Equipment load detection using deep learning for building energy management

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Abstract. The present work will develop a learning-based approach for a demand-driven control system which can automatically adjust the Heating, Ventilation and Air Conditioning (HVAC) setpoints and supply conditions in terms of the actual requirements of the conditioned space. Internal heat gains from typical office equipment, such as computers, printers and kettle will be the focus of this paper. Due to its irregular use during scheduled heating or cooling service periods, an opportunity is offered to reduce unnecessary energy demands of HVAC systems related to the actual use of the equipment and its heat gains, i.e. over- and under-utilization of equipment indicate whether interior spaces are required to be conditioned or not. The work will be using deep learning enabled cameras which can locally run trained algorithms to analyse and take action based on how equipment is utilised in a space. This proposed strategy automatically responds to the equipment usage for optimising energy consumption and indoor conditions. The work will compare the performance of the developed approach with a conventional approach such as the use of static heating or cooling profiles. To highlight its capabilities, the approach is applied to detect the equipment usage in a real open plan office and the output (i.e. deep learning profile) is used as input for a building energy simulation model. The initial results showed that while maintaining thermal comfort levels, up to 19% reduction of the annual energy consumption can be achieved by employing the proposed strategy in comparison to conventionally-scheduled HVAC systems, while only focusing on three types of equipment.

Keywords: Equipment detection, Deep learning, Building energy efficient, HVAC

1. Introduction

In recent years, there has been an emphasis on "smart" technology, and everything has been imbued with intelligence. The popularity and applications of using smart technology to create digital and energy efficient buildings have increased and show no signs of slowing down [1]. Artificial Intelligence (AI) technology is used in this study to achieve the goal of smarter built environment and reduce its consumption, up to 36% of global total energy demand. Specifically, the deep learning (DL) method is a form of machine learning (ML) based on neural networks and excel at processing images or videos to implement classification tasks. In this study, it is selected to automatically generate real-time equipment usage profiles for Heating, Ventilation and Air-conditioning (HVAC) controls without using costly measurement meters. Unlike traditional ML algorithms, DL performance in terms of object detection increases with the amount of input data and extracts features by itself reducing the complexity of the data [2]. In this study, a streamlined and intuitive technique based on convolutional neural network
CNN) is proposed to automatically process the images or videos captured by cameras and obtain the actual equipment information. It can not only enhance the number of load detection of equipment, but also collect an intuitive and real-time equipment usage profile which can be used to assign the operation settings of HVAC to achieve efficient controls and comfortable indoor environment in office buildings. To achieve this aim, a deep CNN based model for detecting different types of equipment will be developed and deployed in an actual office environment within the selected case study building to evaluate the performance of equipment detection. Then the equipment usage profile generated by deep learning model will be utilized for building energy simulation to assess the capability and feasibility on increasing energy efficiency of the HVAC system.

2. Previous related work
In general, there are three techniques commonly found in commercial buildings to control HVAC by performing equipment prediction – following predefined schedule, or detection - using power meters and analyzing clustered occupant information.

Following the load schedules predefined by relevant standards, such as CIBSE and ASHRAE Standard 90.1 [3], is a traditional and widely used method for controlling the HVAC systems [4, 5]. However, for a specific building, it may not be appropriate to apply typical schedules to control the HVAC system because different types of buildings or spaces have different functions and features. Moreover, the stochastic and diversified information of the equipment patterns could not be reflected by the predefined profiles in reality [6].

As the awareness of energy saving increases, a number of portable devices for measuring and visualizing the energy consumption of equipment are increasingly being utilized. Power meters, which are installed on the equipment such as personal computers and printers, are frequently used for energy use measurement as investigated by studies [7-9]. However, considering deployment in energy intensive building such as commercial offices, it could be costly and impractical to install smart meters on every appliance.

In previous occupancy detection studies, many techniques were developed to collect occupancy and thermal state information, which is further processed to predict the equipment usage within a space and then fed into the HVAC control system. Frequently used techniques for occupancy data collection are wireless ambient sensors [10, 11], passive infrared sensor (PIR) [12], WIFI [13], radio frequency identification (RFID) [14], and cameras [15, 16]. In recent studies, ML algorithms were commonly selected to implement data analysis, such as support vector machines (SVM), hidden Markov model (HMM), and neural network (NN). For instance, Ortega et al. [10] proposed an approach to monitor occupancy behavior using SVM to deal with the complex dataset of different features gathered from wireless ambient sensors. Although the equipment load is strongly related to occupancy, this method is still limited due to the necessity of the combination with multiple sensors to improve its performance.

As reviewed, only a few researches explored the detection and prediction of the magnitude and profile of equipment usage in offices. Thus, there are only a few studies which established models which are able to provide comprehensive equipment information for the optimal design, performance simulation and control of building systems instead of using typical profiles. DL method has been popularly used in real-time detecting and predicting applications. Given this circumstance, the present approach in this study was proposed to fill these gaps by using a DL algorithm to detect real-time equipment information and generate the load patterns.

