Energy and Buildings 74 (2014) 69–77

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Reduced-order residential home modeling for model predictive control

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ARTICLE INFO

Article history:
Received 26 June 2013
Received in revised form 2 October 2013
Accepted 20 January 2014

Keywords:
Building energy simulation
Model reduction
EnergyPlus
OpenStudio
Model predictive control
Precooling
Thermal energy storage

ABSTRACT

Building simulation software packages such as EnergyPlus are useful energy modeling tools. These software packages, however, are often not amenable to model-based control due to model complexity or difficulties connecting control algorithms with the software. We present a method for automatically generating input/output data from an EnergyPlus residential home model using the OpenStudio software suite. These input/output data are used to create a simple reduced-order model that can be evaluated in fractions of a second. The reduced-order model is implemented in a model predictive controller to minimize the home's electricity costs during summer months in Austin, Texas, USA. The controller optimally precools the home in the morning and turns down or off the air conditioning system in the afternoon. For this example, electricity prices were taken from actual market prices in the Austin area. The optimal precooling strategy given by the model predictive controller reduces peak energy consumption from the air conditioning unit by an average of 70% and reduces operating costs by 60%. Precooling, however, consumes more total energy versus not precooling. Reducing peak energy consumption by 1 kWh results, on average, in an increase of 0.63 kWh in overall energy consumption.

1. Introduction

As of 2011, there were over 132 million housing units in the United States [1], and of those 87% had air conditioning units [2]. In the southern United States, the percentage of homes with air conditioning approaches 100% [2]. These air conditioning units tend to exacerbate peak demand issues. For example, during the 2011 summer peak in the ERCOT (Electric Reliability Council of Texas) grid, over 50% of the total electrical load was from residential homes [3], whose loads were primarily driven by their air conditioning systems. Because of this, the residential sector has enormous potential to be a key player in the future of grid management.

Modeling tools have been developed to help understand the best way to manage building energy consumption, primarily heating, ventilation, and air conditioning (HVAC) energy consumption. Models provide insights into a building's design and operation that can lead to significant cost savings over the lifetime of the building. Some building certification programs (e.g., LEED) even require building simulation to be performed.

From the building operation side, model predictive control (MPC) has become increasingly popular for determining the optimal operation of building HVAC systems [4], so much so that new software that help to evaluate MPC methods for building controls and help educate building control engineers about MPC tools have been recently developed [5]. Model predictive control uses a model of the system that is being controlled to determine optimal controller actions. These control actions are generally implemented on a receding horizon basis, meaning that after an optimal control sequence is calculated, only the first control action is actually implemented. The problem is then updated with new data at the next time step and re-solved to determine the next control action.

Creating a suitable dynamic building model is one of the primary challenges of MPC [4,6]. Accurate high-order dynamic models are readily available, but are generally not suitable for optimization and control algorithms. The higher-order models can be computationally expensive and often have model forms that are nonconvex, making it difficult for algorithms to converge to an optimal solution in time for the solution to be implemented. Therefore, model reduction is an important part of dynamic building modeling [7].

Creating a reduced-order model proceeds in two steps. First, an appropriate model structure is identified. Second, the values of the model parameters are estimated. Generating actual test data to perform model reduction can take months or years, and many of the inputs are not controllable (e.g., outdoor temperature). Building modeling software has been identified as a tool for creating input/output datasets for model reduction and parameter estimation [4,6]. This allows inputs to be exactly specified and allows the system to be perturbed in ways that would be unacceptable

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http://dx.doi.org/10.1016/j.enbuild.2014.01.033

to building occupants or harmful to equipment operating in an actual building. With a building simulation package, a wide range of operating conditions can be simulated to produce a data set that can be used to fit a simpler model, which is more amenable to optimization-based control. Furthermore, the synthetic data can be generated in a matter of minutes, rather than the months or years required to generate a similar data set from an actual building.

Dynamic reduced-order building models come in a variety of forms [8,9]. One common reduced-order model form is the resistor-capacitor (RC) model. In these models the buildings are modeled like an electric circuit with thermal resistances and capacitances. For example, Karmacharya et al. [10] created a lumped-node RC model of a residential home. They used the model to predict indoor air temperature and required HVAC energy for a heating environment. The model is implemented in MATLAB/Simulink and validated using BESTEST. In [11] Gouda et al. used nonlinear constrained optimization to reduce a model of a campus building to a lumped-parameter RC model. Optimization was used to determine the optimal parameters in the reduced-order model. They benchmarked their model against a 20th order model and found that the reduced-order models suffered only minor accuracy losses yet had considerably better computational efficiency.

Another popular model structure for reduced-order modeling is the ARX (autoregressive with exogenous inputs) family of models. ARX models use previous inputs and outputs to predict future outputs. Malisani et al. [12] used a data-driven ARX model for building thermal modeling and discussed identification methods, including time-scaled methods. They benchmarked their reduced-order model against a 47th order model and found good agreement.

