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Development of a Bayesian based adaptive optimisation algorithm for the thermostat settings in agile open plan offices

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ABSTRACT

The development of a Bayesian based adaptive optimisation algorithm for optimising the indoor thermostat settings in a large agile open plan office is presented. Occupant expressions of thermal dissatisfaction and indoor environmental conditions were collected using densely-placed devices over a period of approximately 19 months. A logistic regression model was employed to identify the optimal settings, using regression coefficients that were estimated using Bayesian inference. A series of optimisation scenarios with and without considering the temporal variations of occupant thermal preferences and the spatial deviation of the indoor conditions was designed and implemented to evaluate their potential benefit in terms of overall occupant thermal dissatisfaction reduction. We developed two metrics that were tailored to quantify the overall reduction of thermal dissatisfaction when using optimal air temperature and PMV thermostat settings. These two metrics represented the average reduction of overall indoor thermal dissatisfaction each time a thermostat value was updated. The results showed that it was useful to consider the temporal variations of occupant thermal preferences to reduce the overall indoor thermal dissatisfaction each time a thermostat value was updated. The case study demonstrated that the optimal adaptive temperature and PMV thermostat settings led to an overall thermal dissatisfaction reduction of 1.47% and 1.21% in the whole office, respectively (as opposed to 0.25% and 0.19% when single fixed temperature-based and PMV-based thermostat settings were used). By applying the proposed adaptive optimisation algorithm on individual zones in the office, the occupant thermal dissatisfaction reductions ranged from 0.88% to 5.17% for PMV-based settings, and from 1.20% to 5.19% for temperature-based settings.

1. Introduction

Optimal operation of HVAC systems has a significant role in better managing the typically conflicting relationship between energy consumption and thermal comfort in buildings. However, the complexity of HVAC operating systems in commercial buildings and the dynamically changing indoor conditions, occupancy profiles and occupant preferences make it challenging to develop efficient control operation algorithms [1]. Conventional HVAC control logic usually relies on rigid operating schedules that ignore occupancy presence and the continuously changing characteristics of occupants with regard to their preference for the indoor conditions [15]. In addition, large HVAC systems of commercial buildings are often served by a limited number of room sensors and as a result, in particular, in large open plan office spaces, the indoor microclimates (dynamic variations of the indoor conditions locally within the space) are not taken into account. These room sensors that serve HVAC systems in large office spaces are usually temperature sensors and will not account for other parameters that could have an impact on indoor comfort, such as mean radiant temperature, air velocity, relative humidity, etc. As a consequence, predetermined standardised temperature set points do not always guarantee satisfactory thermal conditions in all indoor environments, as demonstrated by previous studies [21] and [39].

The fact that comfort at the workplace is not always achieved could result in loss of productivity of occupants, and thereby in financial and performance losses of a company or an organisation [25]. Previous attempts have been made by researchers to better understand the relationship between occupant productivity and indoor environment [6,33,2] and Valancius and Jurelionis [36]. These studies demonstrated that the indoor thermal comfort was one of the key factors affecting occupant productivity, but a consensus has not been fully reached on definite approaches that
would optimise operational set points for HVAC systems to take into account occupant preferences in order to maximise productivity.

To capture the thermal preferences of occupants, most of the previous studies were based on post occupancy evaluations with questionnaires and spot measurements that do not have high spatial and temporal accuracy, but nevertheless they demonstrate the importance of accounting for the preferences of occupants when operating buildings. Nowadays, with the advances in the development of low cost sensors and low cost small computer devices (e.g. Raspberry Pi), it would be possible to record and predict in real-time knowledge the diversified needs of occupants with regard to the indoor thermal environment in order to be able to adjust the indoor microclimate in an optimum way [21] and avoid potential incidents of productivity loss in buildings. To achieve such a task, it would be essential to implementing methods that use highly deployable sensing, ensure reliable data gathering and most importantly have the means to perform data processing with machine learning techniques, which could be used for obtaining adaptive, well-optimised operation recommendations for the building spaces. The low cost of sensing and computing devices makes it possible nowadays to measure a high number of relevant parameters in buildings [38], but learning and adapting the building operation to suit specific occupant schedules, individualised occupant preferences and spatial variations in building spaces is not a trivial task. This is especially challenging for agile large open plan working spaces, which feature high occupant mobility and were increasingly popular in the recent pre-COVID-19 era since they promote a collaborative environment while improving the management of spaces that come at premium cost in popular CBD areas [24], [22] and [37].

To address the demand for intelligent HVAC system control while maintaining an efficient operation, various learning frameworks have been proposed and applied by a number of researchers. For instance, Gunay et al. [16] developed and applied a recursive thermostat learning algorithm in commercial building controllers for private cellular office spaces. In this algorithm, the frequency of the occupant thermostat interactions was recursively approximated as a univariate discrete-time Markov logistic regression model for preferred indoor temperature set point prediction. It was found that the implementation of this algorithm rationally identified the indoor thermostat according to occupant thermal preferences, while reducing energy use by adjusting the temperature set point by 2 – 3 °C during the heating and cooling seasons. The specific algorithm required the collection of office occupancy data, which is an onerous task for highly occupied large agile open plan offices. Gupta et al. [17] developed a real-time occupant feedback and environmental learning framework for collaborative thermal management in multi-zone, multi-occupant buildings. This algorithm was triggered by the changes of occupancy patterns, environmental conditions and occupant preferences, and aimed to identify an optimal temperature setting for minimising the occupant thermal dissatisfaction quantified by a quadratic discomfort model. Among the various learning frameworks, Bayesian inference has been recognised as one of the effective and useful kernels to facilitate the classification of occupant thermal preferences for optimal building operation. Lee et al. [26,27] proposed and implemented a Bayesian-based framework to identify the thermal preference profiles of occupants in small cellular offices. Bayesian clustering and a classification algorithm were combined with a model predictive control (MPC) to develop a self-tuned HVAC controller for a radiant floor system in order to provide in real-time customised thermal conditions to occupants while minimising energy consumption [28]. The authors demonstrated that the self-tuned controller can decrease occupant dissatisfaction compared to a baseline MPC controller that was tuned based on general comfort bounds, and can rationalise the trade-off between thermal comfort and energy efficiency. Auffenberg et al. [4] also proposed a Bayesian-based HVAC control algorithm to learn personalised thermal comfort of occupants and reduce energy consumption. This algorithm was reported to have the capability to reduce energy use by 7.3% to 13.5% and reduce occupant discomfort by 24.8% in comparison with some other existing alternative algorithms. Awalgaonkar et al. [5] developed a preference elicita-
tion (PE) framework to better satisfy the personalised thermal preferences of occupants by learning and optimising the indoor air temperature settings. In this framework, sequential intelligent queries were posed to occupants to collect their thermal preferences over the indoor temperatures, based on which the optimal temperature was then approximated using a Gaussian process model trained by Bayesian inference. The authors verified the algorithm could effectively infer the maximally preferred indoor air temperature settings through a real-time experiment, and demonstrated that it was a relatively simple algorithm, with high robustness, and attractive computation cost-effectiveness. In parallel to our study, Wang and Hong [35] used a Bayesian-based data-driven approach to identify appropriate ranges of temperature set points for US office buildings by accounting for the occupants’ personal characteristics and preferences. Wang and Hong concluded that Bayesian Inference is a suitable method for accounting for uncertainties in the context of inferring temperature set points.

The above studies and the learning frameworks presented in them focused on the optimisation of personalised thermal comfort in spaces where the occupancy densities and the occupant schedules are known. However, the applicability of these studies for agile large open plan working spaces that have continuously varying occupancy densities and occupancy characteristics in terms of preferred thermal conditions is challenging (e.g. occupants may work in different locations within the large office space every day and their thermal preferences may also change over time). We present here the development of a Bayesian-based adaptive algorithm for the optimisation of indoor microclimate conditions in agile open plan offices through real-time learning of occupant thermal preferences. To achieve this, we deployed pervasive sensing and occupant feedback equipment in an agile open plan office and we then designed and tested different scenarios for implementing and assessing the proposed adaptive algorithm. In Section 2, we present the method used for the development of the algorithm, while in Section 3 we provide the results of the test scenarios and a discussion in this regard.

