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ALOS: Automatic learning of an occupancy schedule based on a new prediction model for a smart heating management system

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ABSTRACT

In our day and age, lowering energy consumption in buildings is a must. Smart-buildings will provide the answer if and when they can adjust the required indoor temperature to the occupancy. Developing an occupancy model that forecasts the time of arrival and departure is therefore mandatory. Our article deals with the occupancy prediction model of a building meant for an inteligent heating management system. The prediction also integrates short and long duration of occupation/unoccupation. ALOS is based on an unsupervised clustering method (to classify the events 'departure' and 'arrival') and on the EM (Expectation Maximisation) algorithm with a new mixture model to determine short and long duration of the events. While most previous studies focused on either the residential or the tertiary building, our approach predicts occupancy in both types of buildings. In order to demonstrate the efficiency of our approach, it was tested on real occupancy datasets (familly consisting of 4 people and elderly person living alone). The results indicate that ALOS achieves excellent average prediction accuracies, notebaly from 80% up to 90%, which makes it efficient and provides easy implementation. Finally, a major strength of the ALOS method is that it only needs just under a week to integrate a change of the occupants' habits.

1. Introduction

In France, energy consumption in the residential-tertiary buildings represented 45% of the total energy consumption (Source: The French Ministry of the Environment, Energy and the Sea, 2015), and was responsible for 18% of national greenhouse gas emissions. Representing 68% of this consumption, heating is the main energy consumer. Simply improving the building's insulation quality and the efficiency of heaters is generally insufficient to minimise energy expenditure in the residential-tertiary building. The performance of Heating Management Systems (HMS) also needs to be optimised. We propose to perform an advanced control systems for energy and comfort management [1]. One way to achieve this, is to manage occupancy transition [2]. However, one of the main obstacles we face in the case of HMS is the relatively long time required by this type of system to produce an effect on the room temperature. In this case real-time occupancy information is insufficient to achieve energy savings and maximize occupants comfort. It is therefore essential to not only identify the current state of occupancy, but also to predict the upcoming transition.

This work is a part of the AliceTher[1] project which aims to reduce energy consumption of HVAC (heating, ventilating, and air conditioning) equipment by working on three axes: building analysis, communication of products with their environment and decision-making (intelligence). Our study falls within the overall objective to consume less energy by optimizing the control of the heating system in relation to the context of use. Various studies have shown that most users are not able to optimize their heating schedule [3–5]. Hence the need to develop an intelligent system able to analyse the habits of the occupants and to self-program through learning algorithms; this constitutes the main interest of our work. In this paper, a new occupancy prediction approach is proposed for the intelligent control of HMS. Our approach is based on an unsupervised clustering method and on EM algorithm with a new mixture model. It learns two patterns: arrival and departure event, and their corresponding presence and absence durations.

The contribution of our paper is articulated around the following points:

- A novel and an automatic method for occupancy prediction without user intervention and without prerequisite knowledge.

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[1] AnaLyse et IntelligenCe pour les Equipements THERmiques du bâtiment.

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- A dynamic method which quickly integrates the current occupancy state and any unforeseen events (early or late arrival or departure) or long-term changes in the occupancy patterns.
- A new mixture model has been developed to statistically characterize the different types of occupancy behaviour in buildings.
- The ALOS method is able to predict occupancy both in residential/tertiary buildings and it is compatible with thermostats (independent and integrated) and home energy management systems.
- Simulations with real occupancy data were carried out to validate the proposed method (house-level and room-level).
- Our approach is currently being industrialised (Intuitiv®); it does not call for deep-learning and it is not combinatory.

This paper is structured as follows: in section 2, we deal with related work. Section 3 describes in details our proposed method of Automatic Learning of the Occupancy Schedule (ALOS) and presents the learning approaches used in this work. Then in section 4, we discuss results obtained with real data, leading finally to section 5 in which we conclude our paper.

2. Related work

Several researchers have undertaken studies related to the occupancy criterion management in several applications such as security applications [6], lighting control [7] and thermal control in buildings [8]. The occupancy information can be categorised into four types; Occupancy status (0 or 1), occupancy rate (the number of occupants in a space), occupant behaviour (activities) and occupant location. The latter can be detectable (current state) and/or predicted (future state). In the presented work, we are interested in the prediction of the occupancy state for the HMS. Numerous studies have demonstrated the significant energy savings achieved by integrating occupancy information in control strategies [9,10]. Oldewurtel et al. [2] studied the potential of using household occupancy information to achieve this goal. To evaluate this potential, they benchmarked an MPC (Model Predictive Control) controller based on a fixed occupancy schedule, in comparison with three other control strategies that use the same MPC controller but incorporate instant occupancy data. This study shows very clearly the gain realized on energy consumption when occupancy information is taken into account. The MPC approach has been also used in several occupancy based control approaches for HVAC systems [11–13]. In Ref. [14], a study was carried out to develop and implement algorithms for modelling occupant behaviour in intelligent buildings and to link this model to the construction of the energy management system through simulation tools.

