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Occupancy learning-based demand-driven cooling control for office spaces

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A B S T R A C T

Occupancy in buildings is one of the key factors influencing air-conditioning energy use. Occupant presence and absence are stochastic. However, static operation schedules are widely used by facility departments for air-conditioning systems in commercial buildings. As a result, such systems cannot adapt to actual energy demand for offices that are not fully occupied during their operating time. This study analyzes a seven-month period of occupancy data based on motion signals collected from six offices with ten occupants in a commercial building, covering both private and multi-person offices. Based on an occupancy analysis, a learning-based demand-driven control strategy is proposed for sensible cooling. It predicts occupants' next presence and the presence duration of the remainder of a day by learning their behavior in the past and current days, and then the predicted occupancy information is employed indirectly to infer setback temperature setpoints according to rules we specified in this study. The strategy is applied for the controls of a cooling system using passive chilled beams for sensible cooling of office spaces. Over the period of two months both a baseline control and the proposed demand-driven control were operated on forty-two weekdays of real-world occupancy. Using the demand-driven control, an energy saving of 20.3% was achieved as compared to the benchmark. We found that energy savings potential in an individual office was inversely correlated to its occupancy rate.

1. Introduction

The latest 5th Assessment Report of the Intergovernmental Panel on Climate Change has indicated that anthropogenic greenhouse gas (GHG) emissions will continue to cause further warming of the Earth's surface and cause long-lasting changes to the world's climate system. The contribution of buildings to global energy use and energy-related GHG emissions are, in fact, significant. Globally, buildings in the residential, commercial, public and service sectors accounted for about 35% of total final energy use and were associated with 18.4% direct GHG emissions and indirect carbon dioxide (CO2) emissions (e.g. electricity) in 2010. Moreover, building-related energy demand is projected to increase by about 50% between 2010 and 2050 [1–3].

The main services consuming energy in buildings are space heating, ventilation, and air-conditioning (HVAC), domestic hot water, lighting, and electrical appliances. HVAC alone accounts for the largest share. Worldwide, HVAC services account for approximately 40% of total energy consumption in buildings [4]. In particular harsh climate, such as the tropical context of Singapore, HVAC accounts for over 50% of the building stock's electricity consumption [5].

Improving the energy efficiency and utility of existing and future HVAC systems will, therefore, be an important objective for developing future low-carbon economies. Developing a better understanding of occupants' behavior in buildings will also be an increasingly important concern in this process. The presence and absence of building occupants indicate whether indoor spaces are required to be air-conditioned or not. Building HVAC systems need to provide comfortable indoor conditions when the building spaces they serve are occupied. On the other, they do not need to ensure indoor conditions are comfortable with spaces unoccupied [6]. Whilst this may be intuitive, the poor anticipation of occupant behavior has been found to increase building energy consumption by a third [7]. Furthermore, not all occupants in buildings are sufficiently aware of this or other energy saving initiatives, especially in commercial buildings, as energy costs are not directly paid by

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Nomenclature

Abbreviations

GHG	Greenhouse gas
CO2	Carbon dioxide
HVAC	Heating, ventilation, and air-conditioning
RFID	Radio frequency identification device
KNN	K-nearest neighbor
HMM	Hidden Markov model
M	Multi-person office
P	Private office
HMI	Human machine interface
DOAS	Dedicated outdoor air system
FCU	Fan coil unit
PCB	passive chilled beam
AHU	Air handling unit
PID	Proportional-integral-derivative
WSI	Web service interface
REST API	Representational state transfer, application programming interface
M-Bus	MeterBus
TD	Time delay
RBC	Rule-based control
BMS	Building management station
DCC	Demand-driven cooling control
MID	The measuring instruments directive
COV	Change of value
IMBPC	Inteligent Model Based Predictive Control
PIBCV	Pressure-independent balancing and control valve
CDD	Cooling degree-days
S1	Six offices that are used to evaluate the sensible cooling energy gap
S2	Six offices for the DCC study: P1, P2, P3, P4, M1, M2
CPU	Central processing unit
RAM	Random-access memory
RC	Resistance-capacitance
LCD	Liquid crystal display
VAV	Variable-air-volume

