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A NEW DEEP LEARNING APPROACH FOR ENERGY MANAGEMENT AND OPTIMISATION OF HVAC SYSTEMS FOR THE BUILT ENVIRONMENT

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ABSTRACT

Conventional heating, ventilation and air-conditioning (HVAC) features such as use of static occupancy schedule profile to control HVAC operation or traditional controls may not be enough to cope with requirements of the next generation-built environment. This work introduces a demand-driven deep learning-based framework which can be integrated with building energy management systems (BEMS) to accurately predict occupancy's activity for HVAC systems which can minimize unnecessary loads and produce satisfactory thermal comfort conditions for occupants. The developed framework utilises a trained deep learning algorithm and an artificial intelligence (AI)-powered camera. Tests are performed with new data fed into the framework which enables predictions of typical activities in buildings such as walking, standing, sitting and napping. To initially test and validate the framework, building energy simulation was used with various occupancy profile schedules under a modelled UK office building with 4 occupants. Initial results present occupancy heat gains were 23.5% lower when Deep Learning Influenced Profile (DLIP) was used as compared to static office occupancy profile. Further developments include; framework enhancement to increase detection accuracy and to provide automated set point adjustment for HVAC system. Initial data indicates the method could resolve occupancy related problems within buildings and enhance building performances through accurate occupancy activity prediction.

Keywords: Artificial intelligence, deep learning, building energy management, occupancy detection, activity detection, HVAC systems

NOMENCLATURE

Abbreviations	
AI	Artificial intelligence
BEMS	Building energy management systems
BES	Building energy simulation
CIBSE	Chartered Institution of Building Services Engineers
CNN	Convolutional neural network
DL	Deep learning
DLIP	Deep learning influenced profile
HVAC	Heating, ventilation and air-conditioning
IESVE	Integrated Environmental Solutions Virtual Environment
ML	Machine learning
UK	United Kingdom
2D	Two-dimensional

1. INTRODUCTION

Heating, Ventilation and Air-conditioning (HVAC) systems are responsible for up to 40% of the UK energy consumed by buildings in the commercial sector [1]. Many technological advancements enable new solutions through developments of more intelligent buildings [2]. Current building energy management systems (BEMS) highlights the need of further exploration and development into AI and expert systems with influential strategies that can be implemented into building HVAC systems for greater accuracy and control. Building occupancy behaviour are rapidly changing, with many occupants in offices adopt a flexible work hour which results in variations towards the scheduled operating time of HVAC systems which leads to increase in building energy usage [4]. Hence, accurate identification of

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occupant behaviour is important for enhancing the energy performance [5]. Traditional methods of detection such as motion sensors are useful for detecting the number of people within a desired space [6]. However, more developments are necessary to enable detection of occupant's activities.

Artificial intelligence is increasingly being adopted to allow HVAC systems to perform more efficiently and accurately. Existing works that implements AI techniques to solve building related problems such as [7] assessed AI techniques for occupancy detection to enhance HVAC system's performance. The study of [8] implemented AI into home geofencing for occupancy detection. Highlighted in [9]; implementation of IoT and AI within building controls results in energy savings of more than 50% for an office building. The camera is the most popular type of sensing technique for human activity recognition with [10] indicated the ability of using deep learning. However, it is identified that existing method solely utilise camera for occupant detection but not activity recognition in buildings.

Deep learning (DL) is an end to end machine learning technique that interprets data features and its relationships solely based on neural networks to form a unique model designed for desired application. The high flexibility provides an effective tool to solve built environment related problems via building energy predictions [11]. The study [12] utilised DL to develop demand-based solutions to enhance accuracy and response time of thermal load forecasting in district heating with considerations towards occupant comfort. While [13] utilises the DL concept for energy prediction, enabling buildings to achieve high occupant comfort index and HVAC system energy saving of 32.7%.

Based on the review, studies employing deep learning for built environment applications are limited. Several have used smart technologies such as Wi-Fi-enabled IoT devices integrated with deep learning for activity recognition [14, 15]. Results showed high accuracy occupancy detection with validation as a reliable sensing technique. However, to the author's knowledges there is no work that implements a feasible strategy that enables occupant activity recognition via camera detection and deep learning methods. Therefore, the present work will address this by developing a novel framework.

