Pervasive and Mobile Computing 46 (2018) 49–72

Contents lists available at ScienceDirect

Pervasive and Mobile Computing

journal homepage: www.elsevier.com/locate/pmc

RUP: Large Room Utilisation Prediction with carbon dioxide sensor

Irvan B. Arief-Ang *, Margaret Hamilton, Flora D. Salim

School of Computer Science and Information Technology, RMIT University, Melbourne, Australia

ARTICLE INFO

Article history:
Received 6 August 2017
Received in revised form 4 January 2018
Accepted 1 March 2018
Available online 9 March 2018

Keywords:
Ambient sensing
Building occupancy
Presence detection
Number estimation
Cross-space modelling
Contextual information
Human occupancy detection
Carbon dioxide

ABSTRACT

Human occupancy information is crucial for any modern Building Management System (BMS). Implementing pervasive sensing and leveraging Carbon Dioxide data from BMS sensor, we present large Room Utilisation Prediction with carbon dioxide sensor (RUP), a novel way to estimate the number of people within a closed space from a single carbon dioxide sensor. RUP de-noises and pre-processes the carbon dioxide and indoor human occupancy data. We utilise both seasonal-trend decomposition based on Loess and seasonal-trend decomposition with moving average to factorise both datasets. For each trend, seasonal and irregular component, we model different regression algorithms to predict each respective human occupancy component value. We propose a zero pattern adjustment model to increase the accuracy and finally, we use additive decomposition to reconstruct the prediction value. We run our model in two different locations that have different contexts. The first location is an academic staff room and the second is a cinema theatre with up to 300 people. Our results show an average of 4.33% increment in accuracy for the small room with 94.68% indoor human occupancy counting and 8.46% increase for the cinema theatre in comparison to the accuracy of the baseline method, support vector regression.

1. Introduction

Data obtained from the Australian Department of the Environment and Energy indicates that approximately 40% of total maintenance costs within a building are for heating, ventilation, and air conditioning (HVAC) [1]. Hence, there are substantial investments in the energy usage research area to automate HVAC control in buildings based on occupancy patterns. Reducing HVAC usage will massively lessen overall energy consumption. However, this may compromise the comfort of the dwellers. A Building Management System (BMS) can intelligently adjust the HVAC based on the occupancy pattern.

The majority of buildings, especially older ones, do not have an adequate infrastructure to sense people and where they are within a building accurately. Hence it is challenging to determine the precise ground truth value for analysis purposes. Some researches use simulation models [2,3] to reduce energy consumption. Methods of simulating the occupants' behaviour with the aim of reducing energy consumption based on their behaviours were proposed in [4,5]. Unfortunately, simulations with agent based models do not reflect the behaviour and uncertainty from the actual environment and are not adaptable to different types of rooms and buildings. Therefore, the better approach is to analyse the data collected from the real world.

Using sensor data for indoor human occupancy detection is the current trend in ambient sensing research area [6–14]. In [6], it was highlighted that carbon dioxide (CO_2) is the best ambient sensor predictor for detecting human presence. By using only CO_2, 91% accuracy was achieved for binary prediction, knowing the room is occupied or vacant [15] and have

* Corresponding author.
E-mail addresses: irvan.ariefang@rmit.edu.au (I.B. Arief-Ang), margaret.hamilton@rmit.edu.au (M. Hamilton), flora.salim@rmit.edu.au (F.D. Salim).

https://doi.org/10.1016/j.pmcj.2018.03.001

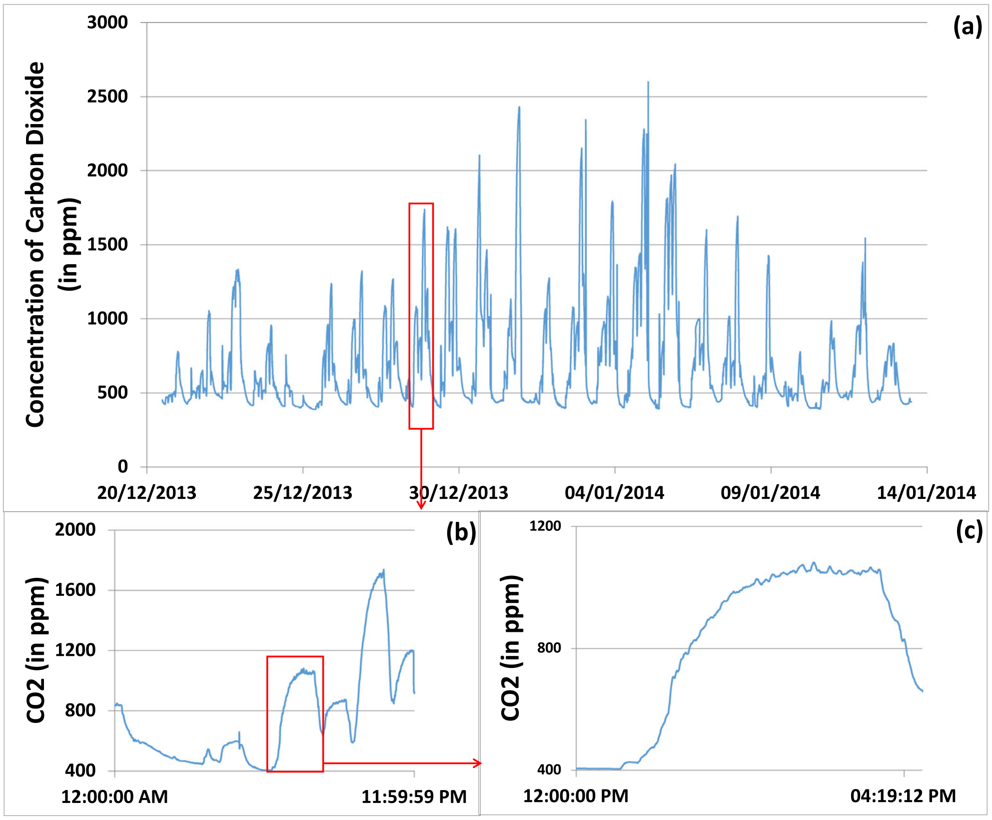

Fig. 1. CO_2 concentration in the movie theatre over the time. Fig. 1a shows an overview of all measurements. Days, times and movies screening can be easily identified. Fig. 1b shows the concentration on December 28th. Movie screening can be seen and the shape of each screening can be identified differently. Fig. 1c shows the CO_2 concentration during the movie "The Hunger Games 2: Catching Fire" on December, 28th 2013 at 13:15.

15% accuracy for recognising the number of occupants. A hidden Markov model (HMM) was implemented for CO_2 dataset to predict human occupancy and 65%–80% range of accuracy was achieved for predicting up to 4 occupants [16].

In this paper, we propose large Room Utilisation Prediction with CO_2 sensor (RUP), a new method to count indoor human occupancy based on the amount of CO_2 in the air. There is a need to monitor CO_2 concentration because for example Green Building Council of Australia (GBCA) gives building 1 to 2 green points score if CO_2 levels are maintained below 800 ppm or 700 ppm respectively [17]. One sample of CO_2 data regression chart is shown in Fig. 1.

The main reason we utilised CO_2 based occupancy counting is that CO_2 sensors are an integral part of infrastructure for demand-controlled ventilation [15]. There is a need to monitor CO_2 concentration in public indoor places at real time. A higher level of CO_2 concentration could have an adverse effect on the occupants' health [18]. Besides, CO_2 based occupancy counting is not prone to accumulated counting errors, as are sensors that detect state transition between vacant and occupied [15]. With common sensors such as temperature and CO_2, there is usually no need to equip the building with any additional occupancy counting sensors [19].

As humans exhale CO_2 while they breathe, there is a correlation between CO_2 and occupancy. Machine learning model experiments were performed on two different sized rooms with the capacity up to 300 occupants. We believe that if the algorithm works well with low occupancy number and also works adequately with high occupancy up to three hundred occupants, this algorithm is robust. Three advantages of this method are: (a) RUP ensures that users' privacy is protected; (b) it employs low equipment cost due to pre-installation; and (c) it only uses CO_2 data, reducing the chance of errors caused by data integration.

1.1. Research motivation

There are four primary motivations for this research. The first motivation is to help space and room utilisation. By knowing the number of people in each room at a given time, the building manager can monitor which rooms are under-utilised and which rooms are over-utilised. For example, after integrating RUP algorithm to the BMS system, the building manager can observe the indoor human occupancy for each room and detect which rooms have low utilisation. With this knowledge, he can adjust room allocation and utilisation accordingly. He can combine two meeting rooms if their usage numbers are both small or convert one of them into a storage chamber.

The second motivation is to support the BMS so it can reduce their power consumption when there is no person in the room. Knowing the number of persons at a given time for each room becomes crucial to achieving this motivation. Further development can be done to automate the BMS to adjust HVAC higher or lower based on the number of occupants or even turn it to low power mode during vacant automatically.

The third motivation is for security purposes. With RUP and its human occupancy counting mechanism, an alarm can be set if the counter returns with value 1 or above in a room that should be vacant. The might be a burglar or uninvited guest inside the particular room. This functionality can be extended to monitor a location that should not be occupied for a very long time such as a restroom. If it happens, there might be an accident or the person inside might be breathing but unconscious.

The fourth and last motivation is for personal indoor comfort. By integrating RUP algorithm to BMS system, the temperature can be adjusted based on the number of occupants in each room from RUP. A room with many people inside may need a slightly lower temperature to compensate for higher level of CO_2 and vice versa.

1.2. Research contribution

The main contributions of this paper are as follows:

- We propose a novel feature engineering method to process both CO_2 and human occupancy data into four main features: trend, seasonal, irregular and zero pattern adjustment.
- We develop a time-series model to predict the number of humans occupying a closed space. The accuracy of the proposed method is higher than the current state-of-the-art machine learning algorithm method known as support vector regression (SVR) and PerCCS [15] technique, non-negative matrix factorisation with ensemble least square regression (NMF-ELSR).
- We compare our proposed two customised seasonal decomposition methods, to solve the human occupancy prediction problem and highlight the advantages of each method.
- We generalise our method to be implemented for any prediction problem Y_n if X_n is known and Y_n is dependent on X_n where n is the number of sample points.

The remainder of the paper is organised as follows. Section 2 presents the related work on current state-of-the-art indoor human occupancy methods. Section 3 covers the problem definition. Section 4 introduces a new carbon dioxide occupancy counter model. Section 5 describes experiments, results, comparisons with the state-of-the-art algorithm and discussion. Finally, Section 6 concludes the paper with directions to the future work.

2. Background and related work

Occupancy detection has been explored in the last decade and one of the biggest challenges is to do this without using image processing from cameras. When using image processing techniques [20–22], the levels of accuracy for human occupancy detection can reach up to 95%. Unfortunately, using cameras raises privacy concerns as people do not want to be identified. Research communities have been doing their best to propose various methods to detect human occupancy without using cameras or image processing. Occupancy prediction using depth sensors [23,24] can result in very accurate prediction, up to 99%. But in this paper, any research with vision-based sensing devices are not considered because we are researching alternatives to the vision-based system. Vision-based systems require a clear line of sight and occlusion is an issue for any vision-based sensing devices [25]. Given the need for clear line of sight, vision-based systems will not work well in counting crowds or a large number of people.

In this section, we divide related works of human occupancy research into six subsections based on their method. Research about human occupancy by simulation is presented in Section 2.2, by radio-based in Section 2.3, by sensor-based in Section 2.4 and the ones that closely relate to this paper using CO_2 sensor in Section 2.5. In Section 2.6, we present our summary of the current state of the human occupancy research domain. Due to the extensive methods of machine learning algorithms that have been used for human occupancy recognition, a machine learning term list is presented in Table A.1 in the Appendix.

