Energy and Buildings 99 (2015) 292–302

Contents lists available at ScienceDirect

Energy and Buildings

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

Field tests of an adaptive, model-predictive heating controller for residential buildings

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ARTICLE INFO

Article history:
Received 28 June 2014
Received in revised form 13 March 2015
Accepted 19 April 2015
Available online 4 May 2015

Keywords:
Model-predictive control
Space heating energy
Residential buildings
Self-learning
Adaptive
Energy signature

ABSTRACT

Conventional weather-compensated heating controllers are often configured to deliver more heating than necessary, resulting in energy losses. Furthermore, they cannot take into account future climate conditions, and yield less than optimal thermal comfort. We have developed a non-invasive add-on module for existing heating controllers that implements an adaptive, model-predictive heating control algorithm. This algorithm helps the heating controller deliver a heating energy just sufficient for maintaining thermal comfort, resulting in energy savings. In this paper we report on the energy savings measured on ten buildings equipped with this device. By monitoring the space heating energy during the 2013–2014 heating season, and by periodically alternating between the new controller and the reference controller, we establish the energy signature of all buildings with both controllers. The comparison of the energy signatures yields the relative energy savings achievable with the new controller. These energy savings are positive for all test sites, with a mean of 28 ± 4% (standard error of the mean).

1. Introduction

Buildings in developed countries account for 20–40% of the total energy consumed [1]. Of this energy, about 50% is used for heating, ventilation and air-conditioning (HVAC). The figures for Switzerland are comparable, with 33% of the domestic final energy being used for space heating of residential and commercial buildings, more than for domestic transportation (30.3%) [2,3].

Buildings, being one of our main consumers of energy, have therefore attracted considerable attention regarding the way they use this energy. Any solution that will help buildings become more energy-efficient will benefit from economies of scale, leading to significant global energy savings, and hence to reductions in CO_2 emissions.

Space heating is one of the largest consumers of energy in buildings, but even professional heating installers find it remarkably difficult to properly configure a central heating installation. Furthermore, there is little economic incentive for them to do so: few customers will be able to prove that a building could use less energy if it were better parameterised. This is especially true for smaller installations such as single-family dwellings. With little information at their disposal, most end-users are satisfied provided that the indoor comfort is maintained. Consequently, the energy demand of much of the existing building stock is significantly higher than needed, although there is little research on the subject.

Several solutions exist to help an existing building become more energy-efficient, ranging from better insulation to the installation of heat pumps. They vary widely in cost and effectiveness, often requiring significant up-front investments from the end user, although many jurisdictions will offer subsidies that partially offset these costs. However, these solutions are often invasive, requiring significant transformations on the building itself. A comprehensive cost–benefit analysis of energy efficiency investments for the Swiss residential sector can be found in [4].

An alternative solution consists in optimizing the heating control algorithm itself. Most commercial systems compute a temperature for the heating fluid as a function of the outdoor temperature (the so-called *heating curve*), but this approach ignores the physics of the building and the expected future climate conditions. A better alternative is the so-called *Model-Predictive Control* (MPC), where a mathematical representation of the building, together with a model of the future climate conditions, let the system compute the flow temperature that minimises the consumed energy while preserving thermal comfort.

The earliest example of a true MPC for HVAC that we are aware of is a PhD thesis [5] whose "Predictive Controller" was programmed, before electronic mail was called email, on an IBM PC 386 with 2 MB

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http://dx.doi.org/10.1016/j.enbuild.2015.04.029
0378-7788/

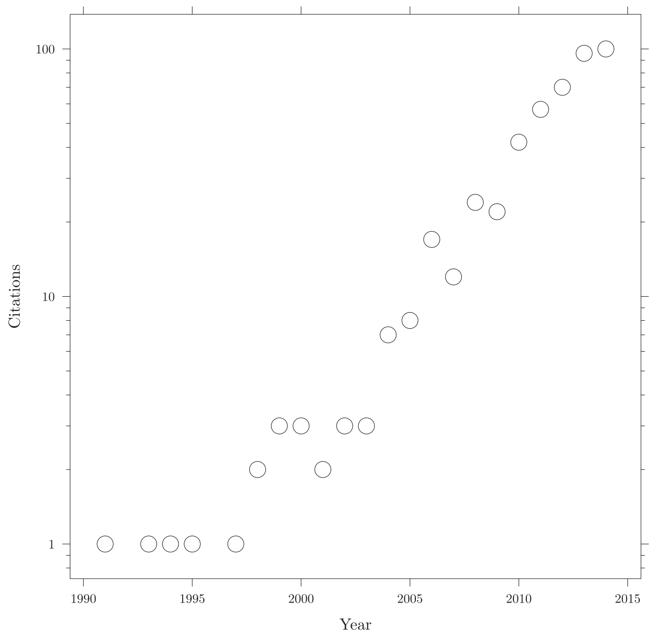

Fig. 1. Number of search results returned by Elsevier's Scopus tool when queried with "model-predictive control buildings". Note the logarithmic scale.

of RAM in QuickBasic. By anticipating solar gains for the next 24 h, and by the use of an accurate thermal model of the building under control, the controller achieved 27% energy savings compared with the reference controller.

