Applied Energy Symposium 2021: Low carbon cities and urban energy systems
September 4-8, 2021, Matsue, Japan
Paper ID: 37

Building Occupancy Prediction Through Machine Learning for Enhancing Energy Efficiency, Air Quality and Thermal Comfort: Review and Case Study

Wuxia Zhang[1*], Paige Wenbin Tien[1], John Calautit[1], Yupeng Wu[1]
1 Department of Architecture and Built Environment,
University of Nottingham, UK NG72RD
e–mail: wuxia.zhang@nottingham.ac.uk (Corresponding Author), paige.tien@exmail.nottingham.ac.uk,
john.calautit1@nottingham.ac.uk, Yupeng.Wu@nottingham.ac.uk

ABSTRACT

Recently, advanced prediction tools based on artificial intelligence are increasingly being employed for predicting occupancy patterns in buildings. The present work carries out a comprehensive review of studies using artificial intelligence and machine learning models to predict occupancy and its applications, covering studies about energy consumption, thermal comfort, lighting use and indoor air quality. The analyses show that while these studies have revealed that occupancy is a critical contributor to the energy prediction model, they have not paid enough attention to the thermal condition, air quality and their effect on occupant productivity and quality of life. In this study, occupancy detection with the vision-based camera is employed, which captures specific occupancy activities and other related behaviour like window opening behaviour. These activities will generate real-time deep learning influenced profile formation, which can train the prediction model. The results showed that the current CNN model framework provided an initial average detection accuracy of 84.48%. The ability of the deep learning detection to inform HVAC systems with significant help towards reducing building energy loads with the temperature setpoint changed. Therefore, it is important to develop an effective solution to increase the performance of buildings by assisting the HVAC control system in providing adequate indoor thermal comfort and air quality, while improving the building energy performance.

Keywords: machine learning, occupancy prediction, thermal comfort, energy consumption

NOMENCLATURE

Abbreviations	
HVAC	Heating, Ventilation and Air-Conditioning
PV	Solar Photovoltaic
PMV	Predicted Mean Vote
SET	Standard Effective Temperature
MPC	Model Predictive Control
ML	Machine Learning
AI	Artificial Intelligence
RFID	Radio Frequency Identification Devices
PIR	Pyroelectric Infrared
SVM	Support Vector Machine
DT	Decision Tree
KNN	K-Nearest Neighbour
ANN	Artificial Neural Network
IAQ	Indoor Air Quality
LSTM	Long Short-Term Memory
DLIP	Deep Learning Influenced Profile

1. INTRODUCTION

Buildings consume about 40 % of the total energy [1] and 30% of greenhouse gas emissions [2] which has made building energy conservation an important task worldwide. Despite the energy cost, it is common to find buildings with unsatisfied thermal conditions [3]. Occupant behaviour has been regarded as one of the most significant considerations for building and system design. Various occupancy models have been developed during the last two decades to mimic occupants' randomness and diversity and generate stochastic

Selection and peer-review under responsibility of the scientific committee of CUE2021

occupancy profiles for building performance simulation and heating, ventilation, and air-conditioning (HVAC) controls. Advanced prediction tools based on artificial intelligence (AI) are increasingly being employed to predict occupancy patterns in buildings. The present work carries out a comprehensive review of studies using artificial intelligence and machine learning models to predict occupancy and its applications, covering studies about energy consumption, thermal comfort, lighting use and indoor air quality.

This study proposed a modified convolutional neural network (CNN) model that enables occupancy prediction to better understand occupancy behaviour within a building space. The prediction result will inform the occupants and make adjustments to the HVAC system control. The aim and objectives are as follow:

1) Development of a deep learning vision-based detector for occupancy recognition
2) Deployment of the model to an AI-powered camera that enables real detection with the generation of data in form of the Deep Learning Influenced Profiles (DLIP).
3) Test the performance of the developed method and apply it to case study buildings.
4) Assess the impact of the proposed approach on the overall building performance.