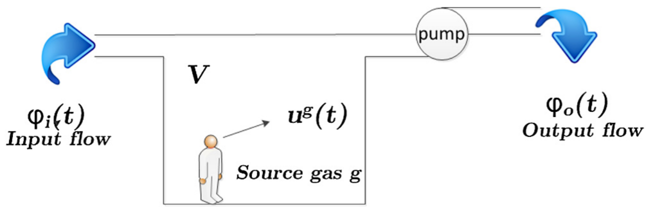

Fig. 2. Simplified presentation of gas exchange in the respiratory chamber where $\varphi i(t)$ is the flow rate of input air at time t, $\varphi o(t)$ is the flow rate of output air at time t, V is the volume at time t, $u^g(t)$ is the gas production rate at time t.

2.1. Background study of human occupancy calculation

This subsection discusses human occupancy calculation with flow rate of CO_2 using metabolic rates. A person exhales CO_2 as the natural process of breathing, but the amount varies from person to person. Eq. (1) below gives the exhalation rate equation of CO_2, derived from the metabolic rates formula [26].

$$V_{CO_2} = \frac{M \cdot RQ\sqrt{H \cdot W}}{21132 \cdot (0.23RQ + 0.77)} \tag{1}$$

V_{CO_2} flow rate of CO_2
M metabolic rates (in W/m^2)
RQ respiratory quotient (CO_2 eliminated/O_2 consumed)
H height (in cm)
W weight (in kg).

We note a non-linear relationship between the flow rate of CO_2 and the average value of person's height (H) and weight (W). Due to this fact, the non-linear relationship issue needs to be considered if we wish to correlate human features (height and weight) with CO_2 data only. In our methodology, the way we have addressed this non-linear gap will be explained further in Section 4.3.

The size of the room is the next aspect that we need to consider to ensure our data is useful for indoor human occupancy prediction. Fig. 2 explains the flow rate of inhalation [27]. For any given room that has standard ventilation, there will be an input flow $\varphi i(t)$ and pump out by a specific output flow $\varphi o(t)$. For specific room size V at the time t, the gas production rate is $u^g(t)$. From this finding, the size of the room is crucial for understanding the gas production rate.

From Eq. (1) and Fig. 2, to be able to have accurate indoor human occupancy measurement by using metabolic rates formula and flow rate of CO_2, we can see that many parameters are required. Parameters include the occupant's weight, height, the rate of breathe and also the size of the room. The need for occupant's weight and height can lead to privacy issues. In addition, it is very difficult to obtain accurate readings of room size.

2.2. Simulation based indoor human occupancy detection

The common method for detecting human occupancy is to construct a simulation model for a room or building [2–5]. Simulation models will not be accurate for multiple buildings with different features and characteristics as there are many variables including the ones were mentioned in Section 2.1 that need to be considered for indoor human occupancy.

2.3. Radio-based indoor human occupancy detection

Radio-based devices include but are not limited to WiFi, Bluetooth, any electromagnetic waves and gamma rays. A summary of the radio based research is in Table 1.

A model using only WiFi power based on its received signal strength indication (RSSI) is used for occupancy detection [28]. By using the line of sight analysis, outdoor human occupancy accuracy can be up to 96%.

A low-power pulsed radar was utilised for people counting in [30]. The counting is modelled with support vector regression (SVR) for up to 40 occupants. A correlation coefficient of 0.97 was achieved with 2.17 mean absolute error between the estimated count and the ground truth.

Using wireless signals, device-free occupancy recognition is achieved [33]. They managed to distinguish the state of the wireless signal between an empty environment and an occupied one. Furthermore, this study successfully detected the occupants' activities such as walking, lying, crawling or standing.

In [31], a microwave motion sensor is used to detect motion and then the lighting is controlled with time delays to reduce electricity consumption. Duta et al. take advantage of ultra-wideband radar that can function beyond the line of sight to detect people [29]. However such equipment is expensive and rarely justified for the purpose of occupancy detection alone.

Table 1
Models, parameters and reported accuracies for radio-based occupancy detection research.

Ref.	Occupancy detection algorithms	Detailed devices	Max. # of people	Duration	Location	Accuracy (Occupancy)
[28]	Multipath fading (MP) with line of sight, Kullback–Leibler (KL) divergence	WiFi transmitter and receiver	9	Not stated	Indoor and outdoor	96% for outdoor and, 63% for indoor
[29]	Doppler equation, Neyman-Person detector (noise detector), Exponentially-weighted moving average (EWMA)	Ultrawideband radar	Binary occupancy	Not stated	Outdoor	Not stated
[30]	Support Vector Regression (SVR)	A low-power pulser radar	40	750 min	Four rooms	Not stated
[31]	Pareto distribution of occupancy's inactivity	Microwave motion sensor	Not stated	10 days	Staff office room	Not stated
[32]	Neural Network (NN), SVM and Sequential Counting (SC)	WiFi Access Point, Samsung Galaxy S3	50	Five hours	Two classrooms	93%
[33]	K-nearest neighbours (KNN)	Radio Frequency (wireless signal)	3	Not stated	Corridor	Not stated

2.4. Indoor human occupancy detection with sensors

Indoor human occupancy detection with sensors refers to research using any type of sensors for person counting. A summary of the sensor based related work can be found in Table 2.

Algorithms to detect indoor human occupancy for the purpose of reducing energy cost are proposed in [34,35,39,40,51]. Energy saving results vary from 5% up to 60%.

The most common device that is used for person counting is a passive infra-red (PIR) sensor which is used as a motion sensor with a reed switch as the door sensor [34,36,37,39–41,44,48,51]. In [37], single, double and triple PIR sensors are compared to detect the presence of humans and the accuracy is 20.1%, 97.8% and 99.9% respectively.

Using sensor network data, 50 PIR sensors were deployed and the data was utilised to build a modified Bayesian forecasting method [41]. They compared the accuracy with several other machine learning methods such as seasonal autoregressive integrated moving average (ARIMA), neural networks (NN) and SVR with their techniques (modified Bayesian combined forecasting) and mentioned that their techniques have the lowest error. Their accuracy results were not presented.

ThermoSense, a system for estimating occupancy by using thermal array sensor combined with passive infrared sensor was presented in [35]. Using k-nearest neighbour (KNN), linear regression (LR) and artificial neural network (ANN), ThermoSense could predict the room occupancy and reduce energy saving up to 25%.

In [52], electricity consumption data from electricity meters was used as the feature in occupancy analysis. The article presents four models of the regression in SVM, KNN, thresholding (THR) and HMM.

The Building Level Energy Management Systems (BLEMS) project from University of Southern California uses a combination of sensors (light, sound, motion, CO_2, temperature and humidity sensor) to create a model to estimate the human occupancy. A radial basis function (RBF) method was used to find 87.62% for self-estimation and when the model was implemented in another room, the cross-examination result showed 64.83% occupancy accuracy [14]. Various machine learning algorithms such as multi-layer perceptron (MLP), Gaussian processes (GP), LR, SVM and ensemble voting (EV) were implemented resulting occupancy accuracy ranging from 46% to 95% [12].

Utilising density-based spatial clustering of applications with noise (DB-SCAN), [47] produced 95% accuracy with ultrasonic distance sensors for height sensors, motion sensors and magnetic reed switch sensors. In [8], using temperature sensors only, they achieved 85% and 83% to predict two persons in a single room. Their accuracy can be up to 95%–99% with all predictors including light, CO_2 and humidity sensors.

An estimation algorithm based on unsupervised clustering of both overlapped and non-overlapped conversational data with a change point detection algorithm for locomotive motion of the users to infer the occupancy was proposed as a mobile app in [43]. Users installed the app and provided consent for the app to access the smartphone sensors data. Using the random forest (RF) algorithm, they applied occupancy detection and the accuracy was 76% for counting a maximum number of 8 people.

A framework was created to produce occupancy estimates at different levels of granularity and provide confidence measures for effective building management in [11]. By using KNN and SVM, their accuracy varied from 64.6% up to 94.7%.

A real-time occupancy detection by using decision trees (DT) with multiple types of sensors such as light, sound, CO_2, motion and computer power sensor was conducted by [10]. The lowest accuracy was received from sound sensors (90.79%) and the highest one from motion sensors (98.44%).

A model for real-time estimation of building occupancy sensing was presented by [9,38]. Both papers utilised ANN and ran in the Waikato Environment for Knowledge Analysis (WEKA) and MATLAB for an open plan office occupancy detection

Table 2
Models, parameters and reported accuracies for sensor-based occupancy detection research.

Ref.	Occupancy detection algorithms	Detailed devices	Max. # of people	Duration	Location	Accuracy (Occupancy)
[34]	Using hardware (CC2530 micro controller) built in capability	Reed switches and PIR sensors	Binary occupancy	2 weeks	10 offices	Not stated
[6]	MLP, GP with RBF, SVM, RF and NB	Temperature, humidity, CO_2, sound, pressure and illumination (light) sensors	Binary occupancy	2 weeks	One single person office room	96%–99%
[15]	Non-negative matrix factorisation (NMF), Ensemble Least Square Regression (ELSR) and SVR	CO_2 sensors	15 (lab) 42 (classroom)	13 days	A lab and a classroom	91% for vacant prediction and 15% for occupied prediction
[35]	KNN, Linear regression (LR) and Artificial neural networks (ANN)	PIR and thermal array sensors	Not stated	3 weeks	A 17-node deployment covering 10 building areas	Not stated
[8]	Random Forest (RF), Gradient Boosting Machines (GBM), Linear Discriminant (LD) analysis and Classification and Regression Trees (CART)	Rasberry Pi with light, CO_2, DHT22 (temp/humid) sensors, Zigbee radio and digital video camera	2	Not stated	A room	95%–99% with all predictors and 83%–85% by using temperature only
[36]	Latent dirichlet allocation (LDA)	PIR sensors	Not stated	24 weeks	3 floor Innotek building	Not stated
[37]	Bayesian probability theory and Belief Network (BN)	3 PIR sensors and telephones sensor	Binary occupancy	2 days	2 offices	1 PIR: 20.1% 2 PIR: 97.8% 3 PIR: 99.9%
[9]	ANN with MATLAB and WEKA	CO_2, sound, relative humidity, temperature (air and computer) and PIR sensors	39	7 days	An open-plan office	84.59%
[38]	ANN with MATLAB and WEKA	Sound, case temperature, humidity, light, CO_2, motion, Volatile Organic Compounds (VOCs) and PIR sensors	6	30 days	An open-plan office	75%
[39]	KNN and learning-based model predictive control (LBMPC)	Microsoft Kinect, infrared sensor and laser pointer	Binary occupancy	More than 3 months	Office room	Not stated
[40]	Motion detection	PIR sensors	Binary occupancy	Not stated	Office room	Not stated
[10]	Decision Trees (DT)	CO_2, computer current, light, PIR and sound sensors	1	7 days	A single cubicle	CO_2: 94.68% Current: 96.27% Light: 81.02% Motion: 98.44% Sound: 90.79%
[41]	Modified Bayesian combined forecasting approach with seasonal ARIMA model, historic average, time delay NN and SVR	50 PIR sensors	Not stated	2 years	2 large buildings	Not stated
[42]	Not stated	64 wired BMS sensors, 50 moveable sensor boxes and several cameras	8	2 weeks	7 rooms	Not stated

(continued on next page)

Table 2 (*continued*)

