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Developing a whole building cooling energy forecasting model for on-line operation optimization using proactive system identification

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HIGHLIGHTS

- Developed and verified a novel general methodology for building energy forecasting.
- Quantitatively evaluated energy system nonlinearity and system response time.
- Developed and adapted system identification model for building energy forecasting.
- Compared the proposed system identification model against four inverse models.

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ABSTRACT

Optimal automatic operation of buildings and their subsystems in responding to signals from a smart grid is essential to reduce energy demand, and to improve the power resilience. In order to achieve such automatic operation, high fidelity and computationally efficiency whole building energy forecasting models are needed. Currently, data-driven (black box) models and hybrid (grey box) models are commonly used in model based building control. However, typical black box models often require long training period and are bounded to building operation conditions during the training period. On the other hand, creating a grey box model often requires (a) long calculation time due to parameter optimization process; and (b) expert knowledge during the model development process. This paper attempts to quantitatively evaluate the impacts of two significant system characteristics: system nonlinearity and response time, on the accuracy of the model developed by a system identification process. A general methodology for building energy forecasting model development is then developed. How to adapt the system identification process based on these two characteristics is also studied. A set of comparison criteria are then proposed to evaluate the energy forecasting models generated from the adapted system identification process against other methods reported in the literature, including Resistance and Capacitance method, Support Vector Regression method, Artificial Neural Networks method, and N4SID subspace algorithm. Two commercial buildings: a small and a medium commercial building, with varying chiller nonlinearity, are simulated using EnergyPlus in lieu of real buildings for model development and evaluation. The results from this study show that the adapted system identification process is capable of significantly improve the performance of the energy forecasting model, which is more accurate and more extendable under both of the noise-free and noisy conditions than those models generated by other methods.

1. Introduction

Buildings are responsible for over 40% of the primary energy and 70% of the electricity consumption in the U.S. [1] More than 25% of the U.S. electricity demand could be dispatchable if buildings can respond to the dispatch through advance operation strategies and smart grid infrastructure [2]. Recently, model based predictive control (MPC) has been proven to be a promising solution for this active operation [3]. As the basis of MPC, high fidelity and computationally efficient building energy forecasting models are indispensable. How to develop an accurate, robust, and cost-effective building energy forecasting model is an urgent problem and therefore the objective of this study. The goals of this paper are twofold. One is to propose a system identification methodology

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that is able to adapt based on a building's characteristics, to generate a whole building cooling energy forecasting model. The other one is to compare the performance of the proposed methodology with other modeling methods reported in the literature.

Although there are a large number of studies regarding building energy forecasting using different methods, they all can be categorized as white box, black box and the grey box models. All these three types of models have their own limitations in application to real field building control. For example, black box models, such as autoregressive exogenous (ARX), Artificial Neural Networks (ANN), Support Vector Machine for Regression (SVR), and N4SID state space model have been applied in building energy forecasting and control studies [4–11]. These data-driven models, however, often require long training period and the model extensibility is limited to the training data. In this study, model extensibility is defined as the forecasting accuracy of a model, when it is subject to weather and operation conditions that are different from those during the model training period. This is an important model property because building systems are often nonlinear systems. A model that is trained using one range of operating/weather conditions often is not usable for a different operating/weather condition. Grey box models, such as Resistance and Capacitance (RC) network and lumped parameters models, are popular models in building control and operation studies [3]. They are widely used in MPC for buildings such as those to estimate the cooling energy consumption [12–14], to utilize the building passive thermal mass storage [15–17], or to utilize active thermal storage devices [18,19] and the energy generation systems [20,21] to reduce energy consumption or energy cost. Even though different advance parameter determination methods have been implemented to identify the parameters of the grey box models [12,13], the parameter determination process is often computational demanding. In [14], the authors developed a method for parameters and variable selection using Singular value decomposition and solving the RC equation in frequency domain. Developing the structure of a gray box model, however, often requires expert knowledge, and the parameter determination process is also time consuming. Therefore, when applying these modeling approaches in the real field, each of these approaches has its own barriers such as training data availability/quality, implementation time, and implementation cost (when expert knowledge is required).