3. Methodology
The implementation framework of the proposed CNN-based approach is presented in Fig 1. Firstly, a large number of images is collected, resized if the original size differs from what required, and randomly divided into training, validation and testing sets in a certain proportion. After that, the model is optimized via a number of rounds of training and intermittent validations, and then tested to evaluate the detection accuracy. Finally, the optimized model is utilized to detect the equipment status within a space and generate the usage profile.
3.1. CNN-based strategy
Before testing the algorithm, a dataset of images of different appliances within offices is required for the purpose of training and validation. Through using web search, large amounts of images in different views, scale and illumination are collected from several offices. They are classified into four categories: PC in use, a printer in use, kettle in use and nothing in use. The architecture of the network, which is the initial configuration for equipment detection, is composed of three convolutional layers, a fully connected layer and a softmax layer. A generalization with the reduction of spatial size is carried out on the input data when the input data goes through the architecture. Finally, the type of office equipment presented in each input image is predicted in the softmax layer after the fully connected layer.

3.2. Case study building and energy modelling
The Mark Group house at the University of Nottingham was selected as the case study building. The initial experiment was conducted in the open plan office on the ground floor. Two cameras were set in the office’s corners to record the ground truth of equipment usage schedule on a typical weekday. The videos were captured from various locations and orientations by a 5-minute time-lapse interval. With the implementation of CNN-based model, the equipment information was gathered from videos.
To test the approach and estimate the energy use from office equipment, a Building Energy Simulation (BES) tool - IESVE was employed with the use of typical profiles and generated DL profiles. For the “typical office” profile, the building was assumed to be in use from 8:00 to 18:00. To simulate the internal equipment gains, based on CIBSE Guide A [17], the equipment was set to six computers because of less use of the printer and kettle. For the “deep learning” profile, the operation period could be directly obtained after implementing the CNN architecture and detecting the usage of each equipment. Due to the ability of detecting different appliances, the equipment was set to six computers, a printer and a kettle with sensible heat gains listed in Tab 1. The office thermal zone was maintained at 22°C during these periods.

| Tab 1 Heat gains of office equipment in use [17] |
|-------------------------------------------------|
|                                | PC | Printer | Kettle |
|-----------------------------------------------|----|---------|--------|
| Sensible heat gains (W)                   | 113| 88      | 12     |
| Latent heat gains (W)                     | 0  | 0       | 8      |

4. Results
The proposed model was developed using MATLAB R2019. To speed up the training, the CNN architecture, which is a computationally expensive and parallel task, was run on a Graphics Processing Unit (GPU). The test accuracy is achieved by 89.3%, which indicate that the developed model can analyse the new input data very well. After inputting the collected video data to the DL model, the probability for each category is computed. The category with the highest probability is selected as the outcome. Example of the representative recognition results for four categories is presented in Fig 2. The outcome in each case is PC, printer, kettle and nothing in use with the highest prediction score of 0.84, 0.74, 0.86,
and 0.94 out of 1 respectively. It implies that the proposed model deals well with the identification task. However, the specific angles of view and positions currently affect the accuracy of the prediction that it significantly limits the implementation of detection tasks. One of the main reasons is that the amount and quality of collected data are not great enough. It causes the model not to be able to accurately detect from a fresh input data which may have a new characteristic.

Based on the detection results, the usage patterns for each appliance are created and plotted in Fig 3. The schedules made by ground truth data and DL detection results are roughly similar. It illustrates that the detection results of the model do match the real profile of equipment usage. While some apparent errors existed during the period that people were frequently active such as lunchtime. Thus, the stability of the model is required to be improved to tailor the various changes of occupant and equipment status. This process will be automated in the future, i.e. the camera and DL model will detect in real time and process the data automatically to develop a schedule which feeds into the controller of HVAC.

For assessing the effect on energy consumption of the deployed DL model profile, the sensible loads with typical and ground truth profiles are employed for comparison. Fig 4 and 5 present the results of daily sensible loads and annual cooling demands based on typical, ground truth and DL profiles. These initial results highlight that the proposed approach for equipment detection could affect the energy use by making HVAC adapt to actual energy demands in real time. The daily cooling loads when using DL method generated equipment load profile is predicted to be up to 11% lower as compared with using the
typical profile. The reduction of annual cooling demands for the case study building is up to 19% as shown in Fig 7. It should be noted that the case study building is sited in the region with a temperate maritime climate where the demands for heating are much more than cooling. The proposed model may work more effectively in regions with a warm and hot climate.

5. Conclusion and Future Works

In this study, a deep learning based approach, which utilizes a pre-trained deep CNNs algorithm, is proposed for detection of the equipment usage in office spaces. The ability of this approach is initially examined based on the collected dataset. It achieved a high accuracy of 89.3% on the test dataset. Moreover, the approach is applied to detect the equipment profile in a real open plan office and the output is used for energy simulation by IESVE to test its capabilities. The initial results show that the utilization of the deep learning model for equipment detection could affect the energy use by making HVAC adapt to actual energy demands in real time. The annual cooling demands by using deep learning generated equipment load profile is 19% lower in maximum compared with using the typical scheduled profile. In practice, this method will use the profile to adjust the setpoint of the HVAC which will result in an increase or decrease of energy loads.

The proposed approach shows significant potential for reducing energy demand in buildings. However, there are some limitations that should be solved in future works. The model is evaluated only using limited dataset. To improve accuracy, using more dataset collected from different types of office and equipment is intended due to the various characteristics in different dataset. Second, an optimal ratio for data division is proposed to reduce the overfitting to narrow the gap between train and test accuracy. Third, a more advanced equipment load detection model based on the present approach, which will be embedded in a camera, is expected which can automatically create real-time usage patterns and send them to a control system. Moreover, examining the performance of the designed model in the regions with a hot climate may be more effective and possible to achieve a larger potential of energy savings.

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