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Extended virtual in-situ calibration method in building systems using Bayesian inference

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ABSTRACT

Measurements from sensors and knowledge of key parameters are of great importance in the operation of modern building systems. Accurate and reliable information as these serves as the base for ensuring the desired performance of control algorithms, fault detection and diagnostics rules, analytical optimization strategies. They are also crucial for developing trust-worthy building models. However, unlike mass produced industrial devices, building systems are generally one of a kind and sparsely instrumented. Despite the indispensable need, dense deployment of sensors or a periodic manual calibration for ensuring the quality of thousands variables in building systems is not practical. To address the challenge, we extend our virtual in-situ calibration method by marrying it with Bayesian inference, which has a better capability in handling uncertainties. Strategies, including local, global, and combined calibration, are evaluated in a case with various sensor errors and uncertain parameters. The detailed procedure and results are presented.

1. Introduction

Energy used for heating, ventilation, air conditioning, and refrigeration systems (HVAC&R) is a large part of the total energy consumed in buildings to provide a proper indoor environment for occupants [1,2]. Issues, including problematic or inferior control sequences and set points, equipment performance degradation and various faults occurring in HVAC&R and building energy systems further increase energy use or can lead to undesired indoor environmental quality. To address the challenges in the building sector, a comprehensive solution package, including continuous fine-tuning of building automation systems, automated analytical optimization, and automated fault detection, diagnostics and repair, is needed. Research into these challenges has been conducted in order to help mitigate increasing energy use in buildings [3–8]. Most of the proposed approaches will be effective only if the data obtained from sensors are reliable and accurate [3]. In the field of smart buildings, the role of sensors is significant for ensuring and enhancing building performance.

Physical sensors that measure variables in terms of the building or system conditions are vulnerable to the working conditions and tend to have errors related to these vulnerabilities. The sensor errors can be categorized into two major types [9]: (1) systematic errors (bias or offset) and (2) random errors (noise). Systematic errors are indicated by the discrepancy between the mean of measurements and measurands (their true value). They may occur because of the sensor's physical condition, measured phenomena, working environments, or other factors. For instance, Yu. et al. [10] found that systematic errors of commonly preinstalled supply-air temperature sensors in compact rooftop air conditioners could be have errors up to 19.2 °C due to their compact size, poor air distribution, and intensive thermal radiation of a gas heating chamber. Random errors are indicated by the difference between the measurements and their mean. They are caused by external problems that affect the sensor readings or hardware noise. Random errors can be detected by a probability distribution, such as Gaussian, in some cases. A random error with a large standard deviation indicates measurement inaccuracies. Regardless of how advanced the building automation and control algorithms are, these rudimentary errors from sensors adversely affect analysis and thereby lead to inferior building system performance.

Periodic calibration is needed to improve the reliability of measurements from working sensors. In a conventional calibration [11–15], working sensors can be calibrated by reducing the difference between the values obtained from working sensors or using benchmarks from standards and reference sensors in given conditions [14,15]. Usually, such a calibration requires a process of removing and reinstalling the sensor to its working environment. Considering the features of building sensor network, the conventional method has practical problems [16]: (1) time and monetary cost for reinstalling sensors; (2) disruption to a normal operation; (3) difficulty in accessing various sensors in pipelines, hidden spaces, etc.; and (4) different working environments with the performed conditions for a calibration. Recently, to overcome these limitations in building systems, Yu and Li [16] proposed a virtual in-situ calibration method. This method can determine the benchmarks that are either statistically established or mathematically modeled, without removing the embedded working sensor in a system or adding extra reference sensors as in a conventional calibration. More specifically, the statistical-based method

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determines a benchmark value by calculating a mean of measurements. It requires a redundancy of sensors for measuring the same phenomenon. This is useful for detecting random errors from individual working sensors when sensor redundancy exists. On the other hand, the modeling-based method can reduce both systematic and random errors without sensor redundancy. This method uses mathematical equations of a system model and known relative variables in the model to estimate the benchmark values of working sensors. The calibration function is determined by casting the problem as an optimization problem, i.e., minimizing the difference between the sensor's measurements and the benchmarks.

With respect to an operational building system, the relative or dependent variables used in the benchmark model for a specific working sensor may be defined by (1) measurements from other working sensors in a system and (2) parameters in the system model. There are uncertainties from both of the sources. Even though all relative variables of the benchmark are defined by measurements from other sensors, which might have higher reliability than the target working sensor itself, we cannot assure that the measured values are always accurate. The accuracy is subject to influences from the physical environment when the measurements are taken. As well, parameters may naturally contain uncertainties not accounted for when they were determined, e.g. a heat transfer coefficient, thermal capacitance, etc. Because of these potential inaccuracies, it is more beneficial to consider all critical working sensors of a system and relevant unknown parameters of the system in order to model a virtual in-situ modeling-based calibration process.