2. LITERATURE REVIEW

Although these machine learning models have been applied and tested successfully in previous studies, the selection of suitable algorithm varies from one model to another, the model setting depends on many factors like the available data used as inputs, the timeframe wanted, the time resolution (from every minute to annually), the scale (from a simple building to a whole country consumption). Therefore, with the increasing number of papers published in this field, it is crucial to have an in-depth overview of the accomplishments and achievements, major challenges, and critical research gaps in this field.

2.1 Data collection for occupancy data

Occupancy is one of the most important factors of building energy consumption, and it has direct consideration of humans. Therefore, an accurate real-time occupancy detection technique is very useful as input would help build energy models. Many data collection methods have been developed recently to improve the accuracy of occupancy detection. Some researches showed the potential of occupancy sensing to improve energy savings up to 30% [4] as well as significantly influence building indoor air quality[5].

Higher resolution and accuracy can be achieved by using proper monitoring equipment with appropriate control of HVAC and other systems in buildings. Also, since the occupancy status is always connected to private concerns [6], it is not always easy to choose the proper sensor, especially when linked to indoor vision. Existing data collection methods can be divided into direct counting methods, which record the occupancy number directly, and environmental parameters, which indicate occupancy state indirectly. In this paper, the advantages and disadvantages of these methods with regards to accuracy, cost, and ethical considerations, unresolved issues were identified, and future research recommendations were developed.

2.2 Machine learning algorithmic for prediction and its application

There are three common machine learning methods in occupancy prediction: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning uses labelled examples as training data and makes predictions for all unknown points [7]. Models using supervised learning include [8] models (e.g., multiple linear regression, generalised linear model, regularised regression and partial least squares), models based on decision trees [9] (e.g., gradient boosting tree and), classifiers (e.g., Bayes classifier, k-NN, and support vector machine), and some neural network-based models [10] (e.g., feed-forward back-propagation network and cascade correlation). In addition, according to the data structure, these models can be divided into linear and nonlinear models. Linear models are selected when the response and predictive variables are linearly related [11] or transformed into a linear relationship. When the scale of the multiple variables differs greatly, data transformation techniques [12], including normalisation, log transformation, and rank transformation, can be employed. In most cases, linear models are simple to develop, easy to use and often applied as the first prediction attempt. When the response and predictive variables are unlikely to be linearly related, other nonlinear models can be used more effectively regardless of the data structure.

2.3 Validation of the prediction result

Most research has a stage of validation after prediction results, including evaluating the model and discussing the proposed model's limitations in view of statistical significance and applicability. The most common validation algorithm is the leave-one-out cross-validation. To develop a statistical model to predict IAQ, the overall data set is usually split into three for the model's training, validation, and testing.

2.4 Gaps in research

In summary, the number of occupancy state predictions outnumbered other applications until 2020, it shows the research concern in occupancy prediction moves from simply identify if a room is occupied to a more complicated target like the occupant's specific activity which will lead to a more accurate result of building models. However, The studies in thermal comfort prediction using machine learning are not enough to compare to the other fields like occupancy state prediction, IAQ prediction and energy consumption prediction. The concept of thermal comfort changes to the overall comfort of occupant which need more attention in future works[13]. Also, the diversity of individual occupants should be noticed and future models could focus more on detailed comfort feedback which could be achieved by new thermal-based data collection methods like thermal imaging and thermal comfort voting application.

In the existing literature, a standard framework to describe the models with adequate details that enable model exchange or reuse lacks. The best and most suitable algorithm for specific cases varies in different situations. An analysis of data character should be done, for instance, if the data is linear or continuous or otherwise, and if it needs data mining before being put into the algorithm. Considering that a new and more advanced algorithm could occur at any time, it is recommended to compare the performances of different models before selecting the most suitable one.

3. METHOD

In the existing literature, even though a standard framework to describe the models with adequate details that enable model exchange or reuse lacks, the most popular and best-performing algorithms are neural network-based algorithms. This study proposed a modified convolutional neural network (CNN) model that enables specific occupancy activity prediction to better understand occupancy behaviour within a building space. The prediction result will inform the occupants and adjust the HVAC system control.

