A deep learning framework for energy management and optimisation of HVAC systems

Paige Wenbin Tien*, John Kaiser Calautit, Jo Darkwa, Christopher Wood, Shuangyu Wei, Conrad Allan Jay Pantua and Weijie Xu
Department of Architecture and Built Environment, University of Nottingham, Nottingham, United Kingdom

*Corresponding author: paige.tien@nottingham.ac.uk, paige.tien@gmail.com

Abstract. To enable heating, ventilation and air-conditioning systems to effectively work for the next generation-built environment by reducing unnecessary energy loads while also maintaining satisfactory thermal comfort conditions, this present work introduces a demand-driven deep learning-based framework, which can be integrated with building energy management systems and provide accurate predictions of occupancy activities. The developed framework utilises a deep learning algorithm and an artificial intelligence-powered camera. Tests are performed with new data fed into the framework which enables predictions of typical activities in buildings; walking, standing sitting and napping. Building energy simulation was used with various occupancy profile schedules: two typical static office occupancy profiles, a schedule generated via the deep learning framework and an actual prediction profile. An office space within a case study building was modelled. Initial results showed that the overall occupancy heat gains were up to 30.56% lower when the deep learning generated profile was used; as compared to the static office occupancy profile. This indicated a 0.015 kW decrease in occupancy gains, which also influenced the increase in building heating loads. Analysis indicates the occupancy detection-based framework is a potential solution for the development of effective heating, ventilation and air-conditioning systems. Additionally, the requirement for the deep learning framework to work for multiple occupancy activity detection and recognition was identified.

1. Introduction and Literature Review
Advanced Building Energy Management Systems (BEMS) with control strategies that enables Heating, Ventilation and Air-conditioning (HVAC) systems to adapt to occupants’ actual behaviour instead of static operation schedules can decrease energy loads during unoccupied periods [1]. It highlights the potential of using AI based strategies for implementation into building HVAC systems for greater monitoring and control [2]. Accurate identification of occupant behaviour is important for enhancing building energy performances [3]. Traditional methods of detection such as motion sensors are useful for detecting the number of people within a desired space [4]. However, more developments are necessary such as enabling the detection of occupant’s activities.

Artificial intelligence can be used for occupancy detection to enhance HVAC systems and minimise building energy consumption [5]. Current applications include occupancy sensing solution via detection of several occupant activity. Distinguishing between different activities performed over time and accurate human daily activity recognition results were achieved with accuracy of up to 97.6% [6].
Therefore, this presents the feasibility for further development and integration of AI techniques for occupancy detection within the built environment towards the optimization of buildings.

Deep learning (DL) is a specific subfield of machine learning based on the use of neural networks to form a unique model designed for a required application. It becomes an effective tool for improving HVAC system performances through building energy forecasting and management [7] and building thermal comfort and occupancy satisfaction [8]. Shaikh et al. [9] utilised DL concept for energy prediction, enabling buildings to achieve high occupant comfort index and HVAC system energy saving of 32.7%.

In comparison to other machine learning techniques, the use of deep learning within the built environment application is currently limited. Based on the review of previous studies, no work explored the use of deep learning-based occupancy activity recognition technique for building HVAC controls and energy management. Therefore, the present work will discuss the initial development of the proposed framework and future research direction.

2. Methodology

2.1. The Proposed Approach

The proposed approach focuses on a data-driven deep learning framework for occupancy activity detection and recognition that generates data for building energy management systems to effectively manage energy loads while satisfying indoor thermal comfort conditions. This approach is based on two main parts. Part 1 focuses on the development and utilisation of the deep learning model. Part 2 is based on the formation of the deep learning predicted occupancy profile. Ideally, the profile would be directly fed into a control system to optimise HVAC system operation. For the analysis; building energy simulation (BES) was used to enable building energy performance analysis; whereby a comparison with a typical “static” occupancy profile was performed.

