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Model predictive control for indoor thermal comfort and energy optimization using occupant feedback

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ABSTRACT

This study developed two model predictive control (MPC) algorithms, a certainty-equivalence MPC and a chance-constrained MPC, for indoor thermal control to minimize energy consumption while maintaining occupant thermal comfort. It is assumed that occupant perceptions of thermal sensation can be continually collected and fed back to calibrate a dynamic thermal sensation model and to update the MPC. The performance of the proposed MPCs based on Actual Mean Vote (AMV) was compared to an MPC using Fanger's Predicted Mean Vote (PMV) as the thermal comfort index. Simulation results demonstrated that when the PMV gives an accurate prediction of occupants' AMV, the proposed MPCs achieve a comparable level of energy consumption and thermal comfort, while it reduces the demand on continually sensing environmental and occupant parameters used by the PMV model. Simulation results also showed that when there is a discrepancy between the PMV and AMV, the proposed MPC controllers based on AMV expect to outperform the PMV based MPC by providing a better outcome in indoor thermal comfort and energy consumption. In addition, the proposed chance-constrained MPC offers an opportunity to adjust the probability of satisfying the thermal comfort constraint to achieve a balance between energy consumption and thermal comfort.

1. Introduction

Reducing building energy consumption and providing a better indoor thermal condition not only improves the environmental quality due to reduced emission rate, but also keeps people more productive at work and away from building health related problems. Current building control algorithms are mainly rule based (if-then-else based rules) and thus the performance of a large number of buildings heavily depends on the experience of building managers. In recent years, various advanced control techniques, such as fuzzy logic control [1,2], agent-based intelligent control [3], neural network control [4], optimal control [5], and model predictive control [6–19] have emerged in building control applications.

In particular, model predictive control has gained increasing popularity in utilizing passive or active thermal storage to save energy [7–9]. With weather predictions and occupancy schedules, free cooling at night was used in cooling applications and night setback was adopted for heating applications [7,8]. Peak-load shifting was implemented in MPC to save electricity cost by taking advantage of the time-of-day rate of electricity price [9]. MPC was also applied to determine optimal temperature set-points at the top level of a hierarchical control, for which simple PID or on-off controllers were used for lower-level components such as fans, heating/cooling coils and thermal storage tanks [7]. Alternatively, low level components could be directly managed by a MPC to achieve a higher level of efficiency [11].

While on one hand energy saving is important, on the other hand, occupant thermal comfort plays a key role in the control of Heating, Ventilating and Air Conditioning (HVAC) systems for low-energy buildings. A large number of the existing control algorithms were designed such that the neutral temperature was achieved based on the Fanger's thermal comfort model. Alternatively, the so-called effective temperature, which is a combination of the indoor temperature and relative humidity, could be used as the index for thermal comfort [10]. Though the existing HVAC control algorithms seldom directly optimize a PMV index (or use it as a constraint), a numerical study demonstrated that using the PMV in defining the thermal comfort constraint in a MPC could reduce energy consumption and improve thermal comfort, compared to utilizing a comfort zone from a psychrometric chart [10].

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Nomenclature

AMV	virtual occupants' actual mean vote
A_w	wall area, m^2
α	percentage of violation in chance constraint
C_i	thermal capacitance of ith node in thermal network model, J/K-s
CLO	occupants' clothing insulation
c_{pa}	specific heat of air, J/kg-K
c_{pw}	specific heat of water vapor, J/kg-K
d	offset parameter
e	process noise
G_{int}	internal gain, W
h	convection coefficient, W/m^2-K
h_{in}	outdoor specific enthalpy of moist air, J/kg
h_{out}	indoor specific enthalpy of moist air, J/kg
h_{we}	evaporation heat of water at 0 °C, J/kg
J_t	cost at time step t in MPC formulation
k	conduction coefficient, W/m-K
K_p	proportional gain
K_I	integral gain
l	wall thickness, m
M	metabolic rate
$\dot{m}$	air mass flow rate, kg/s
q	slack variable for constraint
q_{vent_flow}	ventilation heat flow, W
R_{ij}	thermal resistance between node i and j, K/W
RH	relative humidity
T_a	ambient air temperature, K
T_i	temperature of ith node in thermal network model, K
T_o	outdoor air temperature, K
T_{mr}	mean radiant temperature, K
T_N	adjacent room temperature, K
TS	predicted thermal sensation in a generic model
ΔT	sampling time, s
t	time step
u	control input, W
V_a	air velocity, m/s
v	measurement noise
W_{in}	indoor humidity ratio
W_{out}	outdoor humidity ratio
W_s	saturation humidity ratio
w	random noise in AMV
x	thermal sensation state
y	observed mean vote of thermal sensation