Fig 1 presents the framework approach. Deep learning techniques were employed to develop a vision-based detector, enabling the detection and recognition of typical occupancy activities such as sitting, standing, walking, and their actions towards opening and closing windows. It consisted of the configuration and training of a convolutional neural network-based model using an image dataset. The trained model was then deployed to form an AI-powered camera which was used to perform

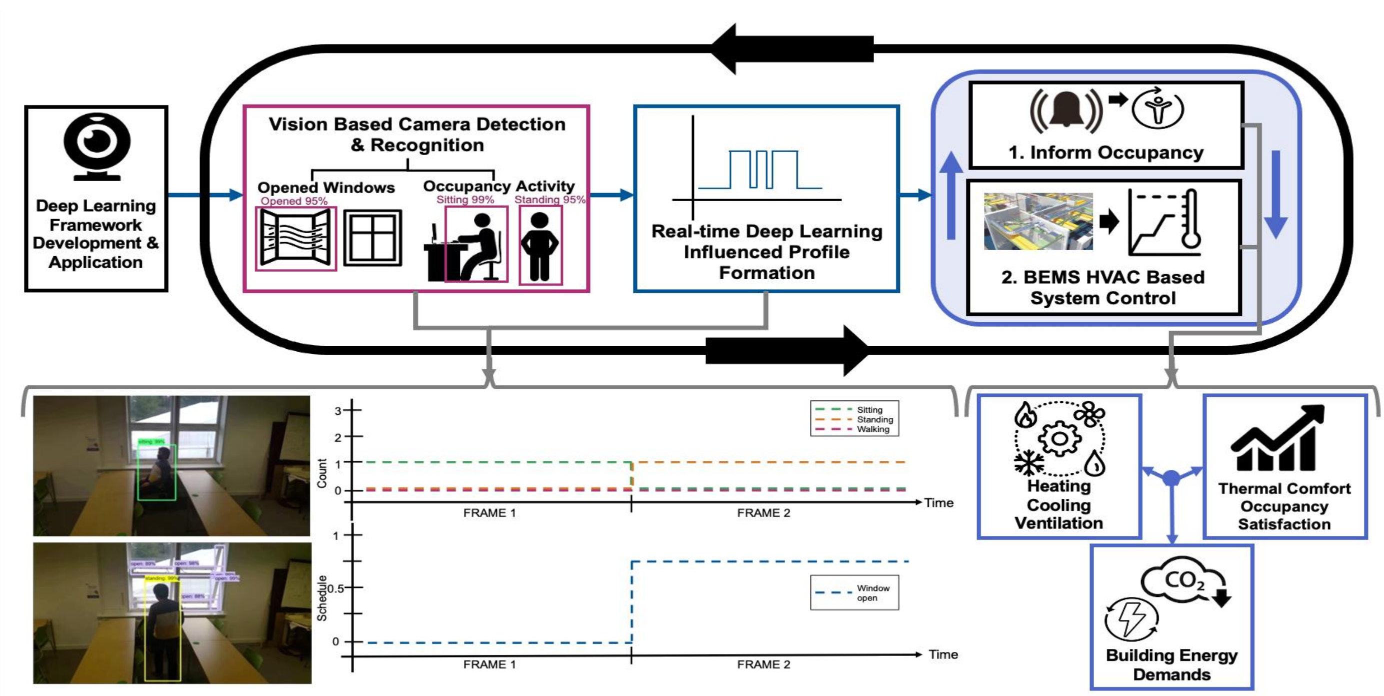


Fig 1 A deep learning-based occupancy detection framework approach.

live detections. The detection results were recorded in the form of the generated deep learning influenced profile (DLIP). Such results were used to provide different system responses designed to assist the HVAC control system in providing adequate indoor thermal comfort and air quality while improving the building energy performance.

