Applied Energy 164 (2016) 341–351

Contents lists available at ScienceDirect

Applied Energy

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

Occupant feedback based model predictive control for thermal comfort and energy optimization: A chamber experimental evaluation

Xiao Chen [a], Qian Wang [a,*], Jelena Srebric [b]

[a] Department of Mechanical and Nuclear Engineering, The Pennsylvania State University, University Park, PA 16802, United States
[b] Department of Mechanical Engineering, University of Maryland, College Park, MD 20742, United States

HIGHLIGHTS

- This study evaluates an occupant-feedback driven Model Predictive Controller (MPC).
- The MPC adjusts indoor temperature based on a dynamic thermal sensation (DTS) model.
- A chamber model for predicting chamber air temperature is developed and validated.
- Experiments show that MPC using DTS performs better than using Predicted Mean Vote.

ARTICLE INFO

Article history:
Received 20 August 2015
Received in revised form 31 October 2015
Accepted 29 November 2015

Keywords:
Model predictive control
Thermal comfort
Energy
Occupant feedback
Predicted mean vote
Actual mean vote

ABSTRACT

In current centralized building climate control, occupants do not have much opportunity to intervene the automated control system. This study explores the benefit of using thermal comfort feedback from occupants in the model predictive control (MPC) design based on a novel dynamic thermal sensation (DTS) model. This DTS model based MPC was evaluated in chamber experiments. A hierarchical structure for thermal control was adopted in the chamber experiments. At the high level, an MPC controller calculates the optimal supply air temperature of the chamber heating, ventilation, and air conditioning (HVAC) system, using the feedback of occupants' votes on thermal sensation. At the low level, the actual supply air temperature is controlled by the chiller/heater using a PI control to achieve the optimal set point. This DTS-based MPC was also compared to an MPC designed based on the Predicted Mean Vote (PMV) model for thermal sensation. The experiment results demonstrated that the DTS-based MPC using occupant feedback allows significant energy saving while maintaining occupant thermal comfort compared to the PMV-based MPC.

1. Introduction

Model predictive control (MPC) has shown its potential to reduce building energy consumption while maintain thermal comfort in both simulations [1–8] and experiments in laboratories, class rooms or even entire buildings [9–15]. Furthermore, MPC plays an important role for the renovation of old buildings and design of new low-energy buildings. Renewable energy such as solar, wind, and geothermal energy has been used more frequently nowadays in buildings due to their much lower impact on environment. However, most of the renewable energy could not serve as a stable energy resource alone and usually requires an energy storage system associated with them in order to supplement the electric power. In such applications, MPC has demonstrated a strong capability to utilize power storage in shifting the peak-load and in saving energy [13,16–19].

In addition to energy savings, occupants' indoor thermal comfort is just as important in the design of building thermal control. In many MPC formulations in the existing literature, thermal comfort was often represented simply by air temperature, where occupants were assumed to be comfortable as long as the room temperature was within a certain range [3,5,9,13,20]. However, it is known that thermal comfort also depends on many other factors such as relative humidity (RH), mean radiant temperature (MRT), air velocity, occupants' clothing insulation level, and their activity level, based on Fanger's Predicted Mean Vote (PMV) model [10,21]. Though the existing heating, ventilation, and air conditioning (HVAC) control algorithms seldom directly optimize a PMV index (or use it in a constraint), a numerical study demonstrated that

* Corresponding author at: The Pennsylvania State University, 325 Leonhard Building, University Park, PA 16802, United States. Tel.: +1 (814)8658281; fax: +1 (814)8659693.

E-mail address: quw6@psu.edu (Q. Wang).

http://dx.doi.org/10.1016/j.apenergy.2015.11.065
0306-2619/

using PMV in defining the thermal comfort constraint in an MPC could reduce energy consumption and improve thermal comfort, compared to utilizing a comfort zone from a psychrometric chart [4]. Nevertheless, direct incorporation of the PMV in an MPC design for HVAC systems could also raise several challenges. One concern relates to the additional computational burden due to the iterative computation of PMV. Past work tried to approximate the PMV with a neural network model [11,22,23] or with a linearized parameterization model [24]. A second concern relates to the additional cost of sensing, noting that most buildings typically do not have sensors to continually measure humidity, air velocity and MRT needed to compute the PMV. Even though for laboratory facilities where the aforementioned environmental sensing data are available, occupant clothing insulation and activity levels, which could vary with respect to time and vary among occupants, are seldom monitored continually and individually. Assuming a uniform and constant clothing level for occupants could cause errors in predicting occupant thermal sensations [10]. Furthermore, field studies often showed that there could be a discrepancy between Fanger's PMV and occupants' actual mean vote (AMV) [25]. Finally, occupants' awareness of opportunities to control their environment could affect their perceptions of thermal comfort [26], and occupants did often express their wishes to intervene automated control systems [27]. Though under the current building environment it might not be practical for an individual occupant to directly control HVAC systems to achieve a personalized thermal environment, it is reasonable to assume that there is a feedback channel for occupants to communicate their thermal sensation perceptions to the controller. There has been work on taking into account occupancy schedules and patterns in energy optimization [28]. However, this study, to the best of our knowledge, is the first one to conduct experimental evaluation of HVAC control that uses feedback of occupants' votes on thermal comfort.