However, direct incorporation of the PMV in a MPC design for HVAC systems could pose practical implementation challenges. The calculation of PMV involves iteration, which could raise computation concerns, especially for MPC which is known to be computation intensive. Past work tried to approximate the PMV with a neural network model [4,12,20] or with a linearized parameterization model [21]. In addition, most buildings typically do not have sensors to continually measure humidity, air velocity and mean radiant temperature. 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 [11].

In this study, the MPC problem formulation used a data-driven dynamic thermal sensation (DTS) model developed using occupants' feedback on thermal perceptions [22]. A distinctive feature of this DTS model lies in that the time-varying offset parameter of the proposed Wiener-logistic model can be estimated through an extended Kalman Filter (EKF) using real-time occupant votes to capture the variability of thermal sensation due to environmental or occupant-associated changes. Rather than assuming that a "PMV sensor" exists [10], this study assumed that occupants act as a sensor for indoor thermal comfort and there exists a feedback channel for occupants to provide their thermal sensation votes to the controller. Field studies showed that there could be a discrepancy between Fanger's PMV and occupants' AMV [23]. Furthermore, occupants' awareness of opportunities to control their environment could affect their perceptions of thermal comfort [24], and occupants did often express their wishes to intervene automated control systems [25]. 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.

Replacing Fanger's PMV by such a dynamic thermal sensation model in the MPC formulation enables the proposed MPC design for HVAC systems to adapt to uncertainties and variations associated with occupants' thermal perceptions. In addition, a chance-constrained MPC was also developed using the DTS model, which provides an opportunity for the controller to adjust the probability level of violation of thermal comfort to achieve a balance between energy consumption and thermal comfort.

2. Models

This section presents a data-driven dynamic thermal sensation model and a building model, which were used in the performance evaluation of the proposed MPCs.

2.1. Experiments with human subjects

Chamber experiments with human subjects were approved by the Institutional Review Board at the Pennsylvania State University (IRB # 41077). The experiments were conducted in a climate chamber with its dimension shown in Fig. 1. The chamber was divided into two identical rooms and each room has its own HVAC unit. A HOBO U12 data logger was positioned in the middle of each room to measure air temperature and relative humidity. The mean radiant temperature of each room was measured by the BlackGlobe Temperature Sensor for Heat Stress (BlackGlobe) mounted at the same position as the HOBO U12 data logger. In the experiments, all environmental parameters were controlled to be the same for both rooms of the climate chamber, and both rooms were used at the same time to provide enough space for all participants. Therefore, the chamber can be viewed as a single virtual room and subject votes from the two rooms were not differentiated.

The experiments were conducted in February, with outdoor temperature around 5 °C to 7 °C, and outdoor humidity level around 50%. There were two sessions and each session lasted 2.5 h. In the first session, the room temperature was initially set at 21 °C for 50 min, then raised to 30 °C for another 50 min, and reduced back to 21 °C again for the rest of the first session. The temperature of the second session started at 30 °C for 50 min, then reduced to 23 °C for another 50 min, and back to 30 °C for the rest of the session. The available humidifier was not used to mimic the indoor environmental conditions typical for buildings without humidification. When the indoor air was heated to 21 °C to 30 °C, the resulting relative humidity of the chamber varied between 15% and 25%, with an average of 21%. Since the experiments were designed to model