

NRC Publications Archive Archives des publications du CNRC

Opportunistic occupancy-count estimation using sensor fusion: a case study

Hobson, Brodie W.; Lowcay, Daniel; Gunay, H. Burak; Ashouri, Araz; Newsham, Guy R.

This publication could be one of several versions: author's original, accepted manuscript or the publisher's version. / La version de cette publication peut être l'une des suivantes : la version prépublication de l'auteur, la version acceptée du manuscrit ou la version de l'éditeur.

For the publisher's version, please access the DOI link below. / Pour consulter la version de l'éditeur, utilisez le lien DOI ci-dessous.

Publisher's version / Version de l'éditeur:

<https://doi.org/10.1016/j.buildenv.2019.05.032>

Building and Environment, 159, 2019-05-17

NRC Publications Archive Record / Notice des Archives des publications du CNRC :

<https://nrc-publications.canada.ca/eng/view/object/?id=8e77d138-bc74-4c71-bc41-c81df25cbfb6>

<https://publications-cnrc.canada.ca/fra/voir/objet/?id=8e77d138-bc74-4c71-bc41-c81df25cbfb6>

Access and use of this website and the material on it are subject to the Terms and Conditions set forth at

<https://nrc-publications.canada.ca/eng/copyright>

READ THESE TERMS AND CONDITIONS CAREFULLY BEFORE USING THIS WEBSITE.

L'accès à ce site Web et l'utilisation de son contenu sont assujettis aux conditions présentées dans le site

<https://publications-cnrc.canada.ca/fra/droits>

LISEZ CES CONDITIONS ATTENTIVEMENT AVANT D'UTILISER CE SITE WEB.

Questions? Contact the NRC Publications Archive team at

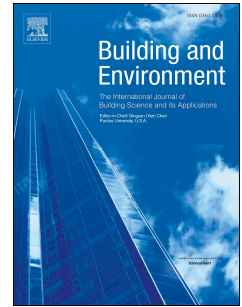
PublicationsArchive-ArchivesPublications@nrc-cnrc.gc.ca. If you wish to email the authors directly, please see the first page of the publication for their contact information.

Vous avez des questions? Nous pouvons vous aider. Pour communiquer directement avec un auteur, consultez la première page de la revue dans laquelle son article a été publié afin de trouver ses coordonnées. Si vous n'arrivez pas à les repérer, communiquez avec nous à PublicationsArchive-ArchivesPublications@nrc-cnrc.gc.ca.

Accepted Manuscript

Opportunistic occupancy-count estimation using sensor fusion: A case study

Brodie W. Hobson, Daniel Lowcay, H. Burak Gunay, Araz Ashouri, Guy R. Newsham



PII: S0360-1323(19)30350-6

DOI: <https://doi.org/10.1016/j.buildenv.2019.05.032>

Reference: BAE 6154

To appear in: *Building and Environment*

Received Date: 20 January 2019

Revised Date: 27 April 2019

Accepted Date: 16 May 2019

Please cite this article as: Hobson BW, Lowcay D, Gunay HB, Ashouri A, Newsham GR, Opportunistic occupancy-count estimation using sensor fusion: A case study, *Building and Environment* (2019), doi: <https://doi.org/10.1016/j.buildenv.2019.05.032>.

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

Corresponding Author: H. Burak Gunay

Main Address:

Carleton University
Department of Civil and Environmental Engineering
1125 Colonel by Drive
Ottawa, Ontario, Canada K1S 5B6
Email: burak.gunay@carleton.ca
Tel: +1 613 520 2600 x 3357
Fax: +1 613 520 3951

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Opportunistic occupancy-count estimation using sensor fusion: A case study

Brodie W. Hobson¹, Daniel Lowcay¹, H. Burak Gunay¹, Araz Ashouri², Guy R. Newsham²

¹Department of Civil and Environmental Engineering, Carleton University, Ottawa, Canada

²Construction Research Centre, National Research Council Canada, Ottawa, Canada

Abstract

Estimation of occupancy counts in commercial and institutional buildings enables enhanced energy-use management and workspace allocation. This paper presents the analysis of cost-effective, opportunistic data streams from an academic office building to develop occupancy-count estimations for HVAC control purposes. Implicit occupancy sensing via sensor fusion is conducted using available data from Wi-Fi access points, CO₂ sensors, PIR motion detectors, and plug and light electricity load meters, with over 200 hours of concurrent ground truth occupancy counts. Multiple linear regression and artificial neural network model formalisms are employed to blend these individual data streams in an exhaustive number of combinations. The findings suggest that multiple linear regression models are the superior model formalism when model transferability between floors is of high value in the case study building. Wi-Fi enabled device counts are shown to have high utility for occupancy-count estimations with a mean R² of 80.1 to 83.0% compared to ground truth counts during occupied hours. Aggregated electrical load data are shown to be of higher utility than separately submetered plug and lighting load data.

Keywords: Occupancy detection; Occupancy-count estimation; Sensor fusion; Occupancy-centric controls

1. Introduction

It is estimated that 15 to 30% of the energy used by heating, ventilation, and air conditioning (HVAC) systems in commercial and institutional buildings is wasted due to inefficiencies in their operation [1-3]. Considering that HVAC systems in said buildings account for ~15% of the secondary energy use and ~10% of greenhouse gas (GHG) emissions [3], improvements to their operation represent a key opportunity to reduce global energy consumption and CO₂ emissions.

As stated by Shen et al. [4], the key to improving the operation of HVAC systems is to provide heating, cooling, and ventilation only when and where they are needed, in the amount that they are needed. Notably, this is inherently dependant upon having access to high-resolution occupancy information. By knowing the first arrival and the last departure times, one can schedule the HVAC start and stop times and/or apply temperature setbacks. By knowing the number of occupants, one can adapt the ventilation rates (i.e., demand control ventilation). Implementation of such occupancy-centric control strategies are reported to achieve energy savings of 18 [5] to 55% [6] depending on the building archetype and climatic conditions. Further, occupancy-centric HVAC controls are reported to reduce the peak energy demand by diversifying the HVAC needs of individual zones [7].

Despite the importance of high-resolution occupancy information for energy efficient HVAC operation, there is no perfect, cost-effective sensor to count the number of occupants in a building accurately and non-intrusively. However, sensor fusion is a promising statistical approach to combine imperfect information from disparate data sources [8]. Rather than deploying sensors dedicated for occupancy detection, sensor fusion can take advantage of pre-existing data streams (e.g., Wi-Fi access points, CO₂ sensors, motion detectors, electrical

1 load meters) that are commonly available in existing buildings and expected to be correlated with occupancy,
2 allowing for cost-effective occupancy-count estimations. This opportunistic approach is referred to as implicit
3 occupancy sensing [9].

4 This paper focuses on using implicit occupancy sensing via sensor fusion models to develop occupancy-
5 count estimations for HVAC control purposes. By using the Wi-Fi device count, CO₂ concentration, passive
6 infrared (PIR) motion detector trigger, plug load, and lighting load data from an academic office building,
7 multiple linear regression and artificial neural network (ANN) models are developed to estimate occupancy
8 counts. These estimates are compared to ground truth data. The effectiveness of different sensors, sensor
9 combinations, and the model formalisms for the purpose of occupancy-count estimation is discussed. The
10 transferability of models developed in one floor and used in another is explored in the case study building
11 throughout. Criteria are put forward for selecting the most suitable model for occupancy-count estimation, and
12 these models are identified for the case study building given the data examined. The data used in this study have
13 been made publicly available as a supplemental file to facilitate the development and validation of different
14 occupancy sensing methods.

15 The remainder of this paper is structured as follows: Section 2 examines the state-of-the-art in the field of
16 occupancy sensing; Section 3 introduces the dataset and methodology; Section 4 presents the experimental
17 results; Section 5 discusses the findings, limitations, and develops future work recommendations.

