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Hidden factors and handling strategies on virtual in-situ sensor calibration in building energy systems: Prior information and cancellation effect

Sungmin Yoon, Yuebin Yu*

Durham School of Architectural Engineering and Construction, University of Nebraska-Lincoln, United States

HIGHLIGHTS

- VIC can be applied in building automation systems to calibrate erroneous measurements.
- We investigate the hidden factors that could reduce the accuracy of a VIC.
- Prior information and cancellation effect are explained and illustrated with examples.
- Inclusion of local calibration and applying a prior update are proposed to solve the challenges.
- Case studies show a system performance analysis can be improved with the calibrated data.

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ABSTRACT

Sensor errors greatly affect the performance of control, diagnosis, and optimization systems within building energy systems, negatively impacting energy efficiency. Virtual in-situ sensor calibration (VIC), a Bayesian theory based method, can improve building energy performance by calibrating erroneous sensors in working building energy systems on a large scale. Working sensors do not need to be removed nor will reference sensors need to be added, as is done in a conventional calibration. To improve the calibration accuracy, hidden factors and their negative effects on the accuracy of a VIC must be addressed properly. In this study, we define (1) prior information and (2) cancellation effects as the negative effects. The suggested VIC method is applied to a single energy system component and to a LiBr-H_2O absorption refrigeration system, respectively, to discuss the two primary effects (mentioned above). In addition to adding data sets, two strategies—inclusion of local calibration and conducting repetitive prior updates—are proposed to solve the hidden factors' issue. The case study (1) shows that the proposed local calibration with the prior updates can solve the two negative effects, thus suggesting the high calibration accuracy and (2) demonstrates that the calibrated measurements improve the accuracy of energy performance analysis for a building energy system (up to 17.82%).

1. Introduction

Advanced building automation systems have been applied to improve building performance and indoor environmental quality, and to reduce a large portion of the total energy consumption in buildings. They include comprehensive solution packages to address problematic or inferior control sequences and set points, equipment performance degradation, and various faults occurring in HVAC&R and building energy systems. These solutions, including automated optimization [1,2] and automated fault detection and diagnosis (AFDD) [3–7], are effective only if the data obtained from sensors are trustable [3]. If dependent sensors are malfunctioning, AFDD algorithms may run incorrectly. Even AFDD methods for detecting erroneous sensors [6,7] need accurate measurements to use as training data sets. Without a high level of confidence in overall measurements from sensors, superior building performance cannot be realized [8]. Because of these inherent problems, sensors are increasingly important for high performance and smart buildings.

Recently, Zhang and Hong [8], using building energy simulations, investigated the impacts of outdoor air temperature sensor errors and thermostat errors on energy consumption (the cooling energy consumption increase of 0.8–13.6% and the cooling and heating energy consumption increase of 19.07–34.24%) and thermal comfort. Verhelst et al. [9] analyzed the economic impact of sensor and actuator faults and HVAC performance under these faults in a concrete core activated office building (the economic impact ranged from +7% to +1000%).

* Corresponding author.
E-mail address: yuebin.yu@unl.edu (Y. Yu).

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Roth et al. [10] identified the energy impact of thirteen faults including sensor errors in commercial buildings (between 4% and 18% of the sum of commercial building HVAC, lighting, and refrigeration energy consumption). Kao et al. [11] studied the effects of air-handling sensor errors on the annual building energy consumption (the increase of 30–50%). These results show the considerable impact of sensor errors on building energy performance, illuminating the importance of handling such sensor errors.

In many industries, virtual sensor methods obtain measurements indirectly without installing new physical sensors. These measurements are based on the mathematical relationship between the phenomenon of interest and the phenomenon observed by existing physical sensors in a given system model [12]. With the virtual sensor method, various measurements that would require more expensive sensors, or phenomena that are impossible to measure, can be estimated using related physical sensors that are relatively low-cost. In areas where the number of sensors and degree of redundancy is insufficient, virtual sensor techniques [12–16] have been applied to HVAC&R systems. These are able to overcome problems associated with the limited number and the environment of working sensors, e.g., virtual partition surface temperature sensors [13], air temperature sensors of air-handling units [14], and virtual refrigerant charge and pressure sensors [15,16]. Virtual sensors need accurate measurements from existing physical sensors because of the high level of dependency on those measurements. The virtual measurements regarding the building phenomena and performance estimated based on erroneous physical data could propagate uncertainties to entire energy systems in a building.

