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Detection of Window Opening Using a Deep Learning Approach for Effective Management of Building Ventilation Heat Losses

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Abstract

Occupant behaviour within buildings has a significant impact on building energy consumption and represents one of the main sources of excessive energy use. This paper introduces a data-driven deep learning framework that enables the detection and recognition of opening and closing of windows. This approach is based on a control strategy which can detect and recognise the period and state of the window opening in real-time and simultaneously adjust the heating, ventilation and air-conditioning (HVAC) system to minimise energy wastage and maintain indoor environment quality and thermal comfort. The framework is based on a trained deep learning algorithm deployed to an artificial intelligence (AI)-powered camera. To assess the capabilities of the proposed deep learning framework, building energy simulation (BES) was used with various operation profiles of the opening of windows; fixed profile, actual observation profile and deep learning influenced profile (DLIP). The DLIP is the profile generated via the framework which uses the data obtained from the real-time window detection. A university lecture room with a south-facing window was selected for the modelling and testing of the method. The initial results using the deep learning model showed that it can recognize the state of the window openings with an accuracy of up to 77.8%. Further developments include framework enhancement to improve detection accuracy for multiple window opening types and sizes and to provide automated setpoint adjustment for HVAC systems.

Introduction and Literature Review

Heating, ventilation and air-conditioning (HVAC) systems and its associated operations is currently the largest contributor to the energy consumption of the built environment (Li, 2019). Reducing the energy consumption of buildings is crucial towards meeting global carbon emission reduction targets. Ventilation systems and its associated strategies are critical, as ventilation accounts for 30% of the heat loss in commercial buildings and 25% in industrial buildings (CIBSE, 2015). Energy-efficient strategies are continuously being developed to reduce ventilation heat loss, such solutions include implementing various types of heat recovery-based systems, strategies to help avoid uncontrolled air infiltration losses and to reduce the demand of controlled ventilation.

Window opening is a common method for naturally ventilating buildings. It relies on natural forces of wind and temperature differences to ventilate and cool building spaces. However, the effectiveness of this strategy is highly dependent on the conditions between the indoor and outdoor environment and the window opening patterns (Kyritsi and Michael, 2019). Occupancy presence and behaviour can influence building indoor thermal conditions, air quality and building energy loads (Tahmasebi and Mahdavi, 2017) (Andersen et al., 2013). This leads to concerns towards ineffective usage of window openings which impacts building energy consumption (Wang and Grennberg, 2015). This indicates the need for the development of solutions such as demand-based controls that adapts to occupancy behaviour while also optimising building operations and to provide adequate comfort conditions.

Artificial intelligence (AI) is increasingly being adopted to enhance buildings performance (Panchalingam and Chan, 2014). AI techniques such as Deep Learning (DL) is becoming a popular and widely used tool for solving building-related problems and improve building HVAC systems (Dounis, 2010). This includes the use of DL based models for detecting and recognising problems in buildings such as damage, faults and diagnosis issues (Guo et al., 2018). Other applications include energy prediction methods (Singaravel, 2018) and energy management and control (Zhang et al., 2019) to improve building energy efficiency (Konstantakopoulos et al., 2019). Furthermore, there are arising number of vision-based techniques designed for applications within indoor building spaces, including the detection of occupancy activities (Tien et al., 2020) and office equipment (Wei et al., 2020). This suggests that emerging deep learning-based methods are becoming a fundamental technique that can provide solutions to several building problems, in particular related to occupancy behaviour within buildings (Dong and Lam, 2011).

Deep learning techniques have recently been adopted for the development of window opening models. Markovic et al. (2018) used a deep feed-forward neural network to model the opening of windows in offices which showed a prediction accuracy between 86 and 89%. In addition, Markovic et al. (2019) suggest that deep learning can be used as a prediction method to address the time when window opening actions are performed by occupants. This study shows the potential of using deep learning techniques for enhancing building system operations.