2.2. Deep Learning Method

Deep learning method is selected to perform the initial stage. It is established through defining the objectives to train a deep learning convolutional neural network (CNN) to identify occupants performing various activities through live detection and recognition by an AI powered camera. Datasets are used to define predictions of occupancy activities relating to the output responses of ‘standing’, ‘sitting’, ‘walking’, ‘napping’ and ‘none’.

2.3. Deep Learning Framework

An overview of the deep learning framework is given in Figure 1.
Part one focuses on the training of the model. Training data set consisted of hundreds of images saved within each of the categories of the defined responses. Pre-process allows to prepare the data for it to become ready for training. A specific convolutional neural network model is established to develop a suitable model to identify the detected occupant activities.

Part two of the deep learning framework consists of utilizing the developed model to enable live detection and recognition using an AI powered camera. Continuous predictions of all activities were performed during a desired experimental time frame. Live detection results are processed as data to form two different variations of the same building energy HVAC profiles, the ‘Actual Observation Profile’ and the ‘Deep Learning Influenced Profile (DLIP)’.

DLIP was formed by results of the detected occupant activity. CIBSE Guide A [10] was used to identify the total rate of heat emission of the 5 main activities. An example of the process of profile formation is displayed in Figure 2. Ideally, the DLIP profile will be used to control HVAC systems based on occupant’s activities. However, to analyse the feasibility of this application, results from the BES simulation enables analysis in terms of building energy demands, occupancy thermal comfort and satisfaction.

Figure 2. Formation process of deep learning influenced profile from activity detection data and analysis using BES.

2.4. Case Study Building
The Energy Technologies Buildings at the University of Nottingham, UK with an office space of 12.4m² was used as a case study building for the analysis of the performance of the proposed occupancy detection method. For the typical “static” occupancy profile, sensible and latent heat gain of 70 and 45W/person were assigned.

3. Results and Discussion
3.1. Occupancy Profile
Figure 3 presents the four generated profiles; Typical Office Profile 1 and 2, Actual Observation Profile and the Deep Learning Influenced Profile (DLIP). Typical Office Profile 1 and 2 presents the typical average occupancy heat output for ‘constant sitting’ (115W) and walking (145W). This is a representation of how current schedules are assigned within the operations of HVAC systems. The DLIP represents the activity detection results using the proposed framework and camera. The Actual Observation Profile defines the ‘actual’ activity performed by the occupant. As observed in Figure 4, DLIP still alternates between several detected activities hence further improvements are required.

3.2. Energy Modelling
To assess and compare the energy performance, occupancy profiles (Figure 3) were assigned to the building model with one occupant assigned to case study building 1 and four to case study building 2 with an experimental time of 14:00 to 17:30. Figure 4 and 5 presents the results of occupancy sensible gains achieved in both case study buildings.

Figure 4. Occupancy sensible heat gains within the selected office space in case study building.

Scheduled typical office profiles results did not accurately represent the actual internal gains in the office (Actual Observation). In comparison to the Actual Observation, Typical Office 1 and 2 presented an average of 29.34% and 32.72% higher in terms of occupancy gains. While DLIP resulted a difference
of 3.16% with the Actual Observation results. Although it provided a good estimation, further developments are required to increase accuracy. Accurately monitoring occupant activities can help minimise cooling loads due to inaccurate estimation of occupancy heat gains. Hence, typical values and scheduled profiles used in the current guidelines is not sufficient for building energy performance calculations and HVAC system operations. In future work, this model will be further developed to enable multiple occupancy activity detection as occupancy gains would have varied if detection was made for each individual occupancy.

![Heating Load Results](image)

**Figure 5.** Heating load results for a winter day (8th January) within the selected office space in the case study building.