2. Research methodology

Our overall research methodology is summarised in Fig. 1. We developed low cost, programmable, network-based sensing and occupant feedback devices and placed them in a mechanically conditioned, large agile open plan office in Sydney, Australia, to continuously collect long-term data of indoor thermal conditions and capture the thermal preferences of occupants in regards to the localised indoor conditions. We undertook a data cleaning process, involving outlier detection for the indoor environmental data and the handling of duplicated thermal preference records that were expressed within short time frames. We then formulated indoor microclimate optimisation scenarios with the aim of minimising indoor thermal dissatisfaction of occupants by deriving the most rational thermostat settings in terms of air temperatures or predicted mean vote (PMV) values. The term “indoor thermal dissatisfaction” in this paper is used as an expression of the likelihood for the occupants to express an alternative thermal preference.

Different optimisation scenarios with the considerations of temporal and/or spatial factors were designed and implemented according to the thermal preference records collected from occupants. In the optimisation process, Bayesian ordered logistic regression was utilised as the tool to identify the optimal HVAC thermostat settings in each optimisation scenario. Finally, we compared the results using different optimisation scenarios and provided recommendations for the optimal operational setting of the agile open plan office.

2.1. Building and data acquisition equipment

The office space that was occupied by ARUP in Sydney CBD up until October 2018 is used for the data collection part of the study (Fig. 2). The majority of the space has a typical for a commercial CBD office open plan layout with permanently closed high performance tinted windows. The office has a floor area of approximately 2700 m² and workstations for approximately 375 staff members. The HVAC system was scheduled to operate between 7:00 and 18:00 on weekdays and the required set point temperature, as reported by the Facility Managers, was aimed to be approximately 23 °C throughout the year. In addition, and as noted in Fig. 2, most office employees do not have pre-allocated working desks, but could instead use any of the desks on the south side of the office area. Similarly, the area on the north side of the office where employees had traditionally their own allocated desks, was also converted to a flexible agile space within a short period from the start of our study.

The indoor environmental sensors and occupant feedback devices that were developed and used in this study comprised of a number of low cost Arduino sensors linked to a Raspberry PI unit (Fig. 3). Fig. 2 also shows the ID numbers of the devices, and the 21 locations where these devices were placed in the office space. Most devices were placed in the open plan office area, except for device 19 that was placed in an individually conditioned meeting room on the south side of the office. All of the devices were placed on working desks of occupants (at a height of around 0.6 m for non-adjustable desks, i.e. the height recommended by ISO Standard 7726 for sitting occupants). We collected the following environmental parameters that were relevant to this paper with each device: 1) dry bulb air temperature ($T_{db}$); 2) relative humidity (RH); 3) black globe temperature ($T_{bg}$); 4) air velocity ($v_{air}$). The corresponding sensor characteristics are summarised in Table 1. The black globe temperature was measured by globes with a relatively small diameter (40 mm) in order to determine the mean radiant temperature according to ISO 7726 [19]. These sensors were calibrated both in lab and on-site by undertaking repetitive measurements with a testo 480 150 mm globe probe instrument, and their offsets were defined and accounted for in our calculations. All data from the sensors were collected at 5-minute intervals and were wirelessly sent and stored in a secure SQL database. We have included in our analysis data collected for a bit more than 1.5 years, from 01/03/2017 to 11/10/2018.

Three push buttons were integrated on each device to obtain instant occupant feedback in relation to the indoor environmental conditions (see Fig. 3). We labelled two of these buttons as “Want Warmer” and “Want Cooler”, and the third button was labelled as “Too noisy” because noise was reported informally by the occupants to be an important issue for the open plan office. However, the findings from the occupant responses with regard to noise remain outside the scope of this paper. In this way, an expression of dissatisfaction (a mild complaint or a preference) with regard to the occupants’ thermal environment is indirectly logged, and can be compared with the above-mentioned collected indoor thermal data. To avoid causing unnecessary burden to the office employees, reminders to press the buttons were not sent and it was left up to the occupants’ discretion to use the available buttons. This means that the typical “neutral” response from the occupants was not collected in this study and that there were often occupants who were unaware of the available push buttons.

Thermal comfort is also affected by the clothing levels and the metabolic rates of occupants, however, these are often two variables that an HVAC controller can never monitor. Instead, knowledge of the expected ranges of these values can be pre-set in a controller (or in a predictive model) based on the expected use of the building spaces.
The collected indoor environmental data and the occupant thermal preference responses during the air conditioning hours on weekdays were therefore analysed and used to develop suitable optimisation algorithms for the HVAC thermostat settings of this agile open plan office space.

2.2. Data cleaning

2.2.1. Data cleaning of indoor environmental data records

The collection of high resolution spatial and temporal data in this study resulted in the development of large useful datasets. However, the large datasets might suffer from outliers due to the failure of the sensing and occupant feedback devices or errors introduced by external stimulations. Procedures were therefore put in place to clean up the recorded indoor environmental data, to identify and eliminate the outliers, and to replace/impute the missing values due to outlier elimination (see Fig. 1).

The indoor environmental data recorded by our sensing and occupant feedback device are time series data, in which the dry-bulb temperature, the relative humidity, the black globe temperature have obvious periodical characteristics. These time series data with periodical characteristics were first reassembled as a matrix containing 422 daily parameter profiles, excluding weekends, and then further divided into several sub-matrices to avoid the masking of the outlier characteristics due to different HVAC operation modes at different seasons. Each sub-matrix included 65 daily...

Fig. 1. Research methodology for the development of the optimisation algorithm.
parameter profiles, which correspond to a span of around 3 months or a season, except for the last sub-matrix that had 32 daily parameter profiles. The missing values in these sub-matrices were imputed by the mean values of all values present at the corresponding time of days (i.e. “CrossMean”) through “imputation” function in R package “longitudinalData”, to temporarily prepare continuous time series data without missing values for outlier detection. Afterwards, the prepared time series data were decomposed into “trend”, “seasonal”, and “remainder” components using “seasonal decomposition of time series by Loess (STL)” [7] through

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**Fig. 2.** The agile open plan office layout.

**Fig. 3.** The sensing devices developed and used in this study.
the “stl” function in R package “stats”. For the “remainder” component data, we used boxplots to identify the suspected outliers outside the 1.5 interquartile range (IQR) of the “remainder” component data. The outlier detection process was completed with a series of Rosner’s tests [31] and Rosner [32] for each indoor environment variable to verify the detection of multiple outliers from the previous stages of the cleaning process. Rosner’s tests were commissioned by using the “rosnerTest” function in R package “EnvStats”. Eventually, the detected outliers were treated as missing values and were imputed again using the “CopyMean” method [14]. Consequently, the verified outliers were replaced by the mean value of the records that were recorded at that same time of the day within a 65-day sub-matrix. It should be noted that we implemented the above outlier detection process separately for the air velocities because of the majority of the time, with the exception of devices with ID 7 and ID 28, 0.5 m/s was used as a threshold, above which the measured air velocity in this office hardly exceeded 0.5 m/s for these periods.

A relatively simple data cleaning procedure was implemented for the air velocity measurements on weekdays since, as opposed to the other indoor environmental variables, the air velocity did not present clear periodical characteristics. Considering that the measured air velocity in this office hardly exceeded 0.5 m/s for the majority of the time, with the exception of devices with ID 7 and ID 28, 0.5 m/s was used as a threshold, above which the measured velocities were regarded as suspected outliers. The suspected cases were then also passed through a verification process through Rosner’s test. For the sensing devices whose measured air velocities have a boxplot whisker higher than 0.5 m/s (i.e. only for devices with ID 7 and ID 28), the air velocities above the whisker were directly regarded as outliers. The outliers identified were replaced by the median values of the air velocity measured by the corresponding sensing device.

2.2.2. Data cleaning for occupant thermal preference responses

Duplicated thermal preference responses from the sensing and occupant feedback devices may exist if an occupant kept pressing a button on the devices to express the same thermal preference within a short period of time. To overcome this potential issue, a duplicated thermal preference response was removed, if it matched the previous thermal preference from the same device and the time difference between them was less than 15 min.