Since most buildings do not have strict operational times, it leads to uncontrolled operations of windows. This is also strongly influenced by occupancy behaviour and the variation within the indoor-outdoor conditions. It results in windows being frequently left opened and increases building energy losses. This suggests that there are still limitations towards the developed approaches. The time delay between the prediction results and the ability to inform of the occupants of the situation and the effectiveness of the system performance is important. In addition, the approach suggested by Markovic et al. (2019) only focuses on the accuracy of the detection and prediction of the window opening. Future works should quantify the impact of the approach on energy performance and practicality. In addition, there is a need for further developments towards the use of DL techniques for building window detection specifically for the application for natural ventilation systems (O'Keefe and Roach, 2017). the Additionally, Fabi et al. (2012) indicates that existing studies on window opening behaviour are aimed at investigating the state of the window itself instead of the transition from one state to another (opening and closing). Hence, there is a need to develop a solution which recognises the condition between open and closing along with the time when these actions were performed.

Aims and Objectives

This study aims to develop a vision-based deep learning framework that enables the real-time detection and recognition of the conditions of windows being opened or closed by occupants. A faster region-based convolutional neural network (Faster R-CNN) was constructed and trained for classification and detection of windows using a camera. Validation of the developed deep learning model is conducted through the use of a set of testing data and the accuracy and suitability for live detection was also evaluated. Experiments are carried out within a case study university lecture room to test the capabilities of the proposed approach. Using building energy simulation, the case study building was simulated with both 'static' and deep learning influenced profiles (DLIP) to assess the potential energy savings that can be achieved.

Method

The Proposed Approach

Figure 1 presents an overview of the proposed framework. It is based on a data-driven deep learning framework that enables the detection and recognition of window openings and the data is used to form Deep learning Influenced Profiles (DLIP). This method can inform occupants about the window condition and whether changes to the window conditions should be made. In addition, the profiles would feed into the control system of the HVAC system to make adjustments to minimise unnecessary loads.

To initially test the approach, various types of window profiles were assigned to a building energy simulation (BES) model to identify potential reductions in building energy consumption and changes within the indoor environment.

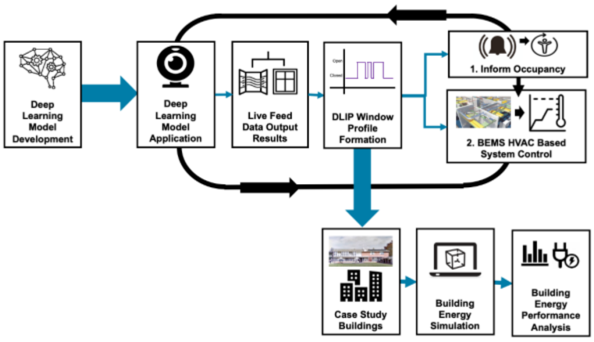

Figure 1: Overview of the proposed framework.

Deep Learning Method

The initial step of the proposed framework was to develop a suitable deep learning model to enable live detection of window openings. For a CNN based deep learning method, images were gathered and labelled to form the input training datasets with the desired format. Images from the two categories, opened and closed windows were specifically selected to form the large input dataset used to define the condition of windows. Training dataset consisted of a total of 200 images and 272 labels and the testing dataset consisted of 50 images and 63 labels. Figure 2 shows an example of the images used in the two datasets of window open and window closed. Additionally, it shows how bounding boxes are drawn manually around the specific region interest of each image.

Figure 2: Example dataset images of windows and the ROI of labelled images. Images are obtained via Google image search of the relevant keywords.

A Faster R-CNN (With Inception V2) based CNN model was used progressively used to identify window openings through live detection. The architecture and the pipeline configuration of the model used is given in Figure 3.

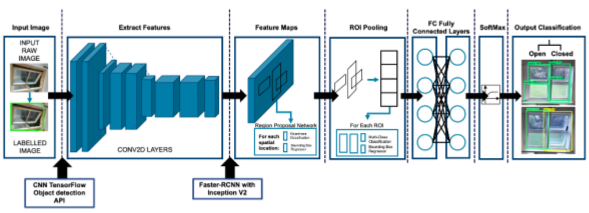

Figure 3: Image of the configured deep learning model for window detection.

As shown in Figure 3, the pre-existing CNN TensorFlow Object detection API, Huang et al. (2016) was used as the base configuration for this current detection model. This object detection model is part of the TensorFlow official pre-defined model's repository, it consists of the incorporation of high levels API's with the ability to localize and identify multiple objects in a single image. For the initial development of the deep learning model, the COCO-trained model of Faster R-CNN (With Inception V2) was selected as the initial type of model used for training of the network. Tests using different training model types would be implemented in future cases to provide an analysis and validation of the most suitable training model application.

