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DEMAND-DRIVEN BUILDING CONTROLS: A FRAMEWORK AND LESSONS LEARNT

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ABSTRACT

Demand-driven building control is an emerging approach to mitigate the increasing pressures on buildings and facilities for requirements of energy and comfort services. This study proposes a framework that integrates online learning capabilities to make building systems adapt to occupants' actual energy and comfort demand. Based on the framework, two types of control strategies are developed: occupancy-based and thermal-preference-based demand-driven controls. Both of them have been implemented in an office building, keeping occupants in the loop of building operation under realistic conditions. This paper first introduces the proposed framework, and then presents two types of controls applied in for a case study. Lastly, lessons learnt from conducting them in the field tests are discussed.

Keywords: smart buildings, occupant behavior, thermal comfort, demand response, machine learning

NONMENCLATURE

Abbreviations	
HVAC	Heating, ventilation, and air-conditioning
PID	Proportional-integral-derivative
BMS	Building Management System
HMI	Human-machine interface

1. INTRODUCTION

Globally, heating, ventilation, and air-conditioning (HVAC) in buildings are critical services, consuming significant amounts of energy and providing comfortable indoor environment for occupants.

Occupant behavior in buildings such as presence, absence, and preferences on the local indoor climate has a significant impact on energy use of building operation and occupants' thermal comfort. The conditioned rooms are not always fully occupied by occupants, especially in office buildings [1,2]. This kind of occupant behavior could cause more energy to be consumed by building systems during non-occupied hours than during occupied hours [3]. Moreover, occupants' thermal preferences are individual, as they are influenced by time of day, age, sex, and culture [4,5]. Instead of deploying average thermal comfort for the built indoor environment, creating occupant-centric indoor climate based on occupants' thermal preferences can improve their comfort satisfaction. Therefore, having a better understanding of occupant behavior and preferences is crucial to achieving both occupant comfort and energy-efficient building operation. This paper proposes a framework for demand-driven building controls, and discusses lesson learnt from a case study.

2. FRAMEWORK

Controlling HVAC systems to respond to occupants' actual requirements on energy and comfort is a challenging task. First, occupants' demand for energy services is variant because their presence and absence are highly stochastic within buildings. Likewise, their perception of comfort is individual and subjective, influenced by dynamic conditions. Second, HVAC control systems should have adaptive capabilities for dynamic, time- and space-varying contexts, with the objective of reducing engineering and implementation costs.

For these challenges, we propose a framework [6] embedding online learning capabilities for HVAC system controls. It is designed to integrate a two-layer control scheme: high-level control and local control, as shown in Fig 1. The intelligent demand-driven control adapting to occupant behavior is employed for the high-level control. It determines control commands (temperature setpoints and operational modes) over time for the local control by learning occupants' actual demand on energy and comfort services under relevant environmental contexts.

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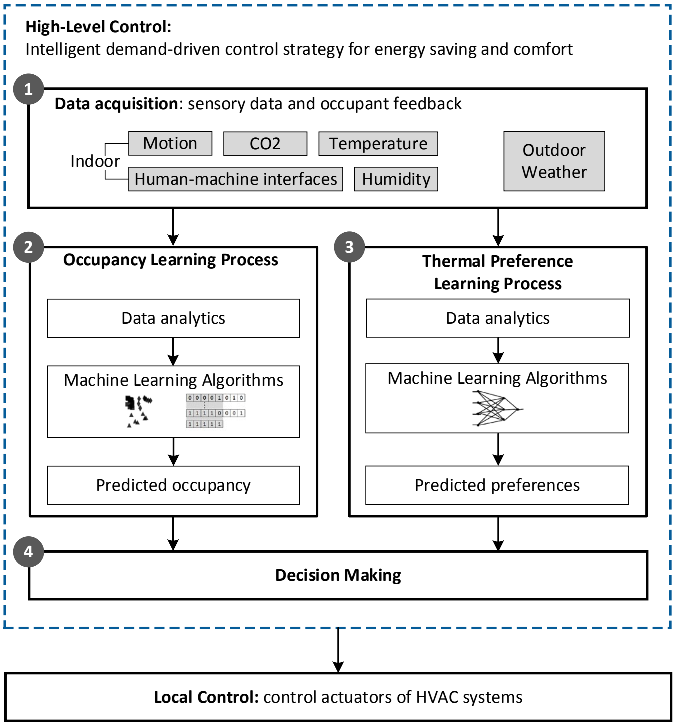

Fig 1. Framework for demand-driven building controls

According to the control commands specified by the high-level control, the local control with proportional-integral-derivative (PID) algorithms is in charge of adjusting actuators to maintain indoor space at an approximately constant climate level.

For the high-level control, four modules are deployed into three sub-layers to achieve demand-driven control:

- **Data acquisition (Module 1):** Collects sensor data and occupant feedback from the space controlled, as provided from a Building Management System (BMS) or from sensing infrastructure directly.
- **Learning processes (Modules 2 and 3):** Process sensor signals into the required information and maintain datasets that store historical and current data. Machine-learning algorithms are employed to learn room occupancy and occupants' thermal preferences from the prepared datasets.
- **Decision making (Module 4):** Determines time-dependent commands for the local control, according to the occupants' current and predicted behavior provided by the above modules.

