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Learning decision rules for energy efficient building control

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ABSTRACT

While rule based control (RBC) is current practice in most building automation systems that issue discrete control signals, recent simulation studies suggest that advanced, optimization based control methods such as hybrid model predictive control (HMPC) can potentially outperform RBC in terms of energy efficiency and occupancy comfort. However, HMPC requires a more complex IT infrastructure and numerical optimization in the loop, which makes commissioning, operation of the building, and error handling significantly more involved than in the rule based setting. In this paper, we suggest an automated RBC synthesis procedure for binary decisions that extracts prevalent information from simulation data with HMPC controllers. The result is a set of simple decision rules that preserves much of the control performance of HMPC. The methods are based on standard machine learning algorithms, in particular support vector machines (SVMs) and adaptive boosting (AdaBoost). We consider also the ranking and selection of measurements which are used for a decision and show that this feature selection is useful in both complexity reduction and reduction of investment costs by pruning unnecessary sensors. The suggested methods are evaluated in simulation for six different case studies and shown to maintain the performance of HMPC despite a tremendous reduction in complexity.

1. Introduction

About 20–40% of total primary energy usage is spent for the heating, ventilation and cooling (HVAC) of commercial buildings and private housing [1]. While currently most buildings are equipped, if at all, with simple automatic control systems, many studies have indicated the merits of advanced building automation over current state of the art control practice in terms of energy usage and comfort regulation, see e.g. [2–6] and the references therein.

Particularly the field of model predictive control (MPC) offers a systematic framework for optimal operation of buildings. Incorporating a model of the building, these controllers can combine measurements available through on-site sensors with weather forecast data to control the building such that energy consumption is minimized while respecting specifications (constraints) on occupancy comfort [7,8]. These advanced controllers generally outperform current state of the art solutions and thus have a huge potential in reducing green house gas emissions when widely applied.

However, the field only slowly adapts to these advanced optimization based control strategies mainly due to two practical reasons. First, the resulting optimization problem, which needs to be re-solved after new measurements are available, requires substantial IT infrastructure both in terms of hardware and software. Second, commission engineers are not trained to set up complex control systems based on numerical optimization, tune them and respond adequately to eventual malfunctions or error codes. Contrary to the petrochemical industry, where optimization based control of large scale dynamic systems emerged in the early 1970s, a building is usually operated without on-site engineers carefully monitoring and supervising the correct functioning of the building control system. It therefore remains a major challenge to derive control schemes which allow both an *energy efficient* operation of the building and, at the same time, a *simple implementation* of the control algorithm.

In this paper, which is an extended version of [9], we suggest a framework that allows automatic extraction of decision rules from simulation data generated with advanced control schemes such as hybrid MPC (HMPC). We use the term *learning* to describe the process of approximating a controller from data. The result is a significant complexity reduction, while our simulations suggest that much of the HMPC control performance can be maintained by the extracted set of rules. These can be automatically transformed into computer code for various embedded control platforms. We show that for a certain choice of synthesis methodology, the resulting

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rules are simple enough to be readable by humans. This enables building operators to adjust the controller on-site if the behavior is unsatisfactory due to model-plant mismatch, for example.

Ranking of measurements in terms of importance for approximation performance is also discussed. This *feature selection* allows pruning sensors or data streams which contain information irrelevant to a decision and further reduces the complexity of the resulting controller. When used with accurate building models, feature selection potentially saves investment costs in unnecessary sensor infrastructure. In our simulations, near-optimal control is achieved with only a small number of sensors and weather predictions.

We focus in this work on learning binary decisions, since optimization problems with integrality constraints can take a long time to solve even on powerful computers due to their combinatorial nature [10]. Moreover, expensive numerical optimization software is to be deployed with the real-time control system when an online implementation is considered. On the other hand, it is sensible to assume that offline simulation can be carried out in reasonable time at control design stage to generate the data needed for learning. Once the discrete decisions have been set by the learned controllers, the resulting MPC optimization problem is continuous. Computation of local solutions to these problems on embedded control platforms has been subject of intensive research, and software tools are available for this task. Widely used methods are multiple shooting [11] and solving a sequence of linear MPC problems arising from a linearization of the dynamics using efficient convex programming solvers such as presented in [12,13].