Application of the Deep Learning Model

Once the model was trained to a sufficient level where losses did not decrease any further, the trained model was saved and exported with the associated files to enable the use of the model for live detection via the deployment to a camera. During the live detection, continuous predictions of the windows were classified to one of the two desired predicted output responses 'open' or 'closed', while also displaying the accuracy of the recognition in terms of percentages.

The building simulation tool IESVE was used to assess the building energy performance. A lecture room located within the first floor of the Marmont Centre at the University Park Campus, University of Nottingham, UK was used as a case study building to provide a platform to support various stages of this framework. This includes the location for live occupant detection utilising the developed deep learning method and the desired building for energy simulation. The lecture room has a floor area of 96.9m^2, with a floor to ceiling height of 2.5m. The room consists of three sets of windows, one external and internal door. Figure 4 shows an image of the Marmont Centre and the experimental setup. The setup consists of a 'detection camera', which is a standard 1080p camera with a wide 90-degree field of view connected to a laptop which runs the trained deep learning model and it also highlights the selected window used in the initial experiment. The windows have a top guided opening strategy and was double glazed with a U-value of 2.20 W/m^{2}K.

(a)

(b)

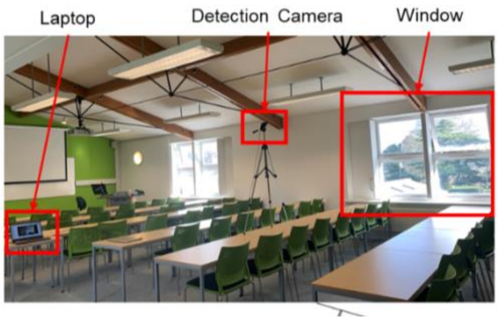

Figure 4: a). Case Study Building: Marmont Centre, University Park, University of Nottingham. b). Selected experimental room: Marmont Lecture Room B5 with experimental set up.

For the simulations, the IES simulation weather files for Nottingham, UK was used as the assigned weather data file for the selected building model. Assignment of the building operational hours of 08:00 to 18:00 with correlated typical profiles for heating and cooling was used to maintain the room at 21°C. Associated profiles for ventilation and occupancy were also assigned. For the air exchanges, infiltration rate value was set to 0.5ach.

Results and Discussions

Deep Learning Model Training Results

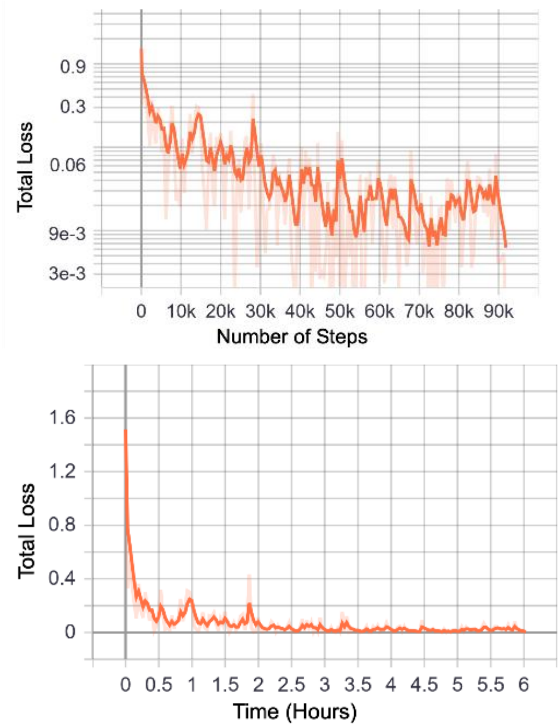

Figure 5: Deep learning model training results using the Faster-RCNN with InceptionV2 model. Total loss against number of a). steps and b). the training time (hours).

Using the Faster-RCNN with InceptionV2 as the training model, the results provided training for 91339 steps giving a maximum loss of 1.516 and a minimum loss of 0.0000379. The training results are shown in Figure 5. The convergence of the loss function implies that the model has been effectively trained. Observations made for this proposed approach can be used to compare with different modifications applied. Further developments to the model configuration included the assignment of more training and test data and to also apply variations to the different types of models that can be used for training.