Ref.	Occupancy detection algorithms	Detailed devices	Max. # of people	Duration	Location	Accuracy (Occupancy)
[11]	KNN and SVM	Motion PIR, acoustic noise, temperature, light and humidity sensors	20	14 days for low traffic area and 10 days for high traffic area	A large commercial buildings	Not stated
[43]	RF	Acoustic (microphone), locomotive (accelerometer) and location (magnetometer) sensors	8	Not stated	Not stated	Not stated
[16]	Hidden Markov Models (HMM), NN and Support Vector Machines (SVM) Latent	CO_2 for both inside and outside room	4	58 days	An open plan office with 16 rooms and one conference room	65%–80%
[44]	Classical Linear Minimum Variance (LMV) estimator	Binary motion sensors	1	Not stated	One room	Not stated
[12]	Rule-based heuristic, Multi-Layer Perceptron (MLP), Gaussian processes (GP), LR, v-SVM-R and Ensemble Voting (EV)	BLEMS sensors	16	Several weeks	2 shared labs space	46%–95%
[45]	Otsu's thresholding and modelling thermal noise distribution	GirdEYE IR array sensor and a Raspberry Pi	3 person	Fixed scenario experiment	An university lab, classrooms, computer labs and conference rooms	93%
[19]	Random Forest, Decision Tree	Temperature, CO_2 and PIR	36 (study zone) 85 (classroom)	1 month	A study zone and a classroom	Not stated
[46]	Principal component analysis (PCA), density-based spatial clustering of applications with noise (DBSCAN) and Sabine acoustic model	Transducer with microphone and tweeter	10 (conference room) 24 (class room) 150 (auditorium)	Quick scenario	A conference room, a classroom and an auditorium	90%
[47]	Density-based spatial clustering of applications with noise (DB-SCAN) and Maximum Likelihood Estimate (MLE)	Ultrasonic distance sensor for height on the doorway, motion sensors and magnetic reed switch sensors	20 (lab) 4 (home residents)	5 days	1 lab and 3 homes	95% (identification accuracy)
[48]	Non-homogeneous Poisson model with two different exponential distributions	Infrared sensor behind a fresnel lens	Not stated	1 year	35 single person offices	Not stated
[49]	Regularised regression	LED	20 volunteers	6 months	5×6 m lab	Above 90%
[14]	SVM, ANN with Radial Basis Function (RBF) and HMM	Light, sound, motion, CO_2, temperature, relative humidity and PIR sensors	9	20 days	2 shared labs space	87.62% for self estimation and 64.83% for cross-estimation
[50]	ANN, DT, KNN, Naïve Bayesian (NB), Tree augmented, Naïve Bayes Network (TAN) and SVM	Light, sound, PIR, CO_2, Reed door sensor, relative humidity and temperature sensors	3 (single occupancy rooms) 9 (multi occupancy rooms)	1 month (single occupancy rooms) 20 days (multi occupancy rooms)	Two single-occupancy rooms and two multi-occupancy rooms	ANN: 92.5%–97.1% DT: 96.0%–98.2% KNN: 95.4%–97.5% NB: 88.9%–94.3% TAN: 95.3%–98.0% SVM: 95.1%–97.5%

and the accuracy is between 75% and 84.59%. With ambient sensors such as temperature, relative humidity, sound, light and CO_2, they used volatile organic compounds (VOCs) data as one of their features.

A systematic approach to occupancy modelling by using various ambient sensor data for both single occupancy and multi-occupancy room was proposed by [50]. With ANN, DT, KNN, naïve Bayes (NB), tree augmented naïve Bayes network (TAN) and SVM, human occupancy can be predicted with up to 98.2% in DT.

By utilising a smart phone sensor such as the microphone, Bluetooth and WiFi, one study [53] obtained a precision and recall of over 80% with 45 participants using mobile crowd sensing on group-aware recognition.

A model that utilises temperature, humidity, CO_2, sound, pressure and illumination sensor was used to detect whether the room is occupied or vacant in [6]. The occupancy detection was improved by using feature engineering and various machine

Table 3
Algorithms, devices and reported accuracies for Carbon Dioxide sensor-based occupancy detection research.

Ref.	Occupancy detection algorithms	Detailed devices	Max. # of people	Accuracy (Occupancy)
[15]	Non-negative matrix factorisation (NMF) Ensemble least square regression Support Vector Regression (SVR)	CO_2 sensors (BACNet server)	15 (lab) 42 (classroom)	Binary prediction: 91% Counting prediction: 15%
[54]	Mass balance equation	CO_2 sensors	12	Binary prediction: 95.8% Counting prediction: 80.6%
[55]	Time-lagged mass balance approach	PP Systems SBA-5 CO_2 Gas Analysers	3	Not stated
[10]	Decision Trees (DT)	CO_2 sensors	1	94.68%
[16]	Hidden markov models Neural networks Support Vector Machines (SVM) Latent	Gas detection CO_2 sensor network	4	65%–80%

learning algorithms such MLP, GP with RBF, SVM, RF and NB were compared. The human occupancy can be detected above 95% with multiple machine learning algorithms such as MLP, GP-RBF and RF.

2.5. CO_2-based indoor human occupancy detection

Since CO_2 sensors are already integrated with the Australian BMS and ventilation infrastructure, we focus on utilising only CO_2 sensor data to estimate the number of indoor human occupancy. CO_2 sensors in general cost more than PIR sensors. Due to taking advantage of BMS sensors, the operational cost can be reduced by not purchasing or installing extra sensors compared to using PIR or motion sensors. Table 3 presents a summary of related work on indoor occupancy detection using CO_2 sensors.

Machine learning algorithms including HMM, NN and support vector machine latent (SVM latent) were implemented in [16] by using CO_2 data with the sensors deployed both inside and outside a room. By feature engineering CO_2 data with first order and second order difference of CO_2, the accuracy achieved is between 65% and 80% for binary occupancy prediction.

A method to assess human occupancy and occupant activity estimation in ten hospital rooms was conducted in [55] as part of the Hospital Microbiome Project. Using time-lagged mass balance approach, Dedesko el. al. aimed to determine occupant characteristics and understand the interactions between humans and microbial communities. The accuracy result was not mentioned in the paper.

CO_2 based occupancy detection in office and residential buildings was conducted in [54]. The testing and validation have been done for both residential and non-residential buildings. Mass balance equation was implemented and vacant-occupied prediction accuracy is 95.8% and human counting prediction accuracy is 80.6%.

A heterogeneous sensor array was equipped in office workspace for the purpose of a real-time occupancy detector [10]. Decision Trees was implemented to perform the classification and to explore the relationship between different types of sensors, features derived from sensor data, and occupancy. The prediction accuracy for human occupancy using CO_2 sensor is 94.68%, lower than both motion sensor (98.44%) or current sensor (96.27%), but higher than light sensor (81.02%) and sound sensor (90.79%).

PerCCS is a model with a non-negative matrix factorisation method to count people [15] using only one predictor in CO_2. In predicting vacant occupancy, they achieved up to 91% but only 15% accuracy in predicting the number of occupants.

2.6. Summary of related work

After reviewing all the literature in occupancy detection, a few key points are derived as follows:

- PIR is the most commonly research sensor in the literature for indoor human occupancy. PIR sensors are cheap, but they are not scalable, i.e. for new rooms, new PIR sensors need to be bought. To be able to predict occupancy for 100 rooms, at least 100 PIR sensors need to be provided, one for each room;
- not every research paper gives their accuracy. This makes the direct comparison between each model difficult;
- poor sensor calibration and lower frequency reduce the accuracy prediction result;
- CO_2 is one of the best types of sensors to measure indoor human occupancy, but the majority of indoor human occupancy papers with CO_2 provide binary occupancy analysis, not real people counting analysis;
- using too many types of sensors as features can result in lower accuracy;
- there is no single formula available to calculate the number of occupants, and from Section 2.1 we conclude that collecting all the parameters related to indoor human occupancy is not practical and is subject to privacy breaches;
- the majority of previous experiment datasets are not publicly available;
- ambient sensor research is done without the involvement of user consent (the cons of smartphone-based apps).

Overall, sensor-based detections have higher accuracy compared to radio based detections. For example, Wi-Fi and RSSI signals achieved 63% accuracy for indoor detection [28] with 9 occupants. For occupancy counting, CO_2 sensors only have been experimented with the maximum of 42 occupants and accuracy limit of 15% [15].

Table 4
Example of indoor human occupancy history data.

Timestamp (t)	CO_2 (ppm)	Occupancy (person)	Activity
18/05/2015 09:36:53 AM	457	0	(Room empty)
18/05/2015 10:01:55 AM	550	1	(Arrived)
18/05/2015 10:41:59 AM	596	0	
18/05/2015 11:37:05 AM	580	3	(Group meeting)
18/05/2015 12:07:07 PM	725	3	
18/05/2015 12:32:10 PM	500	0	(Lunch break)
18/05/2015 12:42:11 PM	510	0	
18/05/2015 12:47:12 PM	514	1	(Back from lunch)
18/05/2015 02:02:23 PM	508	0	(Went to seminar)
18/05/2015 03:52:35 PM	503	1	
18/05/2015 03:02:30 PM	397	0	(External meeting)
18/05/2015 04:26:55 PM	570	1	
18/05/2015 05:38:22 PM	475	0	(Went home)
...	...	...	

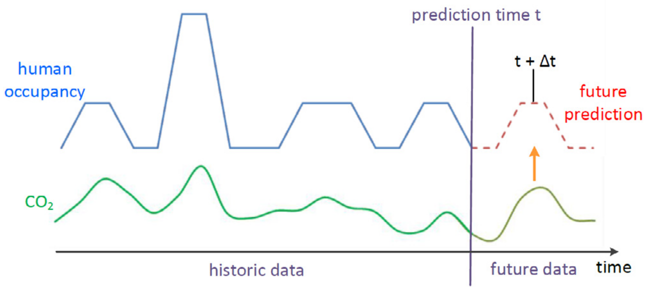

Fig. 3. Real-time prediction scenario for continuous t showing the amount of CO_2 fluctuations. The fundamental task is to predict the number of occupants at time $t+\Delta t$.

3. Problem definition

In Table 4 and Fig. 3, the data shows there is a dependency between CO_2 and occupancy data. Our research question is how can we predict the number of people by using a single CO_2 sensor with the accuracy similar to the state-of-the-art techniques in the occupancy detection field?

3.1. Scenario assumption

Assume TS represents the length of a time series and is expressed as $TS = \{ts_1, ts_2, \ldots, ts_q\}$, where q means the number of sample points. In our time series datasets, we have two aspects:

- Carbon dioxide (CO_2) concentration C, defined as $C = \{C_1, C_2, \ldots, C_q\}$
- Indoor human occupancy O, the number of people in the room at TS defined as $O = \{O_1, O_2, \ldots, O_q\}$

3.2. Problem definition

In time series prediction, analysing one-step-ahead prediction is different from analysing multi-step-ahead prediction. Predicting multi-step-ahead needs a more complicated method due to the accumulation of errors and the number of uncertainties increasing with time. We focus on multi-step-ahead prediction with the support of one dependent variable to reduce uncertainties.

We have two different types of datasets: CO_2 concentration C and indoor human occupancy O. In order to explore the relationship between both factors above, there are two problems that need to be solved:

- Decompose both CO_2 concentration and indoor human occupancy to reduce the level of complexity.
- Explore the correlation between CO_2 concentration and indoor human occupancy and all of their decomposed components to find what correlations exist between each component.