18 **2. Literature Review**

19 Traditional occupancy sensing technologies have numerous shortcomings. A majority of occupancy sensors
20 are motion detectors (e.g., PIRs or ultrasonic motion detectors); thus, they can only detect presence, not the
21 number of occupants in a space. These sensors are also unable to distinguish between a lack of movement and an
22 absence of occupants, which can lead to false vacancy detections if the time-out period is too short [10-13].
23 Increasing the time-out period of 5 to 60 minutes after the last detected movement could reduce the frequency of
24 false vacancy detections [14]. However, increasing the length of this time-out period also increases the
25 possibility of false occupancy detections; this trade-off reduces the savings potential. Additionally, if the sensor
26 detects a motion and activates building services such as lighting, the occupants may deem this undesirable and
27 resort to methods of disabling the motion detector, such as intentionally blocking the sensor to obstruct its line-
28 of-sight [15, 16]. This will either diminish or completely negate the sensors' functional purpose. Furthermore,
29 because motion detectors require a direct line-of-sight to detect occupants, they need to be deployed in a fine
30 grid to ensure their field-of-view is not obstructed by architectural partitions or furniture; this dense
31 configuration incurs additional cost both for the sensors and labour. To address the binary nature of PIR sensors,
32 Wahl et al. [11] proposed a system whereby PIR sensors were installed on either side of a door at the lintel level.
33 This configuration produced an analogue output that could be used to determine if an occupant was entering or
34 leaving the studied space. The system kept track of the net occupancy within the space of interest. However, this
35 system suffered from inaccuracies when multiple occupants move through the door simultaneously, if two or
36 more occupants moved in opposite directions, or if individuals or crowds gathered on either side of the door
37 within the sensors' range. Liu et al. [12] also used PIR sensor data combined with a hidden Markov model to
38 predict room level occupancy with accuracies ranging from 81% to 97%. However, this required a dense sensor
39 grid and computationally expensive computer algorithms that are only applicable to the studied space. Similarly,
40 Duarte et al. [13] proposed a network of PIR sensors to establish occupancy patterns in an office building

1 testbed. While this system was able to establish high-level occupancy patterns, the resolution was not high
2 enough to develop zone-level HVAC control strategies and required a dense sensor grid. The first-cost of
3 installing such a granular PIR system has deterred implementation of these systems in spaces outside those
4 required by codes – such as the National Energy Code for Buildings in Canada and ANSI/ASHRAE 90.1. This
5 shows that the method by which motion detectors are implemented currently is not appropriate for occupancy-
6 count estimation for HVAC control purposes. As such, some researchers have turned to the use of CO₂ sensors
7 for inferring occupancy levels [6, 17]. However, problems have been noted with calibrating the models to
8 account for the latency between occupants' arrival/departure and the corresponding increase/decrease in CO₂
9 concentration, as well as the sensitivity of this technology to sensor position and reading accuracy.

10 As such, significant research over the past decade has focused on occupancy-detection studies using new
11 sensor technologies explicitly built for occupancy counting. Many of these technologies involve optical [5, 18-
12 23] and/or infrared [5, 20, 21] camera-based technologies coupled with complex image recognition algorithms.
13 However, many of these studies are limited to a single room office-type occupancy [5, 18, 20] with a limited
14 number of occupants to monitor. Even with low occupancy, Cao et al. [5] specifically note that significant
15 computational resources are required for this type of image processing approach. The first-cost attached to these
16 sensors and the related infrastructure, as well as the labour required to integrate them into an existing building
17 automation system (BAS) cannot be neglected. Additionally, the algorithms used to extract the occupant count
18 from the camera-based sensors can suffer from inaccuracies when numerous occupants enter the frame, or if
19 occupants are moving too quickly to be captured by the camera's framerate, which is typically reduced to a
20 frame every couple of seconds to reduce the computational resources needed for real-time processing [5, 18-23].
21 Like motion detectors, this system cannot detect occupants that are outside the cameras line-of-sight,
22 necessitating numerous well-placed sensors if adequate occupancy counting is to be expected. Cameras also
23 inherently raise questions about privacy. Although these studies make use of methods to pixelate and analyze
24 images without compromising occupant identity, it has been shown that even a perceived threat to privacy
25 associated with monitoring technologies such as cameras can deter the implementation of said systems [16]. Due
26 to these many challenges and shortcomings, Petersen et al. [21] acknowledge that the applications of these
27 technologies should be limited to gathering ground truth data until more robust and privacy conscious occupancy
28 counting methods are developed.

29 Another technology used in occupancy-detection studies is radio-frequency identification (RFID) tags.
30 Carreira et al. [24] used RFID tags and a web-based application to track occupants and their vote to raise or
31 lower the room temperature by 1°C. Li et al. [25] also used RFID tags to gather information about occupants'
32 location and identity. These studies showed that RFID devices do not suffer from the same line-of-sight pitfalls
33 as motion and camera-based sensors, however, their direct tracking of individual occupants' movements only
34 exacerbate security and privacy concerns. The cost of implementing these sensors and their integration into the
35 BAS are similarly a barrier to their deployment and implementation when compared to camera-based sensors,
36 although Li et al. [25] note that sensor cost has decreased substantially over the past several years. Other
37 proposed proprietary sensing methods include using electrical load data to characterize occupancy. Akbar et al.
38 [26] applied k-nearest neighbor (KNN) or support vector machine (SVM) machine learning classification
39 algorithms on data from a ZigBee smart energy unit, which submeters electrical loads down to the appliance
40 used at the desk level. It was found that this method could detect whether an occupant was present or absent
41 from their desk with 94% accuracy. Labeodan et al. [27] deployed an office chair with various sensing

1 technologies that allowed it to detect when the occupant was seated. However, in both these cases, the scalability
2 of this method is questionable as every workstation would require an additional sensing unit; this method would
3 also only work in cases where every occupant has a desk or workstation with plug-in equipment. Therefore,
4 these kinds of systems may not be practical for many occupancy types where non-habitual users or the broader
5 public represent a large fraction of the buildings occupants.

6 To address the weaknesses of any individual sensor technology, numerous studies have been conducted that
7 take advantage of sensor fusion. Sensor fusion is a technique that combines data collected from multiple sensors
8 and sensor technologies to provide enhanced performance over any single sensor. These studies have looked at
9 different combinations of sensors and data, ranging from indoor air temperature [20, 28-34], indoor relative
10 humidity [18, 29, 31-36], CO₂ levels [18, 28-35, 37], volatile organic compound (VOC) concentrations, [28, 31,
11 32, 36], PIR trigger events [28, 30-33, 35, 36, 38], lighting loads [28, 30-33, 35, 37], noise levels [30-33, 36, 39],
12 Wi-Fi device counts [30, 34, 40-44], and other sensors such as door triggers [30, 35, 38] and Bluetooth device
13 counts [40, 41, 45]. This data is then analyzed using different machine learning algorithms to generate
14 occupancy-count estimations with a high enough resolution to attain HVAC energy savings anywhere from 18
15 [5] to 55% [6]. However, many buildings do not monitor parameters such as VOC concentration or noise levels.
16 Door entry and exit activity is not monitored in many buildings with public or semi-public access. Bluetooth has
17 also been shown to be less prevalent than Wi-Fi enabled devices [46] and therefore less useful for occupancy-
18 count estimation [47]. As Bluetooth and Wi-Fi depend on signal propagation, both suffer from potential dead-
19 zones or poor coverage in buildings with large amounts of internal mass. Privacy concerns with the use of these
20 signals remains a tangible barrier to their widespread use. These studies were also performed either in an
21 experimental testbed or using ad hoc sensor arrays in a pre-existing built environment; this additional hardware
22 drives up the cost of detecting occupants within the building. It would be advantageous to explore leveraging
23 existing data streams within buildings using in-situ sensors further, as these opportunistic data streams would
24 reduce the cost needed to facilitate occupancy-count estimation. Additionally, the models in these studies were
25 developed for a single space over the measured occupancy period, without consideration for how these models
26 will perform if implemented in a different context. Overall, these studies showed that a limitation of sensor
27 fusion is that models can differ vastly in terms of their predictive accuracy due to a variety of factors [16]. The
28 model formalism chosen and its complexity can substantially affect the model accuracy. Similarly, the data
29 streams, sensors, and sensor combinations available for analysis will have different levels of utility for
30 occupancy-count estimation purposes. Furthermore, the calibration of a model with space-specific ground truth
31 data will impact its ability to determine occupancy levels. As the ground truth data collection process is invasive
32 and resource/time intensive, it would be advantageous to explore the transferability of models to another context.
33 This might include if a model trained and validated in one space at a certain time can be applied in an entirely
34 different temporospatial context.