Symbols(unit)

T_{sp}	Temperature setpoint (°C)
T_{air}	Air temperature (°C)
N_x	The number of vacancy days in past x days
S_{td}	The size of the training dataset
K_{value}	The value of K
$P_{thrshld}$	The threshold of the occupancy possibility
t_{np}	Time of next presence (minute)
t_{dcc}	The time at which starting the demand-driven cooling control (minute)
t_{sd}	The time at which the facility department shuts down the air-conditioning system in the case study space (minute)
t_{arr_lmt}	The time at which the cumulative probability of the first arrivals is equal to a specified value (minute)
t_{dprtr_lmt}	The time at which the cumulative probability of the last departures is equal to a specified value (minute)
t_{drtn}	Presence duration of the remaining day (minute)
t_{drtn_lmt1}	The first threshold of presence duration (minute)
t_{drtn_lmt2}	The second threshold of presence duration (minute)
E_{nbl}	Normalized daily average cooling energy use of a room (kWh)
E_{bl}	Measured daily average cooling energy use of a room (kWh)
S_r	The area of a room (m^2)

them [8].

There are two features of conventional HVAC systems that have historically made it difficult for these systems to automatically respond to the stochastic nature of occupants' behavior in buildings [9,10]. The first regards to the behavior of physical controllers in existing HVAC systems, employing mostly two-position (i.e. on and off) control or proportional, integral and derivative (PID) control to keep indoor climates conditioned to temperature, humidity, and CO2 setpoints [11]. The second is the use of scheduled occupancy profiles to assign operating hours of HVAC control systems in commercial buildings.

Demand-driven control is an emerging HVAC control strategy that has shown promising results in coordinating real-time HVAC use to occupant presence and vacancy, reducing energy use and maintaining indoor thermal comfort in buildings [10,12–14]. Energy savings can be achieved by decreasing the temperature difference between the air-conditioned indoor climate and the outdoor weather or reducing the operating time of HVAC systems [15]. In the same manner, demand-driven HVAC control strategies decrease heating temperature setpoints or increase cooling temperature setpoints when spaces are unoccupied, and they keep the indoor spaces at comfortable levels when they are occupied. Furthermore, a demand-driven control system can automatically deactivate an HVAC system after the occupants have left a building instead of waiting for scheduled shutdown times.

Central to the effective implementation of a demand-driven HVAC control strategy is information on: 1) real-time occupancy and 2) upcoming room occupancy [10,14]. Networks of occupant-monitoring sensors are essential to measure occupants' behavior, while, at the same time, algorithms with learning capabilities are crucial for predicting future room occupancy. Prior research has shown that HVAC systems incorporating these features have yielded significant energy savings potential.

For instance, in a residential application, Scott et al. [12] developed a preheat heating system to anticipate to occupants' demand. They used radio frequency identification devices (RFID) and motion sensors to monitor real-time room occupancy status and utilized the K-nearest neighbor (KNN) algorithm to develop an occupancy forecast. Their control system then modified room temperature setpoints to preheat homes according to the expected occupancy periods. Test results showed that, on the implementation of this method, total gas consumption for heating decreased by 8%–18% over a 61-day period. Lu et al. [13] explored the energy-saving potential of a similar application in an EnergyPlus [16] simulation environment. They collected data from motion sensors and door sensors installed in each room of a house to generate room occupancy information, and they used a Hidden Markov Model (HMM) to forecast the probability of occupants' behavior (i.e. sleep, active, and not in the home) according to the generated occupancy datasets. Their simulated result produced an average energy reduction of 28% for cooling and heating over 14 days in summer and winter.

As more and more occupants in offices adopt flexible work hours [17], the total scheduled operating time of HVAC systems