3. CASE STUDY

Based on the proposed framework, two types of demand-driven strategies have been developed to improve energy efficiency and thermal comfort during building operation. The first type is occupancy-based demand-driven control, consisting of Modules 1, 2, and 4 in the high-level control together with the local control. It aims to make HVAC systems adapt to room occupancy for saving energy without compromising room temperatures during occupied periods. The second type is thermal-preference-based demand-driven control with the purpose of enhancing occupants' indoor thermal comfort. For the latter, a thermal preference learning process in Module 3 replaces Module 2 that based on the occupancy learning process.

To obtain realistic results and to validate the effectiveness of the proposed approaches, the controls have been implemented in an office building under real-world use conditions. To make controls more 'generic' to actual buildings and avoid expensive cost for the building operation, the data used for the controls is selected from standard sensing units, including occupant movement, human interaction with the conditioned environment, indoor and outdoor climate. To evaluate energy-saving potentials, each room is equipped with one or two energy meters to record cooling energy usage.

The high-level controls in this study have been coded in MATLAB and executed on a workstation with network access to a BMS of the case study building. Throughout the field tests, the high-level controls ran in "while" loops on the workstation to read and process sensor signals, learn occupant behavior and preferences online while at the same time—updating datasets, and infer real-time control commands for the local controllers.

3.1 Occupancy-based demand-driven control

Using the case study, two different occupancy-based demand-driven control strategies were developed and conducted in the building [1,2]. Three commonly used sensing units are selected to measure required data: temperature sensors for monitoring indoor climate, passive-infrared motion sensors for extracting room occupancy, and human-machine interfaces (HMI) for occupants to view and modify temperature setpoints.

For the first control strategy in [1], an occupancy learning process is embedded to predict occupants' next presence and duration in the remainder of the current day. In this process, a supervised learning algorithm (k-nearest neighbor) is used to learn room occupancy from the datasets captured from the individual rooms. Then the predicted information is used by rules specified in the decision-making module to infer temperature setpoints of the comfort and setback modes for the local controllers to adjust room temperatures.

To further explore occupant behavior for improving the operational performance, the second occupancy-

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based demand-driven control extracts more occupancy-relevant features from the motion signals [2]. These features were defined into three categories: time-based, quantitative, and deviation features. They are then used by two learning sub-modules in the occupancy learning process: occupancy pattern learning, and occupants' next presence and duration learning. To recognize occupant patterns without manually labeling data, the first learning sub-module uses an unsupervised learning algorithm (i.e. k-means) to cluster them. The clustered occupancy patterns are transformed into two types of datasets: global and local training datasets. According to the occupancy-related features in the current day, the second learning sub-module selects the final training dataset from the datasets clustered by the first learning. It then predicts the occupancy information using the k-nearest neighbor algorithm. Finally, rules defined in the decision-making module use the predicted occupancy information to determine comfort, idle (1°C higher than the comfort), deep idle (0.5°C higher than the idle), and economy (shut down systems) temperature setpoints for the local controllers to control the cooling systems.

Fig 2 displays examples of thermal distributions of 11 rooms in two moments of a day during the experiment. The cooling systems in half of the rooms have entered into the setback mode at 5 pm to saving cooling energy as their occupants are not in the offices or are highly likely not to return on the current day. Across the entire space, the experimental results of the proposed occupancy-based demand-driven controls reported up to 21% energy savings as compared to the operational mode using standard schedules to control the HVAC systems. Both field tests indicated that the energy-saving potentials were inversely correlated to the occupancy rates of the individual rooms. More Energy was saved in meeting rooms and single-person offices than in multi-person offices. The change of the temperature setpoint in a space using the available HMI was used to infer occupant satisfaction with the thermal environment. During the test period of the first occupancy demand-driven control, the temperature setpoint was only modified once by an occupant [1]. During testing of the second strategy, the temperature setpoints were not adjusted by the occupants throughout the entire test [2].

3.2 Thermal-preference-based demand-driven control

To reduce the amount and types of sensors necessary, the thermal-preference-based demand-driven control in [5] first extracts the most effective features from each category of time, indoor and outdoor climates, and occupant behavior. Based on the selected features (hour of day, outdoor and indoor temperatures, and room carbon dioxide concentration), preference-related and noise data is defined to construct the final datasets in the thermal preference learning process. Previously evaluated for performance among four different machine-learning algorithms, the learning process uses a two-layer feed-forward neural network for supervised learning of occupants' thermal preferences. Finally, the thermal preference models of the individual rooms and rules defined in the decision-making module are used to infer real-time temperature setpoints for controlling room temperatures.

