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Application of mobile positioning occupancy data for building energy simulation: An engineering case study

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ABSTRACT

Occupancy data is a critical input parameter for building energy simulation since it has a big impact on the precision and accuracy of building energy model performance. However, current approaches to get such data through the conventional occupancy detection technology require either implementation of a large-scale sensor network and/or sophisticated and time-consuming computational algorithms, which to some degree limits the application of the real-time occupancy data for building energy simulation. In the era of the mobile internet, the massive people position data, which is generated by smartphone users and stored on cloud servers, offers a potential to solve this important problem. Such mobile data source is precisely monitored, real-time updated, and accessible with affordable time and labor cost upon customer's agreements in some regions, and therefore could be one of the alternatives to traditional occupancy detection methods.

This paper presents an investigation of whether and how the mobile-internet positioning data can benefit building energy simulation. This paper first summarizes the pros and cons of several mainstream occupancy detection methods. Then, the principle of the proposed mobile-internet-based occupancy detection method is introduced. The methodology of using such occupancy data for building energy simulation is developed. An energy performance model of a complex building in Shanghai with a whole building simulation software EnergyPlus is used as a pilot case study to demonstrate the effectiveness of the proposed methodology. A calibration is performed using the building automation system data and the mobile-internet-based occupancy data. The simulation results show that mobile-internet-based occupancy data can help improve the building model prediction accuracy.

1. Introduction

The building sector is responsible for approximately 40% of total energy consumption in the world [1,2]. Among that part, nearly more than one half is used to support the operation of building heating, ventilation, and air-conditioning (HVAC) systems [3]. Such a significant level of consumption urges us to unravel the complexity of building's thermal behavior to optimize building operation and reduce building energy consumption [4]. Building energy performance simulation is one of the most powerful analytic tools to fulfill this purpose. A typical building energy model needs a number of inputs deriving from a wide range of fields including weather file, heating and cooling source, lighting, plug equipment, ventilation, etc. The accuracy of these inputs directly determines the credibility and effectiveness of the simulation results [5,6].

Recent studies show that building energy usage is highly correlated to the occupancy [7]. People influence building performance by both their presence and behaviors as illustrated in Fig. 1. Andersen et al. [8] conducted a simulating study to investigate the relationship between occupant behaviors and building energy consumptions. The results suggested that occupants' opening window behavior had a large effect on building energy usage. Yu et al. [9] examined the influences of the occupant behaviors on building energy usage with a basic data mining technique (i.e., cluster analysis). The authors organized similar buildings among all the investigated cases into various groups based on four user-behavior-unrelated factors. Grey relational grades were used as weighted coefficients of attributes in the cluster analysis. The results revealed that occupant behavior led to a huge difference in Energy Usage Intensity (EUI). A large variability of end-use loads that ranged from close to zero to about four times of the mean value was introduced

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Nomenclature

Variables, parameters, and indices

a_n	Fourier coefficients
AVG	Average value
b_n	Fourier coefficients
(CV)RMSE	Coefficient of variation of root-mean-square error
i	Parameter/input variable index
M	Monitored value
MBE	Mean bias error
MBE_{month}	Monthly data
MBE_{year}	Yearly data
n	Number of inputs
R	Coefficient of determination (R-squared value)
RMSE	Root-mean-square error
S	Simulating value
SC	Shading coefficient
ST_{summer}	Summer temperature setpoint
ST_{winter}	Winter temperature setpoint
U	Rate of heat transfer, W/(m2.°C)
VT	Visible transmission
x	Hour of the day
y	Target value of the regression
$\hat{y}$	Predicted value of the regression

