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Data-driven model predictive control using random forests for building energy optimization and climate control

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HIGHLIGHTS

- A novel approach to data-driven predictive control (DPC) using Random Forests.
- Accuracy, scalability & robustness of the algorithm are verified with three studies.
- Case Study I: DPC shows comparable performance to a physics-based MPC controller.
- Case Study II: DPC provides Demand Response curtailment for an EnergyPlus building.
- Case Study III: DPC provides up to 50% energy savings in a real off-grid house.

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ABSTRACT

Model Predictive Control (MPC) is a model-based technique widely and successfully used over the past years to improve control systems performance. A key factor prohibiting the widespread adoption of MPC for complex systems such as buildings is related to the difficulties (cost, time and effort) associated with the identification of a predictive model of a building. To overcome this problem, we introduce a novel idea for predictive control based on historical building data leveraging machine learning algorithms like regression trees and random forests. We call this approach Data-driven model Predictive Control (DPC), and we apply it to three different case studies to demonstrate its *performance*, *scalability* and *robustness*. In the first case study we consider a benchmark MPC controller using a bilinear building model, then we apply DPC to a data-set simulated from such bilinear model and derive a controller based only on the data. Our results demonstrate that DPC can provide comparable performance with respect to MPC applied to a perfectly known mathematical model. In the second case study we apply DPC to a 6 story 22 zone building model in EnergyPlus, for which model-based control is not economical and practical due to extreme complexity, and address a Demand Response problem. Our results demonstrate scalability and efficiency of DPC showing that DPC provides the desired power curtailment with an average error of 3%. In the third case study we implement and test DPC on real data from an off-grid house located in L'Aquila, Italy. We compare the total amount of energy saved with respect to the classical bang-bang controller, showing that we can perform an energy saving up to 49.2%. Our results demonstrate robustness of our method to uncertainties both in real data acquisition and weather forecast.

1. Introduction

Control-oriented models of energy system's dynamics and energy consumption, are needed for understanding and improving the overall energy efficiency and operating costs of a building. With a reasonably accurate forecast of future weather and building operating conditions, dynamical models can be used to predict the energy needs of the building over a prediction horizon, and use them to determine optimal control actions to save energy and guarantee thermal comfort, as is the case with Model Predictive Control (MPC) [1]. However, a major

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challenge with MPC is in (accurately) modeling the dynamics of the underlying physical system. The task is much more complicated and time consuming in the case of a large buildings and often times, it can be even more complex and involved than the controller design itself. After several years of work on using first principles based models for peak power reduction, energy optimization and thermal comfort for buildings, multiple authors [1,2] have concluded that the biggest hurdle to mass adoption of MPC in intelligent building control is the cost, time and effort required to capture accurate dynamical models of the buildings. The user expertise, time, and associated sensor costs required to develop a model of a single building is very high. Thus, the payback period for the upfront hardware and software installation is expected to be too high, making MPC an uneconomical choice for energy management. This is probably the main reason why rule-based control strategy have been widely used so far. Indeed, there are several reasons why physics-based modeling is hard for complex systems like buildings:

1. **Model capture** – a building modeling domain expert typically uses a software tool to create a model to reproduce the geometry of a building from the building design and equipment layout plans, and add detailed information about material properties, equipment and operational schedules. However, there is always a gap between the modeled and the real building, and the domain expert must then manually tune the model to match the measured data [3]. Moreover, the modeling process also varies from building to building with the construction and types of installed equipment. Another major downside with physics-based modeling is that enough data is not easily available, so guesses for parameter values have to be made, which also requires expert know-how.
2. **Change in model properties over time** – even if the model is identified once via an expensive route as in [1], as the model changes with time, the system identification must be repeated to update the model. Thus, model adaptability or adaptive control is desirable for such systems.
3. **Model heterogeneity** further prohibits the use of model-based control. For example, unlike the automobile or the aircraft industry, each building is designed and used in a different way. Therefore, this modeling process must be repeated for every new building.

