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Shortest-prediction-horizon model-based predictive control for individual offices

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ABSTRACT

When employing model-based predictive control (MPC) for zone level heating and cooling systems, in many cases weather forecasts were imported to predict a thermal zone's temperature response over a time horizon. However, an office's thermal response is strongly influenced by an occupant's presence and behaviours. As illustrated through the analysis of an EnergyPlus simulation, propagation of the uncertainty introduced by an occupant's presence and behaviours into the temperature response of a thermal zone can result in suboptimal control decisions when the prediction time horizon extends beyond one hour. Results indicate that modest, yet robust to occupant behaviour, energy savings can be achieved by limiting the prediction time horizon to one hour in zone level MPC implementations. Choice of this prediction time horizon also eliminated the need for importing weather forecasts. In an effort to discuss the implementation challenges, this MPC algorithm has been implemented in a commercial controller to automate a ceiling radiant panel heater and a variable-air-volume (VAV) terminal unit serving to a west-facing office in Ottawa.

1. Introduction

Buildings play a significant role in our environmental impact (e.g., about 40% of the primary energy use and greenhouse gas emissions in North America [1,2]) and the adoption of model-based predictive control (MPC) strategies for building systems, such as auxiliary heating/cooling systems and window shading systems, has shown great potential to reduce this impact [3–7].

1.1. Problem definition

The main premise behind MPC is that there is useful information in the future of a system —which can be used to improve the control process [8]. However, the challenge lies in revealing this useful information at a reasonable accuracy and consistency. In MPC of a heating or cooling system, this useful information is the indoor temperature predictions over a time horizon. Using these predictions, an appropriate optimization algorithm can be employed to identify the optimal control decision. However, if the predictions are inaccurate, the control decisions executed based on them will become suboptimal.

It is therefore necessary to identify the most influential predictors so that MPC is an effective energy-saving strategy. Although weather forecasts can be a predictor for an office's future temperature response, an occupant's presence and behaviours are also influential factors. The uncertainty associated with an occupant's presence and behaviours makes it harder to predict the temperature response of an office accurately. This, in turn, undermines the potential of MPC use in zone level applications where individual occupants play a substantial role in the temperature response by using window blinds, lighting, operable windows, and office equipments.

1.2. Literature review

Researchers have been studying model selection and system identification methodologies in order to improve the predictive accuracy of MPC in buildings. Before delving into the literature on the model selection and system identification, it is necessary to define the nomenclature used throughout this paper: (1) the model order refers to the number of nodes in a thermal network

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model, (2) parameters in system identification refer to the resistances and capacitances used in a thermal network model, (3) disturbances in system identification refer to the heat gains/losses due to uncontrolled natural processes (e.g., solar gains), (4) control outputs refer to the heat gains/losses due to controlled processes (e.g., radiant heating panels), (5) prediction time horizon refers to a time period starting from the current time over which control outputs were planned. MPC with white-box control models, such as those implemented in BPS tools [e.g., [9]], were excluded from the scope of this study. Instead, self-adaptive control models that can learn model inputs autonomously were studied considering the practicality to implement them in local (zone level) building controllers [10].

1.2.1. Model selection

Sourbron et al. [11] studied the influence of model selection. They concluded that accurate predictions can be made both using a second-order and a fourth-order model, when the prediction horizon is two days and the disturbances are ideal (i.e., predefined). After trying two first-order, one second-order and one third-order thermal network models, Fux, et al. [12] reached a similar conclusion. It was reported that simplified thermal network models can be used to make short-term predictions, when a system with its disturbances and model parameters is identified —in this case using Extended Kalman Filter (EKF). In line with this, numerous researchers [10,13–16] confirmed the adequacy of the low-order thermal network models for short-term predictions (to be used in MPC of zone level heating and cooling systems), when a system is properly identified with its parameters and disturbances.