4. DEEP LEARNING METHOD

A studying space in Paton House in the University Park Campus, University of Nottingham, UK was used as the desired location to provide a platform to support various stages of the design and testing of this framework. It consisted of a 36.62 m^2 floor area. The Nottingham, UK weather data file was used for the simulations. The building operates between the hours of 08:00 to 18:00, with a setpoint temperature maintained at 21 C.

The model was deployed from the connected laptop to the camera, from the room set up to allow real-time detection during the experimental test. The view from the detection camera is showed in Fig 2, which provides a wide-angle vision, enabling a large detection region.

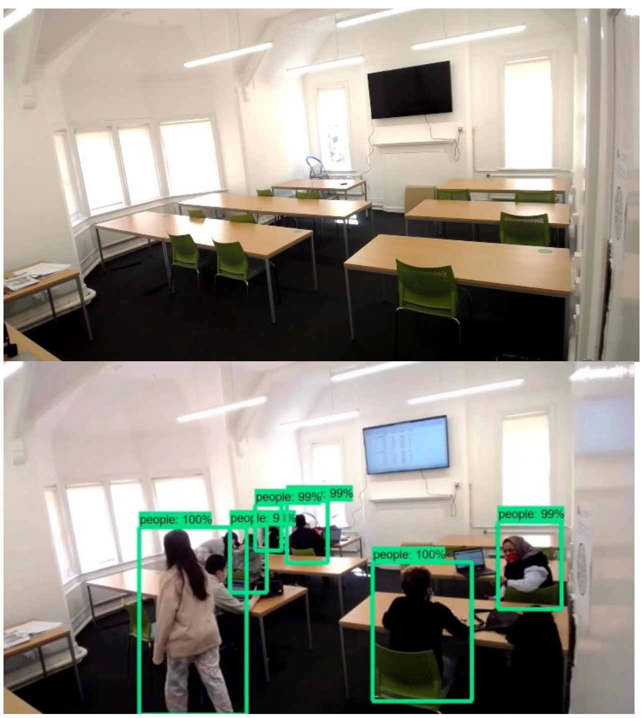


Fig 2 View From the Detection Cameras

The building conditions were assigned, and a comparison between a series of different deep learning influenced profile DLIP with Typical constant profiles was conducted. As represented by the Typical Office 1 and 2 profiles in Fig 3, it suggests that current buildings are operated based on the assumption with predefined or