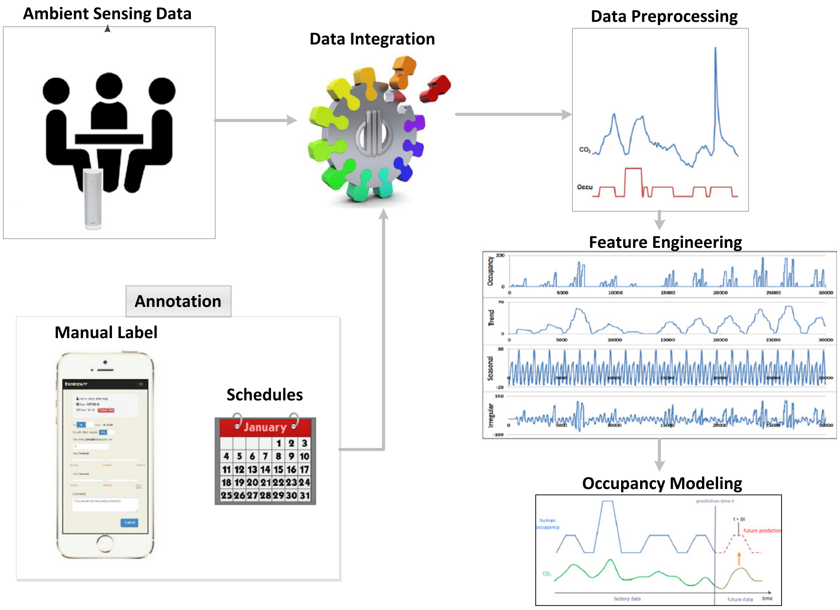

Fig. 4. Data collection and analysis framework.

4. Method

We assess our model in two different locations with very different contexts to ensure this model works under various conditions. The first location is one academic office belonging to one staff member at RMIT University, Australia. This room is chosen for human occupancy prediction since a controlled experiment can be conducted for an extended period of data collection. The picture of the room is shown in Fig. 5.

The second dataset was collected inside a cinema theatre in Mainz, Germany [56]. Cinema theatre is chosen as another setting due to its nature of having fluctuating numbers of people throughout the day. The numbers of people in the audiences can reach hundreds and can decrease to zero within a few hours.

The ventilation system refreshes the air once the CO_2 concentration reaches a limit where it is unhealthy for humans to breathe. Within RUP algorithm, we assume that the reason the CO_2 level reaches the peak is because the number of occupants reaches the peak.

4.1. Data collection experiment setup

4.1.1. Academic staff room

We use a commercial off-the-shelf Netatmo urban weather station (Range: 0–5000 ppm, accuracy: $\pm$50 ppm) to read and collect ambient CO_2 data, shown in Fig. 5. The experiment took place between May and June 2015 and the data frequency is 5 min. The dataset is uploaded to a cloud service for integration purposes. Due to the small room characteristic ($3 \times 4 \times 5$ m), N for time lag is 0 as we assume that there is a negligible time period between exhaling process and sensor reading. We selected 2 weeks data from the whole dataset and used them in the further analysis. To obtain actual occupancy data for this room, one staff volunteered to manually label the occupancy for the whole duration of the experiment. Once the labels are obtained, the annotation is cross checked with the online calendar to mitigate any errors.

4.1.2. Cinema theatre

The cinema dataset was collected between December 2013 and January 2014 [56]. The air-flow measurement and device arrangement for the cinema dataset is shown at Fig. 6. The dataset was collected using mass spectrometry machinery installed on the air ventilation system. The air flows from the screening room via the ventilation system to the mass spectrometer (Range: $10 - 500$ m/z with a Time-of-flight (TOF) acquisition sampling time per channel of 0.1 ns, resolution: $\pm$3700 m/Δm) for data analysis. To obtain actual occupancy data for this cinema theatre, we collaborated with the cinema theatre and acquired the total number of tickets that were sold for each movie session. We applied a smoothing method to reduce the number by 20% during the first and the last 5 min of movie duration to model people entering and leaving the theatre.

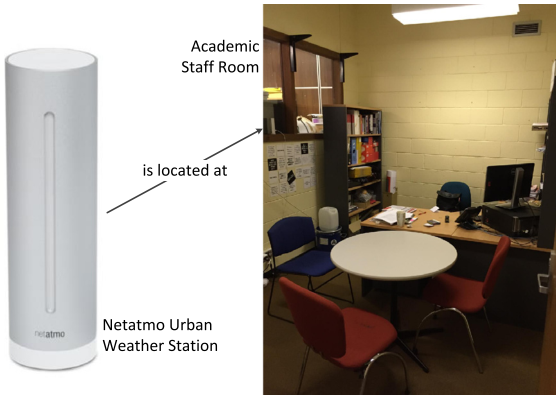

Fig. 5. The left picture is a Netatmo urban weather station, a sensor device to gather ambient CO_2 data which was set up near the window in the academic staff room (right).

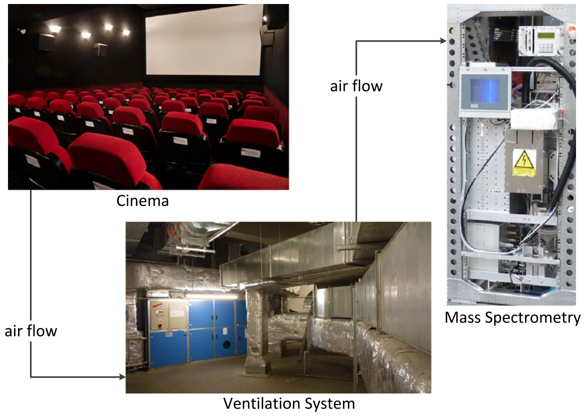

Fig. 6. Measurement in the cinema theatre. Air is drawn out through the screen room via the ventilation system and is transported to the mass spectrometer [56].

4.1.3. Experiment tool

We utilised WEKA, MATLAB and R to help us perform this experiment. WEKA is used for polynomial linear regression with the M5 method for both correlation models for trend (Section 4.3.2.1) and irregular features (Section 4.3.2.3). MATLAB code is run for the baseline method, SVR and its prediction result. We used R to integrate all the data, including decomposition of STD and STL, the majority of data pre-processing and compute another baseline algorithm, NMF-ELSR. We imported the data from R into Microsoft Excel for data analysis and visual output.

4.2. Data pre-processing

This section explains our data pre-processing and the reason why data pre-processing is important for our model. We gathered both the CO_2 concentration from the sensor data and indoor human occupancy from our annotations as shown in Fig. 4. Both data are integrated and pre-processed using our pre-processing method described below in Section 4.2.1 (autocorrelation and the line of best fit) and Section 4.2.2 (time lag). With feature engineering, we factorised the data into different features and applied prediction models described in Section 4.3 to predict the indoor human occupancy.

To solve a time delay issue between CO_2 data and our prediction indoor human occupancy number, the data needed to be pre-processed. The time delay issue means that when one person enters a room, it will take some time before the CO_2 level in the air increases proportionally.

4.2.1. Autocorrelation and the line of best fit

In order to analyse the data between CO_2 and the number of occupants, a data lagging issue needs to be considered. Data lagging means that it will take some time for CO_2 to populate the room as there is a delay between the time of people entering (or exiting) the room and the increment (or decrement) of the CO_2 reading. For each dataset from 0 min time lag to

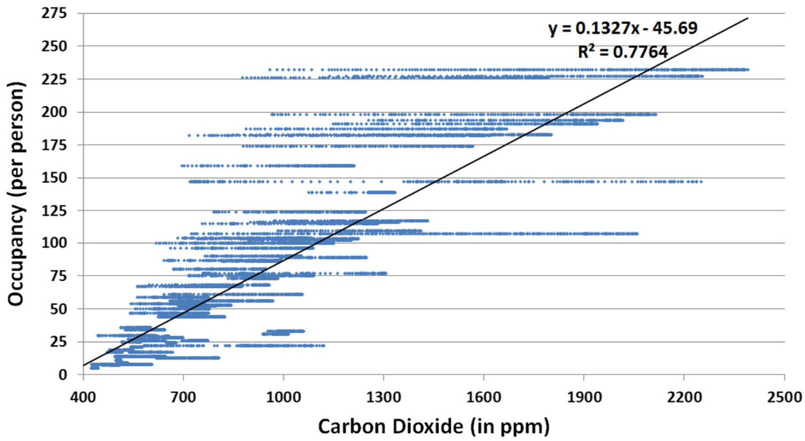

Fig. 7. Correlation between the number of occupants and CO_2 readings in ppm with time lag 0.

Upper Bound (UB) minutes time lag, the correlation of CO_2 data with the number of occupancies is drawn. The UB value is the maximum value that can be used to calculate the time lag value in Section 4.2.2 and is defined by the formula in Eq. (2).

$$UB = \|(roomlength * roomwidth * roomheight)/100\|. \tag{2}$$

For the academic staff room, the UB value is 1. This small value means the usefulness of time lag for this room analysis is minimal. For cinema data [56], the UB value is 60 due to the large size of the studio in the cinema theatre. A line of best fit is drawn as shown in Fig. 7.

To calculate a line of best fit, first we calculate the slope value between CO_2 and occupancy data. The formula is defined in Eq. (3).

$$SL = \frac{\sum(O_t - \bar{O_t})(C_t - \bar{C_t})}{\sum(O_t - \bar{O_t})^2} \tag{3}$$

SL slope of the linear regression line
O_t occupancy value
$\bar{O_t}$ sample means (the averages) of the known occupancy value
C_t CO_2 value
$\bar{C_t}$ sample means (the averages) of the known CO_2 value.

After getting the SL value, intercept value between both data needs to be calculated with formula in Eq. (4).

$$INTC = \bar{C_t} - SL * \bar{O_t} \tag{4}$$

$INTC$ intercept (the value at the intersection of the y axis) of the linear regression line
$\bar{C_t}$ sample means of the known CO_2 value
$\bar{O_t}$ sample means of the known occupancy value.

The main formula for the line of best fit (LBF) is shown in Eq. (5).

$$LBF = (O_t - (SL * C_t + INTC))^2 \tag{5}$$

O_t occupancy value
SL slope of the linear regression line
C_t CO_2 value
$INTC$ intercept of the linear regression line.

4.2.2. Time lag

For each line of best fit, the mean squared error (MSE), root-mean-square deviation (RMSD) and the normalised root mean squared error (NRMSE) are calculated. The formula for calculating NRMSE is shown in Eq. (6).

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(C_t - \bar{C_i})^2}}{O_{max} - O_{min}} \tag{6}$$

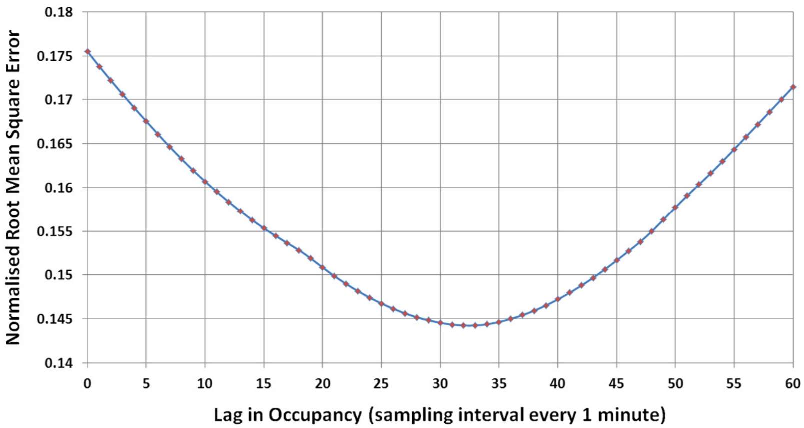

Fig. 8. Ordinary least square regression normalised root mean squared error (NRMSE) between CO_2 data and actual occupancy for 60 min time lag.

$NRMSE$	normalised root mean square error
t	total number of dataset
C_t	CO_2 value
$\bar{C_t}$	sample means of the known CO_2 value
O_{max}	maximum occupancy value
O_{min}	minimum occupancy value.