The field test in the office building indicated that occupant thermal preferences differed from each other in both time horizon and temperature levels (a 4.5°C temperature difference). The results reported 4%-25% energy consumption reduction as compared to static temperature setpoints at the low values of the preferred temperature range. During the field test, the control strategy successfully reduced occupant interventions in adjusting room temperatures to fit their thermal preferences. The interventions were reduced to a maximum of one daily occurrence per month from four to nine daily occurrences per month.

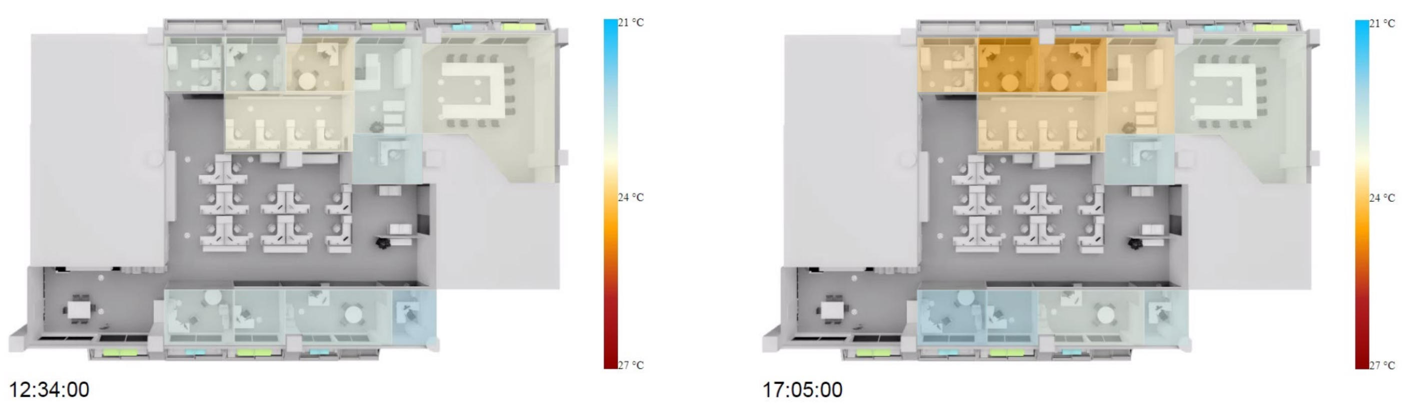

Fig 2. Thermal distributions of the case study rooms during the filed test

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4. LESSONS LEARNT

The proposed occupancy-based and thermal-preference-based demand-driven controls, as explored in the case study, demonstrate energy savings potentials and indicate improvements regarding the comfort of the office occupants. The proposed framework features the following advantageous traits:

- **Cost consideration:** To avoid costly implementation and maintenance for sensing infrastructure, the framework operates using standard building sensors and HMIs, which usually exist in conditioned buildings or can be installed without high costs.
- **Features and datasets:** According to multiple features selected from the sensor signals, the case study provides valuable views on structuring datasets for modeling occupant behavior: first defining the concepts of global and local training datasets, preference-related and noise datasets.
- **Online learning:** The proposed framework embeds learning capacities to allow HVAC systems to respond to different room conditions with fewer human interventions during the engineering and implementation phases. Meanwhile, the data-driven learning processes can re-learn from new data captured from local rooms to adapt to changes of occupants' demand during standard operation.
- **Scalability:** In a broader sense, the proposed framework can be extended to other building systems to realize demand-driven or occupant-centric design and operation.

In addition to the above discussion, this study finds the following aspects also important to discuss advanced control strategies such as the ones proposed.

Deployment and upgradability: More sophisticated algorithms are hard to deploy into local controllers due to limits of onboard computing and memory resources [1]. In order to embed demand-driven approaches and control a much larger number of rooms adapting to complex applications, advanced algorithms in the high-level control layer could not only be coded in a computer-based workstation, but could also be embedded in the BMS directly as application functions or be deployed into cloud computing services. Such deployment can achieve an agile upgrade of functions in the high-level control without additional development on hardware and software of local controllers.

Data communication: The reliability of data communications between sensing infrastructure, controls, and actuators is critical for daily operation. In this study, a primary fault detection such as for lost connection has been coded into the control strategies to generate alarms and recover the connection. For large-scale applications, improving the communication reliability of the sensing, actuators, and communication technologies themselves is also relevant.

Short presence: An additional 2%-6% energy saving could be achieved by keeping setback setpoints when short presence occurs in the periods of the setback mode [2]. Future research on distinguishing short presence from all types of presence that occur in buildings will offer the possibility to bridge this saving gap.

Shared space: For spaces with larger numbers of occupants (e.g. an open office), further considerations of what proportion of the space is occupied, occupants' conflicting interests regarding the indoor climate, and a suitable spatial resolution of HVAC supply are required and critical for such strategies.

Privacy: In this study, all occupant-related and corresponding climate data was not tagged to individual occupants in order to ensure appropriate privacy. For research on and application of occupant-centric approaches, privacy need to be considered from design to operation.

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