Live Detection and Window Profile Results

Along with the selected case study building, a time frame of 13:00 -15:00 was used to perform the initial live detection. The response output window detection data were recorded to form the 'Deep Learning Influenced Profile (DLIP)'. For the analysis of the impact of DLIP towards building energy performances using building simulations, this profile was compared along with four other profiles; constant open, constant closed, opened during typical office hours and the actual observation. The Actual Observation Profile represents the true window condition during the experimental time frame which enables verification of the results obtained for the DLIP.

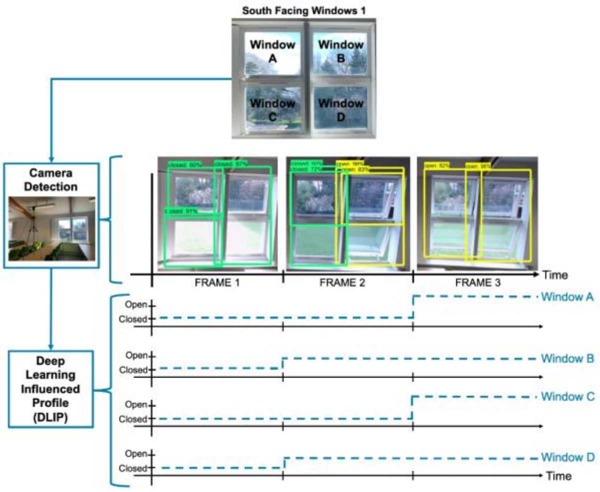

Figure 6: Formation process of the deep learning influenced profile from window detection data.

Figure 6 shows an example of the process of DLIP formation. It presents several snapshots of the recorded frame indicating the detected window condition and the percentage of prediction accuracy. This led to the formation of the profile results indicated in Figure 7 for the desired 2-hour experimental test. The results present the comparison of the DLIP with the Actual Observation. The DLIP provided an average detection accuracy of 77.78%. This shows that the DLIP still alternates between the two conditions, indicating further improvements is required to enhance the detection accuracy.

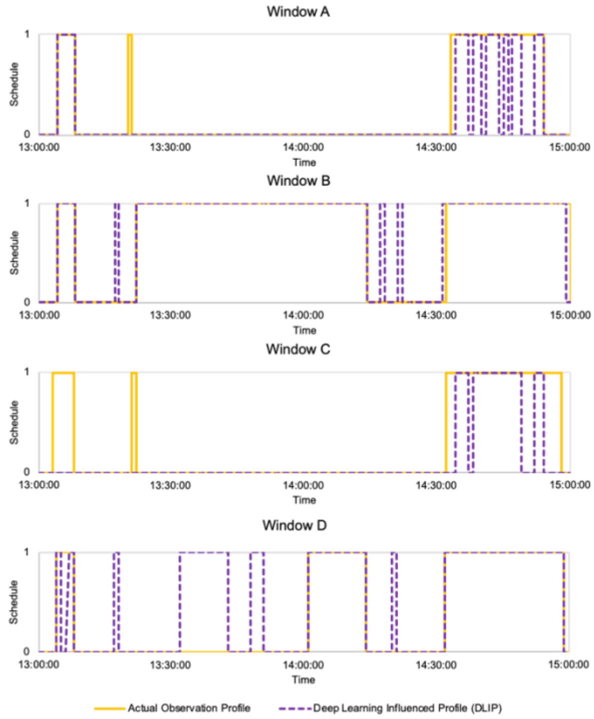

Figure 7: Generated deep Learning Influenced Profile (DLIP) results for window A, B, C, D with corresponding actual observation.

Building Energy Performance

Various window profiles were assigned to the building model to enable the performance of a series of building energy simulation to enable the analysis of the impact towards building performance when the DLIP approach was used instead of typical window profiles.

Figure 8 presents the results of the total heating load achieved between 12:30 – 15:30 with the inclusive of the 2-hour test period. It suggested that windows were assumed to be constantly opened required a heating load of 24.56kWh. This is based on a worst-case scenario which indicates the maximum amount of heating that is essential to maintain the room at 21°C. In comparison for constantly closed windows, heating of 3.47kWh is needed. Due to the closed window, there are no heat losses through windows, which potentially reduces the heating requirements to the minimum. Besides this, occupancy was assigned to the lecture room which indicated that due to the significant amounts of occupancy gains within the room, less heating was needed. Given by Actual Observation, the actual total demand is 8.01kW. This suggests typical constant profiles for windows cannot accurately represent the actual window conditions to provide an accurate determination of the building heating loads.

