Energy and Buildings 56 (2013) 8–22

Contents lists available at SciVerse ScienceDirect

Energy and Buildings

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

Building modeling as a crucial part for building predictive control[☆]

Samuel Prívara [a,*], Jiří Cigler [a], Zdeněk Váňa [a], Frauke Oldewurtel [b], Carina Sagerschnig [c], Eva Žáčeková [a]

[a] Department of Control Engineering, Faculty of Electrical Engineering, Czech Technical University in Prague, Czech Republic
[b] Power Systems Laboratory, Department of Electrical Engineering, Swiss Federal Institute of Technology in Zurich (ETHZ), Physikstrasse 3, 8092 Zurich, Switzerland
[c] Gruner AG, Gellertstrasse 55, CH-4020 Basel, Switzerland

ARTICLE INFO

Article history:
Received 18 September 2012
Received in revised form 6 October 2012
Accepted 10 October 2012

Keywords:
Building modeling
Predictive control
Co-simulation
HVAC control

ABSTRACT

Recent results show that a predictive building automation can be used to operate buildings in an energy and cost effective manner with only a small retrofitting requirements. In this approach, the dynamic models are of crucial importance. As industrial experience has shown, modeling is the most time-demanding and costly part of the automation process. Many papers devoted to this topic actually deal with modeling of building subsystems. Although some papers identify a building as a complex system, the provided models are usually simple two-zones models, or extremely detailed models resulting from the use of building simulation software packages. These are, however, not suitable for predictive control. The objective of this paper is to share the years-long experience of the authors in building modeling intended for predictive control of the building's climate. We provide an overview of identification methods for buildings and analyze their applicability for subsequent predictive control. Moreover, we propose a new methodology to obtain a model suitable for the use in a predictive control framework combining the building energy performance simulation tools and statistical identification. The procedure is based on the so-called co-simulation that has appeared recently as a feature of various building simulation software packages.

1. Introduction

1.1. Motivation for advanced control in buildings

Building climate control has drawn a lot of attention in recent years in both academia and industry. Buildings account for 20–40% of the total final energy consumption, and in the developed countries, the amount per year increases at a rate 0.5–5% [1]. In addition, the building sector is responsible for 33% of global CO_2 emissions. The savings related to buildings are therefore a natural objective of many research groups. Apart from retrofitting and modernization, one of the most popular current approaches is the application of advanced control strategies to the building automation systems (BAS) or to some of their parts.

1.2. Current control approaches, trends and possible improvements

Even though a number of advanced control solutions have been suggested by researches, the most widely used method in building temperature control has been until recently a controller supervised by heating-curve (HC) which require no model of the process (see e.g. [2,3]). The respective subsystems of heating, ventilation, and air conditioning (HVAC) are then controlled making use of rule-based controllers (RBC, "if–then–else") [4], which are mainly responsible for a specific and space-limited area. On the level of the whole building, there is no optimization (even though there are often highly sophisticated local controllers). This is caused by extreme complexity of the respective RBCs and the fact that it is practically impossible to generalize their rules for the building level. This problem becomes even more severe in view of the rising complexity of BAS tasks in modern office buildings.

One can distinguish two main research directions in advanced HVAC control (i) learning based approaches of artificial intelligence (AI) like neural networks, genetic algorithms, fuzzy techniques, support vector machines, etc. (ii) Model predictive control (MPC) techniques that stand on the principles of classical control. Generally, learning based techniques are easier to implement (if lots of on-site measurements are available) but the subsequent AI model is not suitable for optimization, lacks a physical insight and does not deal well with changes as caused by varying occupancy behavior or physical changes in the building.

MPC is a well established method for constrained control and has also been in focus of researchers in the area of buildings [5–9]. Among the first notes about MPC for supervisory control of a building was the work presented by [10], however, due to the

[☆] The results in paper were partly written during the visit at IfA, ETH Zurich.

* Corresponding author at: Department of Control Engineering, Faculty of Electrical Engineering, Czech Technical University in Prague, Technická 2, 166 27 Praha 6, Czech Republic. Tel.: +420 776 697 672.
E-mail address: samuel.privara@fel.cvut.cz (S. Prívara).

0378-7788/$ – see front matter © 2012 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.enbuild.2012.10.024

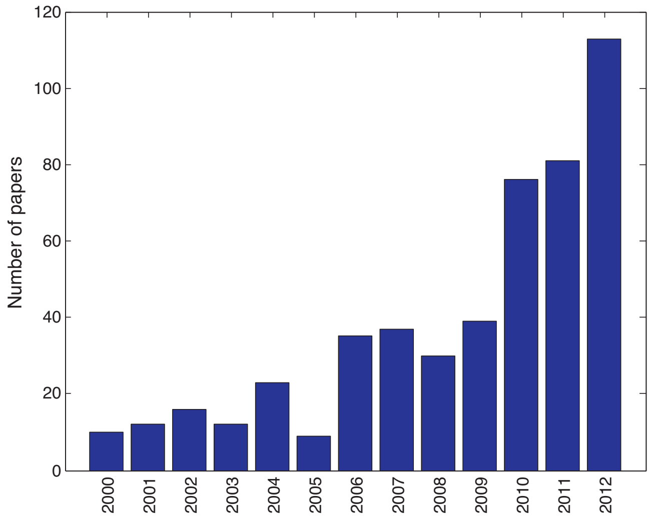

Fig. 1. Number of papers devoted to MPC in buildings in journals Energy and Buildings, Building and Environment and Energy.

computational demands, this framework has not received much attention until the past decade when MPC was applied to various types of buildings systems often using standard simulation tools. The growing interest in the use of MPC for buildings is well demonstrated by Fig. 1. Lately, the concept of predictive control has found a way to the practical applications as well [5,11,12].