1.1 Aims and Objectives

The aim of this work is to develop a data-driven deep learning framework that obtains in-depth knowledge about occupant activities that can feed into building energy management systems to manage building energy loads. A convolutional neural network will be developed and trained for detection and classification of occupant activities using an AI-powered camera. Validation of live detection based on accuracy and suitability is made through a set of testing data. Experiments is carried out to provide data of occupant detection over a timed duration. Through the use of IES Virtual Environment energy modelling, the case study building is simulated with both 'typical office' and 'deep learning influenced' occupancy profiles to identify the influence on the energy demand and the capability of the proposed strategy.

2. RESEARCH METHOD

2.1 The Proposed Approach

The proposed approach is based on a deep learning framework to enable occupancy detection. Occupant activities recorded are compared with a deep learning predicted profile for HVAC. To initially test the approach, profiles are assigned to a building energy simulation model of case study office building to evaluate the heat gains and energy demand. In the future we aim to integrate the approach with an actual building control system. Meanwhile, initial simulation results provide a comparison between the influence on building energy performance of the assigned general HVAC system profile and an occupant activity driven or Deep Learning Influenced Profile (DLIP).

2.2 Deep Learning Method

A convolutional neural network (CNN) is utilised to identify occupant activities within a workspace through live detection. Datasets are used to define predictions of human activities with output responses of 'standing', 'sitting', 'walking', 'napping' and 'none'. More formally, given a short video sequence of N image frames I = {I1, . . . , IN }, our network predicts five output labels: {ystanding, ysitting, ywalking, ynapping, ynone}. The general approach is 1. To process images for classification through training data stored through a datastore 2. Perform training and compare classifiers 3. To classify the streaming 'live' videos from camera to one of the predictors. The workflow of the deep learning method is given in Figure 2 with Part 1 describing the training stages and Part 2 relates to the application of the developed framework to provide predictions of occupant detection.

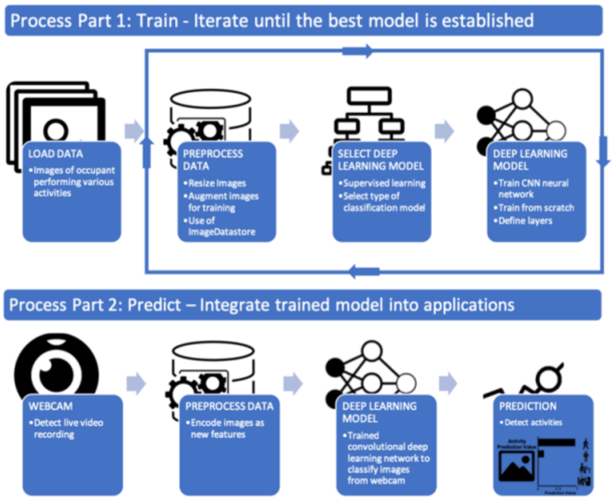

Fig 2 Workflow of the proposed deep learning method.

The training data set consists of hundreds of images saved within each of the categories of the defined responses. The amount of data used follows the Pareto Principle. A CNN classification algorithm is established to develop a suitable model for classifying the detected occupant activities. Figure 3 presents an overview of the designed CNN architecture which is progressively used for live detection. Respectively, each of the given input training image data, filters are applied within the desired most common layers of convolution, ReLu (Rectified Linear Units) and pooling to perform alterations for the intent of feature learning and to reduce spatial complexity of the network.

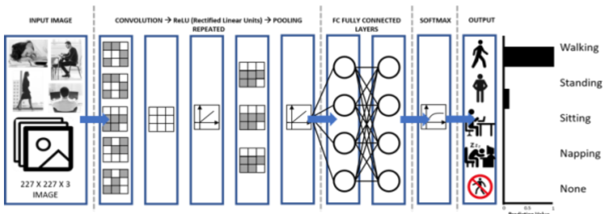

Fig 3 CNN architecture.

2.3 *Building Energy Simulation (BES)*

Acknowledging the utilisation of deep learning to perform occupant detection, data achieved would be fed into the creation of new operations for HVAC systems. This research will use the BES tool IESVE [16] to initially assess the building energy performance.