This step is repeated up to UB times for each different time lag. For time lag analysis, we use least square regression to compare each NRMSE from time lag 0 until time lag UB. We use the lowest number of NRMSE value, time lag value (TL), as our baseline time lag for the data analysis shown in Eq. (7).

$$TL = min(NRMSE). \tag{7}$$

By calculating NRMSE beyond the limit of UB, the TL result would not be significantly better. On the other hand, setting a lower UB value than the suggested output of (refers to Eq. (2)) may result in incorrect TL and potentially reduce the overall prediction accuracy. For the academic staff room, the TL value is 0. This value represents no time lag is needed for this analysis. For the cinema theatre, the lowest number of error value happens at time lag TL = 32 as shown in Fig. 8. This TL value is our base for the cinema theatre data analysis. So for the entire cinema data analysis process, we use time lag 32. The TL value needs to be calculated only once for every domain.

4.3. Room utilisation prediction algorithm

Since there is no linear relationship between CO_2 and indoor human occupancy, we introduce a new prediction model to address this non-linear correlation issue by decomposing both CO_2 and occupancy data. There are two variants of this model, RUP seasonal trend decomposition (RUP-STD) and RUP seasonal trend decomposition based on Loess (RUP-STL), which will be discussed in the following subsections. Each decomposition extracts a feature and correlation can be developed from each feature.

The next following subsections explain the core prediction model for this paper, shown in Fig. 9. In the first subsection, we discuss two data decomposition methodologies. The next subsection explains the correlation model for trend, seasonal and irregular features. The last subsection presents a new method for analysing conditions when the room is vacant which we term zero pattern adjustment, to increase the overall accuracy. This model needs to be re-trained for each location to obtain the best accuracy result.

4.3.1. Decomposition methodologies

There are two variants of decomposition methods that are utilised for RUP, seasonal-trend decomposition (STD) in Section 4.3.1.1 and seasonal-trend decomposition based on Loess (STL) in Section 4.3.1.2.

4.3.1.1. Seasonal-trend decomposition. STD is a mature technique in time series analysis. One of the most popular variants is the version X-11 method for using moving average [57] and the most recent variant is the version X12-ARIMA [58]. STD is an integral part of our framework.

To understand the time series data better, we use STD to decompose the model into four main features: trend, cyclical, seasonal and irregular. The trend feature (T_t) reflects the long-term progression of the time series during its secular variation. The cyclical feature (C_t) is a repeated but non-periodic fluctuation during an extended period of time. The seasonal feature

Fig. 9. RUP: Large room utilisation prediction with carbon dioxide sensor.

(S_t) is a systematic and regularly repeated sequence during a short period of time. The irregular feature (e_t also known as error or residual) is a short-term fluctuation from the time series and is the remains after the trend, cyclical and season features have been removed. For this paper, as our experiment is within a short period of time (one month for each case), we decide to combine the cyclical feature into trend feature to make the model simpler without sacrificing the accuracy.

Below is the core logic for STD (using Henderson moving average):

1. Calculate 2×12 moving average in the raw data (both CO_2 and occupancy datasets) to obtain a rough trend feature data T_t for all period.
2. Calculate ratios of the data to trend, named "centred ratios" (y_t/T_t).
3. To form a rough seasonal feature (S_t) data estimation, apply separate 2×2 moving average to each month of the centred ratios.
4. To obtain the irregular feature (e_t), divide the centred ratios by S_t.
5. Multiply modified e_t by S_t to get modified centred ratios.
6. Repeat step 3 to obtain revised S_t.
7. Divide the raw data by the new estimate of S_t to give the preliminary seasonal adjusted series, y_t/S_t.
8. The trend feature (T_t) is estimated by applying a weighted Henderson moving average to the preliminary seasonally adjusted values.
9. Repeat step 2 to get new ratios by dividing the raw data by the new estimate of T_t.
10. Repeat Steps 3–5 using the new ratios and applying a 3×5 moving average instead of a 3×3 moving average.
11. Repeat step 6 but using 3×5 moving average instead of a 3×3 moving average.
12. Repeat step 7.
13. Finally the reminder feature is obtained by dividing the seasonally adjusted data from step 12 by the trend feature obtained in step 8.

Our customised STD formulation is:

$$STD_t = f(T_t, S_t, e_t) \tag{8}$$

t	time
STD_t	actual value of a time series at time t
T_t	trend feature at t
S_t	seasonal feature at t
e_t	irregular feature at t.

The function $f()$ can be additive or multiplicative, yielding an additive decomposition or a multiplicative decomposition. Additive decomposition model is a data model in which each factor is added to model the data. Multiplicative decomposition occurs when the seasonal feature pattern is increased as the number of data increases. For multiplicative decomposition,

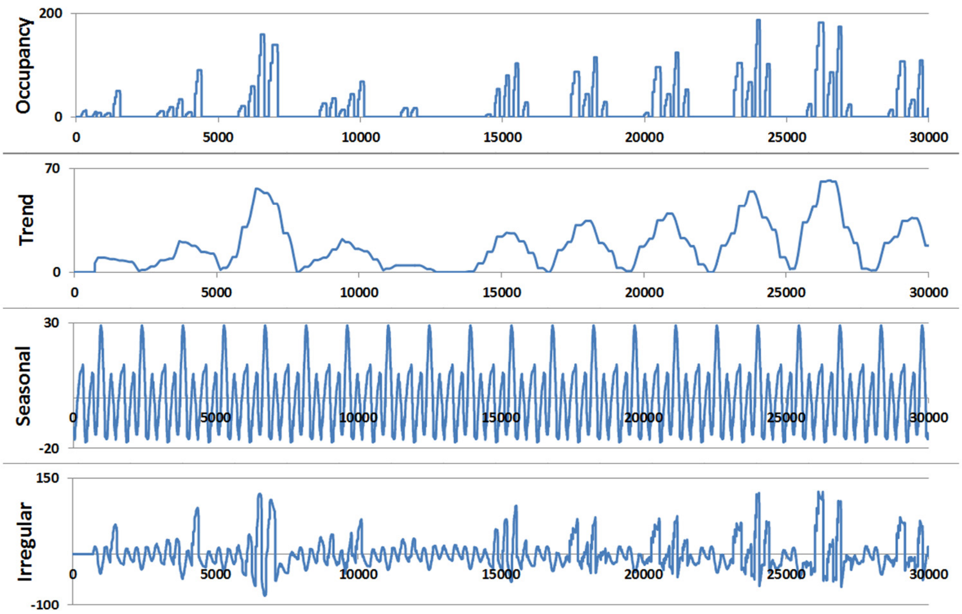

Fig. 10. Example of time series decomposition.

the trend and seasonal features are multiplied and then added to the irregular feature. In our case, as the magnitude of seasonal feature pattern in the data does not depend on the magnitude of the overall dataset, we decided to use additive decomposition as shown in Fig. 10. From Eq. (8), our general STD formula becomes:

$$STD_t = T_t + S_t + e_t. \tag{9}$$

This general STD formula is applied to both time series for the CO_2 dataset and the human occupancy dataset:

$$C_t = T_t^C + S_t^C + e_t^C \tag{10}$$

$$O_t = T_t^O + S_t^O + e_t^O. \tag{11}$$

To predict O_{t+1} up to O_{t+n}, we need to create a model to systematically predict each of T_{t+1}^O, S_{t+1}^O and e_{t+1}^O up to T_{t+n}^O, S_{t+n}^O and e_{t+n}^O and then reconstruct the new prediction dataset using the additive method. In this paper, we explore two variants of STD for our model and compare the accuracy result with the baseline. The first one is standard STD that is implemented using moving average and the second one is seasonal-trend decomposition based on Loess (STL) [59].

4.3.1.2. Seasonal-trend decomposition based on loess. Loess stands for locally weighted scatterplot smoothing, a non-parametric local regression method that is built on least square regression. This method is designed to estimate a non-linear relationship in a dataset. STL is a filtering procedure for decomposing a time series into trend, seasonal and irregular components with loess smoother. To be compared with other STD variants such as X-12 ARIMA, STL has several advantages namely:

- STL method is very versatile and robust. It can handle any type of seasonality and will not be limited to a monthly or quarterly dataset;
- The seasonal feature and the smoothness of the trend-cycle both can be controlled by the user;
- STL is robust on outliers, so occasional unusual data will not ruin the estimation of trend-cycle and seasonal features. However, they will affect the irregular feature.

4.3.2. Correlation models

There are three correlation models below for trend features in Section 4.3.2.1, seasonal features in Section 4.3.2.2 and irregular features in Section 4.3.2.3.

4.3.2.1. Correlation model for trend feature (T_t). As the definition of the trend feature (T_t) is the long-term non-periodic progression of the time series during its secular variation, we assume that the trend feature for the CO_2 dataset (T_t^C) will be similar to the trend feature for indoor human occupancy (T_t^O).

To check the similarity between both trend features, we use the Pearson product-moment Correlation Coefficient (PCC) as shown below:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \tag{12}$$

r correlation coefficient
x dataset x
y dataset y
n number of sample points.

The range of Pearson's r value is from -1 to $+1$. If the value is > 0.7, the correlation between both datasets is strongly positive.

Once the validation step is done, we implement polynomial M5 linear regression. The M5 method will build trees whose leaves are associated with multivariate linear models and the nodes of the tree are chosen over attributes that maximise the expected error reduction, given by the Akaike Information Criterion (AIC - a measure to check the relative goodness of fit of a statistical model) [60]. The purpose of using AIC is to evaluate the model. The value for each of trend feature needs to be a positive value so we put the absolute value on both the CO_2 ($|T_t^C|$) and human occupancy trend features ($|T_t^O|$). The main formula for trend feature correlation is shown below:

$$T_t^O = \alpha_0 + \alpha_1(T_t^C) + \alpha_2(T_t^C)^2 + \cdots + \alpha_n(T_t^C)^n + \epsilon. \tag{13}$$

Linear regression with M5 will output each α_n and ϵ value. With these parameters, the future trend for T_{t+n}^O can be obtained.

Algorithm 1 Finding a repeated pattern sequence inside seasonal feature.

procedure REPEATED_SEQUENCE(S_t)
  $s_t^{temp}, s_t^{fin} \subset S_t$
  $len \leftarrow 0$ ▷ *len*: Length for s_t^{temp}
  $a \leftarrow S_t[len]$ ▷ *a*: Start Point
  for each node $i \in S_t$ **do**
    len++
    $s_t^{temp} \leftarrow s_t^{temp} + S_t[i]$
    if $a = S_t[i]$ **then**
      if DTW($s_t^{temp}, S_t[i+1..i+len]$) > 95 **then**
        $s_t^{fin} \leftarrow s_t^{temp}$
        break
      end if
    end if
  end for
  return s_t^{fin}
end procedure

4.3.2.2. Correlation model for seasonal feature (S_t). The seasonal feature (S_t) is a systematic and regularly repeated sequence during a short period of time. Due to this characteristic, every seasonal feature can be fitted by a finite Fourier series. To correlate S_t^C and S_t^O, we use Dynamic Time Warping (DTW), a pattern matching technique to score the similarity between the shape of particular signal within certain duration [61]. The full correlation algorithm is implemented in Algorithm 1 to find regularly repeated sequences within each S_t.

Once we find a sequence that is repeating in s_t^{fin} for both the CO_2 and occupancy seasonal features, we compare the length of $s_t^{fin(O)}$ and $s_t^{fin(C)}$. If the length of $s_t^{fin(O)} < s_t^{fin(C)}$, we apply an interpolation method inside $s_t^{fin(O)}$, so both have the same length. If the length of $s_t^{fin(O)} > s_t^{fin(C)}$, we apply data reduction method so finally both have the same length. The final regression equation for seasonal feature correlation is shown below:

$$s_t^{fin(O)} = f(s_t^{fin(C)}). \tag{14}$$

With this equation, the future trend for $S_{t+n}^{fin(O)}$ can be obtained.