MPC opens up possibilities of exploiting thermal storage capacities. It makes use of prediction of future disturbances (internal gains due to people and equipment, weather, etc.) given requirements such as comfort ranges (single value set-points still remains possible to set) for controlled variables. The control ranges (constraints) are either known in advance or at least estimated for controlled variables, disturbances, control costs, etc.

1.3. Dynamic model as a crucial part of MPC

Reliable predictions from the identified dynamic model are crucial for a sound performance of MPC. It is a well-known fact that modeling and identification are the most difficult and time-consuming parts of the automation process as such [13], particularly for predictive control. The basic conditions that each model intended for MPC usage should satisfy are reasonable simplicity, well estimated system dynamics and steady-state properties as well as satisfactory prediction properties. These requirements do not need to be of the same quality on the whole frequency range, rather they should comply with the quality requirements for the control-relevant frequency range (see e.g. [14–16]). The key question therefore is what kind of model should be searched for?

Two basic paradigms to derive a total model of building dynamics are at hand. The first one originated in HVAC engineering and building automation communities, a "traditional" approach, which uses knowledge of the structure and physical and material properties of a building. A detailed building model is then assembled from simple subsystems mutually physically interacting, making use of computer aided modeling tools, e.g. Trnsys [17], EnergyPlus [18], ESP-r [19], etc. Their objective is to simulate the behavior of the building, however, they do not provide an explicit model,[1] thus can be hardly classified into control oriented modeling approaches even though there is a challenging project GenOpt aiming at employing a (predictive) control framework directly without the need of a simple model [20]. This is however very computationally demanding, hardly scalable and therefore not further considered here.

An alternative is to use statistically based, i.e. data-driven approaches, resulting in a model in an explicit form. We must emphasize that even physically-based parametric models are classified into statistically-based models here as the parameters are identified using measured or simulated data.

Basically, following categories of building modeling techniques suitable for predictive control that can be considered as statistical.

Subspacemethods(4SID) [21] belong to the black-box identification algorithms and provide a model in a state space form.

The main advantage of 4SID methods is their ability to handle large amount of data. This was demonstrated for instance in the identification of a thermodynamic model of a small residential building that was equipped with tens of wireless sensors collecting temperatures, humidity and solar radiation [22]. 4SID methods were also used for an identification of a university building: at first, the authors compared prediction error methods with 4SID methods [23], then showed that a suitable identification experiment can significantly increase quality of the resulting model [24] as the quality of input–output data is a key factor for 4SID methods. Further on, 4SID algorithm was also applied for the identification of a large office building [25].

Predictionerrormethods(PEM) [26] are the most commonly used statistical identification techniques. Their objective is to minimize one-step ahead prediction error by optimizing parameters of a prespecified model structure.

Typically, autoregressive moving average with external input (ARMAX) model structures are preferred. This structure is used for modeling of a room temperature in office buildings as presented in [27], the model is then used for real-time fault detection and control applications. In [28], several black-box model structures are investigated for identification of the thermal behavior of a modern office building. The authors conclude that Box–Jenkins general model results in the best prediction performance among the studied group.

PEM are simple-to-use methods that are, however, suitable mainly for identification of single-input single-output (SISO) systems. As the building systems are normally multiple-input multiple-output (MIMO) systems, these methods have to be carefully used. In [29], the authors show that modeling of air conditioning process by multiple SISO ARMAX models of all system components leads to poor performance compared to the proposed MIMO ARMAX counterpart.

MPCrelevantidentification(MRI) is an approach minimizing multi-step ahead prediction errors [30–32]. The horizon for error minimization commensurate with the prediction horizon of the predictive controller.

A multi-step ahead prediction error cost function for selection of a building model is examined in [33]. The authors adapts the MRI algorithm for usage on building data that are usually highly correlated and then show that the proposed algorithm results outperforms standard one-step ahead PEM methods.

Deterministicsemi − physicalmodeling(DSPM) uses resistance capacitance (RC) network analogue to an electric circuitry to describe the process dynamics and is often referred to as a gray-box modeling.

This approach was presented in a wide variety of papers. Gray-box technique is used to obtain a model of a university building in [11]. With this model, the MPC applied in a real operation saved 16–28% energy compared to the previous well-tuned conventional control strategy. RC networks are also used by the leading projects dealing with predictive control of buildings, i.e. UC Berkeley [5], ETH Zurich [34], KU Leuven [6].

[1] Note that in this context, we call a model explicit if there are mathematical formulas describing a state evolution, i.e. a set of differential or difference equations is available. Otherwise the model is called implicit. Notice that AI models are also implicit.