2.3. Formulation of the optimisation algorithm for thermostat settings

2.3.1. Optimisation objective

The objective of this study was to optimise the operational thermostat settings of an agile open plan office to better match the thermal preference responses of occupants. The key to achieving this objective was the identification of the optimal indoor microclimate parameter(s) which could minimise the occupant complaints due to thermal dissatisfaction. The optimal microclimate can be represented by a neutral air temperature, considering that this has been commonly used as the ideal setting of the HVAC system for optimal building operation. More precisely and rationally, the optimal indoor microclimate in mechanically conditioned buildings can be represented by the neutral thermal sensation (assuming pre-set values for clothing and metabolic rate), as PMV includes multiple indoor environment variables and accounts for occupant activity and clothing levels. The PMV value was calculated using the “calcPMV” function in R package “comf”, which applies the same calculations as Fanger [12] and ISO 7730 [20]. Alternative algorithms or softwares can be used to carry out the PMV calculation (19) and ASHRAE Standard-55 [3], and a careful consideration of relative air velocity in the PMV calculation is required under high metabolic rates d’Ambrosio Alfano et al. [8,9] . We have assumed that the optimal air temperature $T_{opt}$ or $PMV_{opt}$ can be defined as the neutral condition at which a minimal percentage of people dissatisfied (PPD) can be achieved. Accordingly, occupants would have the same probability to express a “Want Warmer” and a “Want Cooler” thermal preference under the optimal indoor microclimate conditions characterised by $T_{opt}$ or $PMV_{opt}$, as described in Eq. (1).

$$x_{opt} = \text{argmin}[PPD(y)] = x|\{y_{j}^{-1}, y_{j}^{-2}\}$$

where $x$ is the indoor microclimate variable (air temperature or PMV in this study), $y$ is the thermal preference, and $P$ represents the probability of a thermal preference. The probability of a thermal preference can be determined by the ordered logistic regression, which was proposed by McCullogh [30] to quantify the relationship between multiple response categories and explanatory variables, as described in Eqs. (2) and (3).

$$P(y = k) = \begin{cases} 1 - P(y \leq 1), & \text{if } k = 1 \\ P(y \leq k - 1) - P(y \leq k), & \text{if } 1 < k < K \\ P(y \leq K), & \text{if } k = K \end{cases}$$

$$P(y \leq k) = \log^{-1}(c_k + \beta x) = \frac{e^{\beta y + \beta x}}{1 + e^{\beta y + \beta x}}$$

where $c_k$ and $\beta$ are the regression coefficients in the ordered logistic function, which in this case would correlate the input variable $x$ (i.e. indoor air temperature or PMV) with the probability of the occupants’ thermal preference (i.e. $y$), and $K$ is the total number of the ordered response categories. There were only two categories of thermal preference responses, i.e. “Want Warmer” and “Want Cooler”, represented by $k$ of 1 and 2, respectively. Thus, the probabilities for occupants expressing a “Want Warmer” or “Want Cooler” preference in the office under different air temperatures or PMV values can be determined by implementing an ordered logistic regression. Since there were only two thermal preference categories, the intersection point of the two ordered logistic regression curves would have the same probability of 50% for individual thermal preferences, and this intersection point can be considered as being the most optimal air temperature or PMV value setting for the HVAC thermostat settings.

2.3.2. Recursive Bayesian inference for coefficient identification

The regression coefficients in the ordered logistic function $Eq.$ (2) can be estimated using Bayesian inference. Bayesian inference is a statistical inference method using Bayes’ rule to determine the conditional probability of an event by updating the probabilities of estimates when more evidence related to that event is given [13]. Accordingly, the posterior probability density distribution of the regression coefficients ($c_k$, $\beta$) conditioned on the observations ($D$) can be inferred by $Eq.$ (4). As a consequence, regression coefficients and their standard deviation can be respectively estimated

Table 1 Sensor specifications for monitoring and occupant feedback devices.

| Measured environmental variable | Model | Details |
|---------------------------------|-------|---------|
| Dry bulb temperature & Relative Humidity (RH) | AM2302/DHT22 (Seeed Grove - Temperature & Humidity Sensor Pro) | RTD (digital), accuracy ± 0.5°C for temperature and ± 2% for RH |
| Black Globe Temperature | LM358 | RTD, in a 40 mm diameter black table tennis ball, accuracy ± 0.3°C |
| Air velocity | Modern Device, Wind Sensor Rev C | Thermal Anemometer - analog |

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from the median and standard deviation values of their probability density distributions, as shown in Eq. (5).

\[
P(c_k, \beta | D) = \frac{P(D | c_k, \beta) P(c_k, \beta)}{P(D)} \propto P(D | c_k, \beta) P(c_k, \beta) \tag{4}
\]

\[
\{ c_k = \text{median}(c_k) \} \& \{ \sigma_{c_k} = \sigma_d(c_k) + \Delta \sigma_{c_k} \}
\]

\[
\beta = \text{median}(\beta) \{ \sigma_{\beta} = \sigma_d(\beta) + \Delta \sigma_{\beta} \tag{5}
\]

where \( P(c_k, \beta | D) \) is the posterior probability density distribution of the regression parameters for the ordered logistic regression, \( P(D | c_k, \beta) \) is the likelihood which is the product of distribution with a given sample of data, \( P(c_k, \beta) \) is the prior probability density distribution of the parameters, \( P(D) \) is the margin probability density distribution of the observations \( D \), \( \sigma \) is the standard deviation, and \( \Delta \sigma \) is the additional deviation introduced as a correction factor if needed when there is a significant change in the occupancy characteristics of the space, or when the standard deviation is close to zero which would lead to regression coefficients being approximately constant rather than distributions (i.e. it provides flexibility for altering the thermostat settings if needed). The observations \( D \) can be regarded as the training dataset used for the identification of the regression coefficients.

Involving the prior distribution in Bayesian inference enables a recursive procedure in which the posterior distribution associated with a previous set of observations \( D_i \) becomes prior distribution for the posterior inference of the next set of observations \( D_{i+1} \), as given in Eq. (6) [18].

\[
P(c_k, \beta | D_{i+1}) \propto P(D_{i+1} | c_k, \beta, D_i) P(c_k, \beta | D_i) \tag{6}
\]

\[
P(D_{i+1} | c_k, \beta, D_i) P(D_i | c_k, \beta, D_{i+1}) P(c_k, \beta | D_{i+1})
\]

where \( P(c_k, \beta) \) can be represented using the medians and standard deviations of \( c_k \) and \( \beta \), and \( j \) is the index of training dataset. As the occupants in the large agile open plan office of our study infrequently expressed their thermal preferences without receiving any reminders in this regard, it was difficult to establish a set of observations with a short period. Therefore, a set of observations (i.e. \( D_i \)) was developed to include one or several thermal preference records under extreme hot and cold environments. The next set of observations (i.e. \( D_{i+1} \), given in Eq. (7)) was then updated by replacing the thermal preference record(s) with one or several new thermal preference record(s) while updating the two hypothetical thermal preferences based on the previous optimal thermostat setting for the set of observation \( D_i \) as shown in Fig. 4.

\[
D_{i+1} = \{ (x_{j+1,m}, y_{j+1,m}), (x_{\text{cold}}, y_{\text{cold}}), (x_{\text{hot}}, y_{\text{hot}}) \mid m = 1, 2, \ldots, n_{j+1} \}
\]

\[
= \{ (x_{j+1,m}, y_{j+1,m}), (x_{\text{opt},j} - \Delta x_c, 1), (x_{\text{opt},j} + \Delta x_c, 2) \mid m = 1, 2, \ldots, n_{j+1} \}
\]

where \( n_{j+1} \) is the number of observations (i.e. the number of push button thermal preference records) in the training dataset \( D_{i+1} \) (in this study it is set as 1, considering the occupants did not express their thermal preference quite often), \( m \) is the index of observation in the training dataset. \( (x_{\text{cold}}, y_{\text{cold}}) \) and \( (x_{\text{hot}}, y_{\text{hot}}) \) represent the hypothetical "Want warmer" and "Want cooler" thermal preference responses (i.e. \( y_{\text{cold}} = 1 \) and \( y_{\text{hot}} = 2 \)) under extreme cold and hot environments, respectively. The extreme cold and hot environments (i.e. \( x_{\text{cold}} \) and \( x_{\text{hot}} \)) were calculated by subtracting and adding constant large difference (i.e. \( \Delta x_c \)) from the optimal thermostat settings identified by the previous Bayesian inference based on \( D_j \). The extreme hypothetical \( (x_{\text{cold}}, y_{\text{cold}}) \) and \( (x_{\text{hot}}, y_{\text{hot}}) \) conditions were necessary for defining the training dataset \( D_{i+1} \), given that individual occupant responses were not in most cases expressed within short timeframes (see Fig. 4). However, if there were many thermal preference responses within a short period, a training dataset could include a number of thermal preference records (i.e. \( n_{i+1} \geq 1 \)), without adding the hypothetical thermal preference responses. To start the recursive inference, part of the occupant thermal preference data need to be used as an original training dataset (i.e. \( D_j \)) to carry out a batch Bayesian regression, thereby establishing the initial prior distributions for the regression parameters.

