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Experimental assessment of room occupancy patterns in an office building. Comparison of different approaches based on CO_2 concentrations and computer power consumption

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HIGHLIGHTS

- Considered occupancy indicators: CO_2 concentration and computers power consumption.
- Accurate occupancy time is estimated from CO_2 concentration in low occupancy rooms.
- Increments of CO_2 concentration showed bad performance identifying room occupancy.
- Computer power consumption gave accurate occupancy patterns and number of users.
- Agreement of results from 1 month and 7 years data evidences robustness of results.

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ABSTRACT

This paper reports on various options for estimating room occupancy levels in an office building from the results of testing, and aims to find an efficient way to represent this occupancy, optimizing accuracy, cost effectiveness and the intrusiveness of measuring, which is very useful for commercial applications.

CO_2 concentration and computer electricity consumption were considered alternative indicators of occupancy level. Advantages and drawbacks of both indicators are discussed.

In both cases, ranges when the room was positively empty and when it was positively occupied were identified. This study is based on histograms that represent indicator measurements in each of those ranges during the study period. Afterwards, the ranges identified were used to find room occupancy patterns. Information previously available about the rooms, such as typical work hours, and lunch hours, holidays, weekends, etc., when rooms are empty were used to validate the results.

Data were from a seven-year series acquired while the building was in regular use. The first analysis considers all of these available data making results robust. Accuracy with shorter experimental test periods was also studied.

1. Introduction

The construction industry, which accounts for about 40% of total final energy consumption, has significant potential for energy saving and CO_2 emission reduction. A growing interest in promoting energy efficiency in buildings has led to progressive regulation, highlighting the need to increase knowledge of the energy performance of buildings and driving research activities in this field. Most compliance checking and labelling of the energy performance of buildings is currently done in the design phase by theoretical calculation. However, studies have shown that a building's performance may deviate significantly from this theoretical calculation, as reported in several publications ([1–3], etc.). A review of the literature in Ref. [4] discusses this performance gap and concludes that it can only be bridged by a broad, coordinated approach combining model validation and verification, improved data acquisition, better forecasting, and change in industry practice. Collaborative research on the performance gap has been undertaken in the international context of IEA EBC Annex 58 [5] and in Annex 71 [6]. Further research including full-size dynamic testing, data analysis and simulation is necessary to address this gap and to improve the reliability of building energy performance assessment procedures and simulation design tools, and to support regulation and standardisation for energy saving in buildings [7]. Real building energy consumption is one of the high-priority research and

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innovation themes defined in the IEA EBC Strategic Plan 2014–2019 [8]. The complex relationship between a building and its occupants must be understood to improve design tools for accurate energy consumption prediction. This issue is dealt with in CIBSE Technical Memorandum 54, [9], explaining the importance of accurate estimation of operating hours and probable building occupancy.

A building's occupancy pattern and the energy supplied to it by the metabolic activity of its occupants are relevant inputs in models used for control and energy performance assessment applications in occupied buildings. Accurate estimation of the contribution from metabolic activity to the energy balance of occupied spaces is very difficult. The main difficulties are related to determining how much energy each user supplies, and how many users there are in these spaces. The usual assumptions and approximations used to estimate these contributions lead to high uncertainty budgets of the estimated model parameters and outputs. Occupancy patterns are also significant because of occupant-building interaction through control systems. The significance of occupancy patterns for complete understanding of energy efficiency and comfort are described in Ref. [10], which suggests that the prediction and assessment of energy per occupant may have an important future role in bridging the gap between energy performance and comfort.

Several studies related to measurement and modelling of occupancy patterns have recently been published. Most are related to simulation of occupant presence and behaviour [11–14]. Some highlight the need for a suitable occupancy model for accurate prediction [15]. An algorithm described in Ref. [16] for simulating occupant presence can be included as input in occupant behaviour models in building simulation tools. By considering occupant presence as an inhomogeneous Markov chain interrupted by occasional periods of long absence, the model generates a time series of presence (absent or present) of each of a zone's occupants for every zone in any number of buildings. A wide variety of applications, including occupancy and occupant behaviour simulations, have been reported. For example, Yun et al. [17] proposed models for thermal performance assessment of a naturally ventilated building, Widén et al. [18] reported on its application to lighting demand for the amount of daylight available, Widén and Wäckelgård [19] presented a modelling framework that generates domestic electricity demand, Zhaoxia et al. [15] propose a prediction model for energy consumption, Ding et al. [20] evaluate dynamic interior cooling loads, and Baetens and Saelens [21] described a district energy simulation tool integrating receptacle load, internal heat gain, thermostat settings and hot water tapping models, as well as the uncertainties in such simulations.

