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Model-based predictive control for building energy management: Part II – Experimental validations

Na Yu [a], Saran Salakij [b], Rafael Chavez [a], Samuel Paolucci [a,*], Mihir Sen [a], Panos Antsaklis [c]

[a] Department of Aerospace and Mechanical Engineering, University of Notre Dame, Notre Dame, IN 46556, United States
[b] Department of Mechanical Engineering, Faculty of Engineering, Chulalongkorn University, Bangkok 10330, Thailand
[c] Department of Electrical Engineering, University of Notre Dame, Notre Dame, IN 46556, United States

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ABSTRACT

Indoor climate control of thermal comfort for humans in a residential or commercial building is a major component of building energy management. The goal of optimal temperature and humidity control is to ensure indoor comfort with minimal energy consumption. Model-Based Predictive Control (MBPC) is considered to be one of the most suited solutions to achieve this goal due to its ability to use building dynamics, occupancy schedule, and weather conditions for optimal control. The development and verification of MBPC have been discussed in the Part I [1]. Here, to validate that MBPC achieves reduced energy consumption, while simultaneously satisfying comfort conditions, experiments are performed on a quarter scale shelter structure in a climate-controlled environmental chamber. The MBPC method is compared to three other control methods: conventional constant temperature setpoint control, scheduled control using a Honeywell smart thermostat, and scheduled control using Labview. Temperature variations and energy consumptions resulting from the four methods are analyzed. Compared to the three other methods, MBPC yields superior control performance with lowest energy consumption while still maintaining indoor thermal comfort. We also demonstrate that use of MBPC can reduce the number of sensors required for effective local control.

1. Introduction

According to the US Energy Information Administration, Heating, Ventilation, and Air Conditioning (HVAC) systems account for 48% of US residential energy usage [2], which makes it an attractive target for energy reduction. Excessive energy is consumed in buildings due to inefficiencies in building climate control technologies, particularly in operating HVAC systems and lighting systems [3], such as failing to set appropriate temperature setpoints and thus consuming more energy than necessary, as well as inefficient control of fresh air intake. A report by ASEA Brown Boveri (ABB) [4] shows that by utilizing intelligent building control strategies, 50%, 80% and 60% of energy consumption reduction can be achieved in space heating and cooling, lighting, and ventilation, respectively. Furthermore, considering occupancy information in the building climate control has significant energy-saving potentials [5].

The main objective of building energy management is to minimize the energy consumption while maintaining a desired comfort temperature. One of the effective control strategies is to include a mathematical model in conjunction with an effective dynamic energy response of a building system into the control strategy. In Part I [1] we provide details of the energy modeling, the Building Energy Analysis Model (BEAM) and the corresponding reduced order model (Re-BEAM), and the Model-Based Predictive Control (MBPC) method. In the MBPC method, the building physics are formulated as a mathematical model that is used to predict the future status of a building according to the selected operating strategy, weather conditions, and occupancy. The overall aim is to minimize the energy consumption while maintaining comfortable living conditions. By utilizing the MBPC method, the building's thermal storage capacity is exploited and future disturbances (e.g., weather and internal heat sources) are considered in the optimization to provide more accurate predictions. In this work, we provide the experimental validation of the energy model and demonstrate the energy-saving benefits of the proposed MBPC compared with other three control methods.

A comprehensive review of theory, advantages, and applications of MBPC in building HVAC system control can be found in [6,7]. Právara et al. [8] use a subspace method to implement model identification and integrate the predictive control algorithm with

* Corresponding author.
E-mail address: paolucci@nd.edu (S. Paolucci).

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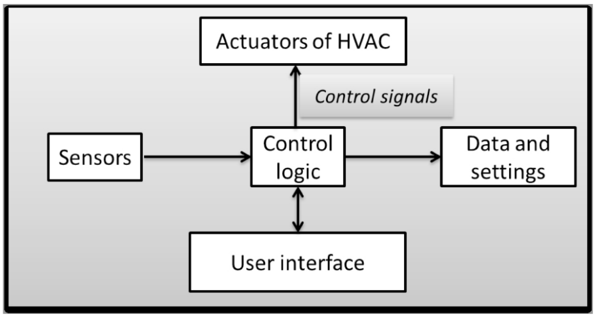

Fig. 1. Structure of a typical thermostat.