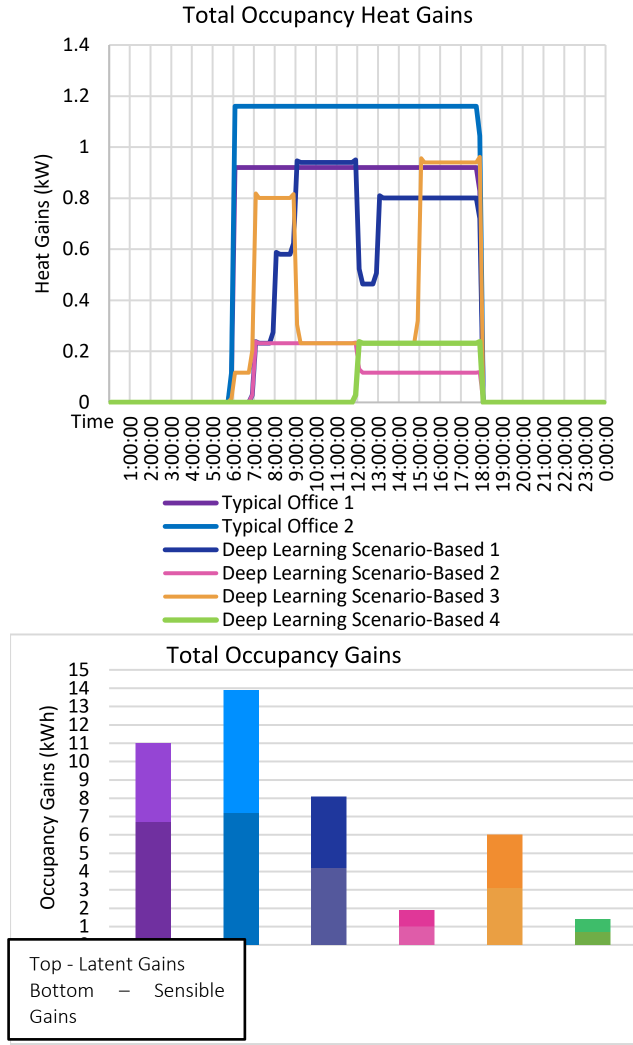


Fig 3 Comparison of the occupancy heat gain profiles generated using the proposed approach and the typical occupancy scheduled profiles. a). Variation of gains across time and b). the total occupancy gains.

fixed schedules. Typical Office 1 assumed that the occupants are performing sedentary activities within the office space. While Typical Office 2 assumed a higher activity rate by the occupants. However, compared to the given Deep Learning Scenario-Based results where the vision-based approach was applied, the occupancy patterns do not follow such patterns as more variation occurs within the number of occupants within the room and the activities they performed. Hence, this indicates the importance of such an approach to employ such a novel occupancy prediction approach to recognise whether a room is occupied or unoccupied, along with the knowledge of the type of activities performed by occupants at a given time.

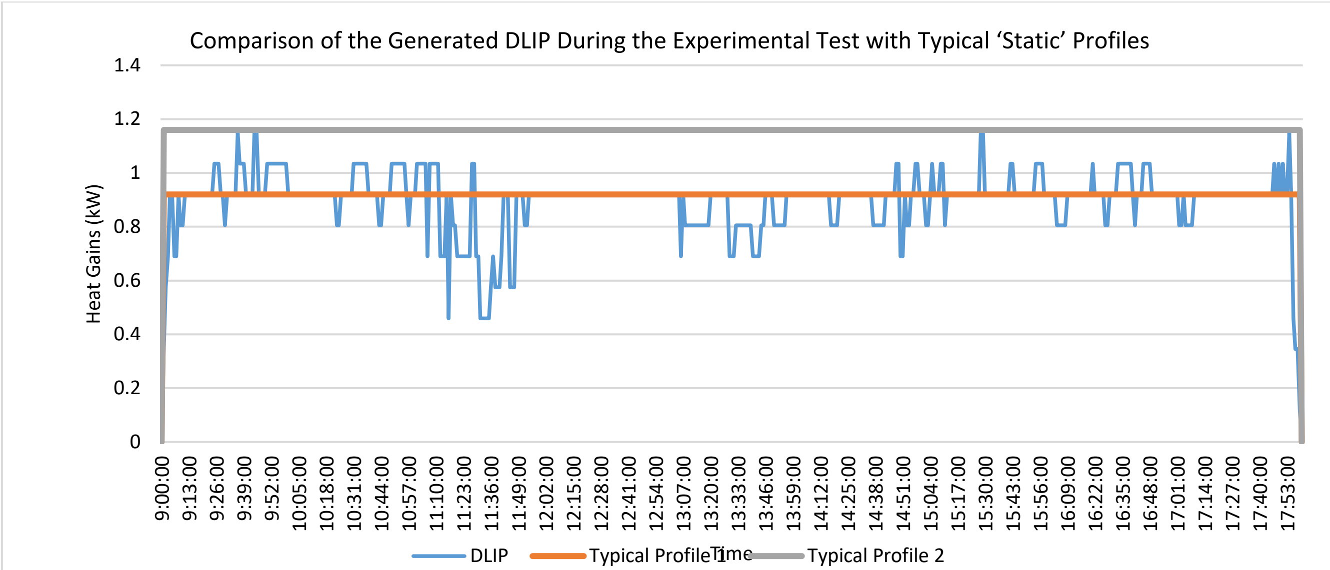


Fig 4 Comparison of the Generated DLIP During the Experimental Test with Typical 'Static' Profiles.