Some studies have used information from surveys to calibrate or identify models. A bottom-up modelling approach including a set of calibration methodologies presented in Wilke et al. [22] predicts residential building occupants' time-dependent activities for use in dynamic building simulation. The stochastic model predicting activity chains is calibrated using time-use survey data. It introduces a statistical approach for modelling transitions between two successive types of activity as a Markov process. A probabilistic model developed in Aerts et al. [23] generates realistic occupancy sequences that include three possible states: (1) at home and awake, (2) asleep or (3) absent. This article reports on the methodology used to construct this occupancy model based on a time-use survey and identifies seven typical occupancy patterns using hierarchical clustering.

Very few studies have considered occupancy sensing and data-based analysis or modelling. The work reported in Ref. [24] proposed a simple algorithm using indoor carbon dioxide concentrations to provide estimated occupancy profiles in office buildings. It concluded that the method proposed is well-suited for the detection of arrivals and departures of employees working in closed-space offices. Two data-mining learning processes proposed in D'Oca et al. [25] extrapolated office occupancy and window operation behaviour patterns from a two-year dataset from 16 offices in a building with natural ventilation. Clustering procedures, decision-tree models and rule induction algorithms were employed to find association rules to distribute building occupants into working user profiles, which can be further implemented as advanced occupant behaviour inputs in building energy simulations. A data-driven interior environment model for occupancy prediction using machine learning techniques was developed in Ryu and Moon [26]. Indoor and outdoor CO_2 concentrations and electricity consumption by lighting and appliances were used in a data-mining study. The model was based on a decision tree and hidden Markov model algorithms. A supervised learning approach for estimating the number of occupants in an office setup proposed in Amayri et al. [27] resulted in a virtual sensor relying on other sensors, but with superior performance. Movement counters using PIR sensors, power consumption sensors, CO_2 concentration, a microphone and door-opening contacts were found to be the best sources of information. The method introduced in Ref. [28] distinguishes heat sources using a priori knowledge of their dynamics. This promising method for identifying occupancy rates provides numerical and experimental evidence from such sources.

Many issues must be addressed in this area of research, which at present is very active, as indicated by several recently published reviews [29–32]. In Ref. [29], research on adaptive occupant behaviours is sorted in three categories. The first group encompasses all observational studies, the second group modelling studies, and the third group simulation studies. It presents the methodologies used in these studies, discusses the limitations associated with their application, and develops recommendations for future work. It remarks that occupant models are typically simulated as discrete-time Markov processes. The review in Ref. [30] outlines state-of-the-art research, current obstacles and future needs and directions for a four-step iterative process: (1) occupant monitoring and data collection, (2) model development, (3) model evaluation, and (4) model implementation in building simulation tools. It identifies major issues including the need for greater rigor in experimental methodologies, detailed honest reporting of methods and results, and development of efficient means of implementing occupant behaviour models and integrating them in building energy modelling programs. The review in Ref. [31] introduces the most recent advances and current obstacles in modelling occupant behaviour and quantifies its impact on building energy use. The major subjects discussed are advances in data collection techniques, analytical and modelling methods, and simulation applications providing insights into behaviour energy savings potential and impact. It concludes that there has been growing research and applications in this field, but significant challenges and opportunities still lie ahead. Yang et al. [32] review occupancy sensing systems and occupancy modelling methodologies for application in institutional buildings, and lists the pros and cons for further consideration. It concludes that a more simplified and accurate methodology should be the research target of future studies.

Several working groups collaborating in an international context are working to address some of these points. One of them is the ASHRAE Multidisciplinary Task Group on Occupant Behaviour in Buildings (MTG.OBB) formed to study and integrate occupant behaviour in ASHRAE research, guidelines, codes and standards, handbooks, and policies. MTG.OBB draws technical expertise from multiple Technical Committees (TCs), Standing Standard Project Committee (SSPC), Multidisciplinary Task Groups (MTGs), and university researchers in natural and social sciences.

Other international collaboration in this area is taking place under IEA Annex 66 in the Energy in Buildings and Communities