When a large number of unknowns is included in a mathematical calibration, the problem becomes under-determined. It means that the total number of unknown variables composed of relative variables and unknown parameters can be inherently greater than that of equations provided from a system model. It is impossible to calculate the accurate benchmarks for every unknown variable in an under-determined calibration problem. Several modeling-based methods have been proposed in different research fields to convert these to determined problems, such as an on-line calibration [17], a collaborative calibration [9], a blind calibration [18], and a self-calibration [19]. In chemistry, various calibration methods [20–23] use more than one reference sensor for benchmarks, which can be considered as a known calibration environment. Literature in this regard mainly comes from fields where sensor redundancy, high quality sensors, or known relationships between sensors do exist. Unfortunately, it is considerably difficult to adopt any of these approaches in a building sensor network because a building system is not mass produced or well instrumented. There is also a limited number and quality of sensors for each phenomenon. As well, many sensors are needed for various building phenomena at different locations and levels (temperatures, mass flow rates, pressures, etc.).

We argue that, compared to other fields, building systems are complicated and stochastic with multiple unknown parameters and uncertainties, especially when occupants, devices, and ambient environment all interact. This paper extends virtual in-situ calibration methods by adding a probabilistic formulation. This approach considers the characteristic of building sensor networks, typical errors of building sensors, and limitations of existing calibration methods when applying to an entire building system. We first briefly present the problem formulation of extended virtual in-situ calibration. Then, we describe the Monte Carlo Markov Chain (MCMC) approach to solving the problem. To verify the suggested method, the algorithm is applied to a LiBr-H_2O absorption refrigeration system in a virtual environment with pre-defined true values.

2. Extended virtual in-situ calibration formulating using Bayesian inference

2.1. Benchmark and correction function in virtual in-situ calibration

Conventional and virtual in-situ calibration is driven by an objective function. It can be expressed as shown in Eq. (1). In this objective function, the measurements from working sensors are corrected by minimizing the distance between the measured values and the corresponding benchmark values that are defined by standards or reference sensors as in Eq. (2).

$$\min_M D(M) = |Y_b - M| \tag{1}$$

$$Y_b = S \text{ or } Y_b = M_R \tag{2}$$

where, D is the distance function regarding the measurement error, M is the measurement from the working sensor, Y_b is the corresponding benchmark for the working sensor, S is the known standard value for the working sensor, and M_R is the measurement from the corresponding reference sensor.

In EVIC (extended virtual in-situ calibration), the benchmarks are mathematically estimated by equations and relative variables (v_r) in a system model, as in Eq. (3), without the additional reference sensors or standards.

$$Y_b = f(v_1, v_2, v_3, \ldots, v_r) \tag{3}$$

where, v is the relative variable of the measurement M, r is the counter for the relative variables, and f is the system model.

Since the relative variables may be defined by measurements from other working sensors or unknown parameters of the model, the benchmarks can be rewritten as Eq. (4). It is deemed that the calculated values can approximate the benchmark values.

$$Y_b = f(M_{v1}, M_{v2}, \ldots, M_{vr}, x_{u1}, x_{u2}, \ldots, x_{uq}) \tag{4}$$

where, M_{vr} is the measured values of the rth relative variables, x_u is the unknown parameter in the system model, and q is the count for the unknown parameters.

This study introduces a correction function g to compensate for the systematic error in the measurements, as shown in Eq. (5). The correction function of one sensor is formulated with offsetting constants and its measurement M. The specific equation is based on a characteristic of the systematic sensor error. A single sensor can have different correction functions according to the different error characteristics over the working conditions. When the systematic errors are identical in a specific measurement range (working stage), the measurements in this range can be calibrated from one correction function. For the relative measurements in Eq. (4), working sensors also have correction functions, as in Eq. (6). Once the relative measurements are substituted with the corresponding correction functions in the benchmark as in Eq. (4), the benchmark can be finally formulated by Eq. (7). Fig. 1 shows the difference between the suggested EVIC method and the previous method [16] in terms of the benchmark formulation.

$$Y_c = g(M, x_1, x_2, \ldots, x_k) \tag{5}$$

$$Y_{c,vr} = g(M_{vr}, x_{vr1}, x_{vr2}, \ldots, x_{vrk}) \tag{6}$$

$$Y_b = f(Y_{c,v1}, Y_{c,v2}, \ldots, Y_{c,vr}, x_{u1}, x_{u2}, \ldots, x_{uq}) \tag{7}$$

where, Y_c is the corrected measurement for the working sensor, g is the correction function for the working sensors, x is the offsetting constant, k is the counter for the offsetting constants, and $Y_{c,vr}$ is the corrected measurement of the rth relative sensor.

2.2. Distance function between benchmark and correction function

This study suggests a distance function of EVIC from the Residual Sum of Squares (RSS) to derive variables of interest that will minimize the difference between the benchmark values and corrected values from the