4.3.2.3. Correlation model for irregular feature (e_t). Due to similar characteristics between trend and irregular features, we apply the same correlation method from the trend feature:

$$e_t^O = \beta_0 + \beta_1(e_t^C) + \beta_2(e_t^C)^2 + \cdots + \beta_n(e_t^C)^n + \gamma. \tag{15}$$

The only difference from the trend feature is that we do not need to validate it using PCC as the shape of the irregular feature will depend more on its trend and seasonal features.

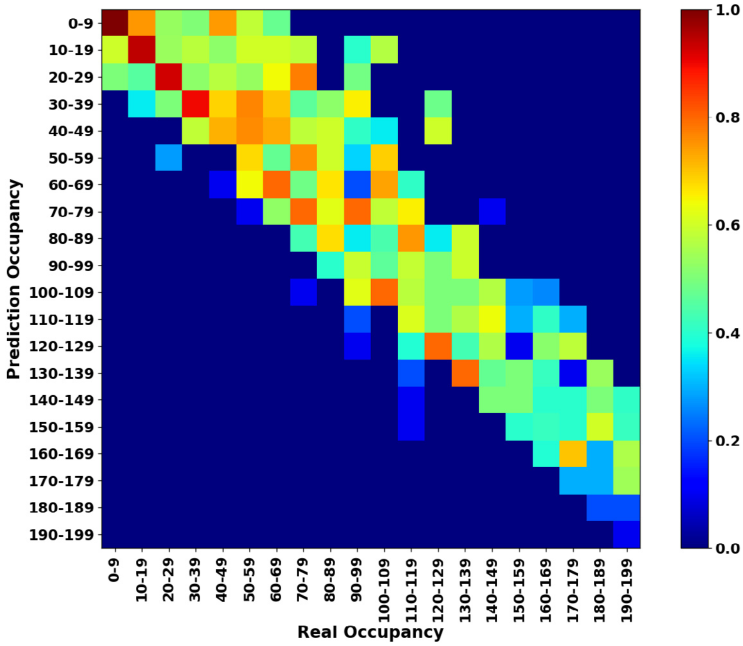

Fig. 11. Confusion matrix between real occupancy and prediction occupancy for cinema theatre.

4.3.2.4. Zero pattern adjustment. In human occupancy prediction research, inferring knowledge when a room is vacant is paramount. By minimising false positives, the accuracy prediction can be improved. The Zero pattern adjustment (ZPA) method learns the behaviour from previous historical data and makes some smart adjustments for a vacant room when the normal algorithm returns incorrect prediction. The ZPA technique overlays all previous dataset and puts them on a single 24-h *x*-axis chart to determine the earliest start and end points when the room is vacant each day during the night to dawn period. We symbolise ZPA as zpa_t^O.

Algorithm 2 Finding the indoor human occupancy.

procedure NUMBER_OCCUPANCY($T_t^O, S_t^O, e_t^O, zpa_t^O$)
  $O_t^{temp} \leftarrow T_t^O + S_t^O + e_t^O + zpa_t^O$ $\triangleright$ O_t^{temp}: temporary occupancy
  if $O_t^{temp} \geq 0$ **then**
    $O_t = O_t^{temp}$
  else
    $O_t = 0$
  end if
  return O_t
end procedure

4.3.3. Occupancy model

Algorithm 2 contains the occupancy calculation model, where we integrate each feature to compute the occupancy prediction value. This model can be trained to have a high accuracy using training data for as little as two weeks. With more training and ground truth data, the accuracy prediction will be improved.

5. Experiments, results and discussion

5.1. Experiment

There are two types of feature decomposition: RUP-STD and RUP-STL. We implement both RUP models for each different combination of training and test dataset. Finally, we compare each RUP accuracy result with both SVR and NMF-ELSR.

RUP model predicts each future value for the whole period of time based on specific time window. To understand this model better and how well it performs compared with the baseline, we define x, accuracy error tolerance parameter. Zero units error tolerance means only the exact number recognised is considered as true positive. For example with ten units error tolerance, if the real indoor human occupancy is 150 people, the prediction shows that 146 or 155 is considered correct as it is within ± 10 units error tolerance. The parameter x value will be different based on the size of the room.

5.1.1. Experiment parameters for academic staff room dataset

For the academic staff room dataset, we used 5-min time window. Total data that we gathered from this room are 4019 data spread in 14 days. Due to the small room size, we decided not to use time lag for data analysis. For this room, we have seven pairs of training-test datasets. It starts with seven days of training dataset and seven days of test dataset. It ends with 13 days of training dataset to predict one day test dataset.

5.1.2. Experiment parameters for cinema dataset

For the cinema theatre dataset, we use a 3-minutes time window for data analysis. The data that we gathered from this cinema theatre consisting of 68 640 instances spread over 23 days. The cinema theatre capacity is up to 300 people and for this experiment, we run the line of best fit for time lag 0 to time lag 60. The lowest normal root mean square error point is at time lag 32 and we use time lag 32 as time lag baseline. This time lag is appropriate as a bigger room needs a larger time lag for the model to have a better accuracy. For this room, we decided to use December 2013 data for training and January 2014 data for testing. Then we replicated it in the similar method by giving one day from testing dataset to training dataset and ran the model again. This method is repeated until the test dataset only consisted of one day of data. Finally, we ran the same training-test dataset using two baseline methods, SVR and NMF-ELSR. The general confusion matrix for cinema occupancy prediction performance is shown in Fig. 11.

5.1.3. Evaluation and baselines

To evaluate the result, we divide the data into 2 equal parts. The first part is the training dataset and the second one is the test dataset. To be able to understand how well the model fits for a longer duration, we repeat the division of training and test dataset by adding one day data from the test dataset to the training dataset. This replication is repeated again until the test dataset has only one single day and the rest belong to training dataset. This incremental days of training and reduction in testing evaluation method ensures the robustness of the model.

We are using two state-of-the-art algorithm baselines to compare our technique. The first one is SVR. SVR is chosen because the latest human occupancy counting method with CO_2 data, PerCCS [15], picked SVR as their baseline. We also use PerCCS technique, non-negative matrix factorisation with ensemble least square regression (NMF-ELSR) as another baseline.

5.2. Experiment result

5.2.1. Experiment result for academic staff room dataset

The average accuracy for indoor human occupancy with RUP-STD is 94.26%, with RUP-STL is 94.68% and with SVR is 90.35%. From Fig. 12, both RUP-STD and RUP-STL performed better than the baseline on average by 4.33%. The last two days are Saturday and Sunday, so both RUP and the baseline model correctly predict zero occupancies for each day.

To understand the model, we run the experiment and check the level of accuracy with one unit error tolerance. The accuracy result is shown in Fig. 13. For this experiment, the maximum number of people is four at one time. The average accuracy with one unit error tolerance for indoor human occupancy with RUP-STD is 99.52%, with RUP-STL is 99.52% and with SVR is 98.34%.

5.2.2. Experiment result for cinema dataset

For the cinema dataset, the comparison accuracy result is shown in Fig. 14. Both RUP methods perform better than the baseline method and on average each RUP method has 8.5% higher accuracy in predicting indoor human occupancy. The highest prediction accuracy was found when we used 22 days data for training to predict the number of human occupants the next day.

Because the maximum number of people allowed in the audience at the cinema is 300, predicting the exact number of people at one particular time is challenging. The accuracy for the baseline method SVR on average is 39.4% and for RUP on average is 47.8%. We decided to calculate the accuracy number with ten units error tolerance, so the difference up to ten occupants is counted as true positive. Ten units error tolerance is acceptable for cinema theatre as 280 people and 290 people will not make a huge difference for analysis and controlling HVAC/BMS purpose. The result for ten units error tolerance is shown in Fig. 15. RUP-STL performs worse than the baseline but RUP-STD is the most accurate for almost every test case with an average accuracy of 73.76%. The average accuracy for SVR is 72.7%.

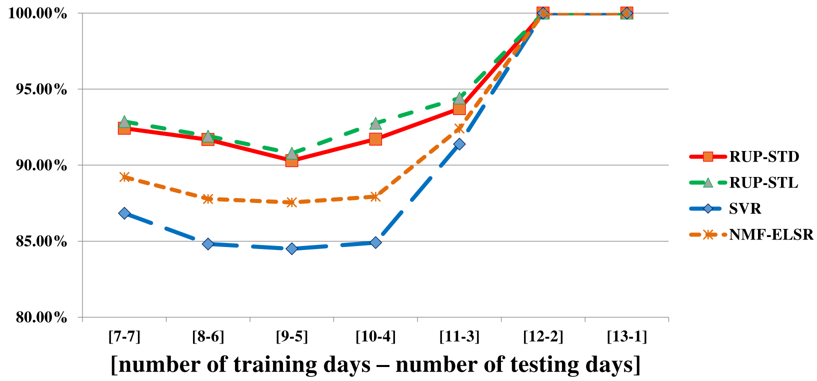

Fig. 12. Academic staff room dataset—the comparison for indoor human occupancy with zero units error tolerance.

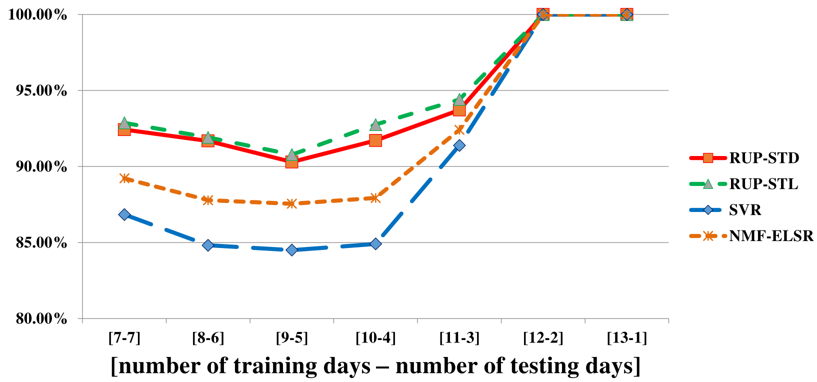

Fig. 13. Academic staff room dataset—the comparison for indoor human occupancy with one units error tolerance.

Table 5
Academic staff room indoor human accuracy result.

# of training days	# of testing days	Zero units error tolerance				One unit errortolerance			
		SVR	NMF-ELSR	RUP-STD	RUP-STL	SVR	NMF-ELSR	RUP-STD	RUP-STL
7	7	86.84%	89.22%	92.42%	**92.87%**	97.81%	98.31%	**99.35%**	**99.35%**
8	6	84.82%	87.78%	91.68%	**91.91%**	97.44%	98.16%	**99.30%**	99.19%
9	5	84.50%	87.55%	90.29%	**90.78%**	97.14%	98.02%	**99.16%**	**99.16%**
10	4	84.90%	87.93%	91.71%	**92.76%**	97.29%	98.15%	**98.95%**	**98.95%**
11	3	91.39%	92.41%	93.71%	**94.41%**	98.72%	99.12%	99.88%	**100.00%**
12	2	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
13	1	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
Average accuracy		90.35%	92.13%	94.26%	**94.68%**	98.34%	98.82%	**99.52%**	**99.52%**

The results from both Figs. 14 and 15 show that overall RUP method is more accurate in predicting indoor human occupancy. RUP-STL is slightly more accurate on zero units error tolerance and RUP-STD is more accurate on average. This result is encouraging as RUP-STD uses moving average and a smoothing method usually work best with some error tolerance. Furthermore, we can observe that the accuracy for less number of days prediction is higher than for more days prediction, which is aligned with the results from academic staff room experiment.