Although it may not be a true reduced-order model by definition, making simplifying assumptions is one way of reducing model complexity and order. For example, Kelman and Borrelli [13] introduced several assumptions to develop a low-order model. The resulting model used for MPC is a bilinear model of a commercial HVAC system.

Once a reduced-order model is obtained, it can be used to determine the best inputs to the system. For example, a building can be precooled to avoid peak energy costs. Using the HVAC system to precool a building has been examined extensively in the literature [13–17]. Precooling takes advantage of the building's thermal mass to store thermal energy before a peak time occurs. The cool thermal mass can then absorb heat during the peak period, which reduces or eliminates the load on the HVAC system. This use of thermal mass is also called passive thermal energy storage [18]. One of the primary factors in determining the economic feasibility of passive thermal energy storage is the electricity rate structure [14,19,20]. However, for building occupants to take advantage of price differences, some sort of enabling technology (i.e., a device that automatically makes changes) is needed. Klos et al. [21] showed that those who have an enabling technology respond much more strongly to pricing signals than those without the enabling technology. Those with enabling technologies reduced peak loads by 21%, while those without the enabling technology reduced their load by 3%. The enabling technology we consider using is model predictive control.

Simple HVAC models can also be used as a basis for developing whole home energy management systems (HEMS), such as in [22,23]. These HEMS manage all the energy consumed in the home, from lighting to electronics. Because the HVAC system is the largest load in the home, modeling it accurately and simply is the first step to creating an effective HEMS.

In this work, we demonstrate an automated method for generating an input/output dataset and discuss how this can be used to create a reduced-order home model. The reduced-order home model is unique in that its inputs and outputs are easy to implement in a HEMS-type system. The manipulated inputs to the model are the home thermostat set points and the outputs are the hourly air conditioning energy consumption (rather than room temperature). An appropriate model structure for this type of model is identified. The reduced-order model is used in an MPC formulation to determine the optimal precooling strategy based on market electricity prices. Finally, the analysis of the cost savings and peak reduction is presented and discussed.

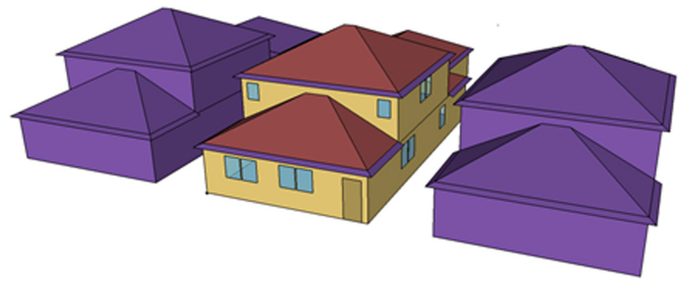

Fig. 1. A Sketchup rendering of the residential home using the OpenStudio Sketchup Plugin. The purple houses on the left and right side of the modeled home represent neighboring homes that provide shading. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

2. Problem description

The purpose of developing the reduced-order model is to have an accurate and computationally simple model that can be used by MPC to control a residential home's thermostat set point so that cost is minimized while staying within comfort bounds. Because MPC requires solving an optimization problem the model must be simple enough for the optimization algorithm to converge before the next time step and accurate enough to be applicable to the actual system. In this work, the desired model is one that takes in weather inputs (dry bulb temperature and relative humidity), thermostat set points, and time of day to predict air conditioning electricity consumption. Solar radiation is not used as an input because solar radiation data are not available. For the MPC, the controlled variable is the air conditioning electricity consumption over the time horizon and the manipulated variable is the thermostat set point. The weather inputs are disturbance variables. The typical controlled variable for an HVAC system is temperature rather than electricity consumption, so the considerations here are somewhat different than those in other related work. More discussion on the consequences of choosing electricity consumption as the controlled variable is found in the model reduction section.

The building used in this analysis is a 197.7 m^2 residential home in Austin, Texas, shown in Fig. 1. This building is part of the Mueller neighborhood, which is part of the Pecan Street, Inc., smart grid demonstration project. Building geometry was taken from Google Building Maker [24] and implemented using BEopt [25,26]. BEopt is a residential home modeling software packaged developed by the National Renewable Energy Laboratory (NREL). BEopt was used to generate an EnergyPlus simulation file. Information for constructions, equipment efficiencies, schedules, duct leakage, etc. came from surveys and energy audits conducted by Pecan Street, Inc., for those people living in the Mueller neighborhood [27,28]. The home was assumed to be unoccupied from 8:00 to 17:00 with allowable thermostat set points given by Fig. 2. Daily home energy use predicted by EnergyPlus (with 10 min time steps) was compared to the metered energy use for homes in the neighborhood and found to be in good agreement. The point is not that this EnergyPlus model is an exact match of the home, but that it is a reasonable representation of a typical home in the area.