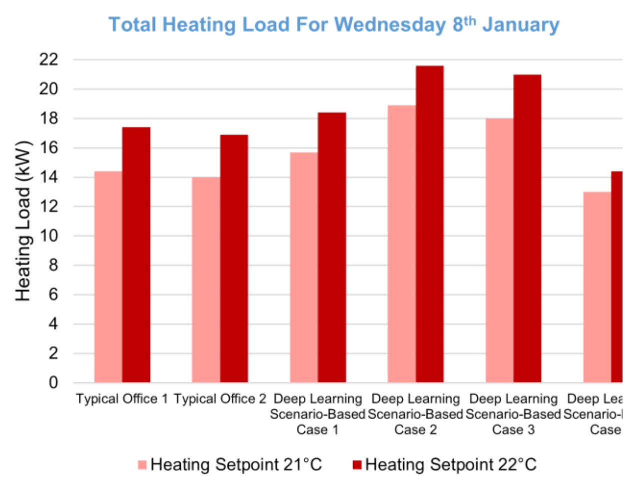
5. RESULTS AND DISCUSSION

The experimental test consisted of a total of 8 people in the space. Typical Office 1 represented the average heat gain by all occupants performing sedentary activities. Typical Office 2 represented the average heat gain by all occupants performing high-intensity activities (such as walking). The average percentage difference between the DLIP and typical profile 1 and 2 was 2.7% and 22.8% respectively. The results suggest the DLIP provides a more accurate estimation of the number of occupants in the detected space, giving the corresponding values in terms of heat gains. The generated DLIP profile and the typical "static" profile are shown in Fig 4.

With the possibility of achieving high variation in occupancy gains, it subsequently affects the building energy demands. Fig 5 presents the predicted heating and cooling loads during typical winter and summer days. The results suggest that using predefined assumptions for occupancy gains can lead to inaccurate estimation leading to the increase in energy demands, increasing unnecessary building energy loads. Furthermore, depending on the occupancy level, slight adjustments to the room setpoint temperature can be made to improve the space's thermal condition. Consequently, this can affect the occupant productivity and quality of life while significantly affecting the energy demand of the building.

6. CONCLUSION AND FUTURE WORK

This study reviewed the typical flow of the machine learning model on the prediction of the occupancy and its application on energy consumption, air quality and thermal comfort in the existing literature. Each step's key factors and potential improvements, including data



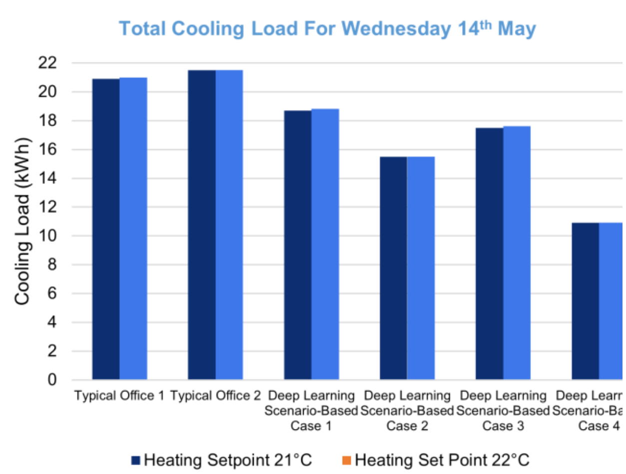


Fig 5 Comparison of the total a). heating and b). cooling

collection, prediction models, and validation, were discussed. In summary, the number of occupancy state predictions outnumbered other applications, it shows the research concern in occupancy prediction moves from simply identify if a room is occupied to a more complicated target like the occupant's specific activity, which will lead to a more accurate result of building models.