In Section 2 we will present a detailed technical example to better illustrate how data-driven approaches can address the above issues and thus reduce the cost of modeling buildings. In practice, due to aforementioned reasons, the control strategies in such systems are often limited to fixed, sometimes ad-hoc, rules that are based on best practices. The alternative is to use black-box, or completely data-driven, modeling approaches, to obtain a realization of the system's input-output behavior. The primary advantage of using data-driven methods is that it has the potential to eliminate the time and effort required to build white and grey box building models. Listening to real data, from existing systems and interfaces, is far cheaper than unleashing hoards of on-site engineers to physically measure and model the building. Improved building technology and better sensing is fundamentally redefining the opportunities around smart buildings. Unprecedented amounts of data from millions of smart meters and thermostats installed in recent years has opened the door for systems engineers and data scientists to analyze and use the insights that data can provide, about the dynamics and power consumption patterns of these systems.

The key question now is: *can we employ data-driven techniques to reduce the cost of modeling, and still exploit the benefits that MPC has to offer?* We therefore look for automatic data-driven approaches for control, that are also adaptive, scalable and interpretable. We solve this problem by bridging Machine Learning and Predictive Control. In this paper, we present a method based on Random Forests which uses historical data for receding horizon control. We begin with a discussion on the related literature and novelty of our contribution.

1.1. Related work

A vast literature exists in building energy applications that deals with Demand Response, peak power reduction, energy saving, thermal comfort, and related topics. Among them, we selected the ones that we believe are more related to our work.

All these approaches can be classified based on two characteristics:

1. the type of system model:
   - model-based, such as "white-box" and "grey-box" approaches: [9,6,10,15,7,11,12,8,27,14];
   - data-based, i.e. "black-box" approaches, mainly done using Neural Networks: [16–20,14,15];
   - simulation tool-based, such as EnergyPlus [28] and TRNSYS [29]: [4,5];
2. the purpose these models are created for:
   - only model identification: [16–18,6,15,7,8,19,14,20];
   - model identification and control, mainly Predictive Control: [9,10,4,11–13].

These references are summarized in Table 1 highlighting the key differences. We also emphasize the case studies the results are applied to, and whether the authors used experimental data to simulate their algorithms. Only in three cases the algorithms are tested on real systems (see Table 1: RI – Real Implementation). We observe that, except for the last six cases [21–26], which we discuss in detail, either model-based approaches or only tools are considered with/without control, or data-driven modeling approaches are considered *only without* control. The last six papers of Table 1 are more related to the methodology presented in this paper, since they address both data-driven modeling and control. In particular, the authors in [21] proposed a predictive control strategy based on Neural Networks, for boilers control in buildings, to decide the optimal time to switch-on the plant to guarantee energy savings and thermal comfort. However, the approach is not easily scalable to different types of plants and does not use optimization in the closed-loop

Table 1
References ordered considering: case study they are applied to; whether they use experimental data, other than simulated data, and if they do real implementation (RI), i.e. implement the methodologies on real systems; if they use simulative tools; the type of the model considered, i.e. Model-Based or Data-Driven or both; if the models are used for control.

Ref.	Case study	Exp.	Tool	MB/DD	Control
[4]	Commercial Building	Yes	E+	None	Yes
[5]	Commercial building	Yes	E+	None	Yes
[6]	Commercial building	Yes	E+	MB	No
[7]	2 office buildings and 1 residential building	Yes	None	MB	No
[8]	2 commercial buildings	n/a	E+	MB	No
[9]	Residential area	No	None	MB	Yes
[10]	2 residential buildings	Yes	E+	MB	Yes
[11]	3 residential buildings	No	E+	MB	Yes
[12]	6 commercial buildings	Yes	E+	MB	Yes
[13]	Residential building	Yes	None	MB	Yes
[14]	Commercial building	No	E+	MB-DD	No
[15]	2 commercial buildings	Yes	E+	MB-DD	No
[16]	Office building	Yes	None	DD	No
[17]	Office building	Yes	E+	DD	No
[18]	Residential house	Yes	TRANSYS	DD	No
[19]	Residential building	Yes	None	DD	No
[20]	Office building	No	E+	DD	No
[21]	Commercial building	Yes + RI	None	DD	Yes
[22]	Living lab (1 room)	Yes + RI	None	DD	Yes
[23]	Commercial building	Yes + RI	None	DD	Yes
[24]	Residential house	Yes	None	DD	Yes
[25]	9 commercial buildings	No	E+	DD	Yes
[26]	Commercial building	No	E+	DD	Yes

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