1.2.2. Parameter and disturbance estimation

The parameter and disturbance estimation in system identification is an inverse modelling problem. Radecki and Hencey [17] studied the potential of learning model parameters sequentially using the Unscented Kalman Filter (UKF) and concluded that the UKF is a robust algorithm to acquire accurate parameter and disturbance estimates. Other researchers [e.g. Refs. [12,18]] studied the EKF and UKF methodologies for learning model parameters and disturbances, they reached conclusions in line with Radecki and Hencey [17]. At this point, it is worth noting a crucial difference between the parameter and disturbance estimation process: parameter estimates are typically time-invariable (e.g., wall insulation), while disturbance estimates should be time-variable (e.g., solar gains). Therefore, using a disturbance estimated at a certain time in a building's operation to predict its future response can become unjustifiable. For instance, if solar heat gains equal to Q at time t, it will likely diverge from Q at time $t+\tau$ as τ increases. In building controls literature, the common approach to mitigate this uncertainty is importing external weather forecasts [17,19–21]. However, weather forecasts inherently introduce error to the model predictions. A part of this error can be corrected by a recursive state-estimation method [21].

Although MPC literature has progressed independent from occupant behaviour research for a long time, recently a pioneering effort by Tanner and Henze [8] acknowledged the substantial influence of occupants' window opening behaviour on the MPC of a heating and cooling system. Although the window opening behaviour overall statistically correlates well with the outdoor temperature [22,23], the timing of an individual window opening action is extremely hard to predict [24]. An occupant can open a window at any point during the operation (even in a heating season for airing purposes) which can perturb the controlled system for a random time period. Similarly, weather forecasts may suggest that it will be sunny during the prediction time horizon, but an occupant can close the blinds at anytime and reduce the transmitted solar radiation significantly at a random instance in the prediction horizon. This would nullify the validity of the predictions made in the controller and lead to suboptimal control decisions. In such cases, it is necessary to limit the prediction time horizon length to a time period whereby the disturbances are unlikely to change. Contradicting to this, based on a recent review article, Afram and Janabi-Sharifi [25] stated that prediction time horizons for the most MPC implementations range from 6 to 48 h —even for individual offices. However, it is perhaps unreasonable to expect the occupancy, blinds, windows, lights and other electrical equipment's state in an office remain unchanged for such a long period of time.

1.3. Scope

It is argued that when long prediction time horizons are used in MPC of individual offices, the model predictions can be corrupted due to the uncertainties introduced by occupants' behaviours and their presence. This was demonstrated through a first-order controller model trying to predict a simulated office's temperature response up to six hours in advance. The simulated office was represented in the building performance simulation (BPS) tool EnergyPlus with existing stochastic occupant behaviour models. The propagation of the prediction error in time was demonstrated and the effect of this error in making useful control decisions was discussed.

Upon this discussion, an alternative MPC approach has been proposed whereby the prediction time horizon was only one hour. The performance of this alternative MPC approach was compared to an MPC controller which inputs ideal weather forecasts and to a classical reactive controller. In an effort to address the implementation challenges of the proposed MPC strategy to an office in operation, it was implemented in a west-facing office in Ottawa.

The scope of this work is limited to the MPC applications for zone level actuators (e.g., a VAV terminal unit or a ceiling radiant panel heater serving to an individual office). It excludes the use of MPC for system level actuators (e.g., air-handling unit) where an individual occupant plays a negligible role over the heating and cooling loads.

1.4. Document structure

The methodology section consists of the building and occupant models, and the control models. Also, this section presents the analysis approach whereby the run-cases for numerical experiments are described. The results and discussion section consists of four subsections: (1) a subsection whereby the predicting accuracy of control models is assessed, (2) a subsection whereby the performance indicators —heating and cooling loads, and controllability of the indoor temperature —of the MPC with a short prediction time horizon (sMPC) are contrasted to that of an MPC with a long prediction time horizon and a classical reactive controller, (3) a subsection whereby the implementation challenges of sMPC is addressed through a prototype implementation in a west-facing office, and (4) a subsection whereby the unresolved issues are discussed and the future work recommendations are developed.

2. Methodology

2.1. Building and occupant models

The building model represents a simple hypothetical south-facing perimeter office in Ottawa, Canada (see Fig. 1) (a). It was developed in EnergyPlus v8.1. The simulation time-step size was 5 min. The floor area of the model was 25 m^2 and the floor-to-floor