35 This paper contributes to the state-of-the-art by analyzing and quantifying the effects these parameters have
36 on the predictive accuracy of sensor fusion models. This study uses in-situ commercial sensors already installed
37 in the case study building and ground truth data, without any other ad hoc data recorded. A dataset with over 200
38 hours' worth of manual ground truth occupancy counts is used to assess the potential of sensor fusion-based
39 implicit occupancy sensing. Models are developed for all possible sensor-type combinations. These models are
40 implemented on different floors of the building to explore their transferability, which – to the authors' best
41 knowledge – has not been previously studied.

1 **3. Methodology**

2 *3.1. Building Layout and Dataset*

3 The analysis was carried out on four floors of an academic office building in Ottawa, Canada. Each floor
4 varies slightly in configuration and size, see Figure 1 and Table 1, respectively. Note that the PIR and CO₂
5 sensors are commercial grade wall units mounted at approximately 1.6 meters in height, with the exception of
6 the ceiling mounted PIR units in the washrooms of floor A and C.

ACCEPTED MANUSCRIPT



Figure 1: Floor and sensor configuration for (a) floor A, (b) floor B, (c) floor C, and (d) floor D.

Table 1: Floor size and use breakdown.

Occupancy Type	Approximate Area (m ²)				Σ
	Floor A	Floor B	Floor C	Floor D	
Private/Semi-private	176	160	129	250	715 (17%)
Laboratory/Classroom	427	618	377	389	1811 (43%)
Utility	98	80	144	96	417 (10%)
Communal	290	281	294	417	1283 (30%)
Total	991	1139	944	1152	4226

All floors contain a mixture of private and semi-private office spaces, as well as classrooms, study spaces, washrooms, and space for utilities/IT services. These office spaces and some laboratories are used by professors and graduate students during the entire year, whereas the classrooms are typically only used during the academic year (i.e., from September to mid-April). The sensor grid density and granularity also vary between floors; sensor counts are shown in Table 2. On floor B, the sensors are disproportionately concentrated in the office spaces on the west side of the floor. The sensor counts are nearly double that of floor B on floors A and C, and the sensors on these floors are distributed over a larger proportion of the floor area.

Table 2: Floor sensor type and count breakdown.

Sensor Type	Number of Sensors			
	Floor A	Floor B	Floor C	Floor D
Wi-Fi	3	5	2	4
CO ₂	26	13	20	16
PIR	26	10	21	19
Plug Meter	1	1	1	1
Light Meter	1	1	1	1

The data from these sensors are accessible through the BAS, including individual CO₂ sensor readings, individual PIR activations, and instantaneous floor-level lighting and plug loads, all provided in a concurrent five-minute timestep. Individual Wi-Fi-enabled device counts are also provided in the same five-minute timestep from the IT network for each Wi-Fi access point. These counts include all mobile devices and ambient devices such as wireless printers and laptops connected to or attempting to connect to the Wi-Fi access points, referred to as associated devices. Note that these data were anonymized before being provided, and therefore no MAC addresses were monitored or stored during the data collection campaign. The CO₂ sensors' readings were verified using a reference CO₂ logger and were found to have a mean absolute error of 96 ppm. The functionality of each PIR sensor was also individually verified. Coverage maps were provided by IT services to verify that the Wi-Fi access points did not have any dead-zones on each floor. Models were developed using these data as-is. The data were selected for the concurrent times that ground truth was available.

In order to verify and compare the models developed using the sensor data, ground truth occupancy counts were collected for each floor. Three cameras were used, with one at the elevator lobby and one at each stairwell to ensure all entrance and exit points were monitored. This footage was then manually reviewed by a researcher and the timing of the entry and exit events were manually logged. Note that for privacy reasons, the cameras used did not record any audio and the footage was deleted immediately after being logged. The methodology

1 was reviewed and approved by Carleton University's Research Ethics Board. Data collection was performed for
 2 floors A, B, C, and D between the periods shown in Table 3. The data from these observation periods was then
 3 grouped to match the same five-minute timestep as the BAS data. Overall, 208.5 hours of ground truth
 4 observations were recorded.

5
 6 *Table 3: Data collection period(s) for each floor, all in 2018.*

Floor	Date(s) & Time(s)	Peak Occupancy
A	Fri, 2-Mar 7:56-12:56	26
	Sat, 3-Mar, 7:31-12:56	
	Wed, 15-Aug, 17:25 to Fri, 17 Aug, 15:15	38
B	Tue, 13-Feb, 7:18-11:08	72
	Fri, 16-Feb, 7:33-11:13	
	Mon, 26-Feb, 7:28-12:38	
	Mon, 30-Jul, 16:00 to Wed, 1-Aug, 14:00	37
C	Tue, 15-May, 15:31 to Thu, 17-May, 14:31	21
D	Mon, 18-Jun, 14:05 to Wed, 20-Jun, 11:40	67

7 3.2. Model Formalisms

8 The data collected was reduced to a simplified dataset with the following six common datatypes for each
 9 floor: 1) the number of associated Wi-Fi devices, 2) the ensemble mean of the CO₂ concentration (ppm), 3) the
 10 fraction of PIR sensors triggered, 4) the plug load (kW), 5) the lighting load (kW), and 6) the aggregated
 11 electrical load (i.e., the sum of the plug and lighting loads). This final datatype was added to explore the value of
 12 having the lighting and plug loads on one submeter for the purpose of occupancy-count estimation versus having
 13 these load types aggregated. Note that in the cases where either the plug or lighting load was considered as a
 14 predictor of occupancy, the electrical load was not considered and vice versa, as this would be redundant. To
 15 further facilitate comparison, the refined dataset underwent feature scaling in the form of a min-max
 16 normalization before analysis. The focus was on the subset of data collected between 6 am and 10 pm, as this is
 17 when occupants were generally observed on all floors. Including data from the overnight period in model
 18 development could artificially inflate the predictive accuracy of the model; a model that can predict that a
 19 building is unoccupied overnight (a relatively trivial exercise) should not be conflated with a model that can
 20 accurately predict occupancy throughout the day. Such a model is not necessarily useful in commercial and
 21 institutional buildings where overnight occupancy is minimal. A similar approach is adapted by Wang et al. [34]
 22 in their model development.

23 Using enumerative combinatorics, all 39 possible unique combinations of the six datatypes were identified.
 24 The effectiveness of each combination for occupancy count-estimation is explored. Note that for floors A and B,
 25 separate models were developed for each of the winter and summer semester to explore how different occupancy
 26 levels in the same space would affect the quality of the resulting model (e.g., will the trends observed in the
 27 summer models hold true in the higher occupancy winter models, and vice versa?). Each of the 39 datatype
 28 combinations were then modelled using multiple linear regression and ANN formalisms for each floor, with
 29 additional models for floors A and B as mentioned. The data was randomly split into 70% and 30% for training
 30 and validation, respectively, and 10-fold cross-validation was performed. The models were then fitted to the

1 datatypes for the floor they were generated from, as well as all other floors. This allows for the predictive
2 accuracy of a model developed in one space to be evaluated when applied to another space. The resulting fits
3 were then compared to the ground truth data. This means that 39 datatype combinations were considered over six
4 different floor scenarios, with 234 unique models developed for each model formalism, referred to as the ‘intra-
5 floor’ fits. Then, each of the models developed for a single floor were tested on all other floors, for a total of
6 1170 fits for each model formalism, referred to as the ‘inter-floor’ fits. In total, there were 1404 fits for each
7 model formalism, for a total of 2808 fits developed over the course of this study.