Instead of PMV, this study considered a data-driven state-space dynamic thermal sensation model (DTS) developed in the authors' prior paper [29]. The DTS model contains a time-varying offset parameter that adaptively changes its value with respect to perturbations in environmental and occupant-associated thermal conditions using an extended Kalman filter (EKF) with the feedback of occupants' thermal sensation votes. A numerical study was then conducted by the authors in a subsequent paper [30], which indicated that the MPC based on the DTS model (MPC-DTS) could potentially produce better thermal comfort and energy outcomes than the MPC based on the PMV (MPC-PMV). Additionally, both MPCs had better thermal comfort and energy savings than a proportional integral (PI) controller. In this study, we conducted chamber experiments to evaluate and compare the performance of the MPC-DTS and MPC-PMV. The experimental study not only evaluated the feasibility of implementing an occupant-feedback based MPC but also revealed underlying causes that allow the MPC-DTS to achieve a better energy saving and thermal comfort than the MPC-PMV.[1]

This paper is organized as follows. Section 2 introduces the climate chamber setup and describes the identification and validation of a chamber model. Section 3 provides an overview of the DTS model. Section 4 presents the MPC formulation, where both MPC-DTS and MPC-PMV are described. Chamber experiment design is presented in Section 5. Experiment results and analysis are given in Section 6, and conclusions are drawn in the end.

[1] Due to the limitation of the chamber experiments for not being able to run three controllers (two MPCs and one PI) in the same day for a fair comparison, PI control was not evaluated in the chamber study reported in this paper. However, a pilot study comparing a PI to MPCs across different days was conducted and results can be requested by contacting the authors.

2. Chamber setup and chamber model

2.1. Chamber setup

The experiments of this study were conducted in the environmental chamber located in Engineering Unit A building at the University Park campus of the Pennsylvania State University. The chamber has its own HVAC system and is able to simulate different indoor conditions. A schematic drawing of the chamber with its basic dimensions is shown in Fig. 1. Thermal couples, with measurement error within 0.5 °C, are installed in both supply and return ducts of the HVAC system. A BlackGlobe temperature sensor is placed in the middle of the chamber to measure the MRT. The thermistor interchangeability error of the BlackGlobe is less than ±0.2 °C from 0 °C to 70 °C. The measured MRT is collected by a HOBO U12 data logger. This particular model of data logger also includes temperature and humidity sensors. The error for measuring air temperature is less than ±0.35 °C from 0 °C to 50 °C and the error for relative humidity reading is less than ±2.5% from 10% to 90%. Four omnidirectional anemometers are placed to monitor the air velocity. The chamber is set up to mimic a typical office environment and the maximum allowed number of occupants is 4.

Fig. 2 shows a schematic plot of the chamber HVAC system. The HVAC system uses an electric resistance heater for heating and chilled glycol/water mixture for cooling. The chamber's sophisticated measuring and data acquisition system (DAS), along with a dedicated programmable logic controller (PLC), allow to test different HVAC control algorithms.

2.2. Chamber model identification

This study started with developing a heat balance model on the zone air under the EnergyPlus [31] simulation environment. However, the resulting predictions on chamber air temperature from such a heat balance model do not agree with measurements. Hence a data-driven regression model was estimated in the following, based on the collected input and output data with input variables being selected based on the energy balance.

In the experiments (for both chamber modeling and control evaluation), the supply air flow rate was kept at 325 m^3/h (with ±5% variation) and the supply air temperature was controlled by the Allen Bradley PLC control system using a PI control. The air velocity is around 0.1 m/s. Dampers for the outdoor air, exhaust, and recirculation in ducts were set at a constant position so that 10% of fresh outdoor air was mixed with 90% return air. The sources of internal gain consist of a shop light, participants and their laptops or Ipads (one by each participant). The supply air temperature is chosen as the *only control input* in the chamber model. Other inputs to this model, including air temperature outside the chamber and internal gains, are considered to be known and measurable inputs. The *output* of the chamber model is the predicted chamber temperature.

Fig. 3(a) shows the time histories of supply air temperature, temperature outside the chamber, occupancy schedule and the resulting chamber temperature, which are used as the training data for model identification. The supply air temperature initially started at 23.7 °C, then stepped down to 13 °C for ~10 h, raised up to 28 °C for another 10 h, and finally went down to 24 °C for the rest of the time. Since the chamber is located inside an office/classroom building, the temperature outside the chamber varied only slightly within a small range between 22 °C and 24 °C. One person with a laptop entered the chamber at $t = 36$ h and stayed for 6 h till $t = 42$ h, which caused the chamber temperature to increase from 24.7 °C to 25.3 °C.