In this study, occupancy detection with the vision-based camera captures specific occupancy activities and other related behaviour like window opening behaviour. These activities will generate real-time deep learning influenced profile formation, which can train the prediction model. The proposed CNN model framework provided an initial average detection accuracy of 84.48%. Also, the constant "static" scheduled occupancy profiles used in current simulations and guidelines are not sufficient for effective HVAC system designs and building energy performance evaluations. The ability of the deep learning detection to inform HVAC systems with significant help towards reducing building energy loads as with temperature set point changed. Therefore, It is important to develop an effective solution to increase the performance of buildings by assisting the HVAC control system in providing adequate indoor thermal comfort and air quality while improving the building energy performance.

The Future works will focus on the enhancement of the deep learning-based model to improve the detection accuracy, providing more accurate system responses. Also, a streamlined framework-based solution will be developed to define the required HVAC control system conditions based on real-time detection data responses. This includes the most suitable indoor/ room setpoint temperature that should be assigned to HVAC systems to provide adequate thermal conditions based on the real-time understanding of the utilisation of the space by occupants.

REFERENCE

[1] X. Cao, X. Dai, and J. Liu, "Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade," Energy and Buildings, vol. 128, pp. 198-213, 2016/09/15/ 2016, doi: https://doi.org/10.1016/j.enbuild.2016.06.089.

[2] U. Sbci, "Buildings and climate change: summary for decision-makers," Buildings and Climate Change Summary for Decision-makers, pp. 1-62, 01/01 2009.

[3] V. Erickson and A. Cerpa, Thermovote: Participatory sensing for efficient building HVAC conditioning. 2012, pp. 9-16.

[4] J. Lo and A. Novoselac, "Localized air-conditioning with occupancy control in an open office," Energy and Buildings - ENERG BLDG, vol. 42, pp. 1120-1128, 07/01 2010, doi: 10.1016/j.enbuild.2010.02.003.

[5] Z. Yang and B. Becerik-Gerber, "The coupled effects of personalized occupancy profile based HVAC schedules and room reassignment on building energy use," Energy and Buildings, vol. 78, pp. 113–122, 08/01 2014, doi: 10.1016/j.enbuild.2014.04.002.

[6] T. A. Nguyen and M. Aiello, "Energy intelligent buildings based on user activity: A survey," Energy and Buildings, vol. 56, pp. 244–257, 01/31 2013, doi: 10.1016/j.enbuild.2012.09.005.

[7] M. Mohri, A. Rostamizadeh, and A. Talwalkar, "Foundations of Machine Learning," 01/01 2012.

[8] A. Ashouri, G. Newsham, Z. Shi, and B. Gunay, Day-ahead Prediction of Building Occupancy using WiFi Signals. 2019, pp. 1237-1242.

[9] M. Koklu and K. Tutuncu, "Tree based classification methods for occupancy detection," IOP Conference Series: Materials Science and Engineering, vol. 675, p. 012032, 11/15 2019, doi: 10.1088/1757-899X/675/1/012032.

[10] M. K. Kim, Y.-S. Kim, and J. Srebric, "Impact of Correlation of Plug Load Data, Occupancy Rates and Local Weather Conditions on Electricity Consumption in a Building Using Four Back-propagation Neural Network Models," Sustainable Cities and Society, vol. 62, p. 102321, 06/01 2020, doi: 10.1016/j.scs.2020.102321.

[11] B. Delcroix, J. Le Ny, M. Bernier, M. Azam, B. Qu, and J.-S. Venne, "Autoregressive neural networks with exogenous variables for indoor temperature prediction in buildings," Building Simulation, vol. 14, 02/21 2020, doi: 10.1007/s12273-019-0597-2.

[12] G. Apostolo, F. Bernardini, L. Magalhaes, and D. Muchaluat-Saade, An Experimental Analysis for Detecting Wi-Fi Network Associations Using Multi-label Learning. 2020, pp. 423-428.

[13] J. Xie, H. Li, C. Li, J. Zhang, and M. Luo, "Review on occupant-centric thermal comfort sensing, predicting, and controlling," Energy and Buildings, vol. 226, p. 110392, 08/01 2020, doi: 10.1016/j.enbuild.2020.110392.