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Building energy consumption on-line forecasting using physics based system identification

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ABSTRACT

Model based control has become a promising solution for building operation optimization and energy saving. Accuracy and computationally efficiency are two of the most important requirements for building energy models. Existing studies in this area have mostly been focusing on reducing computation burden using simplified physics based modeling approach. However, creating even the simplified physics based model is often challenging and time consuming. Pure date-driven statistical models have also been adopted in a lot of studies. Such models, unfortunately, often require long training period and are bounded to building operating conditions that they are trained for. Therefore, this study proposes a novel methodology to develop building energy estimation models for on-line building control and optimization using a system identification approach. Frequency domain spectral density analysis is implemented in this on-line modeling approach to capture the dynamics of building energy system and forecast the energy consumption with more than 90% accuracy and less than 2 min computational speed. A systematic analysis of system structure, system order and system excitation selection are also demonstrated. The forecasting results from this proposed model are validated against detailed physics based simulation results using a mid-size commercial building EnergyPlus model.

1. Introduction

Buildings roughly account for 40% primary energy use in U.S. It costs a total utility bill of more than $400 billion in 2012. Around 30% of the energy used in building is consumed by heating, ventilating and air conditioning (HVAC) [1]. Study has shown that non-optimal control of building energy system could cause the malfunction of equipment or performance degradation from 15% to 30% in commercial buildings [2]. Moreover, it is estimated by the National Energy Technology Laboratory that more than one-fourth of the 713 GW of U.S. electricity demand in 2010 could be dispatchable if only buildings could respond to that dispatch through advanced building energy control and operation strategies and smart grid infrastructure [3]. Therefore building control and operation is significant economically and environmentally.

In strategies used to improve building control and operation, high fidelity building energy model is the most critical component. Existing building energy models can be categorized into white box (physics-based) models, black box (data-driven) models and grey box (hybrid) models. One of the most comprehensive white box models is EnergyPlus, which is a whole building energy simulation program that engineers, architects, and researchers use to model energy and water use in buildings [4]. A Building Controls Virtual Test Bed (BCVTB) was developed by Wetter and Haves to link the building models with control systems [5]. BCVTB is a middleware tool that allows to data sharing among different simulation programs, such as EnergyPlus, Matlab and Modelica, for distributed simulation. Therefore, through this test bed different user defined building control and optimization strategies can be applied into different building simulation models. Ma et al. proposed and demonstrated an economic MPC technique to reduce energy and demand cost [6]. Using BCVTB as middleware, real-time data exchange between EnergyPlus and a Matlab controller was realized. An economic objective function to minimize daily electricity costs was then developed in MPC and applied in EnergyPlus model through the middleware. About 25.3% energy saving and 28.5% cost saving were achieved by this MPC in a single story commercial building located in Chicago, Illinois. Corbin et al. [7] utilized a Matlab-EnergyPlus MPC environment and incorporated it with a particle swarm optimizer to predict optimal building control strategies. Every time step, the schedules and setpoints will be wrote into EnergyPlus input IDF file and then EnergyPlus output results will be evaluated within the MATLAB optimal control module, based upon the objective cost function, then the

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updated temperature setpoints will be sent to EnergyPlus again. This procedure will be repeated until some convergence criterions are satisfied. This on-line optimization environment was also applied in a DOE benchmark building EnergyPlus models [8]. The results showed 5% cost saving just by optimizing the hourly cooling setpoint in large office building model, and 54% energy saving by determining hourly supply water temperature in small office building model. Another important control optimization software environment, Genopt, was also developed by Wetter in 2000 [9], which can iteratively execute any simulation program based on plain text input/output files until an optimal solution is found. Genopt was used by Coffey et al. [10] to incorporate a modified genetic algorithm MPC with an EnergyPlus model to study the temperature control optimization in office buildings and its effect building energy demand. Even though these elaborate simulation tools are very effective and accurate, they require detailed information and parameters of buildings, energy system and outside weather conditions. Identifying these parameters, however, is very time consuming and need expert work. What is even more challenging, the simulation speed is relative low and not suitable to be used in on-line MPC. Therefore, the two major researching objectives of recent studies on building MOC are increasing simulation speed and maintaining simulation accuracy. Cole et al. [11] used OpenStudio to reduce the EnergyPlus model by perturbing the system and fitting the results into a reduced-order linear model The reduced model is able to simulate an one-day simulation within 1 s and the discrepancy between this reduce-order linear model and EnergyPlus model is less than 2.3% under an optimal temperature setpoints setting situation.