The above recursive Bayesian ordered logistic regression provides a recursive approach to adaptively identify the desired thermostat settings for the HVAC system based on the updated training dataset. Meanwhile, the posterior information from the Bayesian regression that was based on the previous training dataset, i.e. before updating the hypothetical thermal preference responses, is used as prior (see Fig. 4). It can be expected that in the recursive Bayesian inference the credible interval may experience a convergent process, however the output will remain adaptive.

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**Fig. 4.** Training dataset in an optimisation scenario using recursive Bayesian ordered logistic regression.
Since the posterior probability density distribution tends to be analytically intractable, we employed Markov Chain Monte Carlo (MCMC) sampling to characterise it. MCMC sampling methods are a class of algorithms for sampling from a probability density distribution based on constructing a Markov chain that has the desired distribution as its equilibrium distribution. This means that after a number of sampling steps, the equilibrium distribution of the MCMC sampling can be identified, and be used to approximate numerically the desired posterior probability density distribution. MCMC sampling is an important technique to facilitate the widely deployment of Bayesian inference, and it allows quantifying the uncertainty of a model and its prediction [26]. The MCMC based Bayesian regression was implemented using the Stan tool [34], which can be called through the R interface “RStan”. Stan is a probabilistic programming language for statistical inference, in which a Bayesian statistical model can be specified with an imperative program to calculate the log probability density function [34].

### 2.3.3. Design of the optimisation scenarios

We considered six optimisation scenarios to meet different temporal and spatial control requirements in the office, as summarised in Table 2. Optimisation Scenarios 1–3 were designed with the objective to gain the optimal HVAC thermostat settings for the whole office without considering the indoor microclimate deviation due to spatial differences.

In detail, all the occupant thermal preference records collected were treated as a training dataset in Optimisation Scenario 1 to identify an optimal thermostat setting for the whole office. For Optimisation Scenario 2, the same training dataset was divided into hourly sub-datasets for the air conditioning hours on weekdays (e.g. all occupant preferences expressed between 7:00 to 8:00 during the period of the study were grouped in one hourly sub-dataset, etc.). Each sub-dataset was used to facilitate the identification of optimal fixed hourly HVAC settings using Bayesian regression. We then combined the derived hourly optimal settings into an optimal daily profile for the HVAC settings. In Optimisation Scenario 2, there were a small number of occupant thermal preference records in each hourly sub-dataset which were not enough to reliably infer an optimal thermostat setting with an acceptable credible interval through a batch Bayesian regression. For this reason, the whole set of thermal preference records during the air conditioning hours on weekdays were used as the prior information in Optimisation Scenario 2.

In Optimisation Scenario 3, as described in Section 2.3.2, a fixed number of thermal preference observations defined a moving dataset window (see Fig. 4) that was updated when new observations were recorded. This moving dataset window was used as the training dataset to identify the adaptive settings for the HVAC system. As opposed to the previous two optimisation scenarios, Optimisation Scenario 3 was carried out by recursive inference (see section 2.3.2). Since there was no significant change in the occupants and occupant characteristics, and the time period investigated was not too long, the manual additional deviations (Δe - see Eq. (5)) for the regression parameters were set to 0. An initial dataset is required in this scenario to provide prior information for the inference of adaptive settings.

Optimisation Scenarios 4–6 were similar to Optimisation Scenarios 1–3 in terms of temporal resolution, except that they were to be implemented based on the thermal preference observations in individual areas (i.e. zones) rather than the whole office, in order to consider the existence of potential indoor deviations on the conditions of the large open plan office.

### 2.3.4. Performance assessment of optimal HVAC settings

To evaluate the potential benefits of the various optimisation scenarios, we define a case without optimisation as being the “original” case for which the desired indoor conditions were based on either a pre-determined temperature setting or, alternatively, on a pre-determined target PMV. In our case, the HVAC system in the large open plan office was assumed to use a pre-determined temperature setting of 24.0 °C, which is equal to the median of the measured air temperatures corresponding to the occupant thermal preference records. Similarly, the pre-determined temperature settings for individual zones were assumed to be the median of the air temperature that corresponds to the occupant thermal preference records in the each zone. Hypothetically, if the HVAC system used a pre-determined target PMV as its thermostat setting, the median PMV value of 0.25 would be used based on the indoor environmental variables (air temperature, relative humidity, mean radiant temperature and air velocity) that were measured during the recorded expressions of thermal preference by the occupants and on an assumed pre-set clothing insulation and metabolic rate in accordance with the ISO 7730 PMV equation. In the PMV calculation, we have used a typical clothing insulation of 0.7 clo and a typical metabolic rate of 1.2 for working occupants in an office space. This fixed clothing insulation value was used because it corresponded to the “Panties, petticoat, stockings, dress, shoes” and “underwear, shirt, trousers, socks, shoes” description in ISO 7730 and it is consistent with the typical daily wear clothing of the majority of occupants in the specific office. The pre-determined target PMV for each zone was calculated by the same rule but based on the indoor environmental variables measured in the corresponding zones. Compared to the “original” case, the indoor air conditions for the “optimal” cases after adopting the optimal HVAC thermostat settings identified from the optimisation scenarios were assumed to follow the relationship in Eq. (8).

\[ x_{\text{exp},i} = x_{\text{opt},i} + (x_{\text{act},i} - x_{\text{opt},i}) = x_{\text{act},i} - \delta_{\text{set},i}, \text{ for } i = 1, 2, \cdots, N \tag{8} \]

where \( i \) represents the index of a thermal preference record, \( N \) is the total number of the thermal preference records; subscripts \( \text{opt} \) and \( \text{act} \) represent the original and optimal cases respectively; subscript \( \text{set} \) refers to an HVAC thermostat setting; subscript \( \text{act} \) represents the actual measured conditions around the monitoring devices at the moment of a thermal preference record when using the original HVAC thermostat setting (assuming there is a difference between original fixed setting and actual measured conditions); subscript \( \text{exp} \) represents the expected conditions when using the optimal HVAC thermostat setting after accounting for the occupant response and for the difference between the actual condition and the original HVAC setting; \( \delta \) represents the difference between the optimal HVAC thermostat setting and the original HVAC setting. In addition, constraints were set for the optimal
HVAC settings to remain within the 18 to 28 °C, and the −1 and 1 ranges when using air temperature and PMV as the HVAC thermostat settings, respectively. The constraint ranges of the air temperature and the PMV were only set to initiate the calculations of the conditions of the thermostat control, and therefore support the initial convergence of the Bayesian based optimal adaptive thermostat setting algorithm. For this reason, instead of using the ranges from by ASHRAE 55 [3], EN 16798–1 [10] and EN 16798–2 [11], wide constraint ranges were utilised, to avoid masking the actual overall thermal preference of occupants in the office.