It presents a considerable large difference with Constant Opened of 206.45% and 56.78% from Constant Closed. This was equivalent to 16.55kWh higher and 4.55kWh lower in heating demands. Since many current HVAC system designs assume windows that are constantly closed within BES and modelling applications, these significant large differences indicate the unreliability for accurate predictions.

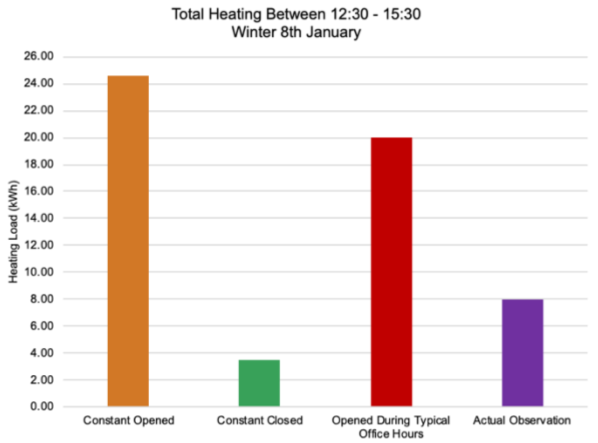

Figure 8: Heating load results for a winter day (8th January) within the two-hour test duration in the lecture room.

Figure 9 presents the ventilation losses within the lecture room. The losses are influenced by the outdoor air conditions on the selected day and directly with the window profiles given in Figure 10. From the Constant Opened and Constant Closed results, it generally shows the maximum and minimum possible losses. The actual observation results indicate the importance of knowing whether windows are either opened or closed, as it can significantly affect the ventilation conditions within an indoor environment, which therefore justifies the importance of the deep learning detection method.

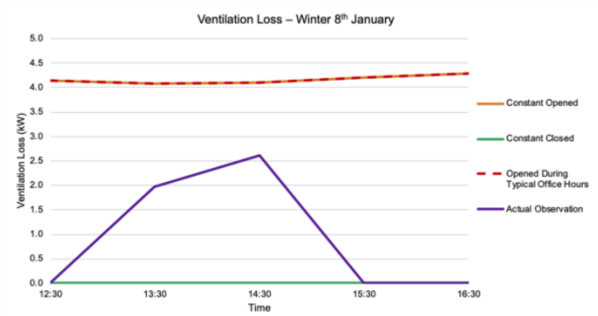

Figure 9: Ventilation loss results for a winter day (8th January) within the two-hour test duration in the lecture room.

Conclusion and Future Works

The main aim of the study was to develop a data-driven deep learning framework for the detection and recognition of window conditions; open or close. This was designed to provide data which supports building energy management systems to optimise energy loads and the development of more effective building HVAC systems. A faster region-based convolutional neural network (Faster R-CNN) was developed and trained for classification and detection of windows using a camera.

Initial deep learning model was validated with a detection accuracy of 77.78%. This will be optimised by adding more training data to improve the detection accuracy in future works. Also, the deep learning model performance can be improved by making modification to the DL model architecture. The experiment was performed at 13:00 – 15:00 within the case study building. Window conditions of ‘opened’ and ‘closed’ were detected. Five types of window profiles were utilised: ‘Constant Opened and Closed’, ‘Opened During Typical Office Hours’, ‘Actual Observation’ and ‘DLIP’.

The case study office building was simulated using different window profiles to evaluate the effect on energy consumption. This initial approach showed the capabilities of this framework for detecting windows and the benefits of monitoring window conditions. The most effective approach in using this DL detection method is to also inform occupancy about the condition so window adjustments can be made. In addition, the DLIP data could be used to make an adjustment to the HVAC based on the detected conditions and make suitable changes to provide better indoor conditions and to minimise energy wastage.

Acknowledgement

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Abbreviations

AI	Artificial Intelligence
BEMS	Building Energy Management Systems
BES	Building Energy Simulation
CNN	Convolutional Neural Network
DL	Deep Learning
DLIP	Deep Learning Influenced Profile
HVAC	Heating, Ventilation and Air-Conditioning
R-CNN	Region-based Convolutional Neural Network
UK	United Kingdom

References

Andersen, R., Fabi, V., Toftum, J., Corgnati, S.P., Olesen, B.W. (2013). Window opening behaviour modelled from measurements in Danish dwellings. *Building and Environment 69, 101-113.*

CIBSE Charted Institution of Building Services Engineers (2015). CTT1 CIBSE Top Tips 1: Ventilation in Buildings. https://www.cibse.org/knowledge/knowledge-items/detail?id=a0q20000006oamlAAA. (Accessed February 2020).

