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Stepwise deterministic and stochastic calibration of an energy simulation model for an existing building

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ABSTRACT

Building simulation tools have been widely used for performance assessment. However, many studies [1] have reported that a performance gap exists between the reality and simulation output, mainly caused by unknown simulation inputs. Therefore, model calibration needs to be introduced. Calibration attempts can fail for the following reasons: coarse initial simulation model, long sampling time, uncertainty in the model, and sensor errors. The aim of this paper is to address the abovementioned issues. For this study, an existing office building was selected and two calibration approaches were presented: deterministic vs. stochastic. For stochastic calibration, a Gaussian Process Emulator (GPE) was introduced as a surrogate of the EnergyPlus model. The stochastically calibrated model performs better than the deterministically calibrated model. It is concluded in the paper that (1) the calibration quality is influenced by the degree of the details of the initial model, (2) the accumulated measured data under a sampling time of up to one day (e.g. gas energy consumption) might be unsuitable for calibration work due to the lack of 'time-series trend', and (3) the calibration quality is also influenced by sensor errors and further calibration needs to take these into account.

1. Introduction

Building Performance Simulation (BPS) tools have been widely used for detection of system errors, optimal design and control, energy retrofitting, etc. However, for the proper use of the BPS tools, many difficulties and limitations remain. In particular, it is difficult to develop an energy simulation model for frail buildings when there is a lack of information (e.g. loss of original drawings and specifications), changes of materials' thermal properties, and deterioration of system efficiency over time. In such cases, a simulationist needs to make a number of modeling assumptions and subjective judgments based on her/his prior experience and expertise. In order to minimize the difference between the simulation prediction and the reality, the calibration efforts of a simulation model becomes indispensable [1–11]. Three calibration approaches can be used: manual (trial and error), deterministic, and stochastic calibration [8,9].

This paper compares deterministic and stochastic calibration. For this study, a 17-year old office building was selected and modeled using EnergyPlus. For deterministic calibration, 'fmincon' in the MATLAB optimization toolbox was used for the EnergyPlus model. Since stochastic calibration requires a significant number of simulation runs, a Gaussian Process Emulator (GPE) was employed as a surrogate model of EnergyPlus. In this study, the following four issues are addressed: (1) importance of the quality of an initial model, (2) influence of sensor errors, (3) difference in sampling time between the model and the measurement, and (4) a comparison between deterministic and stochastic calibration.

2. Target building

A 5-storey office building (floor area: 6900 m^2) located in Yongin city, South Korea was selected for this study (Fig. 1). The HVAC system consists of 5 Constant Air Volumes (CAVs) for interior zones and Fan Coil Units (FCUs) for perimeters. The plant consists of two absorption chillers and two cooling towers. It has 56 fans and 30

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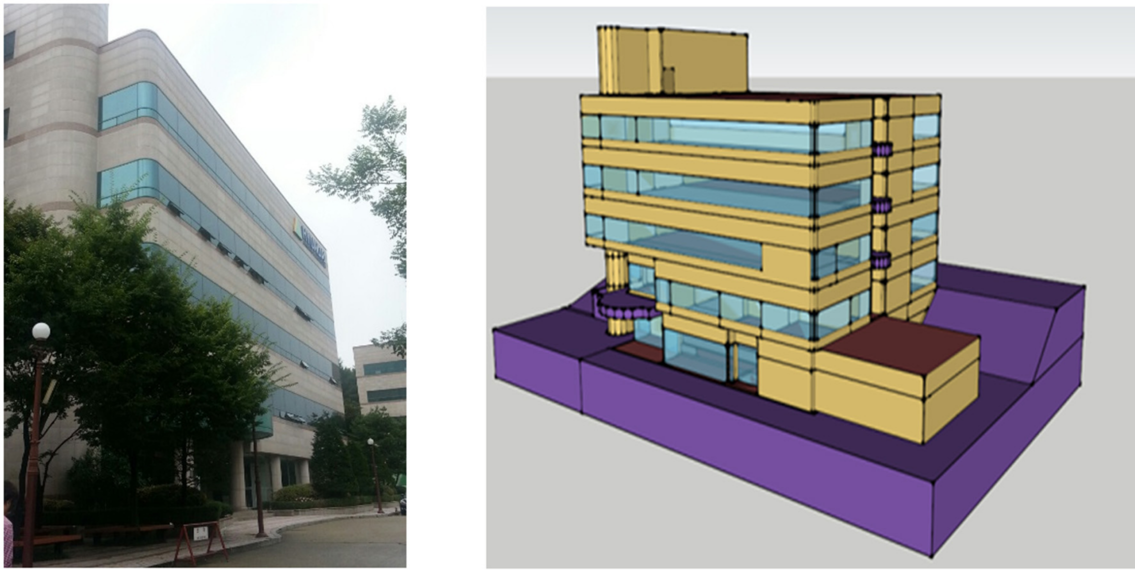

Fig. 1. Target building (left) and EnergyPlus displayed in OpenStudio (right).