In this context, a number of research projects have emerged. One of such important projects is the OOHC[2] (2010–2016, United States) which seeks to develop occupant-oriented heating and cooling technologies based on information provided by new detection systems. The OptiControl[3] (2007–2013, Germany) project has the overall objective of optimizing the thermal control within the habitat using occupancy and weather forecasts. The SmartHeat project (2015–2018, Swiss, Austria, Romania, Italy and Spain) aims to develop an intelligent, secure and user friendly ICT system (information and communication technologies system) for heating control using a set of technologies to detect occupancy and to understand the user needs.

2.1. Occupancy prediction

Multiple research studies have focused on occupancy detection [15–17]. In the case of fast response systems such as lighting, the detection of occupancy at a given moment is largely sufficient. However, to control a heating system effectively, it is recommended to predict occupancy. The occupant's departure is therefore predicted to save energy, and their arrivals are predicted to guarantee thermal comfort.

A Markov Chain model was developed by Page et al. [18] to predict occupant presence in private offices. This model can reproduce key properties of occupant presence; times of arrival and departure, periods of intermediate absence and presence and periods of long absence. Mahdavi and Tahmasebi [19] have developed a non-probabilistic model named MT that uses past occupancy data towards predicting future occupants' presence in workplaces (open, semi-open, and closed office settings). A short-term and mid-term prediction, based on spatio-temporal analysis of historical data and real time occupancy information, was developed by Adamopoulou et al. [20]. To forecast occupancy, they use the Markov Chain model and the Semi Markov model. The proposed models were evaluated using data collected from a tertiary building; the Office, the kitchen and the rest area of a research institute. Other studies also focused on occupancy prediction in office buildings, using supervised machine learning techniques, like in Refs. [21–23]. All the above studies focused on the prediction of occupancy in only tertiary buildings (office building, commercial building) where occupancy schedules are generally unvaried and fixed according to the working hours. In residential buildings, occupancy prediction is more difficult because of the highly stochastic occupants' behaviour. However, in this article, the presented ALOS approach is appropriate for both types of profiles; a stochastic occupancy profile in a residential building and a regular occupancy profile in a tertiary building. Moreover, a novel way to achieve energy saving is to use the Smart/Programmable Thermostat. Unlike the programmable thermostat that operates according to a predefined heating schedule, the smart thermostat adapts its own operation according to the context of use. The “Smart Thermostat” [8] is a probabilistic method based on the Hidden Markov Model (HMM). Using cheap and simple occupancy sensing technology, this approach generates, on average, a 28% energy saving, compared to typical heating control (always “On” system). The principle of this method consists firstly in analysing the occupancy sensor data to recognise the current occupancy state (active, asleep or outdoors) and secondly in combining historical occupancy models with real-time sensor data to decide when exactly to turn on the heating system. The “Self-Programming Thermostat” [24] automatically creates the most optimal heating schedule based on the statistical data of habitat occupancy. This method involves using historical occupancy data to define the lifestyle habits of occupants in terms of presence/absence. However, it produces a static schedule, whereas occupancy patterns change dynamically. Furthermore it does not predict occupancy-related events.

The main idea of the solution developed in Ref. [25] is to add the geolocation functionality to traditional thermostats, thanks to the Global Positioning System (GPS), in order to control heating and cooling. The authors of [26] developed an approach (PP for “*Presence Probabilities*” and PPS for “*Presence Probabilities Simplified”)* for predicting arrivals and departures of occupants using a survey and approximately two months GPS data from 34 participants. According to the comparative analysis of the state-of-the-arts means of predicting occupancy for smart heating control applications conducted by Kleiminger et al. [27], the Presence Probabilities (PP, PPS) approach provides the best overall performance in terms of prediction accuracy with an average of about 85%. The last two mentioned approaches ([25] and [26]) and other applications like those presented in Refs. [28–30] are based on GPS information for presence forecasting. However, controlling the heating system using geolocation may have some concerns in everyday life since it requires the authorization of the occupant to ascertain his location and it also requires the permanent activation of his smart phone or vehicle GPS location. The authors of [31] propose a solution to predict home occupancy and to control the HVAC system by using a Bayesian Learning approach and a Reinforcement Learning (Q-

[2] Occupant Oriented HVAC Control, https://www.nsf.gov/awardsearch/showAward?AWD_ID=1038271.
[3] Optimal building climate Control, http://www.opticontrol.ethz.ch/index.html.