8 The ANN models are two-layer feed forward neural networks developed and applied using the *R* functions
9 *neuralnet* and *compute* from the ‘neuralnet’ package [48]. The single hidden layer uses sigmoid activation
10 functions and contains a varying number of neurons depending on the number of sensors considered in the
11 model. This scales a neural network’s complexity to match the amount of data considered. This approach is
12 adapted from Heaton [49] and involves sizing the hidden layer to be two-thirds the size of the input layer (i.e.,
13 the number of sensor-types considered) plus the size of the output layer (i.e., one or the occupancy-count
14 estimation). The output layer uses a logistic function. The parameters of the ANN are then determined using the
15 resilient backpropagation method with weighted backtracking. Training of the network was terminated when the
16 partial derivatives of the error function reached 10^{-6} or 1000 iterations were performed without convergence. The
17 multiple linear regression models were developed and fitted using the *R* functions *lm* and *predict* from the ‘base’
18 package [50], with the intercept coerced through the origin to account for the data normalization (i.e., minimum
19 observed values should correspond to minimum observed occupancy). The coefficient of determination (R^2) and
20 normalized root mean square error (NRMSE) were computed for the fits produced by these models to assess
21 their predictive accuracy relative to the ground truth data and to facilitate comparison between each other.

22 4. Results

23 4.1. Multiple Linear Regression Models

24 Figure 2 presents the distribution of the R^2 for the 1404 fits developed from the multiple linear regression
25 models (i.e., 36 for each of the 39 sensor combinations). The R^2 values reported in this figure are those of both
26 the intra-floor and inter-floor fits resulting from the multiple linear regression models. Generally, it is observed
27 that the models developed from sensor combinations that contain floor-level associated Wi-Fi device counts
28 have a considerably higher R^2 and lower NRMSE than those without. The maximum and mean R^2 for all Wi-Fi
29 only fits were 96.1 and 74.1%, respectively. The mean R^2 is 80.1% if only the intra-floor fits are considered.
30 These fits have the highest mean R^2 and lowest mean NRMSE when only a single sensor-type is considered in
31 all six floor scenarios studied. The highest observed R^2 is 96.5% with a NRMSE of 5.9%, corresponding to the
32 sensor fusion of the Wi-Fi, CO₂, PIR, plug and lighting load data from the intra-floor fit for floor B (i.e., the
33 model from floor B used to predict floor Bs occupancy count). The highest observed R^2 and the corresponding
34 NRMSE resulting from a model used from one floor to another (i.e., inter-floor model) was 94.7% and 7.5%,
35 respectively, for the sensor fusion of Wi-Fi, PIR, and plug load data from the inter-floor fit between floor D for
36 floor B in the winter semester. The lowest observed R^2 is 11.7% with a NRMSE of 26.4%, corresponding to the
37 sensor fusion of the PIR and plug load data from the intra-floor fit for floor C (i.e., the model from floor C used
38 to predict floor Cs occupancy count). This range of accuracies suggest that multiple linear regression models are
39 suited to producing occupancy-count estimations using sensor fusion, depending on the sensors available.

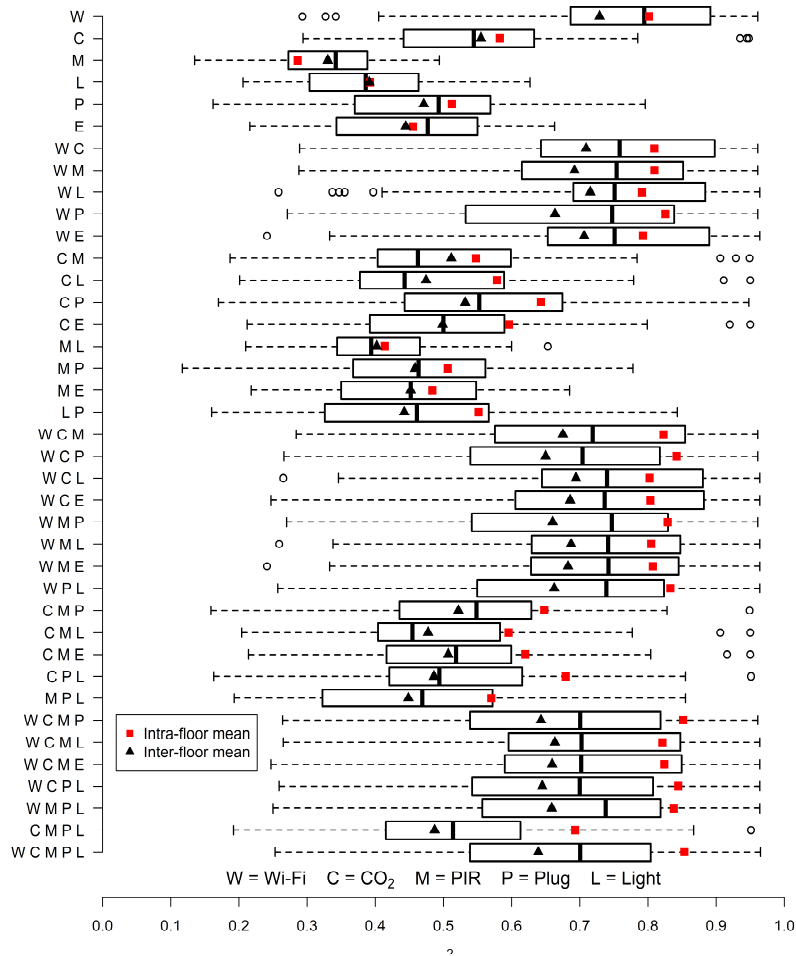


Figure 2: Range of R^2 values produced by multiple linear regression.

4.2. Artificial Neural Network Models

As above, Figure 3 shows the distribution of the R^2 of the 1404 fits for the ANN models. The coefficients of determination reported in these figures are those of both the intra-floor and inter-floor fits resulting from the ANN models. It remains the case that the models which contain associated Wi-Fi device counts have a higher mean R^2 and lower NRMSE than those without. The maximum and mean R^2 for Wi-Fi only fits were 97.4 and 71.4%, respectively. The mean R^2 is 83.0% if only intra-floor fits are considered. These fits have the highest mean R^2 and lowest mean NRMSE when only a single sensor-type is considered in all six floor scenarios studied. The highest observed R^2 is 97.5% with a NRMSE of 5.0%, corresponding to sensor fusion of the Wi-Fi, PIR, and lighting load data from the intra-floor fit for floor B during the winter semester (i.e., the model from floor B used to predict floor Bs occupancy count). The highest observed R^2 and corresponding NRMSE resulting from a model used from one floor (i.e., inter-floor fit) to another was 94.5% and 8.2%, respectively, for the sensor fusion of Wi-Fi and plug load data from the inter-floor fit between floor D for floor B in the winter semester. The lowest observed R^2 is less than 0.1% with a NRMSE of 31.8%, corresponding to the PIR data from the intra-floor fit for floor B (i.e., the model from floor B used to predict floor Bs occupancy count). This range of accuracies suggest that ANN models are similarly suited to producing occupancy-count estimations using sensor fusion, depending on the sensors available.