Black box model is also known as purely data driven model. Statistical models are simply applied to capture the correlation between building energy consumption and several building operation variables. This method needs the on-site measurements over a certain period of time to train the statistical models which can calculate the accurate predictions under different conditions. Autoregressive with exogenous (ARX) model was implemented to predict the 1 h ahead building load by Yun et al. [12]. This predictive model is applied on several different DOE benchmark buildings [8] to choose the building control strategies. Artificial neural network (ANN) is another popular method in building energy prediction for building operation purpose. Adaptive ANNs for on-line building energy prediction was investigated by Yang et al. [13]. These models are capable of adapting themselves to unexpected pattern changes in the incoming data, and therefore can be used for the real-time on-line building energy prediction, which is the fundamental for building optimal control. Chen et al. [14] developed a day-based wavelet ANN method for next day load forecasting. They selected a historical day with the same weekday index and similar weather condition as next day. They similar day load was then decomposed into multiple levels by using wavelet decomposition. These decomposed components were fed into different ANNs to predict the next day load at each component. After all, all these prediction results will be combined into an overall forecasting result. Black box models are easy to build and computationally efficient, however, such models often require long training period and are bounded to building operating conditions that they are trained for which sometimes can cause huge forecasting error when training data does not cover all the forecasting range, and moreover, black box always sacrifice physical insights to obtain high accuracy and calculation speed.

Resistance and Capacitance (RC) network model is the most common grey model for building energy estimation, which requires less training data and has less parameter to determine. RC model usually uses state space model to estimate the building heating and cooling load [15], and control building temperature [16,17]. Different optimization and searching algorithms have been utilized in determining the resistances and capacitances [18,19]. Ma et al. [20] reduced the order of RC model to increase the calculation speed, sing balance realization method. It still took 28 min for this reduced model to run a one-week simulation using a reduced RC model, which is still not suit for on-line building operation optimization. Different to pervious works using single RC models, an integrated 3R2C and EKF (Extended Kalman Filter) model was developed to estimate the building energy consumption in Ref. [21]. In this work, an EKF was used to estimate the state vector X using real sensor measurement data. The estimated load matched the EnergyPlus results within 10% at 93% of the time.

It is common knowledge that determining the parameter of RC model is computational demanded and the model structures and parameters are unique from building to building. It is impossible to utilize a RC model for one building to another building. System identification is the process of developing or improving a mathematical representation of a physical system using experimental data [22]. System identification techniques have started been applied in building energy model area to obtain better and more accurate estimation of building performance. Privara et al. [23] proposed an approach combining a EnergyPlus model and a subspace system identification model to forecast the building performance. In this study, a six-floor office building was modeled by a Matlab toolbox called *N4SID* to estimate the building zone temperature. However, directly using Matlab toolbox cannot guarantee the forecasting accuracy every time. The accuracy of Matlab toolbox is depended on the data properties. It is very hard to guarantee the toolbox suitable to every building under different operation strategies. On the other hand, there is no systematic discussion of model structure selection and parameter determining presented in this paper. Agbi et al. [24] studied system structural identifiability and model parameters identifiability for building energy state space model. Unfortunately, this paper focuses on the discussion of identifiability of the system upon available data without any active building excitation. It did not improve the system identification model developing speed or improve the model forecasting accuracy. And it still uses the RC network model, so the method demonstrated in this paper has the limitation of all the RC model has. For example, the parameters identification for those Rs and Cs is very difficult and time consuming.

In this study, an EnergyPlus model of a mid-size commercial building was used to provide building operation data in lieu of a real building. Then a systematic discussion system identification model development and system excitation base on those operation data is presented in this paper. The combination of active system excitation and a frequency domain spectral density analysis are applied to develop building energy forecasting models that are genetic (can be easily extended to other building types/operating conditions), accurate, and computationally cost-effective. The system identification model development will be discussed in Section 2, followed by the development of system identification based building energy on-line forecasting model in Section 3. The forecasting results will then be analyzed in Section 4. After this system identification approach has been developed and validated in a small commercial building, which is then applied in a medium building.

2. Building energy model development

In this study, the on-line building energy forecasting model is developed based a mid-size reference commercial EnergyPlus simulation model, provided by U.S. Department of Energy (DOE) [25]. This reference building EnergyPlus model has been validated and used for optimize designs, operation and advanced controls in numbers of studies [26–29] The procedure of model structure determining, input and output selection, system exciting and model training and validation will be introduced in detail in this section.