In order to solve technique gaps from these methods, some studies started to combine different methods to improve the model performance. Lee and Tong [22] presented a hybrid grey model with genetic programming for energy consumption forecasting. Fux et al. [23] combined RC model with Kalman filter to improve the model accuracy and robustness. Lü et al. [24] developed a combined RC and autoregressive-integrated-moving-average (ARIMA) model for heterogeneous building energy forecasting. These methods tried to reduce the efforts in the grey-box modeling, but the inherited limitations from the grey box models are still there. It is also difficult to develop a general model structure for different buildings, and it requires high engineering effort in implementing it into real model predictive controllers. On the other hand, data driven models have also been combined with Kalman filter [25,26] to improve the data driven model performance by bringing in the real measurements. Similarly, the inherited drawbacks of data driven models still cannot be solved there.

As results, a novel general methodology for building energy forecasting model development has been proposed and validated in this study to solve the limitations of the existing methods. Different from the above described modeling approaches, which collects system data in a passive manner, system identification (SID) is a process of developing or improving a mathematical representation of a physical system using data that is collected from a designed operation or experiment, in an active manner. Although system identification techniques have been widely used in other engineering applications, there are only limited applications in the building energy modeling field. In an earlier study by the authors [27], a system identification methodology, using frequency response function with an active system excitation, is proposed and tested for building energy forecasting. The method is demonstrated to be able to develop accurate and computationally efficient energy forecasting model for a small commercial building. However, when the proposed SID process is applied to develop an energy forecasting model for a medium commercial building, the model accuracy is not satisfactory. It is suspected that a building system's nonlinearity and response time affect the SID model's accuracy since frequency response function method is better used for more linear systems [28]. Therefore, this study focuses on investigating such impacts and how to adapt the SID process systematically based on a system's nonlinearity and response time. The goal is to develop a systematic SID methodology which can be scaled for buildings with varying nonlinearity and response time.

This study firstly proposes a method to quantitatively determine a system's nonlinearity and response time, and their impacts on the SID model development. Based on such characteristics (nonlinearity and response time), a methodology is then developed to adapt the SID modeling process. A comparison study is also conducted to evaluate the performance of the adapted SID model, developed based on a building's nonlinearity and response time, against literature-reported RC model, SVR model, ANN model and N4SID model. Four criteria, namely, energy forecasting accuracy, calculation speed, extendibility and uncertainty are used for the model performance comparison. Again, forecasting extendibility concerns the model forecasting accuracy when the weather and/or operating conditions are different from those during the training period. Forecasting uncertainty concerns the model forecasting performance when training and forecasting data contains noise. Two commercial building, a small and a medium commercial building, with varying chiller nonlinearity, are simulated using EnergyPlus in lieu of real buildings for model development and comparison. In the following sections, the methodology for system characteristics test and SID model development is introduced firstly in Section 2, the EnergyPlus modeling and data generation process are discussed in Section 3, the system characteristic test results and SID model adaptation results are summarized in Sections 4 and 5, and then the comparison study is presented in Section 6.

2. Methodology

In this section, the test method used to determine a system's nonlinearity and response time is first introduced. How to adapt the SID model development based on the nonlinearity and response time are then discussed.

2.1. Building energy system characteristics test method

2.1.1. System nonlinearity test

It is believed that a system's nonlinearity is one of the most important characteristics for a system's model development, especially for nonparametric methods [29]. In this study, a magnitude squared coherence based method for system nonlinearity test [29] is adopted. This method is based on the cross-spectral density of the inputs and outputs:

$$C_{xy} = \frac{|S_{xy}|^2}{S_{xx}S_{yy}} \tag{1}$$

where the magnitude squared coherence (C_{xy}) estimate the power transfer between input and output to estimate the causality