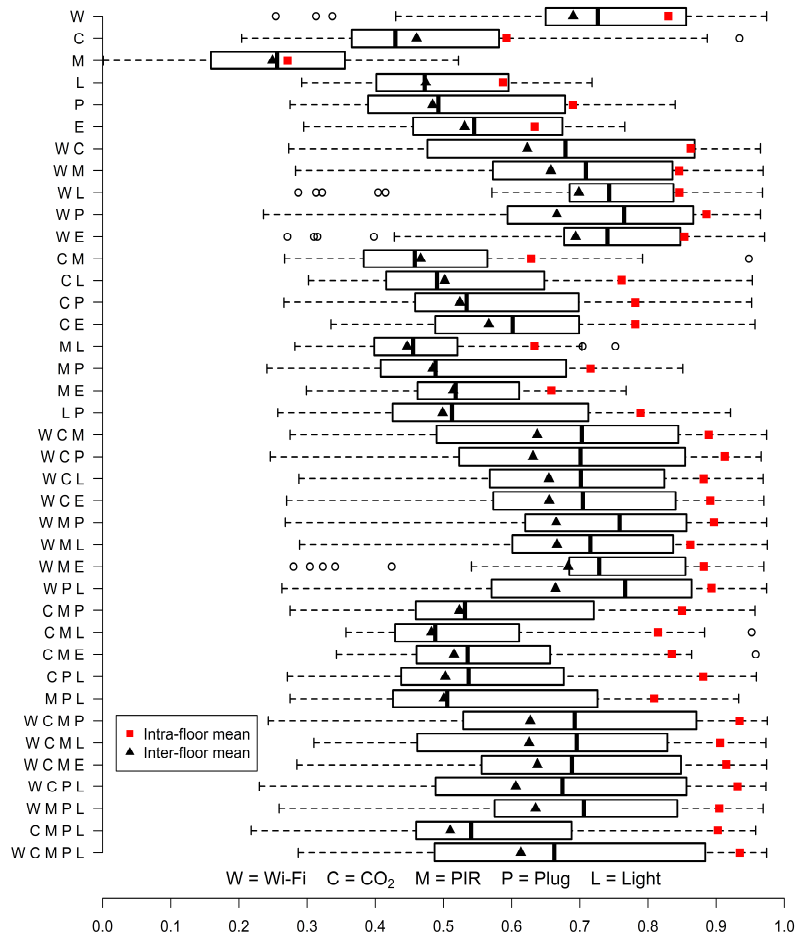


Figure 3: Range of R^2 values produced by artificial neural network models.

5. Discussion

5.1. Model Formalism Comparison

By visual inspection, the trends in the coefficient of determination for both model formalisms bear a resemblance to one another when the same floor is considered. Of the 1404 fits developed for each formalism, ANNs had a higher R^2 on a fit-by-fit basis for 56%. The mean difference in R^2 and NRMSE between the fits using ANNs and the fits using multiple linear regression is 1.7% and 0.8%, respectively. This suggests that ANN models have comparable accuracy to their multiple linear regression counterparts in the case study building. However, if the intra-floor fits are examined in isolation (i.e., the models developed and used on the same floor), there is a shift in favour towards ANN models for both the coefficient of determination and normalized root mean square error. In this case, ANN models had a higher R^2 and lower NRMSE on a fit-by-fit basis for 93% of cases, with a mean change relative to their multiple linear regression counterparts of 11.8% and -2.7%, respectively. The opposite is true when the inter-floor fits are examined (i.e., the models developed on one floor and used on another). In this case, multiple linear regression models had a higher R^2 and lower NRMSE on a fit-by-fit basis for 50.9% and 64.0% of cases, with a mean change relative to their ANN counterparts of 0.4% and -

1 1.6%, respectively. This suggests the following regarding the use of either model formalism to produce sensor
2 fusion models for occupancy-count estimation:

- 3 • ANN models appear to offer higher accuracy over multiple linear regression models in 93% of
4 the cases where the model is fitted to its own floor, making them suited to situations where
5 ground truth data is available for calibration in the case study building; and
- 6 • multiple linear regression models offer comparable accuracy to their ANN counterparts when
7 models are fitted to a different floor, making them a candidate for transferability between
8 floors and therefore suited to situations where ground truth data is not available for calibration
9 for that floor in the case study building.

10 Therefore, for this building and the suggested application of these models, multiple linear regression is the
11 superior model formalism. This is due to their comparable accuracy to ANNs with reduced complexity, and the
12 ease of implementation associated with the limited need for expensive, time consuming, and invasive ground
13 truth data collection.

14 5.2. *Sensor Utility Comparison*

15 The intra-floor fits (i.e., the models developed and used on the same floor) generally benefit from including
16 as many sensor datatypes as possible in their model. However, it is evident in both Figure 2 and Figure 3 that
17 increasing the number of sensor typologies considered in the model formalism does not always equate to a
18 higher R^2 ; a similar trend is observed in the root mean square error. Therefore, additional sensor data are
19 advantageous if ground truth data are available, whereas less sensor data (i.e., one to two sensor datatypes)
20 typically produce inter-floor fits with a higher mean R^2 value. The utility of sensor data produced by sensors for
21 occupancy-count estimation is linked to the sensors' configuration and/or density. Note that the magnitude of
22 this sensitivity depends on the sensor-type considered. If this configuration and/or density varies significantly
23 between spaces, then models developed with these sensors' data between spaces will suffer from inaccuracies.
24 Including numerous sensor-types in models developed between spaces may therefore result in a compounding of
25 these inaccuracies, which is why fewer sensor datatypes typically result in fits with a higher mean R^2 and lower
26 NRMSE between floors.

27 By visual inspection of Figure 2 and Figure 3, it is apparent that associated Wi-Fi device counts are
28 beneficial for floor-level occupancy-count estimation. Recall that sensor fusion models that contain associated
29 Wi-Fi device counts have a higher mean R^2 and lower mean NRMSE than those without. The fraction of PIR
30 sensors triggered alone offers the lowest potential for occupancy-count estimation. However, the range of R^2
31 values produced by the model which uses this datatype alone is narrowest in four out of six cases for both
32 multiple linear regression and ANN formalisms. This suggests that the fraction of PIR sensors triggered is not
33 strongly linked to the sensors' configuration as models developed on one floor performed similarly on others.
34 The utility of these PIR data increased when included in sensor fusion models with other datatypes, especially
35 when ANN models are used. This may be attributable to the fact that the fraction of PIR sensors triggered has a
36 non-linear relationship with occupancy count (i.e., a mean R^2 of 32.3% using linear regression), whereas the
37 non-linear functions used in computing ANN models are able to account for other, non-linear relationships these
38 data have with occupancy count. The mean CO_2 level also increased in utility when included in sensor fusion
39 models and had the second highest mean R^2 of the stand-alone sensor datatypes for predicting occupant count.
40 However, the range of values predicted from models using only the mean CO_2 readings across different floors
41 was large, with a 65% and 70% difference between maximum and minimum values for multiple linear regression

1 and ANN formalisms, respectively. This suggests that the quality of the resulting fit is highly sensitive to sensor
2 configuration and/or density, and therefore mean CO₂ data do not lend themselves well to transferability from
3 one space to another.

4 Floor-level plug, lighting, and aggregated electrical load also exhibited varying levels of utility in sensor
5 fusion models. In general, floor-level lighting load data were more indicative of occupancy than floor-level plug
6 load data. This may be because light levels fluctuated by a factor of more than four on average, whereas plug
7 loads exhibit a fluctuation by a factor of less than two on average. Floors B and D has manual on and automatic
8 off lighting controls, whereas floor A and C has automatic on and off controls. Interestingly, this did not
9 necessarily equate to a stronger correlation between lighting load levels and occupancy for floor A and C that
10 might be expected from an automatic on/off control scheme. With regards to plug load data, it is suspected that
11 submetering of these loads down to the room or workstation level would likely increase their individual
12 contribution to the sensor fusion models, as was noted by Akbar et al. [26]. Models with aggregated electrical
13 load data as opposed to separately submetered plug and lighting load data had a mean R² that was 0.7% and
14 2.6% higher for multiple linear regression and ANN model formalisms, respectively. The range of R² values was
15 also 24.6% and 19.3% smaller for multiple linear regression and ANN model formalisms on average,
16 respectively. This suggests that aggregated electrical data has higher utility for occupancy-count estimation
17 purposes. Ryu et al. [37] also found that electrical load data had higher information gain for occupancy-detection
18 purposes than lighting or plug loads metered separately.