5.3. Discussion

Our research with our new framework has a high accuracy (94.4% as shown in Table 5) for a small room with up to four residents and it performs better than the baseline method for a large room with up to 300 occupants in the cinema theatre.

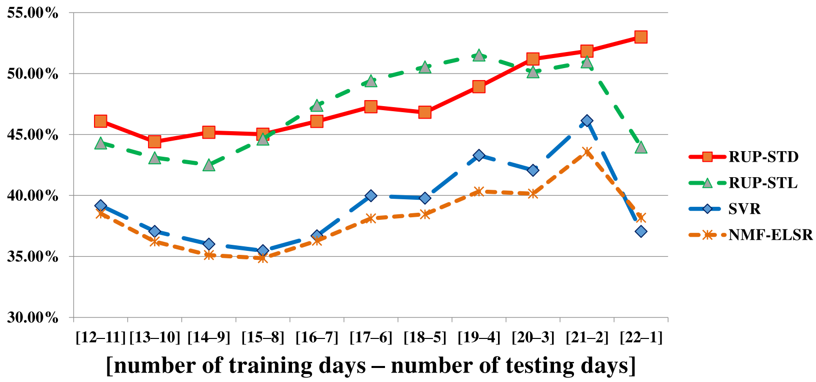

Fig. 14. Cinema dataset—the comparison for indoor human occupancy with zero units error tolerance.

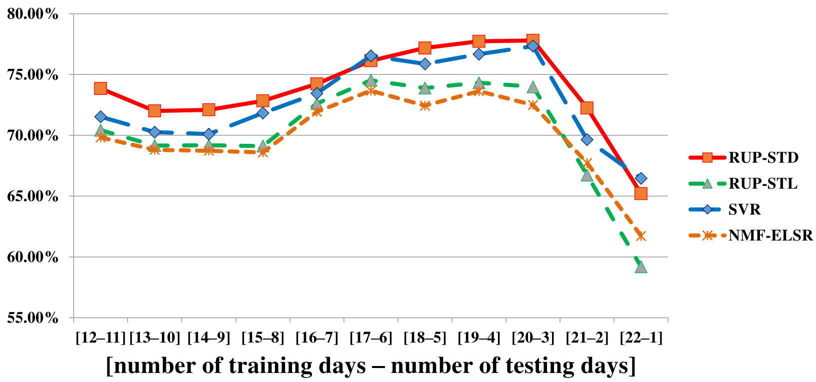

Fig. 15. Cinema dataset—the comparison for indoor human occupancy with ten units error tolerance.

Table 6
Cinema theatre indoor human accuracy result.

# of training days	# of testing days	Zero units error tolerance				One unit error tolerance			
		SVR	NMF-ELSR	RUP-STD	RUP-STL	SVR	NMF-ELSR	RUP-STD	RUP-STL
12	11	39.16%	38.51%	**46.09%**	44.31%	71.52%	69.83%	**73.85%**	70.42%
13	10	37.05%	36.22%	**44.41%**	43.10%	70.26%	68.81%	**72.00%**	69.16%
14	9	36.01%	35.11%	**45.17%**	42.51%	70.10%	68.73%	**72.10%**	69.18%
15	8	35.47%	34.86%	**45.02%**	44.63%	71.83%	68.60%	**72.84%**	69.12%
16	7	36.70%	36.29%	46.08%	**47.40%**	73.46%	71.94%	**74.23%**	72.62%
17	6	39.98%	38.12%	47.27%	**49.42%**	**76.54%**	73.67%	76.13%	74.53%
18	5	39.78%	38.46%	46.82%	**50.54%**	75.87%	72.44%	**77.18%**	73.89%
19	4	43.29%	40.33%	48.92%	**51.53%**	76.68%	73.63%	**77.73%**	74.32%
20	3	42.06%	40.15%	**51.19%**	50.15%	77.34%	72.49%	**77.80%**	73.99%
21	2	46.14%	43.59%	**51.84%**	50.97%	69.64%	67.72%	**72.25%**	66.73%
22	1	37.06%	38.18%	**52.99%**	43.98%	**66.46%**	61.72%	65.21%	59.19%
Average accuracy		39.34%	38.17%	**47.80%**	47.14%	72.70%	69.96%	**73.76%**	70.29%

This RUP model is robust enough to handle different scales of data, proven by doing research in two different environment content such as room size and the maximum number of occupants.

Comparing two baselines, NMF-ELSR performs strongly in an environment with a small number of occupants whereas SVR is more accurate in a room with a huge number of people. With a room of 5 people, RUP-STD is the most accurate method, followed by RUP-STL, then by NMF-ELSR and SVR is the least accurate one. With a large room, both of our RUP models perform better than the baselines by approximately 8%. On average, our RUP algorithms are more accurate than both baselines.

From the cinema theatre result, we can observe that the RUP model performs better than the better baseline method (SVR) and with ten units error tolerance for up to 300 occupants, the occupancy prediction accuracy is 77.8%. Estimating the number of occupants for a large room is a challenging problem and to the best of the authors' knowledge, there is no research for this large number of occupants that is generated with this level of accuracy for occupancy prediction. The best state-of-the-art performance using CO_2 data is 15% accuracy for predicting up to 40 occupants reported by [15]. This is shown by NMF-ELSR perform worse compared to the others RUP and SVR techniques as shown in Table 6.

From the experimental results, after predicting up to 10 days ahead the RUP model's accuracy is reduced to only 6.9% on the average compared to predicting only one day ahead. This result is also encouraging because it shows that RUP model is significantly stable for long term predictions.

The RUP-STL method has a higher accuracy compared to SVR for precise accuracy but the standard accuracy decreased when we consider ten units error tolerance. This means that the value estimated can be very accurate at one time and miss the target in other cases. The ranges fluctuated significantly. RUP-STD, on the other hand, is more stable and has a stable range of prediction. This is aligned because STD is based on the moving average smoothing method.

6. Conclusions, limitations and future works

Research on building and room occupancy counting is becoming more important. By understanding and knowing the numbers of people within a building, the heating, cooling, lighting control, building energy consumption, emergency evacuation, security monitoring and room utilisation can all be made more efficient. Thorough research in this area has implemented with various methods including the use of ambient sensors. However, occupancy models that have been studied in previous work require the use of many sensors, which is expensive for installation and on-going operation. In this experiment, we use a single sensor that is commonly available in the Australian BMSs to reduce the cost and complexity as more sensors mean less reliability. The research of using a single type of information such as CO_2 and inferring it to predict human occupancy is novel. Hence, many possibilities can be explored by using this technique. Furthermore, our model can be trained to have a high accuracy with training data gathered over only two weeks. This algorithm is robust in handling both low and high occupancy number up to three hundred occupants. Furthermore, with CO_2 data, the privacy of every single individual is protected as no personal information is required. This method is device-free in a notion that no device would be attached to the body throughout the experiment phases. Our method produces on average 8.46% better accuracy compared to the baseline method. In addition, our prediction model reduces the accuracy by 6.9% after predicting more than 10 days.

The limitation of this research is the accuracy result based depends on CO_2 concentration. If the CO_2 level is changed due to external reasons, the prediction accuracy will suffer. This condition rarely happens as modern buildings have a proper ventilation system but it needs to be considered. If the buildings do not have a modern BMS system, opening windows can change the CO_2 concentration and hence degrade RUP performance. The other limitation is the larger the room size is, the bigger the TL value is, which means the less real time the result is. Having proper ground truth could be problematic as less accurate ground truth translates to less accurate predictions.

As our research was focussed on two locations and datasets, we plan to extend this research to other places that have different environment dynamics and characteristics. The experiment above was conducted off-line. For future work, real-time on-line learning can be pursued to enhance the performance.

Acknowledgements

The authors would like to thank Jöerg Wicker from University of Auckland for providing the cinema dataset used in this paper. This research is supported by the Australian Government Research Training Program Scholarship and two RMIT and Siemens Sustainable Urban Precinct Project (SUPP) grants: "iCO2mmunity: Personal and Community Monitoring for University-wide Engagement towards Greener, Healthier, and more Productive Living" and "The Greener Office and Classroom".

Appendix. Machine learning techniques and their abbreviations

(see Table A.1).

Table A.1
Machine learning techniques and their abbreviations that are used in related works.

Abbreviation	Machine learning techniques
ARIMA	Autoregressive integrated moving average
ANN	Artificial Neural Network
BN	Belief Network
CART	Classification and Regression Trees
DB-SCAN	Density-Based Spatial Clustering of Applications with Noise
DT	Decision Trees
EV	Ensemble Voting
ELSR	Ensemble Least Square Regression
GBM	Gradient Boosting Machines
GP	Gaussian Processes
HMM	Hidden Markov Model
KNN	K-Nearest Neighbour
KL divergence	Kullback–Leibler Divergence
LBMPC	Learning-Based Model Predictive Control
LD	Linear Discriminant
LDA	Latent Dirichlet Allocation
LMV	Linear Minimum Variance
LP	Linear Regression
MLE	Maximum Likelihood Estimate
MLP	Multi-Layer Perceptron
NB	Naïve Bayes
NMF	Non-negative Matrix Factorisation
NN	Neural Networks
MP	MultiPath fading
RF	Random Forest
RBF	Radial Basis Function
SVM	Support Vector Machine
SVR	Support Vector Regression
TAN	Tree Augmented Naïve Bayes network
THR	Thresholding

References

[1] A. Doee, The Basics of HVAC Energy Efficiency Factsheet, Technical report, 2013.
[2] R. Goldstein, A. Tessier, A. Khan, Schedule-calibrated occupant behavior simulation, in: Proceedings of the 2010 Spring Simulation Multiconference, Society for Computer Simulation International, 2010, p. 180.
[3] J. Page, D. Robinson, N. Morel, J.-L. Scartezzini, A generalised stochastic model for the simulation of occupant presence, Energy Build. 40 (2) (2008) 83–98.
[4] I. Richardson, M. Thomson, D. Infield, A high-resolution domestic building occupancy model for energy demand simulations, Energy Build. 40 (8) (2008) 1560–1566.
[5] D. Saelens, W. Parys, R. Baetens, Energy and comfort performance of thermally activated building systems including occupant behavior, Build. Environ. 46 (4) (2011) 835–848.
[6] I.B.A. Ang, F.D. Salim, M. Hamilton, Human occupancy recognition with multivariate ambient sensors, in: 2016 IEEE International Conference on Pervasive Computing and Communication Workshops, (PerCom Workshops), IEEE, 2016, pp. 1–6.
[7] I.B. Arief-Ang, F.D. Salim, M. Hamilton, Sd-hoc: Seasonal decomposition algorithm for mining lagged time series, in: Fifteenth Australasian Data Mining Conference. Communications in Computer and Information Science, Springer, 2018.
[8] L.M. Candanedo, V. Feldheim, Accurate occupancy detection of an office room from light, temperature, humidity and CO2 measurements using statistical learning models, Energy Build. 112 (2016) 28–39.
[9] T. Ekwevugbe, N. Brown, V. Pakka, Realt-time building occupancy sensing for supporting demand driven hvac operations, in: International Conference for Enhanced Building Operations, Energy Systems Laboratory, 2013.
[10] E. Hailemariam, R. Goldstein, R. Attar, A. Khan, Real-time occupancy detection using decision trees with multiple sensor types, in: Proceedings of the 2011 Symposium on Simulation for Architecture and Urban Design, Society for Computer Simulation International, 2011, pp. 141–148.
[11] A. Khan, J. Nicholson, S. Mellor, D. Jackson, K. Ladha, C. Ladha, J. Hand, J. Clarke, P. Olivier, T. Plötz, Occupancy monitoring using environmental & context sensors and a hierarchical analysis framework., in: BuildSys@ SenSys, 2014, pp. 90–99.
[12] S. Mamidi, Y.-H. Chang, R. Maheswaran, (2012) Improving building energy efficiency with a network of sensing, learning and prediction agents, in: Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems-Volume 1, International Foundation for Autonomous Agents and Multiagent Systems, pp. 45–52.
[13] W. Shao, F.D. Salim, T. Nguyen, M. Youssef, Who opened the room? device-free person identification using bluetooth signals in door access, in: 2017 IEEE International Conference on Internet of Things (IThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data, (SmartData), 2017, pp. 68–75.
[14] Z. Yang, N. Li, B. Becerik-Gerber, M. Orosz, A multi-sensor based occupancy estimation model for supporting demand driven HVAC operations, in: Proceedings of the 2012 Symposium on Simulation for Architecture and Urban Design, Society for Computer Simulation International, 2012, p. 2.
[15] C. Basu, C. Koehler, K. Das, A.K. Dey, Perccs: person-count from carbon dioxide using sparse non-negative matrix factorization, in: Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, ACM, 2015, pp. 987–998.
[16] K.P. Lam, M. Höynck, B. Dong, B. Andrews, Y.-S. Chiou, R. Zhang, D. Benitez, J. Choi, et al., Occupancy detection through an extensive environmental sensor network in an open-plan office building, IBPSA Build. Simul. 145 (2009) 1452–1459.
[17] G.B.C. of Australia (GBCA). Quality of indoor air, 2017.

