ABSTRACT

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Title: Development of Self-Tuned Indoor Thermal Environments.

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Operation of typical heating, ventilation, and air conditioning (HVAC) systems has been based on general thermal comfort models. However, because of individual differences in thermal comfort, typical HVAC systems have not been able to achieve high levels of occupants' satisfaction. Moreover, conservative control settings designed for "widely acceptable" conditions have resulted in a high chance of energy waste.

To resolve these issues, HVAC systems have been proposed that can (i) learn their occupants' thermal preferences; (ii) be self-tuned to provide customized indoor thermal environments. This Thesis presents approaches and algorithms for the realization of self-tuned indoor thermal environments and demonstrates their experimental and simulation implementations.

First, this Thesis presents a new data-driven method for learning individual occupants' thermal preferences developed by combining classification and inference problems, without developing different models for each occupant. The approach is fully Bayesian, and it is based on the premise that the thermal preference is mainly governed by (i) an overall thermal stress, represented using physical process equations with relatively few parameters along with prior knowledge of the parameters, and (ii) the personal thermal preference characteristic, which is modeled as a hidden random variable. The concept of clustering occupants based on this hidden variable, i.e., similar thermal preference characteristic, is introduced. The algorithm also incorporates hidden parameters and informative priors to account for the uncertainty associated with variables that are noisy or difficult to measure (unobserved) in real buildings (for example, the metabolic rate, air speed and occupants' clothing level). Experimental results show that the algorithm provides accurate predictions for personalized thermal preference profiles and it is efficient as it only requires a relatively small dataset collected from each occupant.

Second, this thesis presents a self-tuned HVAC controller that provides customized thermal conditions to satisfy occupant preferences (i.e., online learning) while minimizing energy consumption. The evolution of personalized thermal preference models and the delivery of thermal conditions with model predictive control (MPC) form a closed-loop. To integrate these two parts, a new method that always provides a set of lower and upper indoor temperature bounds is proposed. Experimental and simulation results show that the self-tuned controller can (i) significantly decrease the level of occupant dissatisfaction

compared to a baseline MPC controller; (ii) automatically adjust the system based on comfort-energy trade-off tuning.

Finally, this thesis presents a Bayesian modeling approach which allows incorporating voluntary feedback data (comfort-related responses), collected via participatory interfaces, along with requested feedback data, into the thermal preference learning framework. The incorporation is done by explicitly considering occupants' participation –a type of behavior –in the model. The approach is evaluated with data from real occupants and a smart feedback request algorithm is developed, which determines whether to request feedback at any given time based on the quantified value of the request. Simulation results show that effective -but less-intrusive- user-interfaces can be developed, utilizing the developed models and algorithms for smart and human-centered HVAC operation.