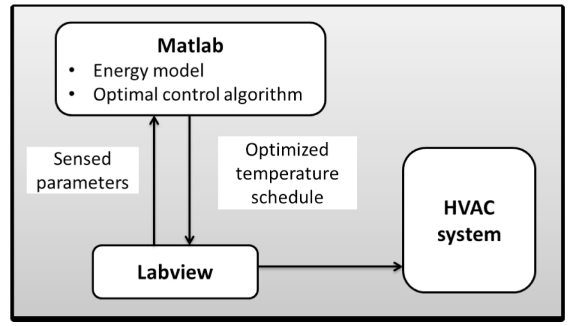

Fig. 2. Experimental thermal-control framework.

a thermal model that only utilizes predictions of outside temperature. The experiment was performed on a large university building yielding a saving of 17–24% compared to a weather-compensated control method. Kolokotsa et al. [9] use a bilinear model-based control in conjunction with a building energy management system to achieve optimum indoor environmental conditions while minimizing energy costs. A parameter identification method is used to determine the coefficients in the characteristic equations, and optimized operations are implemented on window shadings, window openings, lighting system, and air conditioner. Their work demonstrated a satisfactory controller's performance. Ferreira et al. [10] developed a multi-objective genetic algorithm to establish predictive control and the Predicted Mean Vote (PMV) method is used to estimate thermal comfort. The experimental results show an energy efficiency improvement greater than 50%. Castilla et al. [11] present a comparison among several predictive control approaches balancing the tradeoff between thermal comfort and control efforts. They claim that a specific weighting coefficient for the control effort gives the best result based on a variety of experiments in a solar energy research center. Aswani et al. [12] use a learning-based MBPC method that considers a varying heating source due to varying occupancy in the building climate control. The experiment showed a reduction of electricity consumptions at both transient and steady states. Hilliard et al. [13] analyze 19 case studies' advantages of MBPC compared with conventional control strategies, and identify areas that need further improvements. In addition, they develop a set of target parameters for the types of buildings that MBPC can have the most impact on, and propose methods to identify shortfalls. Goyal et al. [14] evaluated two occupancy-based control strategies for a HVAC system in commercial buildings and compared against a conventional baseline controller by performing experiments in a test-zone on the University of Florida campus. They demonstrate that a high degree of energy saving can be realized with simple control algorithms that use real-time occupancy measurements.

In recent decades, programmable thermostats have been commonly used in both residential and commercial buildings to control the heating and cooling systems. A reasonable amount of energy is saved if residents use the thermostat effectively [15]. Fig. 1 displays the internal configuration of a typical thermostat. The temperature sensor embedded in the thermostat measures the indoor air temperature. Based on the difference between this measured temperature and the occupant-defined temperature setpoint, the control logic makes control decisions in heating/cooling and sends control signals to the HVAC system. In addition to the traditional function of regulating the indoor temperature based on a prescribed setpoint, most smart thermostats available nowadays also include the following two functions: enabling remote control through Wi-Fi, which allows users to adjust configurations from anywhere, and an "Auto Away" function, which allows the setting of a temperature setback to reduce heating and cooling operations. Popular products include Honeywell [16], Ecobee [17], and NEST [18]. A study [19] shows that the NEST thermostat saves more energy than a standard programmable thermostat. However, the control decision-making process in all these thermostats is blind to physical information regarding the building, particularly the building's floor plan and the thermal properties of construction materials.

This work is distinguished from past works in three aspects. First, since in the experimental setup, multiple temperature sensors are distributed on the interior and exterior walls and in the interior space of a *q*uarter *s*cale *s*helter (QSS), the temperature measurements are more accurate than those of other works which use few sensors to monitor indoor temperature. This makes the validations of Re-BEAM and MBPC more accurate and reliable. Second, we use an environmental chamber that creates a controllable environment for the QSS, where the environment temperature is regulated and thus making the experiments reproducible. Third, the control performance of using the proposed MBPC is compared with a commercial smart thermostat that is popularly used in residential buildings, thus making the results practically significance.

2. Thermal-control framework overview

BEAM is a program written in Matlab that simulates the dynamics of temperatures and humidities of indoor air and walls of a building and calculates the energy consumption over a specific time period. Re-BEAM is the reduced order model of BEAM. Details regarding BEAM and Re-BEAM are given in [1]. In the MBPC method, Re-BEAM is used for simulations. The inputs to Re-BEAM include the local weather conditions, the building's geometry information, details of construction materials, and occupants information. An optimal control algorithm has been integrated into Re-BEAM to enable MBPC of HVAC systems in buildings [1]. The objective of using MBPC is to optimize the desired temperature schedule so that the energy consumption is minimized while comfort indoor conditions are maintained.

Fig. 2 shows the overall thermal-control framework in the experiments. As can be seen, the function of Labview and Matlab together serves as the "Smart Thermostat." Labview receives information on monitored parameters from the sensors installed in the experimental setup. A user-friendly Labview interface allows the input of desired temperature schedules. Matlab acts as a "schedule optimizer," which runs the Re-BEAM code and the integrated MBPC algorithm. This "schedule optimizer" receives the occupant-defined temperature schedule from Labview, performs the model-based predictive optimization, and outputs the optimized schedule to the Labview program. The temperature setpoint in the optimized schedule is the control variable for the heating/cooling system, and this optimized schedule is presumed to result in minimal energy consumption while satisfying thermal comfort conditions. Note that the use of Labview in the experiments in the present work is to send control signals to the HVAC