilation, and Macdonald [2] presented parameter uncertainty as well as code uncertainty in a building simulation tool (esp-r). Followed by the aforementioned two Ph.D. theses, extensive uncertainty and sensitivity analyses were conducted on diverse performance aspects, e.g., energy efficiency, thermal comfort, indoor air quality, etc. [3–6,19,23–30].

The Monte Carlo simulation propagates simulation cases within probability range of selected uncertain inputs, and then iteratively performs simulation runs. The selection and probability distribution of uncertain inputs is one of the most important parts for uncertainty analysis [31]. To select the dominant inputs, a screening method is usually used to analyze the influence of inputs on outputs. With the chosen dominant inputs obtained from the screening method, Latin hypercube sampling (LHS) method, which is a form of stratified sampling, was employed for the uncertainty propagation [32,33]. The LHS method could provide good convergence of parameter space with relatively few samples compared to the simple random sampling [33–35].

2.2. Multi criteria decision making using Bayesian theory

Decision making is a continuous and iterative search process for finding an optimal design solution. Gololov and Yezioro [36] presented an MCDM procedure using compromise programming (CP) algorithm which was based on an aggregated function having assigned weighting factors according to a DM's preference. National renewable energy laboratory (NREL) developed an MCDM-23 program that has a weighting scheme [37]. de Wit [1] and Kim and Augenbroe [17] showed a method to select the best alternative in decision spaces using Bayesian decision theory. In the light of the previous studies, the decision making studies have evolved from a 'single criterion' to 'multi criteria' [38].

Not only is it necessary to account for multi criteria but also the stochastic nature of the building or systems must be reflected during the decision making. In this study, the authors used a multi attribute utility theory (MAUT), which is a prominent method in decision-making under uncertainty [39]. The MAUT allows decision makers to account for their preferences in the form of multi-attribute utility functions (MAUF). The MAUT technique can be applicable to a stochastic (non-deterministic) MCDM problem by using Bayesian decision theory. The authors performed uncertainty analysis using Monte Carlo simulation and then used MAUT together with Bayesian inference and presented the decision framework using uncertain simulation outputs on a decision space.

Bayesian decision theory is a normative theory using subjective preference of DM, and is suitable for complex decision problems under uncertainty [1]. The theory uses the utility function in which the preference of DM is reflected [40]. A design alternative (a_1) with a higher expected utility ($E\left\{U_{a_1}(x_1, x_2)\right\}$) is selected, as shown in Eq. (1). The utility function can select the most preferred alternative by eliminating the inferior solutions from design option space.

$$a_1 \succ a_2 \Leftrightarrow E\left\{U_{a_1}(x_1, x_2)\right\} \succ E\left\{U_{a_2}(x_1, x_2)\right\} \quad (1)$$

where a_1 and a_2 are design alternatives, E is an expected value, U is an utility function, x_1 and x_2 are attributes (x_1: construction cost, x_2: total energy consumption) generated by design alternatives (a_1 and a_2) respectively.

It should be noted that building design is involved with different building stakeholders (e.g., architect, owner, engineer, occupants, etc.,), and influenced by the subjective preference of DMs. To settle this problem, Bayesian inference was applied to obtain a posterior distribution of expected utilities and the weighting factors of different building stakeholders. Bayesian inference provides the posterior distribution by combining two ingredients. As shown in Eq. (2), two ingredients consist of a likelihood function ($P(y|\theta)$) of unknown quantities (θ) and the observed value of y, and a prior distribution ($\pi(\theta)$) of θ before the observation of the value of y. The integration of marginal distribution ($P(y)$ (Eq. (3)) is a prerequisite to obtain a posterior distribution ($P(\theta|y)$) and is very difficult to calculate. To solve this, the authors used an MCMC method to obtain the posterior distribution of unknown quantities using two ingredients (likelihood function and prior distribution) as shown in Eq. (4).

$$P(\theta|y) = \frac{P(y|\theta)\pi(\theta)}{P(y)} \quad (2)$$

$$P(y) = \int P(y|\theta)\pi(\theta)d\theta \quad (3)$$

$$P(\theta|y) \propto P(y|\theta) \times \pi(\theta) \quad (4)$$