Figure 5 presents the comparison of heating load results of the simulation using the different occupancy profiles. DLIP provided an average heating load of 0.928kW; in comparison to 0.916kW and 0.914kW obtained from the Typical Office 1 and 2. The increase is due to the lowered occupancy gains. CO₂ concentration and occupancy dissatisfaction were also used to evaluate the building energy performances. Results indicates high dependence on the detected occupancy activities. This framework enables identification of changes in occupancy gains, affecting the overall building loads. The proposed method does not solely manage the building loads, it can also be used to optimise indoor conditions through accurate and reliable estimation of occupant activities.

**4. Conclusion and Future Work**

This paper presents the initial development of a data-driven deep learning framework for the detection of occupant activities and the analysis of the results obtained from the initial test of the method within building energy simulation. A convolutional neural network was trained for classification and detection using a camera. Deep learning model was validated with an accuracy of 89.39%. This will be improved via further implementation of more images and alterations to the model training stages. Activities of ‘standing’, ‘sitting’, ‘walking’, ‘napping’ and ‘none’ were detected. Four types of occupancy profiles were utilised: ‘Typical Office 1 and 2’, ‘Actual Observation’ and ‘DLIP’. An office space within a Case Study Building was simulated using the different profiles to set the building internal occupancy gains, enabling identification of the effect upon energy consumption. DLIP performed well compared to the Actual Observations with 30.56% (0.015 kW) decrease in occupancy sensible gains in comparison to results of the Typical Office scheduled profiles. Greater heating was required due to decrease in occupancy gains. The capability of the deep learning framework to detect and recognise multiple occupancy activities will be the main focus of future development of the framework. Overall, the present study highlighted the capabilities to provide more reliable predictions of building internal gains.
Acknowledgements
This work was supported by the Department of Architecture and Built Environment, University of Nottingham and the PhD studentship from EPSRC, Project References: 2100822 (EP/R513283/1).

References
[1] S. D'Oca, T. Hong T, J. Langevin, The human dimensions of energy use in buildings: A review, Renewable and Sustainable Energy Reviews 2018;81:731-742.
[2] F. Asdrubali, U. Desideri, Chapter 1 - Introduction, in: F. Asdrubali, U. Desideri (Eds.), Handbook of Energy Efficiency in Buildings, Butterworth-Heinemann2019, pp. 1-3.
[3] E. Delzendehe, S. Wu, A. Lee, Y. Zhou, The impact of occupants’ behaviours on building energy analysis: A research review, Renewable and Sustainable Energy Reviews 80 (2017) 1061-1071.
[4] P.F. Pereira, N.M.M. Ramos, R.M.S.F. Almeida, M.L. Simões, Methodology for detection of occupant actions in residential buildings using indoor environment monitoring systems, Building and Environment 146 (2018) 107-118.
[5] P. Carreira, A.A. Costa, V. Mansur, A. Arsénio, Can HVAC really learn from users? A simulation-based study on the effectiveness of voting for comfort and energy use optimization, Sustainable Cities and Society 41 (2018) 275-285.
[6] S. Chen, W. Yang, H. Yoshino, M.D. Levine, K. Newhouse, A. Hinge, Definition of occupant behavior in residential buildings and its application to behavior analysis in case studies, Energy and Buildings 104 (2015) 1-13.
[7] C. Fan, J. Wang, W. Gang, S. Li, Assessment of deep recurrent neural network-based strategies for short-term building energy predictions, Applied Energy 236 (2019) 700-710.
[8] G. Gao, J. Li, Y. Wen, Energy-Efficient Thermal Comfort Control in Smart Buildings via Deep Reinforcement Learning, Computing Research Repository (CoRR) abs/1901.04693.
[9] P.H. Shaikh, N.B.M. Nor, P. Nallagowdend, I. Elamvazuthi, Intelligent multi-objective optimization for building energy and comfort management, Journal of King Saud University - Engineering Sciences 30(2) (2018) 195-204.
[10] Chartered Institution of Building Services Engineers, 2015. Environmental design: CIBSE Guide A Table 6.3. London: CIBSE.