2.4 *Case Study Building*

Case study building provides a platform to support various stages of this framework. This includes the location for live occupant detection utilising the developed deep learning method. It also provides the building for energy simulation.

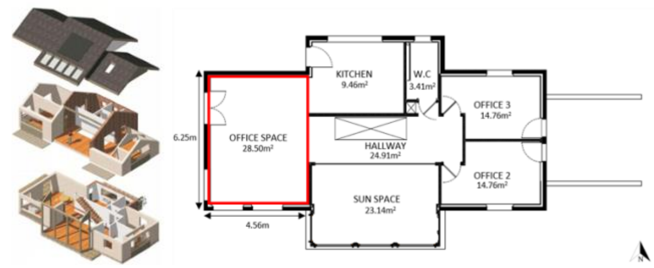

Fig 1 Case study building 3D model and ground floor plan.

The selected case study is an office space within a building in Nottingham (Figure 1). For simplification, some features were not modelled such as the window recess. The areas were represented as thermal zones in Building Energy Simulation (BES) to set different operation profiles. U-value of the wall, roof, ground and glazing were 0.25, 0.18, 0.15 and 0.71 W/m^{2}K, obtained from architectural drawings. The window is triple glazed with argon filled; solar heat gain coefficient was 0.64 while visible transmittance was 0.76.

The Nottingham, UK weather data file was used for simulations. Typically, building operates between 08:00 to 18:00. However, initial simulation modelled 14:00 to 17:30. Office thermal zone was maintained at 21°C. Occupancy density was set to 4 people with a sensible and latent heat gain of 70 and 45W/person, for the standard occupancy profile. For the air exchanges, infiltration rate value was set to 0.1ach.

3. RESULTS AND DISCUSSIONS

3.1 *Deep Learning Occupant Activity Detection*

Training options applied to the CNN model gave an average model training accuracy of 97%. Model validation was performed with an average accuracy of 76% from testing a total of 100 images for all activities.

Live detection of all activities was performed. This formed the two building HVAC profiles; 'Actual Observation Profile' and the 'Deep Learning Influenced Profile (DLIP)'. CIBSE Guide A [17] was used to identify the heat emission of the 5 activities: Napping (105W), sitting (110W), standing (130W) and walking (145W). Figure 4 provides an example of the processed profile.

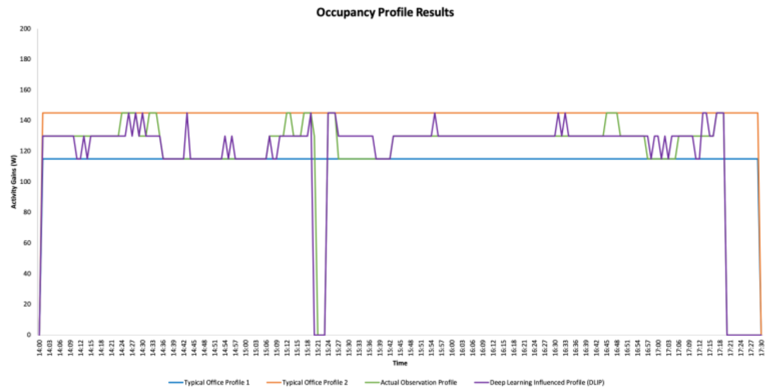

Fig 5 Occupancy profile results.

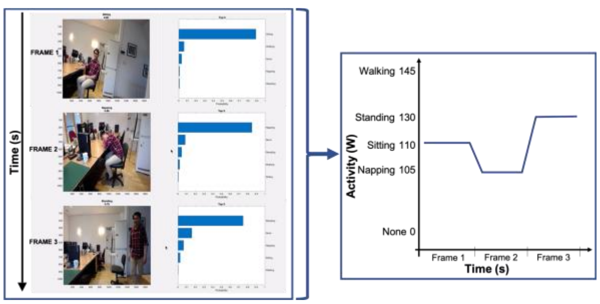

Fig 4 Formation process of deep learning influenced profile from activity detection data.