19 As the sensor configuration on each individual floor did not change between the summer and winter
20 semester, it was hypothesized that the model from one semester should transfer well to the other semester.
21 However, the fits developed from the summer semester models generally have lower mean R² values when
22 compared to their winter counterparts. Floor A had a mean reduction in R² of 13.4% and 14.0% for multiple
23 linear regression and ANN models between summer and winter, respectively. Recall from Figure 1 that the
24 private offices on floor A are concentrated to one side, with laboratory and classroom spaces on the other.
25 Sensors are distributed fairly evenly between these spaces. However, occupancy patterns in the private offices
26 exhibit far less fluctuation between winter and summer compared to laboratories and classrooms. Therefore,
27 because the sensor data have been combined into parameters – such as fraction of PIR sensors triggered across
28 the entire floor, or the whole floors mean CO₂ concentration – the lack of activity on one half of the floor biases
29 these models, producing fits with a lower mean R². This reduction may therefore be attributable to a change in
30 occupancy patterns between semesters. Floor B had a mean reduction in R² of 8.9% and 7.5% for multiple linear
31 regression and ANN models between summer and winter, respectively. One possible explanation is that the large
32 computer lab on floor B was used over the summer to host a camp program for youth. It is likely that these youth
33 did not have any Wi-Fi enabled devices, thus reducing the utility of the fits that contain Wi-Fi enabled device
34 counts as a parameter. Therefore, if only the fits containing Wi-Fi enabled device counts are examined, there is a
35 10.4% and 13.9% reduction in the mean R² value for multiple linear regression and ANNs, respectively. If the
36 fits developed from models that do not contain Wi-Fi enabled device counts are considered, there is only a 3.7%
37 and 0.8% reduction in the mean R² value for multiple linear regression and ANNs, respectively. This suggests
38 that Wi-Fi enabled device counts are useful for occupancy sensing only in a context where Wi-Fi devices are
39 prevalent. Furthermore, the layout of the building or floor should also be considered in the cases where
40 occupancy may be concentrated in a particular location during a particular time. This consideration is especially

1 important if ground truth collection overlaps with an atypical day, as was the case with floor B during the
2 summer semester.

3 5.3. Model Selection Criteria

4 The following criteria were developed for selecting the ‘best’ sensor combination for occupancy-count
5 estimation using sensor fusion in the building studied:

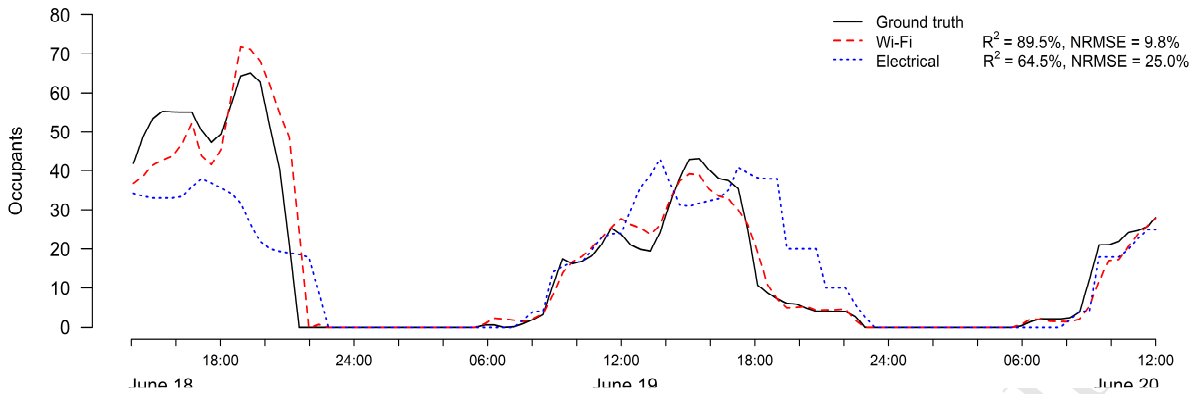
- 6 1) High lower quartile (Q1) R^2 values (see Figure 2 and 3) – to ensure that the models are transferable
7 and can be used in other spaces without recalibration to new ground truth data
- 8 2) High R^2 and low NRMSE of the model fit – to ensure that the models are accurate
- 9 3) Sensor configuration available and cost

10 Using criterion 1 and 2, the top three models are identified in Table 4. In addition, Wi-Fi alone is examined for
11 its novelty and aggregated electrical loads are examined for their widespread availability and ease of access. As
12 it has been established that multiple linear regression is the superior model formalism, the R^2 of these models are
13 reported. Illustrative examples of the fits developed from associated Wi-Fi device count and electrical load data
14 are provided in Figure 4. Note that in Table 4, associated Wi-Fi device count alone ranks higher than the Wi-Fi
15 and electrical as well as the Wi-Fi and CO₂ combinations. This further reinforces the findings that associated Wi-
16 Fi device counts are beneficial for occupancy-count estimation, and that a multiple linear regression formalism
17 can be sufficient to develop a useful model. Fits containing only aggregated electrical load data are observed to
18 have a lower R^2 and higher NRMSE than the models with associated Wi-Fi device counts; regardless, in the
19 absence of other sensors data, this data type can still be used as a regressor for occupancy-count estimation.

20 The third criterion noted but not included in this table is sensor configuration availability and cost. This
21 criterion represents an area where significant differences may be observed between buildings, or even floors of
22 the same building as in this case study. For example, while Dong et al. [16] note that Wi-Fi is considered an
23 ‘expensive’ sensor for occupancy-count estimation, there is virtually no additional hardware cost if these sensors
24 are already installed in the building for other purposes (i.e., access points for internet connectivity). This is the
25 crux of implicit occupancy sensing. Metering of electrical loads is already common practice at the building level,
26 however this study examines submetering at the floor-level. This raises the question: if installing submeters at
27 this kind of resolution is only a moderate cost [16], can this cost be justified given the added benefit it may have
28 for occupancy-count estimation? As this study examines every sensor combination possible given the sensor-
29 types examined, facility managers in the case study building could use these findings to determine the expected
30 level of accuracy they can achieve for occupant sensing given the sensors or data available to them.

31 *Table 4: Selected sensor combinations for occupancy-count estimation using linear regression and sensor*
32 *fusion.*

Ranking (out of 39)	Sensor(s)	R^2 Q1 (%)	Mean R^2 (%)
1	Wi-Fi + Light	69.1	72.8
2	Wi-Fi	68.7	74.1
3	Wi-Fi + Electrical	67.1	72.1
4	Wi-Fi + CO ₂	65.3	72.6
35	Electrical	34.5	44.6



1 *Figure 4: Illustrative example of ground truth and predicted occupancy count over time, for Wi-Fi enabled*
 2 *device count and electrical load data for floor D using linear regression.*

3 5.4. Unresolved Issues

4 While this study has shown that implicit occupancy sensing can be accomplished using sensor fusion, there
 5 are several research questions and issues to be resolved, namely:

- 6 • *How can real-time access to Wi-Fi counts be facilitated?*

7 While Wi-Fi shows great promise for occupancy-count estimation purposes, there is often a gap between
 8 facility managers and IT services when it comes to integrating this information into the BAS. As modern
 9 buildings have their BAS and Wi-Fi networks on the same local area network (LAN), increased communication
 10 between these parties may facilitate future use of Wi-Fi access points as implicit occupancy sensors for HVAC
 11 control purposes. However, addressing this problem will still not benefit buildings where occupants do not have
 12 Wi-Fi enabled devices. Privacy concerns remain an important issue. There are also considerations that need to be
 13 made for the expected prevalence of Wi-Fi enabled personal mobile devices across different cultures, socio-
 14 economic backgrounds, and over time. These differences are expected to have a great impact on the usefulness
 15 of Wi-Fi for occupancy-count estimation depending on these contextual factors.

- 16 • *How much ground truth data is needed to develop an adequate model?*

17 As ground truth collection is a labourious, expensive, and invasive, it would be beneficial to establish the
 18 threshold of data needed to develop a sufficiently accurate model. This may prove to enhance the quality of
 19 models or reveal the point at which the extra data start to have diminishing returns.

- 20 • *To what degree do occupants need to be counted to realize HVAC savings?*

21 The ventilation in buildings is typically controlled by dampers with a discrete number of positions. As such,
 22 an absolute occupancy count may not be necessary to realize HVAC savings. For example, it may be sufficient
 23 to cluster the occupancy count into states such as high, medium, or low. A worthy research question would be
 24 how accurate these models must be to consistently identify the correct occupancy state, and the relationship
 25 between the number of states, model complexity, and the resulting HVAC savings.