When PMV is used for developing a thermostat setting strategy, we developed the function (fPMV) in Eq. (9), to calculate the mean differences of thermal dissatisfaction between a revised PPD under the actual (monitored) PMV (i.e. PMVrev) and a revised PPD under the expected PMV that can be derived by Eq. (8) (i.e. PMVexp) every time an optimal PMV setting (PMVopt) is updated. In this case, the revised PPD is calculated from a revised thermal preference based PPD function from Eq. (10). The optimal PMV setting (PMVopt) is updated based on a specific number of thermal preference records, including the thermal preference records in the training dataset (number of nprior) and the records used in the prior information (number of nprior), depending on the optimisation scenario. It was therefore necessary to include all of the (nprior + nprior) thermal preference records in the calculation of Eq. (9). In Eq. (10), if the neutral PMV (i.e. optimal PMV setting) is 0, two ordered logistic distributions representing the thermal preferences of “Want Warmer” and “Want Cooler” were developed, whose summation was required to approach the original PPD-PMV function in ISO 7730 (2005). The comparison between the sum of the revised PPDs for “Want Warmer” and “Want cooler” distributions need be shifted every time an occupant preference is recorded, which also indirectly involved all the previous occupant preferences by using them as prior information. This derived optimal PMV at that moment of time is considered to be an improved setting for the conditions in the office based on the up-to-date occupant thermal

\[ f_{PMV} = \frac{1}{J} \sum_{j=1}^{J} f_{PMV} \]

where J is the total number of the optimal thermostat settings, which was 1 for Optimisation Scenarios 1 and 4, 11 for Optimisation Scenarios 2 and 5, and equal to the total number of training datasets for Optimisation Scenarios 3 and 6, respectively; nprior represents the number of thermal preference records used in the inference of the prior information (it was 0 for Optimisation Scenarios 1 and 4, equal to the total number of the thermal preference records in the whole office or individual zones for Optimisation Scenarios 2 and 5, and equal to (j − 1) for Optimisation Scenarios 3 and 6 when nprior is set as 1); j is the index of an optimal thermostat setting (out of a total of J settings), and the subscript rev indicates the revised value. An intuitive description of the adopted method when using PMV settings is shown with an example in Fig. 6. An optimal PMV set point (PMVopt) – highlighted by the black bold solid line) can be derived using the recursive Bayesian inference every time an occupant preference is recorded, which also indirectly involved all the previous occupant preferences by using them as prior information. This derived optimal PMV at that moment of time is considered to be an improved setting for the conditions in the office based on the up-to-date occupant thermal

Fig. 5. Comparison between the sum of the revised PPDs for “Want Warmer” and “Want cooler” calculated using Eq. (10) and the original PPD calculated from ISO 7730 [20].
preference records. By using this optimal PMV thermostat setting, \( (PMV_{opt, set}) \), it is assumed that the measured PMV \( (PMV_{act,i}) \) could be improved to an expected PMV \( (PCM_{exp,i}) \) by following the same linear relationship as that between the actual measured PMV and the original HVAC thermostat setting \( (i.e. \, PMV_{act,i} - PMV_{opt, set} = PMV_{exp,i} - PMV_{opt, set}) \). A revised thermal preference based PPD function (highlighted by the red and blue solid curves in Fig. 6) is revised from the thermal preference based PPD function (highlighted by the red and blue dash curves in Fig. 6) after taking into account the derived optimal PMV setting \( (PMV_{opt, set}) \) when an occupant preference was recorded. The neutral of the revised PPD-PMV function was considered to be the optimal PMV thermostat setting, at which the sum of PPDs is minimised based on the up-to-date occupant thermal preference responses. The corresponding revised thermal preference based PPD values of \( PMV_{opt, set} \) and \( PMV_{exp,i} \) were calculated to represent the thermal dissatisfaction when using the original and optimal PMV thermostat settings, respectively. The difference of using the optimal PMV thermostat setting as compared to the original PMV setting is therefore calculated by subtracting the revised thermal preference based PPD value of \( PMV_{exp,i} \) corresponding to the optimal PMV from the revised thermal preference based PPD value of \( PMV_{opt, set} \) corresponding to the optimal PMV \( (i.e. \, PMV_{rev,i}(PMV_{act,i}) - PMV_{rev,i}(PMV_{exp,i})) \) in Fig. 6). When temperature was instead used as a parameter for developing the thermostat setting strategy, we developed a function \( f_T \), as described in Eq. (12), to calculate the mean differences of thermal dissatisfaction \( \langle g_i(T) \rangle \) - see Eq. (13) - between the indoor conditions under the actual (monitored) air temperatures \( (T_{act,i}) \) and the expected air temperatures \( (T_{exp,i}) \) defined in Eq. (8), if an optimal temperature setting \( (T_{opt, set}) \) was updated and used. The main principle used to develop the thermal dissatisfaction function \( \langle g_i(T) \rangle \) as shown in Eq. (13), was that the extent of thermal dissatisfaction caused by a thermal preference of “Want Warmer” tended to be lower under higher air temperatures, and vice versa for that caused by a thermal preference of “Want Cooler”. This approach is similar to the approach followed for the \( f_{PMV} \) function by rescaling the domain of PMV to that of temperature. In Eq. (12), the coefficient for \( (T - T_{opt, set}) \) (i.e. 0.6429773) was derived by multiplying the coefficient for \( (PMV - PMV_{opt, set}) \) in Eq. (9) (i.e. 2.359679) with that of measured indoor air temperature (i.e. 1.75) in the whole office during the air conditioning hours on weekdays.

We then used the average of \( f_T \) in Eq. (14) across all optimal temperature settings to compare the impact of the optimisation scenarios in relation to the original case (i.e. the benefit from using the optimisation to better match the occupant preferences). Accordingly, \( f_T \) provides an indicator to quantify the overall reduction of indoor thermal dissatisfaction in different optimisation scenarios, when using air temperature as settings metric for the HVAC thermostat.

\[
f_{T,j} = \frac{1}{n_i + n_{prior}} \sum \left[ g_{ij}(T_{act,i}) - g_{ij}(T_{exp,i,j}) \right]
\]

(12)

\[
g_{ij}(T) = \begin{cases} 
100 \cdot \left(1 - \frac{6.6429773}{1 + e^{6.6429773(T_{act,i}) - 3.475783}}\right) & \text{for "Want Warmer"} \\
100 \cdot \left(1 + \frac{6.6429773}{1 + e^{6.6429773(T_{act,i}) - 3.475783}}\right) & \text{for "Want Cooler"} 
\end{cases}
\]

(13)

\[
f_T = \frac{1}{J} \sum_{j=1}^{J} f_{T,j}
\]

(14)

Similar to that of using PMV thermostat settings, an optimal set point air temperature can be derived using the recursive Bayesian inference every time an occupant preference is recorded. In this way, the difference of using the optimal temperature thermostat setting as compared to the original temperature setting can be calculated (i.e. \( g_{ij}(T_{act,i}) - g_{ij}(T_{exp,i,j}) \)).

2.4. Clustering for thermostat zone settings

Since it may not be possible to uniformly control the indoor environment for different locations in a large open plan office, the open plan office was divided into several zones with different indoor microclimate characteristics using cluster analysis. This enables the development of thermostat settings to be controlled more precisely in individual zones according to the corresponding localised occupant thermal preferences. We employed the partitioning around medoids (PAM) clustering algorithm [23] to spatially group the monitoring and occupant feedback devices based
on a user-defined dissimilarity measure. Extending the method described in Ma et al. [29], the dissimilarity measure was a combination of the Pearson correlation coefficient (PCC) based dissimilarity of the daily hourly-average temperature profile during the monitoring period \(d_{PCC}(T_p, T_q)\) and the Euler distance (ED) based dissimilarity of the device locations \(d_{ED}(L_p, L_q)\), as shown in Eq. (15).

\[
d = w_1d_{PCC}(T_p, T_q) + w_2d_{ED}(L_p, L_q)
\]

where \(w_1\) and \(w_2\) are weighting factors, \(cov\) stands for the covariance, \(T\) is an 11-dimensional vector of the average daily hourly temperature profile (for the 11 air conditioning hours only during air conditioning hours on weekdays), \(L\) is a two-dimensional vector of the location of a monitoring and occupant feedback device, and subscripts \(p\) and \(q\) represent the ID index of two different devices.

3. Results and discussion

3.1. Overview of indoor measurements and thermal responses

Fig. 7 summarises the measured indoor air temperature daily profiles from each device and for each weekday of the monitoring period. It also shows the ranges of the recorded air temperatures that correspond to the recorded “Want Warmer” and “Want Cooler” thermal preferences during the air conditioning hours on weekdays. Fig. 7a and b show that the indoor air temperature varied from 16.1 to 28.5 °C over the monitoring period, and tended to vary less during the air conditioning hours than the non-air conditioned hours. There were 270 “Want Warmer” and 377 “Want Cooler” thermal preference responses on the weekdays. During the air conditioning hours, the numbers of thermal preference responses were 252 and 336 for “Want Warmer” and “Want Cooler”, respectively. The air temperature corresponding to the “Want Warmer” thermal preferences spanned from 16.9 to 26.6 °C, and from 20.1 to 27.1 °C for the “Want Cooler” responses, as can be seen in Fig. 7c and d. However, most thermal preference responses within the 25th and 75th percentiles in the plots of Fig. 7c and d correspond to air temperature ranges from 22.6 to 24.1 °C for the “Want Warmer” and from 23.8 to 25.2 °C for the “Want Cooler” records.