3.2 Occupancy Profile

Figure 5 presents the four generated profiles, Typical Office Profile 1 and 2 representing standard occupancy gains (static profile), Actual Observation Profile and the DLIP utilising the activity detection results. It envisioned the use of DLIP can lead to better control of HVAC systems. Actual Observation Profile represents actual activity performed by the occupant. This profile was designed to help identify the accuracy of DLIP. Based on the initial results, DLIP still alternates between several detected activities, indicating further improvements is required.

3.3 Energy Modelling

To assess the energy performance, developed occupancy profiles were assigned to the building model. Simulation was performed under four profiles to analyse variations in building heating and occupancy gains. Simulation 1 represents the typical value for occupant sitting rate. For other simulation cases, maximum gains assigned to represent all activities, with walking at 100%, standing at 79%, sitting at 64%, napping at 50% and no activities at 0%. Figure 6 presents the results of the occupancy sensible gains achieved.

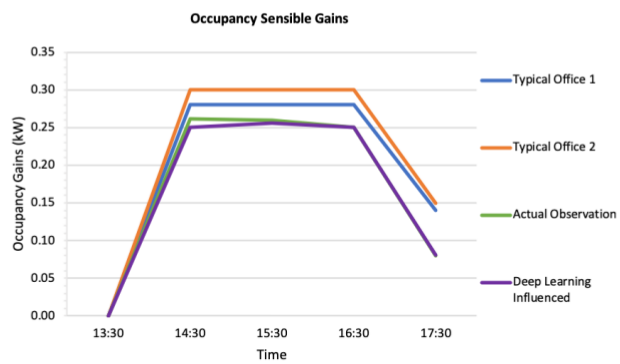

Fig 6 Occupancy sensible heat gains based on typical scheduled profile, deep learning influenced profile and actual observation.

Occupancy sensible gain patterns for Typical Office 1 and 2 correspond to the profile and values set. Results indicates the typical methods did not accurately represent actual internal gains (Actual Observation). The difference between Typical Office 1 and 2 and Actual Observation occupancy gains were an average of 18.04% and 23.5%. Generated DLIP relied upon the accuracy of deep learning framework that resulted a difference up to 1.13% against the Actual Observation. Hence, typical values used in current guidelines does not provide an accurate estimation of occupancy gains and are not sufficient for building energy performance calculations and assigning operating hours/set point of HVAC. Therefore, the proposed approach would accurately manage building heat gains through occupant activity observation.

Figure 7 shows the effect of different occupancy profiles on heating demand. Actual Observation and Deep Learning Influenced provides an average heating load of 1.904kW and 1.906kW compared to Typical Office 2 with 1.873kW, indicating an increase due to lower occupancy gains.

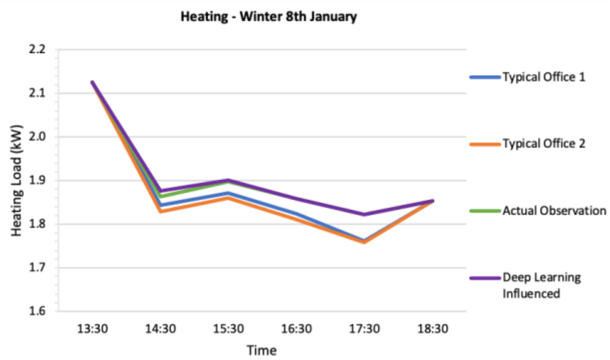

Fig 7 Heating load results for a winter day in the Office Space based on the two Typical Office Profiles, DLIP and Actual Observation Profile.

Depending on the detected activities, this framework enables the identification of change 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. CONCLUSIONS

The main aim of the study was to develop a data-driven deep learning framework for the detection of various occupant activities within typical office buildings which can feed into building energy management systems to optimise building energy loads. A convolutional neural network was trained for classification of the detected occupant activities using a camera. Deep learning model was validated with an accuracy of 76%. This will be improved via more images within the training dataset and in-depth analysis into the selection of the most suitable model training options applied to this CNN model. The experiment was performed at 14:00 – 17:30 within the case study building. 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'. The case study office 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. It provided up to 23.5% decrease in occupancy sensible gains in comparison to results of the Typical Office scheduled profiles. Greater heating was required due to the variation in detected activities. Activities such as napping resulted increase in overall heating of the space as compared to defining a constant activity (sitting) in Typical Office 1 throughout the whole period.

ACKNOWLEDGEMENT

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