[18] X. Zhang, P. Wargocki, Z. Lian, C. Thyregod, Effects of exposure to carbon dioxide and bioeffluents on perceived air quality, self-assessed acute health symptoms, and cognitive performance, Indoor Air 27 (1) (2017) 47–64.
[19] F.C. Sangogboye, K. Arendt, A. Singh, C.T. Veje, M.B. Kjærgaard, B.N. Jørgensen, Performance comparison of occupancy count estimation and prediction with common versus dedicated sensors for building model predictive control, in: Building Simulation, Vol. 10, Springer, 2017, pp. 829–843.
[20] V.L. Erickson, Y. Lin, A. Kamthe, R. Brahme, A. Surana, A.E. Cerpa, M.D. Sohn, S. Narayanan, Energy efficient building environment control strategies using real-time occupancy measurements, in: Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, ACM, 2009, pp. 19–24.
[21] H. Lee, C. Wu, H. Aghajan, Vision-based user-centric light control for smart environments, Pervasive Mob. Comput. 7 (2) (2011) 223–240.
[22] J. Barandiaran, B. Murguia, F. Boto, Real-time people counting using multiple lines, in: Ninth International Workshop on Image Analysis for Multimedia Interactive Services, 2008, WIAMIS'08, IEEE, 2008, pp. 159–162.
[23] S. Munir, R.S. Arora, C. Hesling, J. Li, J. Francis, C. Shelton, C. Martin, A. Rowe, M. Berges, Real-time fine grained occupancy estimation using depth sensors on ARM embedded platforms, in: Real-Time and Embedded Technology and Applications Symposium (RTAS), 2017 IEEE, IEEE, 2017, pp. 295–306.
[24] K.S. Liu, S. Munir, J. Francis, C. Shelton, S. Lin, Long term occupancy estimation in a commercial space: an empirical study, in: IPSN, 2017, pp. 307–308.
[25] J. Teizer, Status quo and open challenges in vision-based sensing and tracking of temporary resources on infrastructure construction sites, Adv. Eng. Inf. 29 (2) (2015) 225–238.
[26] R.C. Arora, Comfort - physiological principles, iaq and design conditions, in: Refrigeration and Air Conditioning, eastern ec ed., PHI Learning Pvt. Ltd., 2010, pp. 819–871 (chapter).
[27] L. Granato, A. Brandes, C. Bruni, A.V. Greco, G. Mingrone, Vo2, vco2, and rq in a respiratory chamber: accurate estimation based on a new mathematical model using the kalman-bucy method, J. Appl. Physiol. 96 (3) (2004) 1045–1054.
[28] S. Depatla, A. Muralidharan, Y. Mostofi, Occupancy estimation using only wifi power measurements, IEEE J. Sel. Areas Commun. 33 (7) (2015) 1381–1393.
[29] P.K. Dutta, A.K. Arora, S.B. Bibyk, Towards radar-enabled sensor networks, in: Proceedings of the 5th International Conference on Information Processing in Sensor Networks, ACM, 2006, pp. 467–474.
[30] J. He, A. Arora, A regression-based radar-mote system for people counting, in: 2014 IEEE International Conference on Pervasive Computing and Communications, (PerCom), IEEE, 2014, pp. 95–102.
[31] T. Leephakpreeda, Adaptive occupancy-based lighting control via grey prediction, Build. Environ. 40 (7) (2005) 881–886.
[32] H. Li, E.C. Chan, X. Guo, J. Xiao, K. Wu, L.M. Ni, Wi-counter: smartphone-based people counter using crowdsourced wi-fi signal data, IEEE Trans. Hum.-Mach. Syst. 45 (4) (2015) 442–452.
[33] S. Sigg, M. Scholz, S. Shi, Y. Ji, M. Beigl, Rf-sensing of activities from non-cooperative subjects in device-free recognition systems using ambient and local signals, IEEE Trans. Mob. Comput. 13 (4) (2014) 907–920.
[34] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, T. Weng, Occupancy-driven energy management for smart building automation, in: Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building, ACM, 2010, pp. 1–6.
[35] A. Beltran, V.L. Erickson, A.E. Cerpa, Thermosense: Occupancy thermal based sensing for hvac control, in: Proceedings of the 5th ACM Workshop on Embedded Systems for Energy-Efficient Buildings, ACM, 2013, pp. 1–8.
[36] F. Castanedo, D. López-de Ipina, H.K. Aghajan, R.P. Kleihorst, Building an occupancy model from sensor networks in office environments, ICDSC 3 (2011) 1–6.
[37] R.H. Dodier, G.P. Henze, D.K. Tiller, X. Guo, Building occupancy detection through sensor belief networks, Energy Build. 38 (9) (2006) 1033–1043.
[38] T. Ekwevugbe, N. Brown, V. Pakka, D. Fan, Real-time building occupancy sensing using neural-network based sensor network, in: 2013 7th IEEE International Conference on Digital Ecosystems and Technologies, (DEST), IEEE, 2013, pp. 114–119.
[39] P.X. Gao, S. Keshav, Optimal personal comfort management using SPOT+, in: Proceedings of the 5th ACM Workshop on Embedded Systems for Energy-Efficient Buildings, ACM, 2013, pp. 1–8.
[40] V. Garg, N. Bansal, Smart occupancy sensors to reduce energy consumption, Energy Build. 32 (1) (2000) 81–87.
[41] J. Howard, W. Hoff, Forecasting building occupancy using sensor network data, in: Proceedings of the 2nd International Workshop on Big Data, Streams and Heterogeneous Source Mining: Algorithms, Systems, Programming Models and Applications, ACM, 2013, pp. 87–94.
[42] F. Jazizadeh, B. Becerik-Gerber, Toward adaptive comfort management in office buildings using participatory sensing for end user driven control, in: Proceedings of the Fourth ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, ACM, 2012, pp. 1–8.
[43] M.A.A.H. Khan, H. Hossain, N. Roy, Infrastructure-less occupancy detection and semantic localization in smart environments, in: Proceedings of the 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services on 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2015, pp. 51–60.
[44] C. Liao, P. Barooah, An integrated approach to occupancy modeling and estimation in commercial buildings, in: Proceedings of the 2010 American Control Conference, IEEE, 2010, pp. 3130–3135.
[45] H. Mohammadmoradi, S. Munir, O. Gnawali, C. Shelton, Measuring people-flow through doorways using easy-to-install IR array sensors, in: The Annual International Conference on Distributed Computing in Sensor Systems, DCOSS, 2017.
[46] O. Shih, A. Rowe, Occupancy estimation using ultrasonic chirps, in: Proceedings of the ACM/IEEE Sixth International Conference on Cyber-Physical Systems, ACM, 2015, pp. 149–158.
[47] V. Srinivasan, J. Stankovic, K. Whitehouse, Using height sensors for biometric identification in multi-resident homes, in: International Conference on Pervasive Computing, Springer, 2010, pp. 337–354.
[48] D. Wang, C.C. Federspiel, F. Rubinstein, Modeling occupancy in single person offices, Energy Build. 37 (2) (2005) 121–126.
[49] Y. Yang, J. Hao, J. Luo, S.J. Pan, Ceilingsee: Device-free occupancy inference through lighting infrastructure based led sensing, in: 2017 IEEE International Conference on Pervasive Computing and Communications, (PerCom), IEEE, 2017, pp. 247–256.
[50] Z. Yang, N. Li, B. Becerik-Gerber, M. Orosz, A systematic approach to occupancy modeling in ambient sensor-rich buildings, Simulation 90 (8) (2014) 960–977.
[51] J. Lu, T. Sookoor, V. Srinivasan, G. Gao, B. Holben, J. Stankovic, E. Field, K. Whitehouse, The smart thermostat: using occupancy sensors to save energy in homes, in: Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems, ACM, 2010, pp. 211–224.
[52] W. Kleiminger, C. Beckel, T. Staake, S. Santini, Occupancy detection from electricity consumption data, in: Proceedings of the 5th ACM Workshop on Embedded Systems for Energy-Efficient Buildings, ACM, 2013, pp. 1–8.
[53] B. Guo, Z. Yu, L. Chen, X. Zhou, X. Ma, MobiGroup: Enabling lifecycle support to social activity organization and suggestion with mobile crowd sensing, IEEE Trans. Hum.-Mach. Syst. 46 (3) (2016) 390–402.
[54] D. Cali, P. Matthes, K. Huchtemann, R. Streblow, D. Müller, CO 2 based occupancy detection algorithm: experimental analysis and validation for office and residential buildings, Build. Environ. 86 (2015) 39–49.
[55] S. Dedesko, B. Stephens, J.A. Gilbert, J.A. Siegel, Methods to assess human occupancy and occupant activity in hospital patient rooms, Build. Environ. 90 (2015) 136–145.

[56] J. Wicker, N. Krauter, B. Derstorff, C. Stönner, E. Bourtsoukidis, T. Klüpfel, J. Williams, S. Kramer, Cinema data mining: The smell of fear, in: Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM, 2015, pp. 1295–1304.
[57] J. Shiskin, A.H. Young, J.C. Musgrave, The X-11 variant of the census method II seasonal adjustment program. Number 15. US Department of Commerce, Bureau of the Census, 1995.
[58] D.F. Findley, B.C. Monsell, W.R. Bell, M.C. Otto, B.-C. Chen, New capabilities and methods of the X-12-arima seasonal-adjustment program, J. Bus. Econom. Statist. 16 (2) (1998) 127–152.
[59] R.B. Cleveland, W.S. Cleveland, J.E. McRae, I. Terpenning, Stl: A seasonal-trend decomposition procedure based on loess, J. Off. Stat. 6 (1) (1990) 3–73.
[60] H. Akaike, A new look at the statistical model identification, IEEE Trans. Automat. Control 19 (6) (1974) 716–723.
[61] F. Petitjean, A. Ketterlin, P. Gançarski, A global averaging method for dynamic time warping, with applications to clustering, Pattern Recognit. 44 (3) (2011) 678–693.