Table 1
Comparison between the measured and model predictions.

Methods	initial model	revised initial model
MBE (%)	−14.98	−10.30
CVRMSE (%)	33.18	30.18

pumps for heat/cold distribution. The Building Energy Management System (BEMS) was installed to monitor and collect relevant energy information. The building was modeled using EnergyPlus 8.0 as shown in Fig. 1.

The two terms used in this paper to describe the models, the initial model and the revised initial model, need to be distinguished. The 'initial model' was developed based entirely on the original drawings and specifications of the building. This model was then revised (hereafter referred to as the 'revised initial model') based on the authors' multiple site visits, interviews with facility operators, and close observation of the stored data in BEMS.

In this study, several updates were made to the initial model. By comparing the lighting fixtures specified in the original drawings with the existing fixtures, the authors realized that the older lighting fixtures had been replaced with new efficient fixtures several years previously. Through multiple site visits, the authors identified indoor setpoint temperatures (for heating: 20 °C, for cooling: 26 °C) and the number of occupants and their schedules. With the help of facility managers, the authors collected information on the schedules and control logics of AHUs and plants.

Table 1 shows a comparison of the total electric energy consumption (July 4–5) between the initial model and the revised initial model. Table 1 shows that the revised initial model is superior to the initial model. As shown in Fig. 2, the results of the revised initial model are closer to the measurement than the initial model.

3. Calibration approaches

It has been well acknowledged that the first principle-based BPS tools are capable of describing the heat and mass transfer around buildings. However, when a BPS tool is applied for an existing building, a number of unknown simulation inputs exist and can cause a gap between the prediction and the reality. For this reason, model calibration efforts are required and are classified into the following [8,9]: (1) manual calibration, (2) deterministic calibration, and (3) stochastic calibration.

Through trial and error, manual calibration attempts to find a set of unknown inputs within feasible boundaries. This approach is appropriate for a simple model with only a few unknown inputs. However, if the number of unknown inputs increases, calibration work would demand significant time and effort.

Deterministic calibration finds a set of unknown inputs by using a cost function defined as a spatial and temporal sum of the difference between the model prediction and the measured data. This approach usually employs an optimization routine such as a gradient-based or evolutionary algorithm. Yoon et al. [7] used gradient-based optimization using 'fmincon' in the MATLAB optimization toolbox to estimate unknown inputs (convective heat transfer coefficient, form loss coefficient, flow coefficient, and flow exponent) in a state space equation of a double skin system. Kim et al. [6] estimated unknown inputs (flow exponent, discharge coefficient, wind pressure coefficient, wind velocity profile exponent, local terrain constant, terminal loss coefficient, duct roughness, emission rate of occupants, etc.) in an airflow simulation model developed for a residential building. They used 'fmincon' in MATLAB to calibrate the airflow simulation model represented in CONTAMW 2.4. The deterministic calibration is advantageous in terms of easy mathematical formulation and fast computation. However, its drawback is that it cannot account for probabilistic characteristics of unknown inputs.

In contrast, stochastic calibration estimates the posterior distribution of unknown inputs. Heo [8] estimated the posterior distribution of unknown inputs (thermal properties of materials, internal loads, indoor set-point temperature, ventilation, and system efficiency) for two buildings represented by ISO 13790 and EnergyPlus, respectively. According to Heo [8], the stochastic calibration could enhance the reliability of the model. However, significant computation time is needed if the model becomes large. To relieve computation time, a Gaussian Process Emulator (GPE) can be employed [12–16].

In this paper, the authors conducted two calibration approaches (deterministic and stochastic) as follows.

- Step 1 (Developing an initial simulation model, refer to Section 2): Calibration is strongly influenced by the quality of the initial model. In this step, attention should be paid to the simplifica-