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Improved occupancy monitoring in non-domestic buildings

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ABSTRACT

Measuring occupancy can facilitate energy efficiency in non-domestic buildings, when control systems are able to adjust heating and cooling based on demand rather than fixed schedules. The variable "occupancy profile" itself is rarely considered as a control system parameter in building energy management systems (BEMS), and this is largely because reliably measuring occupancy in the past has been too difficult, expensive, or a mixture of both. Occupancy detection is possible using e.g. CO_2 sensors, passive infrared (PIR) detectors, which can provide a basic trigger for services, but the actual occupancy count, and therefore the expected load on building services, requires a step change in instrumentation. Advanced occupancy sensors developed from a heterogeneous multisensory fusion strategy offer this, improving control system performance, e.g. turning off services out of hours, and not over-ventilating, saving energy, while not under-ventilating during occupancy, benefitting comfort and health. While this is the case, there is a shortage of any systematic methodology for developing robust and reliable occupancy monitoring systems from heterogeneous multi-sensory sources. In this paper we describe an innovative sensor fusion approach utilising symmetrical uncertainty (SU) analysis and a genetic based feature selection for building occupancy estimation.

1. Introduction

Building energy management systems (BEMS) are often employed to reduce operational energy used in non-domestic buildings. Technology advancements in sensors and telecommunications have seen installation costs of BEMS reduce drastically, widening their uptake (CIBSE, 2009; Loveday & Virk, 1992), energy savings using correctly commissioned BEMS can approach 15% (CIBSE, 2009). However, BEMS have failed to fully optimise energy use in many non-domestic buildings (Zeiler et al., 2006) for several reasons, including that sensors have been reported to suffer from long term drift, lack of scheduled maintenance and technical failure (Levermore, 2000). Control strategies used for running BEMS may not always be optimal (Erickson, Carreira-Perpinan, & Cerpa, 2011). We hypothesise that the BEMS itself could be provided with much better data to make control decisions – conventional heating, ventilation and air-conditioning (HVAC) operations often make use of temperature and humidity as sole control inputs, which often leads to energy waste (Agarwal et al., 2010). While the challenge has been to balance energy efficiency and a comfortable climate (Zhu, Rui, & Lingfeng, 2010), there is little point in maintaining a comfortable empty building (many systems are programmed with fixed occupancy patterns), so a clear energy efficiency improvement would be to feed occupancy data to building controls, services being provided only when needed (during occupied times). This basic idea is not new of course – previous studies suggest up to 56% energy savings with occupancy-driven HVAC (Sun, Wang, & Ma, 2011; Tachwali, Refai, & Fagan, 2007). Ideally, building controls should automatically respond to dynamic occupancy loads, although current BEMS often lack this capacity and usually rely on fixed assumptions to operate HVAC and electrical systems, often wasting energy. For example, such information is useful for determination of HVAC heat loads (Chenda & Barooah, 2010), as well as optimal run time, required heating, cooling and distribution of conditioned air, and optimal selection of temperature set points (Li, Calis, & Becerik-Gerber, 2012).

Using occupancy data to run building controls is compelling, but a precise and reliable way of measuring it has in the past been difficult. Existing building controls may use an abstracted figure from atmospheric gases or a simple binary value, whereas, advanced controllers capable of inferring occupancy numbers from these have not been significantly commercialized, with the few inroads made into commercialization being quite recent (Dounis & Caraiscos, 2009). Current technologies have other shortcomings,

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including at component level, sensor drift (e.g. gas sensors), privacy concerns (video), component failure, but operationally, also intrusiveness, effects of change of use and insufficient commissioning. More reliable and robust building occupancy sensors can be produced using sensor fusion, aiming to estimate occupancy levels by merging information from various indoor environmental sensors (Ekwevugbe, Brown, & Fan, 2012; Ekwevugbe, 2013; Ekwevugbe et al., 2013). Sensor fusion aims to merge the strong qualities of various sensors, whilst minimising their weaknesses, thus outperforming single sensor (Hall & Llinas, 2001). Because of the synergistic nature of sensor use, sensor fusion frequently may be more cost effective than traditional controls (Dodier et al., 2006).

2. Trends in building occupancy measurement

Occupants' behaviours and activities have significant impact on energy use (Richardson, Thomson, & Infield, 2008; Richardson et al., 2010). Many authors have examined various approaches to occupancy detection in a non-domestic setting, a comprehensive overview of existing methods is provided by Nguyen and Aiello (2013), and Yang et al. (2016). In many non-domestic buildings, Passive infrared (PIR) sensors are most commonly used for occupancy sensing, usually for lighting controls (Delaney, O'Hare, & Ruzzelli, 2009), but provide a simple binary output, i.e Occupied/Unoccupied, mainly to limit unnecessary lighting. Often, such sensors fail to detect stationary building users, plunging them into darkness. Sometimes a nuisance, sometimes amusing, but frequently dangerous, a better approach was needed, which is to couple PIR with other sensors using advanced algorithms; Dodier et al. (2006) proposed a Bayesian belief network comprising of three PIR and a telephone sensor, to probabilistically infer occupancy, this being modelled with a Markov chain, to a detection accuracy of 76%. This was an improvement over conventional PIR sensor, but was unable to provide an actual occupant count.