- 26 • *How does sensor grid density and data timestep affect model quality?*

27 While the accuracy of models developed in one space and applied to another was examined for the case
 28 study building, it is impossible to quantify the proportion of the change in the models' accuracies that can be
 29 attributed to different sensor grid densities between floors, as this change is a result of numerous confounding
 30 factors. Additionally, the data used in this study was taken at five-minute timesteps, which may be higher

1 resolution than many traditional BAS systems are capable of logging. The effect of changing these parameters
2 would be a worthy research question.

- 3 • *Where and when are these specific models applicable?*

4 While this study showed that models could be developed in one floor and used in another in the case study
5 building, the transferability of these models was still within a single building with an academic office-type
6 occupancy across all floors. A worthy research question would be how these models would perform in a
7 completely different building of the same occupancy type, or a building of a different occupancy type altogether.

8 **6. Conclusions and future work**

9 This study has shown that sensor fusion models can be used to develop occupancy-count estimations using
10 opportunistic data streams in the building studied, namely Wi-Fi access points, CO₂ sensors, PIR sensors, and
11 plug and lighting load meters. It was shown that multiple linear regression models had similar accuracy to ANN
12 models for the majority of fits produced. In the cases where ANN models offered improved performance over
13 multiple linear regression models, this improvement was not statistically significant for practical occupancy-
14 count estimation purposes to warrant the ANNs complexity and lack of transferability. Therefore, multiple linear
15 regression models are the preferred model formalism for the application and building studied. Associated Wi-Fi
16 device counts were shown to be highly beneficial in developing occupancy-count estimations and out-performed
17 every other individual data stream. The performance of this lone data stream was only exceeded by models
18 which included Wi-Fi data in conjunction with additional sensor data streams; however, the marginal
19 improvements in the prediction accuracy of these models may not justify the additional capital cost in buildings
20 where these sensors are not already installed. The cost-effective, non-intrusive, accurate and simple nature of
21 Wi-Fi device count alone make it the best candidate for opportunistic occupancy-count estimation. Additionally,
22 aggregated electrical load data were observed to be of higher utility for occupancy-count estimation than
23 separately submetered plug and lighting load data.

24 While detecting occupancy in real time may be advantageous to applications such as demand-control
25 ventilation, improved benefits could be gained from developing a forecasting model. An occupancy forecasting
26 model could be used to determine occupancy levels over a 24-hour prediction horizon or even further so that
27 optimal start, stop, and operating times for HVAC equipment can be determined. Future work will examine
28 forecasting methods given the models developed to ascertain prototypical occupancy profiles. Algorithms could
29 then be developed and implemented into the BAS to realize HVAC energy savings.

30 **Acknowledgements**

31 This research is supported by research funding provided by the Natural Sciences and Engineering Research
32 Council (NSERC) of Canada, National Research Council Canada, and Green Power Labs. The authors
33 acknowledge the support of Chris Murray and Eddie Villarta from Information Technology Services; Darryl
34 Boyce, Daniel Redmond, Scott Macdonald, and Gavin Symonds from Facilities Management and Planning at
35 Carleton University; and Trent Hilliard at Green Power Labs. The authors acknowledge the IEA-EBC Annex 66
36 and 79 researchers, as we have greatly benefitted from the associated discussions.

References

- [1] P. Taylor, S. Katipamula, M. R. Brambley, and M. R. Brambley, "Methods for Fault Detection , Diagnostics , and Prognostics for Building Systems — A Review , Part I," *HVAC&R Res.*, vol. 11, no. 1, pp. 3–25, 2005.
- [2] K. W. Roth, D. Westphalen, P. Llana, and M. Feng, "The Energy Impact of Faults in US Commercial Buildings," *Int. Refrig. Air Cond. Conf.*, pp. 600–609, 2004.
- [3] Natural Resources Canada, *Survey of Commercial and Institutional Energy Use - Buildings 2009 - Detailed Statistical Report 2012*. 2012.
- [4] W. Shen, G. Newsham, and B. Gunay, "Leveraging existing occupancy-related data for optimal control of commercial office buildings: A review," *Adv. Eng. Informatics*, vol. 33, pp. 230–242, 2017.
- [5] N. Cao, J. Ting, S. Sen, and A. Raychowdhury, "Smart sensing for HVAC Control: Collaborative intelligence in optical and IR cameras," *IEEE Trans. Ind. Electron.*, vol. 65, no. 12, pp. 9785–9794, 2018.
- [6] M. Jin, N. Bekiaris-Liberis, K. Weekly, C. J. Spanos, and A. M. Bayen, "Occupancy Detection via Environmental Sensing," *IEEE Trans. Autom. Sci. Eng.*, vol. 15, no. 2, pp. 443–455, 2018.
- [7] O. Ardakanian, A. Bhattacharya, and D. Culler, "Non-Intrusive Techniques for Establishing Occupancy Related Energy Savings in Commercial Buildings," in *Proceedings of the 3rd ACM International Conference on Systems for Energy-Efficient Built Environments*, 2016.
- [8] R. H. Dodier, G. P. Henze, D. K. Tiller, and X. Guo, "Building occupancy detection through sensor belief networks," *Energy Build.*, vol. 38, no. 9, pp. 1033–1043, 2006.
- [9] R. Melfi, B. Rosenblum, B. Nordman, and K. Christensen, "Measuring building occupancy using existing network infrastructure," *2011 Int. Green Comput. Conf. Work. IGCC 2011*, 2011.
- [10] S. Rosiek and F. J. Batlles, "Reducing a solar-assisted air-conditioning system's energy consumption by applying real-time occupancy sensors and chilled water storage tanks throughout the summer: A case study," *Energy Convers. Manag.*, vol. 76, pp. 1029–1042, 2013.
- [11] F. Wahl, M. Milenkovic, and O. Amft, "A distributed PIR-based approach for estimating people count in office environments," *Proc. - 15th IEEE Int. Conf. Comput. Sci. Eng. CSE 2012 10th IEEE/IFIP Int. Conf. Embed. Ubiquitous Comput. EUC 2012*, pp. 640–647, 2012.
- [12] P. Liu, S.-K. Nguang, and A. Partridge, "Occupancy Inference Using Pyroelectric Infrared Sensors Through Hidden Markov Models," *IEEE Sens. J.*, vol. 16, no. 4, pp. 1062–1069, 2016.
- [13] C. Duarte, K. Van Den Wymelenberg, and C. Rieger, "Revealing occupancy patterns in an office building through the use of occupancy sensor data," *Energy Build.*, vol. 67, pp. 587–595, 2013.
- [14] Z. Nagy, F. Y. Yong, M. Frei, and A. Schlueter, "Occupant centered lighting control for comfort and energy efficient building operation," *Energy Build.*, vol. 94, pp. 100–108, 2015.
- [15] S. Gilani and W. O'Brien, "Review of current methods, opportunities, and challenges for in-situ monitoring to support occupant modelling in office spaces," *J. Build. Perform. Simul.*, vol. 10, no. 5–6, pp. 444–470, 2017.
- [16] A. Wagner, W. O'Brien, and B. Dong, *Exploring Occupant Behavior in Buildings*. 2018.
- [17] M. S. Zuraimi, A. Pantazaras, K. A. Chaturvedi, J. J. Yang, K. W. Tham, and S. E. Lee, "Predicting occupancy counts using physical and statistical Co2-based modeling methodologies," *Build. Environ.*, vol. 123, pp. 517–528, 2017.
- [18] J. Wang, N. C. F. Tse, T. Y. Poon, and J. Y. C. Chan, "A practical multi-sensor cooling demand estimation approach based on visual, indoor and outdoor information sensing," *Sensors (Switzerland)*, vol. 18, no. 11, 2018.
- [19] M. Aftab, C. Chen, C.-K. Chau, and T. Rahwan, "Automatic HVAC control with real-time occupancy recognition and simulation-guided model predictive control in low-cost embedded system," *Energy Build.*, vol. 154, pp. 141–156, 2017.
- [20] J. P. Roselyn, R. A. Uthra, A. Raj, D. Devaraj, P. Bharadwaj, and S. V. D. Krishna Kaki, "Development and implementation of novel sensor fusion algorithm for occupancy detection and automation in energy efficient buildings," *Sustain. Cities Soc.*, vol. 44, pp. 85–98, 2019.
- [21] S. Petersen, T. H. Pedersen, K. U. Nielsen, and M. D. Knudsen, "Establishing an image-based ground truth for validation of sensor data-based room occupancy detection," *Energy Build.*, vol. 130, pp. 787–793, 2016.