To get an insight into the spatial variability of the conditions in the open plan office, Fig. 8 details the spatial variations of the average hourly air temperatures and their standard deviations over time during air conditioning hours. Fig. 8c also reports the number of responses recorded in different locations of the open plan office. The ID numbers in Fig. 8 correspond to the locations shown in Fig. 2. It can be seen from Fig. 8a and b that the indoor air temperatures tended to be relatively low during the early morning hours (on average between 21 and 23 °C) and had higher average standard deviations that exceeded 1.5 °C between the different days of the monitoring period. However, since the monitoring devices were placed at different locations in the open plan office, the air temperatures were influenced by various factors, such as solar radiation, internal heat loads, distance from the HVAC system diffusers, etc. There were also some clear differences among the numbers of thermal preference responses for individual measurement devices, as presented in Fig. 8c that could be explained not only from the indoor conditions but also from the varying potential individualities of the occupants that were working around these devices at different moments of time. Besides the indoor air temperature, other indoor environmental variables including the relative humidity, the black global temperature, and the air velocity were also recorded by individual devices, and used in the following sections for deriving the PMV-based optimised thermostat settings.

3.2. Results for Optimisation scenario 1 - fixed thermostat settings for the whole office

3.2.1. Optimal fixed HVAC temperature setting

Fig. 9 presents the result of Bayesian ordered logistic regression of the thermal preference probability as a function of air temperature based on all collected thermal preference records during the air conditioning hours on weekdays. The intersection point of the “Want Warmer” and “Want Cooler” probability curves corresponded to the indoor air temperature of around 23.5 °C, at which the occupants in the office had the same probability (50%) for a “Want Warmer” or “Want Cooler” thermal preference. As explained in Section 2.3.1, this temperature was assumed to be the optimal indoor air temperature for minimising the thermal dissatisfaction of occupants. The 95% credible interval of this optimal temperature was 23.3–23.8 °C.
When the proposed optimal fixed air temperature thermostat setting was adopted, the potential benefit in terms of the overall thermal dissatisfaction reduction calculated with Eq. (14) was only around 0.25%. This value indicated that the potential of using HVAC temperature thermostat setting in Optimisation Scenario 1 to reduce the likelihood of occupants to express thermal dissatisfaction in the agile large open plan office was almost the same as that using the non-optimised original HVAC temperature thermostat setting. The reason for this negligible beneficial enhancement of 0.25% was most probably because the optimisation was done for the whole office space retrospectively after all occupant thermal preference responses were collected (similarly to POE methods) and used as a training dataset for batch Bayesian inference. This indicates that a specific response at a moment of time and from a specific location in the office could have been substantially far away from the optimal temperature identified for the whole group.

![Spatial variations of the average hourly air temperatures and their standard deviation: a) Spatial variations of the average hourly air temperatures; b) Standard deviation of average hourly temperatures; c) Number of thermal preference responses for individual locations (device IDs) during air conditioning hours on weekdays.](image1)

![Batch Bayesian ordered logistic regression of the thermal preference records as a function of air temperature based on all thermal preference records during the air conditioning hours on weekdays (the translucent ribbons represent the 95% credible intervals).](image2)
of occupants across the whole office space during the monitoring period, due to the fact that the thermal preference of an occupant may vary from time to time and the occupant may move around in the agile open plan office. Accordingly, the retrospective characteristics of Optimisation Scenario 1 just represented an “averagely compromised” thermal preference of all the occupants in the office over the monitoring period of concern, which made it difficult to satisfy the thermal preferences of individual occupants at particular times and different locations in the office.

3.2.2. Fixed optimal PMV setting

Similar to the optimal air temperature setting, the optimal PMV setting for the HVAC system can be achieved using the batch Bayesian ordered logistic regression, as shown in Fig. 10. The optimal fixed PMV setting corresponding to the intersection point of the “Want Warmer” and “Want Cooler” probability curves was 0.07 with a 95% credible interval from −0.02 to 0.15. By employing the optimal fixed PMV as the thermostat for the HVAC system, the overall thermal dissatisfaction reduction represented by the mean differences of the revised PPD as calculated by Eq. (11) was around 0.19%. This value also represented a negligible benefit from using the optimal PMV setting in Optimisation Scenario 1 to reduce the occupant thermal dissatisfaction compared to simply using the original PMV setting. Similar to that in the temperature setting case (Section 3.2.1), the reason for this negligible benefit is related to the retrospective use of the whole set of occupant responses as a training dataset for batch Bayesian inference in order to identify the optimal PMV for the whole group of occupants across the whole office space during the monitoring period of concern.

3.3. Results for Optimisation Scenario 2 - daily profile settings for the whole office

3.3.1. Optimal HVAC daily temperature profile settings

Fig. 11 presents the daily profile of the calculated optimal HVAC temperature settings during individual air conditioning hours. It can be seen that the optimal temperature settings ranged from 21.2 to 24.6 °C during the air conditioning hours. The optimal temperatures were relatively low in the early morning (i.e. 21.2 °C between 7:00–8:00); however, the corresponding 95% credible interval for that first hour of operation was very wide (i.e. 19.3–22.8 °C) due to the lack of enough thermal preference records in the training dataset. After 9:00am, the optimal temperature setting became more reliable with a narrower 95% credible interval, and the highest optimal temperature setting of 24.6 °C was calculated for the hour between 12:00–13:00.

By adopting the optimal daily temperature profile settings, the overall thermal dissatisfaction reduction calculated by Eq. (14) was around 1.55%. This value indicates that compared to the optimisation scenario where a fixed optimal temperature was used as the thermostat setting (Optimisation Scenario 1 in Section 3.2.1), using the optimal daily temperature profile in this optimisation scenario (Optimisation Scenario 2) can provide a slightly better indoor air condition to the occupants. This improvement can be explained by the fact that the temporal variation of occupant thermal preferences were partially considered in this optimisation scenario. However, as this consideration was done retrospectively by partitioning the whole set of responses into 11 sub-datasets for the 11 air conditioning hours of a day, rather than being done on a real time scale, these settings fail to capture the dynamic occupant thermal preference characteristics varying from day to day, thereby providing only a limited benefit.

3.3.2. Optimal HVAC daily PMV profile settings

Fig. 12 presents the optimal daily PMV profile settings for the HVAC system. Throughout the air conditioning hours on weekdays, the optimal PMV settings spanned from 0.01 to 0.12, and had relatively narrow 95% credible interval. By using the optimal daily PMV profile settings, the reduction of indoor thermal dissatisfaction calculated by Eq. (11) was around 0.24%, which indicated only a slight reduction of the overall indoor thermal dissatisfaction. Similar to the case of using optimal daily temperature thermostat profile settings, the main reason for this relatively minor improvement after optimisation was due to undertaking the optimisation retrospectively for the whole office after collecting and partitioning
the whole set of responses (as opposed to real time optimisation). Another possible explanation for the minor improvement after the optimisation was that, the development of a single PMV profile setting to represent the optimal PMV settings in individual air conditioning hours for all weekdays failed to consider their potential dynamic variations among different days.

Fig. 11. Optimal HVAC daily temperature profile settings (Optimisation Scenario 2).
3.4. Results for Optimisation Scenario 3 - adaptive settings for the whole office

3.4.1. Optimal adaptive HVAC temperature settings and significance of training dataset

As previously mentioned, the original training dataset for recursive Bayesian inference requires to be large enough to carry out reliable inference with small uncertainty. To therefore better determine the initial dataset window for regression coefficient initialisation in this adaptive optimisation scenario we verified the sensitivity of the resulted optimal air temperature to the size of the training dataset by undertaking a parametric study.