Dong et al. (2010) improved occupancy detection robustness, using information from CO_2, acoustic sensing and PIR to estimate occupant count in an open-plan office (Dong et al., 2010; Lam et al., 2009a; Lam et al., 2009b). Using information theory, the most relevant information for occupancy prediction was extracted from sensor data, and fused with three machine learning algorithms (support vector machine, artificial neural networks, and a hidden Markov model), which reached an average accuracy of 73%.

Several stochastic (Page et al., 2008; Richardson et al., 2008) and linear regression (Abushakra & Claridge, 2008) models have also been proposed for modelling occupants' presence and interactions with their space. Generally, they tend to be applied to single occupants' spaces, (or laboratory test cells) where occupancy dynamics are relatively simple. It is not clear, how these models can be applied in non-domestic buildings with more dynamic environments, and greater variations in occupancy.

Monitoring office equipment may facilitate occupancy counting, use of equipment generally indicating a room being used, but is conventionally expensive. Brown et al. (2011) established the electrical appliance usage patterns (such as desktop PCs), using portable (low cost) temperature sensors, and scanning network activity – duty cycles were detected to 97% precision. Melfi et al. (2011), using existing IT infrastructure, monitored MAC and IP addresses, keyboard and mouse activities as occupancy proxies. Reported detection accuracy was 80% and 40% at building and floor level respectively. Others have applied the use of global positioning system (GPS) and Wi-Fi connection for occupancy detection to a reported accuracy of 96.7% (Zhao et al., 2015). Generally, ICT-based occupancy detection systems may be suitable for occupancy driven- power management of electrical appliances, but limited for occupancy numbers estimation in buildings, where routine ICT use may not be a given.

Wearable sensors are increasingly used for monitoring occupants; Gillott et al. (2010), Gillott et al. (2009) determined occupancy patterns in a residential building, using ultra-wideband RF-based tags worn by occupants, tracking them to 15 cm in three dimensions. However, occupants' willingness to wear these may be a critical factor here, often due to privacy concerns. Vision-based systems have also been used (Benezeth et al., 2011; Tomastik, Yiqing, & Banaszuk, 2008), although occupants' privacy is a concern, plus all sensing is line of sight, limiting use in partitioned open plan offices.

It becomes clear from previous work that a methodology for sensor selection for occupancy sensing has yet to be formalised. Arbitrary sensor selection may not always guarantee optimal and robust occupancy sensing. Only a handful of studies which have applied heterogeneous sensors for occupancy number estimation utilised any systematic methodology for sensor features selection. For instance, Dong et al. (2010), applied information gain for its feature selection methodology, although this is known to be biased with data containing more values. This study utilises a symmetrical uncertainty analysis, which is known to overcome this limitation for feature extraction.

3. Control of building energy systems

Building controls should reduce energy use and maintain indoor thermal and visual comfort, as well as indoor air quality. Standard control schemes, such as "on/off" and Proportional-Integral-Derivative (PID) are widespread in buildings (Loveday & Virk, 1992). Simple thermostats have been used for indoor temperature regulation, but temperature overshoots occur, resulting in energy waste (Dounis & Caraiscos, 2009), and generally, do not provide optimal control. PID controllers were introduced, providing a set point (proportion), long term stability (integral) and response speed (derivative), and where controllers are tuned beyond factory tuning, performance may improve markedly, but also incorrect settings may increase instability (Dounis & Caraiscos, 2009). Generally, PIDs struggle for processes with large time constants, significant noise and non-linearities (Kaya, Tan, & Atherton, 2007; Li, Ang, & Chong, 2006), although performance can be improved by cascading multiple PID controllers (Kaya et al., 2007), or by combining feedback and feed-forward controllers (Thomas, Soleimani-Mohseni, & Fahlén, 2005). The use of advanced control schemes, such as computational intelligence (CI) based strategies (or in combination with PIDs), is considered promising (Kukolj, Kuzmanovic, & Levi, 2001; Martins & Coelho, 2000). CI techniques have coped well with noise, are adaptive in highly dynamic environments, can be used to learn and generalize from examples, and can generate predictions quickly (Hagras et al., 2008; Rafiq, Bugmann, & Easterbrook, 2001). Optimal (Zaheer-Uddin & Zheng, 2000), predictive (Chen, 2001; Henze, Dodier, & Krarti, 1997) or adaptive (Curtis, Shavit, & Kreider, 1996) controllers have been used to ensure indoor thermal comfort, as well as to limit set-point overshoots and save energy. These controllers need a bespoke model per building (which is mostly non-linear), and customised control schemes (Gouda, Danaher, & Underwood, 2006). Where >95% of controllers are traditional, e.g. PID or on-off. While fuzzy based learning systems are appearing in e.g. smart thermostats for homes, it is still reasonable to say that generally, more advanced control schemes for non-domestic use are quite rarely seen outside the laboratory (Dounis & Caraiscos, 2009). However, in recent years advanced controllers based on model predictive control (MPC) strategies for HVAC systems are gaining favour, with the benefit of a system model for anticipatory control functions, rather than corrective control (Preglej et al.,