Recent years have seen a growing academic interest in MPC applied to buildings. Fig. 1 shows the number of search results returned by Elsevier's Scopus tool when queried with "model-predictive control buildings". The number of references has been rising exponentially since about 1997.

There are many recent examples of the successful application of MPC to HVAC in buildings, both residential and commercial. Here we enumerate some of the latest, all published in the past four years:

1 The use of a building model with weather forecasting has achieved 17–24% energy savings on a university building, compared with the existing control system [6].
2 An MPC system for HVAC was tested in two commercial office buildings in Australia and yielded an average energy reduction of 19% and 32% respectively, without any impact on the occupant's perceived comfort [7].
3 The optimisation of the space heating of a building equipped with a fuel cell-electrolyzer system has yielded a reported reduction of operating costs of up to 25% [8].
4 An MPC system has been proposed that adjusts the HVAC setpoints on a simulated building (whose model was obtained through system identification) and on a large office building in Milwaukee, WI [9]. The originality of this system resides in that it will not optimise the energy use directly, but instead the monetary cost of the energy, taking into account shifting energy tariffs.
5 One of the most recent, and most complete discussions on the application of MPC systems in real-life systems, can be found in [10,11]. In particular the authors discuss the problem of identifying the system under control. By using so-called Model Predictive Control Relevant Identification Methods (MRI), they achieve models able to predict the indoor temperature in an office building two days ahead with a mean error of about 0.3 °C. The identified system is now used to control the modelled office building, with an average of 17% energy savings.
6 A large, fully occupied and fully instrumented office building is used in the OptiControl project, a large-scale MPC experiment. This project required constructing an accurate model of the building with EnergyPlus; the simulated model was then used to optimise the operation of the building. The project estimates the theoretical energy savings potential on the demonstrator building as being at least 20% [12,13].

MPC has attracted much interest because, provided the model is accurate and provided the prediction of future perturbations is correct, it is not possible to significantly outperform such a system. Furthermore, by choosing a suitable formulation of the objective function, it is possible to incorporate desirable attributes such as time-varying tariffs; future changes in setpoint; night-setback; constraints on control variables; and constraints on the rate of change of control variables. There is no significant additional computational cost for including such constraints.

In simulation studies it is possible to have an MPC system with an almost perfect model and an almost perfect prediction of perturbations. Such a "perfect" controller is often used as a benchmark for testing other, more pragmatic control systems. For example, in a recent study [14], the heating control problem was converted into a linear programming problem (a special form of MPC), and the solution to this problem was used as a benchmark for testing other control systems.

The main drawback of MPC is that it requires an accurate model of the building [15,16]. The most common approach hitherto has been to postulate a model structure, and identify the coefficients of that model either from in-situ data or from simulation data. In either case, once the model has been built it remains fixed for the duration of the operation. This is perhaps fine for research projects, but will not do for a commercial product. Designing such a model requires time and expertise and would drive the cost of the whole system towards unacceptable levels.

So-called *adaptive* heating control systems are seen as a solution to this problem. This is not restricted to MPC: as early as 1985, a report [17] to the Swiss Bundesamt für Konjunkturfragen described the potential of self-learning heating control systems. According to this report, 10–27% energy savings were measured on a set of six experimental buildings by the combined application of the following strategies:

- Optimal stop time (i.e. stopping the heating as early as possible in the evening);
- Night setback (i.e. letting the indoor temperature fall during night, but never below a certain threshold);
- Optimal start time with fast re-heating (i.e. starting the heating as late, and as strongly, as possible).

The report lists 23 commercial heating controllers claimed as being self-learning; all compute the optimal start time, all but four compute the optimal stop time, and all but three adapt their heating curve. It is technically incorrect to label these systems as MPC, since there is no predictive element in their algorithms, but their reported performance was nevertheless remarkable.

The present work traces its roots to the NEUROBAT swiss research project [18–22], an early proposal for a so-called *adaptive model-predictive control* of heating systems. The algorithms enabled an efficient MPC for HVAC without requiring the user to provide an identified model; the model itself, being provided with sensor data, was capable of identifying its own parameters while running. However, computing costs at that time made its commercial implementation impractical.

In this paper we report on experimental tests carried out during the 2013–2014 heating season on ten test sites with a recently introduced commercial model-predictive heating controller that