Controller approximation from simulation data has been considered by means of linear interpolation [14] or nonlinear sparse approximation [15,16] of MPC control laws for continuous inputs. Rule extraction for binary inputs in a building control context has been investigated in [17] with a logistic regression model. The methods used in this paper are based on standard algorithms from the field of *machine learning*, which deals with statistical inference of patterns and decisions from data. In particular, we consider *support vector machines* (SVMs) for classification [18] and *AdaBoost* [19], two well researched and widely applied algorithms. Examples of successful applications of these tools are gene expression profiling [20] for cancer detection, robust real-time face detection [21] and handwritten digit and character recognition [22].

The paper is organized as follows. In Section 2, we outline the considered control scheme along with a possible hybrid MPC formulation. Next, we briefly describe SVM and AdaBoost as well as feature selection in Section 3. The main contribution of the paper is Section 4, where we present simulation studies with approximate controllers synthesized by learning algorithms. Section 5 concludes the paper.

2. Hybrid model predictive building control

2.1. Hierarchical control structure

Consider the hierarchical control scheme depicted in Fig. 1. The high level controller (HLC) computes an optimal plan for a certain prediction horizon subject to parameters such as energy price and comfort constraints, as well as measurements of the current state of the building and weather forecast data. In order to predict the building's behavior, the HLC employs a mathematical model of the building. The resulting setpoint commands are then issued to a low level controller (LLC), which ensures tracking of the given setpoints despite disturbances such as varying occupancy of the building and imperfect weather forecast. The LLC is in practice usually a proportional-integral-derivative (PID) controller or a rule based controller (RBC) [23]. The LLC is however not the focus of this paper, i.e. we assume that the LLC provides a good tracking performance of the setpoints that are provided by the HLC. At the next sampling instance of the HLC, the optimization is repeated based on the current state of the system, and new setpoint trajectories are computed. This scheme is repeated in each sampling time, which coined the term *receding horizon control* (RHC) widely used for MPC in literature.

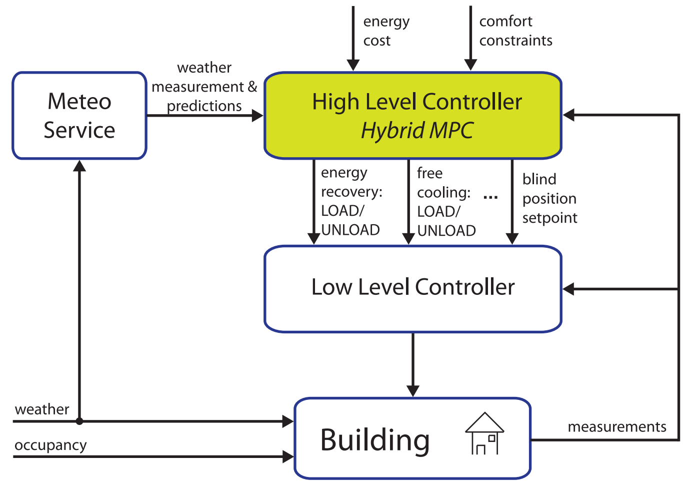

Fig. 1. Hierarchical control system employing model predictive control at the highest level to enhance energy efficiency. The setpoints calculated by the HLC are issued to standard low-level controllers which ensure good tracking despite disturbances.

There are two fundamentally different types of control inputs computed by the HLC: discrete ones, which are referred to as *binary decisions* in the rest of the paper, and continuous ones. An example for the latter is the blind position, while examples for binary decisions used in this paper are *energy recovery* and *free cooling* systems. Energy recovery controls mechanical ventilation and heat exchangers that extract energy from exhaust air, while free cooling controls the amount of available chilled water generated with a wet cooling tower. Both systems have two modes of operation, LOAD and UNLOAD, for increasing and decreasing the thermal energy stored in the building. The HLC decides upon these modes and issues the commands to the LLC, which coordinates the action of heat exchange systems and pumps according to a fixed ruleset to obtain the desired behavior. While these systems might also have binary inputs for switching them on or off, in this paper we are interested in learning the high-level commands that are issued by the HLC, since these significantly affect the energy efficiency of the building.

2.2. Hybrid model predictive control formulation

In this section, we describe the main parts of our hybrid model predictive control formulation for the high-level building controller.

2.2.1. Dynamic building model

In this work, we focus on the control of one zone by integrated room automation (IRA) systems in office buildings. This is common building control practice, and the net energy demand for the whole building can be approximately obtained by aggregating the energy demand of multiple such rooms/zones [24]. The dynamic model and parameters as presented in [7] are employed. This model has been validated with TRNSYS, a well known modeling software for buildings and HVAC systems, in the OptiControl project [25] against real building data. Based on this model, a real Swiss office building has been successfully controlled using MPC [26].

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