Fig. 13 illustrates a series of Bayesian ordered logistic regression results using 10–100% of the collected thermal preference records as the training dataset, with a step increase of 10% for the dataset size (10% is approximately equal to 59 responses). It can be seen that the 95% credible intervals of the “Want Warmer” and “Want Cooler” probability curves were extremely wide when the first 10% of the collected thermal preference records were used as a training dataset. When using the first 20–40% of the thermal preference records as the training dataset, the credible intervals became narrower, while the dataset sizes greater than 60% of the thermal preference records had similar probability regression results with each other. The training dataset using 60% of the thermal preference records (=353 responses) can be therefore regarded as the threshold, above which the optimal air temperature identified using the batch Bayesian ordered logistic regression tended to be stabilised at around 23.3 °C with a relatively narrow credible interval. The corresponding optimal air temperatures and their 95% credible interval based on the training datasets with different sizes are summarised in Table 3. The sensitivity of the resulted optimal PMV to the size of the dataset was also verified through a series of batch Bayesian regressions and the results are also summarised in Table 3.
Fig. 14 presents the optimal adaptive HVAC temperature setting deduced from recursive Bayesian ordered logistic regression. The missing part before the individual temperature setting curve is due to the use of the first 60% of the thermal preference observations in the initial dataset window for regression coefficient initialisation. It can be seen that the optimal adaptive temperature thermostat settings fluctuated over the monitoring period, ranging from 19.4 to 25.5 °C. The 95% credible interval was relatively wide at the beginning, but converged gradually with the recursive process. After around December 2017, the optimal adaptive temperature settings were higher than the optimal fixed temperature setting identified in Section 3.2.1 (i.e. 23.5 °C). Fig. 14 also shows an enlarged section of the variation of the optimal adaptive thermostat setting over a short period from around 21st to 24th of May 2018 together with thermal preference records of that period. It can be seen that the optimal thermostat temperature setting is updated every time a “Want Cooler” (“Response 1” and “Response 2” in Fig. 14) and a “Want Warmer” response is recorded (“Response 3” and “Response 4” respectively).

The overall reduction of the thermal dissatisfaction that was calculated as benefit from the optimisation by Eq. (14) was around 1.47% in Optimisation Scenario 3. Optimisation Scenario 3 considers a continuously updated thermostat setting over time, which led to a slightly higher reduction of the thermal dissatisfaction for the occupants when compared to that of Optimisation Scenario 1 (i.e. 0.26%), but this reduction was almost the same as that of using the optimal daily HVAC temperature setting in Optimisation Scenarios 2 (i.e. 1.55%). To further compare the benefits between Optimisation Scenarios 2 and 3, their upper and lower temperature limits of the 95% credible interval for the optimal daily and adaptive temperature settings were used to calculate the credible interval in the calculation of the overall thermal dissatisfaction reductions. In Optimisation Scenario 3, the overall reduction of the thermal dissatisfaction corresponding to the 95% credible interval of the optimal adaptive temperature setting ranged from 0.47% to 5.42%, whose mean value was 2.95% and higher than that of 2.39% (i.e. mean value of the range from 0.78% to 4.0%) for Optimisation Scenario 2. The main reason for this improvement is that,

| Size of the training dataset | Optimal temperature setting (°C) | 95% credible interval (°C) | Optimal PMV setting | 95% credible interval |
|------------------------------|----------------------------------|---------------------------|---------------------|-----------------------|
| 10% responses                | 21.4                             | [not available, 23.3]     | –                   | [not available, –0.08]|
| 20% responses                | 23.1                             | [21.9, 23.6]              | –0.01               | [0.05, 0.16]          |
| 30% responses                | 22.5                             | [20.5, 23.3]              | –0.15               | [0.05, 0.07]          |
| 40% responses                | 22.3                             | [20.0, 23.1]              | –0.23               | [0.05, 0.01]          |
| 50% responses                | 22.8                             | [21.9, 23.3]              | –0.20               | [0.05, 0.03]          |
| 60% responses                | 23.1                             | [22.7, 23.5]              | –0.07               | [0.05, 0.05]          |
| 70% responses                | 23.0                             | [22.5, 23.3]              | –0.13               | [0.05, 0.01]          |
| 80% responses                | 23.3                             | [22.9, 23.5]              | –0.06               | [0.05, 0.05]          |
| 90% responses                | 23.4                             | [23.1, 23.7]              | 0.03                | [0.12]                |
| 100% responses               | 23.5                             | [23.3, 23.8]              | 0.07                | [0.15]                |
as opposed to using a fixed optimal temperature (Optimisation Scenario 1) or an optimal daily temperature profile (Optimisation Scenarios 2) as the thermostat setting, Optimisation Scenario 3 adaptively adjusted the optimal temperature setting, thereby better matching the overall occupant thermal preferences dynamically.

3.4.2. Optimal adaptive PMV settings

Fig. 15 presents the derived optimal adaptive PMV thermostat settings. Unlike the optimal adaptive temperature settings, the optimal adaptive PMV settings had a relative stable 95% credible interval even at the start of the optimisation. The optimal PMV settings varied from −0.11 to 0.18 during the monitoring period, and slightly exceeded the fixed optimal PMV setting identified in Section 3.3.2 in May 2018. By employing the optimal adaptive PMV settings of Optimisation Scenario 3, the overall thermal dissatisfaction reduction calculated by Eq. (11) reached 1.21%. Even though this value was still relatively low, it was higher than that of Optimisation Scenarios 1 and 2 (i.e. 0.19% and 0.24%, respectively), due to dynamic adjustments of the optimal PMV thermostat setting. It should be noted that PMV considers a number of indoor environmental variables (e.g. mean radiant temperature, relative humidity and air temperature) and therefore the percentage improvements in relation to thermal dissatisfaction can not be directly compared to those that use the temperature as thermostat setting. Since Optimisation Scenario 3 did not account for the microclimate deviations among the different locations of the large agile open plan office, the derived from it benefit indicated a potential for improvement when applied to individual zones within the office space.

3.5. Optimisation scenarios for individual zones

The above discussed three optimisation scenarios can also be implemented for individual zones in a large open plan office, if the local conditions of each zone can be controlled individually.

3.5.1. Zoning process

The open plan office was partitioned into 4 clusters (see Table 4). The devices with IDs 7, 18, 28, 40, 11, 13 and 17 in Zone 2 covered the southwest part of the office (Fig. 2 shows the exact locations); Zone 3 included devices with IDs 97, 98 and 99 at the north part of the office; Zone 4 included only device ID19, given that this was located in an isolated meeting room; while the rest of the measurement devices were attributed to Zone 1, representing the southeast part of the office.

Table 4

| Zone index | Sensing and occupant feedback device ID | Zone          | No. of thermal preference records |
|------------|----------------------------------------|---------------|----------------------------------|
| 1          | 6,10,20,21,22,23,24,26,39,47           | Southeast     | 285                              |
| 2          | 7,18,28,40,11,13,17                    | Southwest     | 189                              |
| 3          | 97, 98, 99                             | North         | 91                               |
| 4          | 19                                     | Isolated meeting room | 23                               |

Table 5 summaries the optimal fixed HVAC temperature and PMV settings for individual zones based on all the thermal preference records in the corresponding zones. For Zone 1, the optimal temperature and PMV settings identified were 23.3 °C and 0.10, respectively, while for Zone 2 they were 23.7 °C and −0.16 respectively. Since the number of thermal preference records in Zones 3 and 4 was small, it may not be reliable to determine optimal settings and could introduce wide credible intervals. For this reason, the following analysis and optimisation of the indoor microclimate focused mainly on Zones 1 and 2. By adopting the optimal fixed HVAC temperature settings, the overall thermal dissatisfaction reductions calculated by Eq. (14) were around 0.32% and 0.61% for Zones 1 and 2, respectively. If optimal fixed PMV settings were instead used for the settings of the HVAC system, the thermal dissatisfaction enhancements calculated by Eq. (11) were 0.25% and 1.03%, respectively. It can be seen that the corresponding benefits were different for individual zones. However, similar to Optimisation Scenario 1 which identified and used a fixed thermostat setting for the whole office (with quantified benefits of 0.25% when using temperature thermostat setting and 0.19% when using PMV thermostat setting), the overall thermal dissatisfaction reduction achieved in Optimisation Scenario 4 was also relatively small. Even through the occupant locations were considered through zoning to identify a more reasonable optimal thermostat setting, the tempo-
eral variations of occupant thermal preferences were still not accounted in this Optimisation Scenario 4 and therefore the calculated reductions of thermal dissatisfaction were still insignificant.