Dong, B., and Lam, K.P. (2011). Building energy and comfort management through occupant behaviour pattern detection based on a large-scale environmental sensor network. *Journal of Building Performance Simulation 4(4), 359-369.*

Dounis, A.I. (2010). Artificial intelligence for energy conservation in buildings. *Advances in Building Energy Research 4(1), 267-299.*

Fabi, V., Andersen, R.V., Corgnati, S., Olesen, B.W. (2012). Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models. *Building and Environment 58, 188-198.*

Guo, Y., Tan, Z., Chen, H., Li, G., Wang, J., Huang, R., Liu, J., Ahmad, T. (2018). Deep learning-based fault diagnosis of variable refrigerant flow air-conditioning system for building energy saving. *Applied Energy 225, 732-745.*

Huang, J., Sun, C., Zhu, M., Korattikara, A., Fathi, A., Fischer, I., Wojna, Z., Song, Y., Guadarrama, S., Murphy, K. (2016). Speed/accuracy trade-offs for modern convolutional object detectors. *arXiv:1611.10012.*

Konstantakopoulos, I.C., Barkan, A.R., He, S., Veeravalli, T., Liu, H., Spanos, C. (2019). A deep learning and gamification approach to improving human-building interaction and energy efficiency in smart infrastructure. *Applied Energy 237, 810-821.*

Kyritsi, E. and Michael, A. (2019). An assessment of the impact of natural ventilation strategies and window opening patterns in office buildings in the mediterranean basin. *Building and Environment 106384.*

Li, X., Zhou, Y., Yu, S.,. Jia, G., Li, H., Li, W. (2019). Urban heat island impacts on building energy consumption: A review of approaches and findings, *Energy 174, 407-419.*

Markovic, R., Grintal, E., Wölki, D., Frisch, J., van Treeck, C. (2018). Window opening model using deep learning methods. *Building and Environment 145, 319-329. 41.*

Markovic, R., Frisch, J., van Treeck, C. (2019). Learning short-term past as predictor of window opening-related human behavior in commercial buildings. *Energy and Buildings 185, 1-11.*

O'Keefe, R.M. and Roach, J.W. (2017). Artificial Intelligence Approaches to Simulation. *Journal of the Operational Research Society 38(8), 713-722.*

Panchalingam, R. and Chan, K.C., (2019). A state-of-the-art review on artificial intelligence for Smart Buildings. *Intelligent Buildings International, 1-24.*

Shen, W., Xu, C., Pan, S., Su, J., Wang, Y., Luo, X., Hassan, T.M., Firth, S., Fouchal, F., Jones, R., de Wilde, P. (2016). Analysis of factors influencing the modelling of occupant window opening behaviour in an office building in Beijing, China. *Proceedings of BS2015: 14th Conference of International Building Performance Simulation Association, Hyderabad, India, Dec. 7-9, 2015.*

Singaravel, S., Suykens, J., Geyer, P. (2018), Deep-learning neural-network architectures and methods: Using component-based models in building-design energy prediction, Advanced Engineering Informatics 38, 81-90.

Tahmasebi, F. and Mahdavi, A. (2017). The sensitivity of building performance simulation results to the choice of occupants' presence models: a case study. *Journal of Building Performance Simulation 10(5-6), 625-635.*

Tien, P.W., Wei, S., Calautit, J.K., Darkwa, J., Wood, C. (2020). A vision-based deep learning approach for the detection and prediction of occupancy heat emissions for demand-driven control solutions. *Energy and Buildings 226, 110386.*

Wang, L. and Greenberg, S. (2015). Window operation and impacts on building energy consumption, *Energy and Buildings 92, 313-321.*

Wei, S., Tien, P.W., Calautit, J.K., Wu, Y., Boukhanouf, R. (2020). Vision-based detection and prediction of equipment heat gains in commercial office buildings using a deep learning method. *Applied Energy 227, 115506.*

Zhang, Z., Chong, A., Pan, Y., Zhang, C., Lam, K.P. (2019), Whole building energy model for HVAC optimal control: A practical framework based on deep reinforcement learning. *Energy and Buildings 199, 472-490.*