- 1 [22] G. R. Newsham *et al.*, “Testing the accuracy of low-cost data streams for determining single-person
2 office occupancy and their use for energy reduction of building services,” *Energy Build.*, vol. 135, pp.
3 137–147, 2017.
- 4 [23] Y. Benezeth, H. Laurent, B. Emile, and C. Rosenberger, “Towards a sensor for detecting human
5 presence and characterizing activity,” *Energy Build.*, vol. 43, no. 2–3, pp. 305–314, 2011.
- 6 [24] P. Carreira, A. A. Costa, V. Mansur, and A. Arsénio, “Can HVAC really learn from users? A simulation-
7 based study on the effectiveness of voting for comfort and energy use optimization,” *Sustain. Cities Soc.*,
8 vol. 41, pp. 275–285, 2018.
- 9 [25] N. Li, G. Calis, and B. Becerik-Gerber, “Measuring and monitoring occupancy with an RFID based
10 system for demand-driven HVAC operations,” *Autom. Constr.*, vol. 24, pp. 89–99, 2012.
- 11 [26] A. Akbar, M. Nati, F. Carrez, and K. Moessner, “Contextual occupancy detection for smart office by
12 pattern recognition of electricity consumption data,” *IEEE Int. Conf. Commun.*, vol. 2015–Septe, no.
13 June, pp. 561–566, 2015.
- 14 [27] T. Labeodan, K. Aduda, W. Zeiler, and F. Hoving, “Experimental evaluation of the performance of chair
15 sensors in an office space for occupancy detection and occupancy-driven control,” *Energy Build.*, vol.
16 111, pp. 195–206, 2016.
- 17 [28] T. Ekwevugbe, N. Brown, and D. Fan, “A design model for building occupancy detection using sensor
18 fusion,” in *IEEE International Conference on Digital Ecosystems and Technologies*, 2012, pp. 1–6.
- 19 [29] Z. Chen, M. K. Masood, and Y. C. Soh, “A fusion framework for occupancy estimation in office
20 buildings based on environmental sensor data,” *Energy Build.*, vol. 133, pp. 790–798, 2016.
- 21 [30] Z. Yang, B. Becerik-Gerber, N. Li, and M. Orosz, “A systematic approach to occupancy modeling in
22 ambient sensor-rich buildings,” *Simulation*, vol. 90, no. 8, pp. 960–977, 2014.
- 23 [31] B. Dong *et al.*, “An information technology enabled sustainability test-bed (ITEST) for occupancy
24 detection through an environmental sensing network,” *Energy Build.*, vol. 42, no. 7, pp. 1038–1046,
25 2010.
- 26 [32] B. Dong and K. P. K. P. Lam, “Building energy and comfort management through occupant behaviour
27 pattern detection based on a large-scale environmental sensor network,” *J. Build. Perform. Simul.*, vol. 4,
28 no. 4, pp. 359–369, 2011.
- 29 [33] T. Ekwevugbe, N. Brown, V. Pakka, and D. Fan, “Improved occupancy monitoring in non-domestic
30 buildings,” *Sustain. Cities Soc.*, vol. 30, pp. 97–107, 2017.
- 31 [34] W. Wang, J. Chen, T. Hong, and N. Zhu, “Occupancy prediction through Markov based feedback
32 recurrent neural network (M-FRNN) algorithm with WiFi probe technology,” *Build. Environ.*, vol. 138,
33 no. April, pp. 160–170, 2018.
- 34 [35] S. H. Kim and H. J. Moon, “Case study of an advanced integrated comfort control algorithm with
35 cooling, ventilation, and humidification systems based on occupancy status,” *Build. Environ.*, vol. 133,
36 pp. 246–264, 2018.
- 37 [36] T. H. Pedersen, K. U. Nielsen, and S. Petersen, “Method for room occupancy detection based on
38 trajectory of indoor climate sensor data,” *Build. Environ.*, vol. 115, pp. 147–156, 2017.
- 39 [37] S. H. Ryu and H. J. Moon, “Development of an occupancy prediction model using indoor environmental
40 data based on machine learning techniques,” *Build. Environ.*, vol. 107, pp. 1–9, 2016.
- 41 [38] K. Whitehouse *et al.*, “Towards occupancy-driven heating and cooling,” *IEEE Des. Test Comput.*, vol.
42 29, no. 4, pp. 17–25, 2012.
- 43 [39] Q. Huang, “Occupancy-driven energy-efficient buildings using audio processing with background sound
44 cancellation,” *Buildings*, vol. 8, no. 6, 2018.
- 45 [40] W. Wang, J. Chen, Y. Lu, and H.-H. Wei, “Energy conservation through flexible HVAC management in
46 large spaces: An IPS-based demand-driven control (IDC) system,” *Autom. Constr.*, vol. 83, pp. 91–107,
47 2017.
- 48 [41] W. Wang, J. Chen, G. Huang, and Y. Lu, “Energy efficient HVAC control for an IPS-enabled large
49 space in commercial buildings through dynamic spatial occupancy distribution,” *Appl. Energy*, vol. 207,
50 pp. 305–323, 2017.
- 51 [42] W. Wang, T. Hong, N. Li, R. Q. Wang, and J. Chen, “Linking energy-cyber-physical systems with
52 occupancy prediction and interpretation through WiFi probe-based ensemble classification,” *Appl.*
53 *Energy*, vol. 236, no. August 2018, pp. 55–69, 2019.
- 54 [43] W. Wang, J. Chen, and X. Song, “Modeling and predicting occupancy profile in office space with a Wi-

- 1 Fi probe-based Dynamic Markov Time-Window Inference approach,” *Build. Environ.*, vol. 124, pp.
2 130–142, 2017.
- 3 [44] W. Wang, J. Wang, J. Chen, G. Huang, and X. Guo, “Multi-zone outdoor air coordination through Wi-Fi
4 probe-based occupancy sensing,” *Energy Build.*, vol. 159, pp. 495–507, 2018.
- 5 [45] W. Wang, J. Chen, and T. Hong, “Modeling occupancy distribution in large spaces with multi-feature
6 classification algorithm,” *Build. Environ.*, vol. 137, pp. 108–117, 2018.
- 7 [46] O. Vermesan *et al.*, *Cluster of European Research Projects on the Internet of Things: Vision and
8 Challenges for Realising the Internet of Things*, no. March. Brussels: European Commission, 2010.
- 9 [47] B. . Simon, J. . Park, and Z. Nagy, “Inferring Space Occupancy by Bluetooth Device Tracking,” Austin,
10 2018.
- 11 [48] S. Fritsch, F. Guenther, M. Suling, and S. M. Mueller, “Training of neural networks. Package
12 ‘neuralnet’. The R project for statistical computing.” p. 13, 2016.
- 13 [49] J. Heaton, *Introduction to the Math of Neural Networks*. St. Louis, MI: Heaton Research, Inc., 2012.
- 14 [50] R Core Team, “The R Base Package. Package ‘base’. The R project for statistical computing.” 2018.
15

Highlights:

- PIR, CO₂, lighting and plug loads, and Wi-Fi data were collected from an academic building.
- Models for occupancy-count estimation were developed with concurrent groundtruth data.
- Wi-Fi enabled device counts were the best regressor to characterize occupancy levels.
- Use of ANNs instead of MLR models reduced the transferability of occupancy-count models.
- Dataset was made publicly available to support occupancy model development and assessment.