The presence of virtual sensors in buildings helps to enable the development of smart buildings, but it also imposes the challenge of maintenance since they cannot be calibrated like conventional sensors. A virtual in-situ calibration (VIC) that works for both physical and virtual sensors was proposed by Yu and Li [17]. A novel VIC method, based on a Bayesian parameter estimation (as a Bayesian sensor calibration method), has recently been studied to calibrate multiple sensors working simultaneously in circumstances where it is difficult to certify which sensors are erroneous in a building system [18–21]. This method addresses the practical problems of a conventional sensor calibration in building energy systems: (1) time and monetary cost; (2) disruption of normal operation; (3) difficulty in accessing various sensors embedded in equipment; and (4) the large number of sensors [17,18]. Additionally, a conventional calibration cannot solve various systematic errors associated with a sensor's working environment within a building energy system because it is generally different from the controlled conditions of the physical calibration. Since the proposed calibration method, using Bayesian inference and system models, is conducted onsite, these potential systematic errors disappear and true measurements for various working conditions can be estimated without removing the working sensor or adding reference sensors.

The calibration accuracy from VIC depends on two terms in Bayesian inference: (1) a prior term and (2) a likelihood term. The prior term provides the information on systematic and random errors for each sensor before a calibration. The likelihood term includes the VIC formulation, representing the overall sensor error in a building energy system. When the prior information describes the errors properly and the calibration problem in the likelihood function has a determined condition, there can be great calibration accuracy. For example, if all sensors are erroneous in a building energy system as an extreme condition, the calibration results may be accurate when the informative priors are given for all sensors. But, accuracy can be poor even with a good prior term if the variables of the calibration problem are underdetermined. That is, in order to improve accuracy, it is fundamental to have an informative prior for each sensor error and make the calibration problem a determined one with Bayesian inference. This is different from a general building model calibration [2,22–25] where unknown parameters of encapsulated building models are estimated from a Bayesian parameter estimation [22–24] or an optimization process [2,25]. The multiple sets of observed energy data (model output) are used with appropriate prior information to make the model calibration problem determined, thus improving the accuracy of estimates. The prior information of the unknown parameters can be appropriately defined based on the previous literature and domain knowledge. Compared to the model calibration, the sensor calibration focuses more on the unknown variables (true measurements) that appear as added or subtracted terms (e.g. temperatures and pressures) in energy system equations. Mathematically, in a VIC, the related equations are needed more to determine the large number of unknown constants than the selected scaling coefficients as in a model calibration. Moreover, it is difficult to define the informative priors of sensor errors during the calibration because various errors are unpredictable before a calibration. These differences make it more challenging for the VIC to estimate the true measurements accurately. Thus, in-depth study is needed to assure successful calibrations.

Not found in previous research, this study investigates how the two main terms in Bayesian inference affect sensor calibration accuracy in various conditions, and it defines their negative effects on accuracy by sensor types. Once the negative effects are minimized, the VIC will provide great accuracy. Therefore, calibration strategies are suggested to address the negative effects from those determination and prior issues, respectively: (1) local calibration and (2) prior update. For a determined condition, multiple data sets are used at first and the accuracy improvement from the incrementing data sets is discussed by sensor types (e.g. temperature and mass flow rate) in order to find which types of variables can be enhanced (determined), and which cannot. Then, this study evaluates whether the suggested local calibration strategy increases the accuracy of the under-determined variables. The negative effects from priors are also addressed in the determined and underdetermined conditions. This will show the effectiveness of the prior update in solving the negative prior effects by demonstrating how the calibration results improve with the local calibration. Finally, this study shows how inaccurate the system performance analysis can be with the sensor errors and negative effects, and it demonstrates the effectiveness of the suggested VIC strategies in improving the measurements and reducing the system performance errors.

As shown in Fig. 1, in Section 2, this paper introduces the main components of Bayesian sensor calibration based on the developed framework of our papers [18–21] and suggests calibration strategies. Section 3 identifies negative effects on calibration accuracy by sensor type through a case study for a single system component. In Section 4, the suggested calibration strategies to account for the negative effects are applied to a LiBr-H_2O absorption refrigeration system including the defined negative effects in Section 3. Their effectiveness and the improvements on the calibration accuracy and the system performance calculation are also discussed.

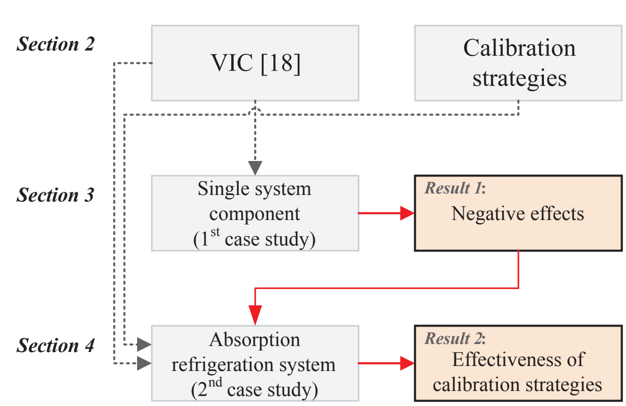

Fig. 1. Research flow for this study.