Greek letters

ω	Angular frequency

Abbreviations

AEC	Architecture, engineering, and constriction
AMY	Actual meteorological year
ASHRAE	American Society of Heating, Ventilation, and Air-conditioning
BAS	Building automation system
COP	Coefficient of performance
EPD	Equipment power density
EUI	Energy usage intensity
FCU	Fan coil unit system
GPS	Global positioning system
HVAC	Heating, ventilation, and air-conditioning
LPD	Lighting power density
MPC	Model predictive control
PIR	Passive infrared sensor
TMY	Typical meteorological year
URE	Use range error
VAV	Variable air volume system

by occupant behaviors. Frauke et al. [10] applied a model predictive control (MPC) algorithm to analyze the energy saving potentials by using the dynamic occupant information for HVAC control. The results showed that the energy savings could be as high as 50% compared with the baseline cases which used occupancy for controls. In addition, an energy saving of 20% was also observed when the occupancy based demand response HVAC control strategy was performed [11]. Other occupancy-based HVAC control studies can also be found in Refs. [12–16].

Although the importance of occupancy information has become a common understanding of the HVAC community, there still lacks a time- and cost-efficient approach to obtain such data. Currently, the occupancy-related inputs of energy model are mainly acquired from the building codes or design manuals of different countries and organizations. This data source is derived based on the statistics and an assumption that buildings with the same type share similar occupancy

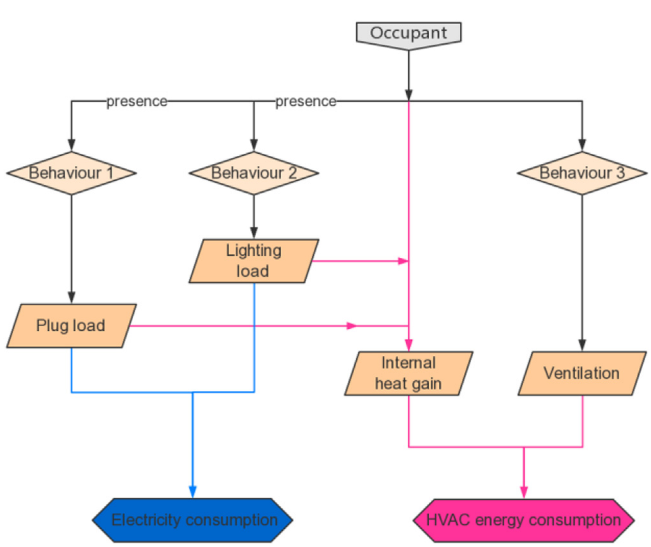

Fig. 1. The influences of occupants on building energy consumption [18].

schedules and densities. When such code-based method is applied, buildings are organized into various groups based on their types and other properties. Thus, through surveying the occupancy profiles in the sample buildings, we can get an averaged description of the occupancy in different building types. This method has been proved to be able to significantly reduce the workload to create an energy performance model since it offers a convenient and moderately accurate source of building occupancy information without requiring practitioners to conduct building surveys one by one.

However, using code-based occupancy inputs for building energy model has a deadly intrinsic problem: they are homogenous and static. So, although in general, it can be applied to buildings with the same type, when it comes to a specific case within the group, the accuracy may not be credible enough. And considering that the occupancy has such a profound influence on building energy consumption, inaccurate inputs associated with occupancy could have large contributions on the discrepancy between the simulated and measured energy consumptions. This mismatch weakens the credibility of the modeling results. Hence, more efforts are required to calibrate the model. Actually, Chang and Hong [17] pointed out that among the wide range of variables which affect building simulation results, the occupancy data is one of the most important ones to cause a model distortion.

Nowadays, to better refine and calibrate building energy performance model for a specified building, how to quickly obtain accurate input associated with occupancy information remains a challenging problem. As usual, two occupancy-related inputs, i.e., occupancy density and occupancy schedule, are required to identify the occupancy pattern of a building in traditional whole building energy simulation program such as EnergyPlus [19], eQUEST [20], and TRNSYS [21]. An occupancy schedule is a set of fractional multipliers which provides values for a 24-h period, starting at midnight. While an occupancy density is a constant parameter representing the maximum occupancy capacity of an occupied zone. It could be expressed as the number of people for a given zone or the number of people per the zone floor area. The product of two parameters gives the occupant number of a specific time for a given zone. For example, if an occupancy density is 200 people in a given zone, a schedule value of 0.5 means that 100 people are assumed to be in that zone at that time.