3.5.3. Optimal HVAC daily temperature and PMV profile settings (Optimisation Scenario 5)

The optimal daily temperature and PMV profile thermostat settings were identified for Zones 1 and 2, respectively, as shown in Fig. 16. As Fig. 16a shows, the optimal hourly temperature settings for Zone 1 varied widely from 19.2 to 25.6 °C during the air conditioning hours, while the variation for Zone 2 was from 22.1 to 25.0 °C. It should be noted that the lower boundaries of the 95% credible interval for the optimal temperature settings between 7:00 and 9:00 were constrained above 18 °C to overcome issues caused by the small number of thermal preference records during the early hours of the morning. From Fig. 16a, it can be seen that the optimal PMV profile settings of Zone 1 was above than that of Zone 2 over the air conditioning hours, demonstrating that the occupants in Zone 1 tended to prefer a slightly warmer indoor environment compared to that in Zone 2. By adopting the optimal daily temperature profile settings per zone, the overall thermal dissatisfaction reduction calculated by Eq. (14) can in this case reach 3.83% and 1.68% for Zones 1 and 2, respectively. These reductions were higher than the reductions calculated in the optimal fixed temperature thermostat settings case in these zones (i.e. Optimisation Scenario 4 in Section 3.5.2). In addition, compared to the optimised settings for the whole office without zoning (i.e. Optimisation Scenario 2 in Section 3.3), using the optimal daily temperature and PMV profiles for each zone tended to be more effective in reducing the overall thermal dissatisfaction of occupants as indicated by the weighted, in terms of occupant responses per zone, mean thermal dissatisfaction reduction of 2.40% and 0.49% when using temperature and PMV thermostat settings, respectively (in this calculation the assumption was that the thermal dissatisfaction reduction for Zones 3 and 4 remained unchanged, i.e. 0).

3.5.4. Optimal adaptive HVAC temperature and PMV settings (Optimisation Scenario 6)

As in Optimisation Scenario 3, parametric studies were carried out for Zones 1 and 2 to identify the suitable initial dataset window size. While the results of these parametric studies are not included in the paper for brevity, the initial dataset window size with narrow 95% credible interval was set to include 80% of the total number of the thermal preference records in both zones (i.e. 228 and 151 responses for Zones 1 and 2 respectively).

The adaptive thermostat temperature and PMV settings were identified and are shown in Fig. 17. It can be seen that the optimal adaptive HVAC temperature settings for Zone 1 experienced significant fluctuating trends from 22.7 to 28.0 °C, compared to that for Zone 2 that ranged between 21.8 and 28.0 °C (Fig. 17a). For Zone 1, over the majority of the monitoring period, the higher limits of the 95% credible interval were constrained at 28 °C. The significant

| Zone | Optimal temperature setting (°C) | 95% credible interval (°C) | Optimal PMV setting | 95% credible interval |
|------|---------------------------------|---------------------------|---------------------|-----------------------|
| 1    | 23.3                            | [22.6,23.8]               | 0.10                | [-0.14,0.19]         |
| 2    | 23.7                            | [23.2,24.0]               | -0.16               | [-0.58,0.06]         |
| 3    | 24.1                            | [23.8,24.4]               | 0.29                | [0.18,0.34]          |
| 4    | 22.8                            | [22.2,24.0]               | 0.13                | [-0.12,0.38]         |

Fig. 16. Optimal daily profile thermostat settings for Zones 1 and 2 for: a) temperature, and b) PMV (Optimisation Scenario 5).
fluctuation of the temperature settings and the wide credible interval were due to the limited number of the thermal preference records collected in individual zones, which can be technically addressed by adopting a relatively long training period to collect enough occupant thermal preference records for individual zones. For Zones 1 and 2, by adopting the optimal adaptive HVAC temperature settings, the overall thermal dissatisfaction reduction calculated by Eq. (14) can reach 5.19% and 1.20%, respectively. It should be mentioned that these values can only qualitatively reflect the benefits of adopting these optimal adaptive thermostat settings, due to the limits set for the temperature setting to stabilise the start of the recursive regression process (from 18 to 28 °C in this study, see Section 2.3.4). In a case where no temperature setting limits were used, the thermal dissatisfaction reduction can reach 8.20% and 1.73%, an improvement that was higher than that derived by using the optimal daily temperature settings for Zones 1 and 2 (i.e. 3.83% and 1.68%), respectively.

Fig. 17b shows that the optimal adaptive PMV settings for Zone 1 and Zone 2 experienced overall increasing trends. The optimal adaptive PMV settings for Zone 1 (ranging from 0.08 to 0.21) were below than that for Zone 2 (ranging from 0.43 to 0.18). This indicates that the occupants in Zone 1 tended to prefer warmer indoor conditions than that in Zone 2. The clear difference between the optimal adaptive PMV settings for the two zones shows the potential necessity for a flexible control of the indoor microclimate of individual zones to reduce thermal dissatisfaction of occupants. However, obvious uncertainties can be found in the optimal adaptive PMV settings for Zones 1 and 2, and their 95% credible intervals were much wider than those calculated for the whole large open plan office (in Section 3.4.2). By adopting optimal adaptive PMV settings, the thermal dissatisfaction enhancement calculated by Eq. (11) can reach 0.88% and 5.17% in Zones 1 and 2, respectively. In comparison to the benefits calculated from using a fixed PMV setting in Optimisation Scenario 4 (i.e. thermal dissatisfaction enhancement of 0.25% and 1.03% for Zones 1 and 2, respectively) and the optimal daily PMV profile settings in Optimisation Scenario 5 (0.28% and 1.09% for Zones 1 and 2, respectively), the overall thermal dissatisfaction reduction in this optimisation scenario was improved. It can also be seen that the zoned approach in this optimisation scenario provided a higher reduction of thermal dissatisfaction (weighted mean thermal dissatisfaction reduction of 2.09%, even when the thermal dissatisfaction reduction for Zones 3 and 4 were assumed to be 0) compared to that using the optimal adaptive PMV settings for the whole office (i.e. 1.21% in Optimisation Scenario 3 in Section 3.4).

3.6. Discussion

The above sections have presented the results of the different scenarios for optimal indoor thermal conditions in a large agile open plan office and are summarised in Table 6. The optimal indoor conditions were achieved by calculating an optimal setting for the HVAC thermostat, which can either be based on air temperature or PMV. The results of the series of optimisation scenarios demonstrated that considering both spatial and temporal variations of occupant thermal preferences could reduce the indoor thermal dissatisfaction of occupants.

The simplest scenario was to identify and use an optimal fixed setting in the HVAC system for the whole office, without considering the temporal and spatial aspects at all. Due to its simplicity, the scenario presented an almost negligible potential to reduce the thermal dissatisfaction of occupants (thermal dissatisfaction reduction less than 0.3% for both optimal temperature and PMV thermostat settings). The small benefit from this scenario was due to the fact that the optimal thermostat settings were deduced retrospectively after collecting all occupant thermal preference responses. A slightly upgraded scenario was Optimisation Scenario 2 which partially considered the temporal aspect on a daily basis.
Even though the temporal factor was partially considered, this optimisation scenario was lacking the resilience to adapt the indoor microclimate to the real-time occupant thermal preferences that were influenced by, for instance, the variations of the occupants themselves (flexibility for working hours, thermal preference, personnel change, agility for the selection of desks), the occupancy density, etc. The issue of optimisation in real-time was addressed in Optimisation Scenario 3, which determined the recursive optimal setting inference according to newly recorded thermal preference responses, while combining these new responses with the historical occupant thermal preferences, as detailed in Section 3.4. However, the results of the metrics used to quantify the benefits of the different scenarios showed that Optimisation Scenario 3 outperformed the optimal fixed thermostat setting scenario but had a similar performance as the optimal daily profile thermostat settings scenario. This indicated that optimising only for the temporal aspect may not be sufficient to reduce the indoor thermal dissatisfaction effectively in a large agile open plan office, due to the deviations in local microclimates, the occupants’ agility for the selection of desks, the occupancy density in different zones, etc.

Optimisation Scenarios 4, 5 and 6 further considered the spatial aspect in the derivation of the thermostat settings by implementing fixed, daily profile and adaptive settings for each zone respectively. In particular, Optimisation Scenario 6 considered both the spatial and temporal aspects of occupant preferences and the results showed that it could be a promising option for being implemented in the control settings of HVAC systems of agile open plan offices. To further guide such implementation, the following pseudo-code in Table 7 was developed for the identification of the adaptive optimal HVAC settings (Optimisation Scenario 6).

### 4. Conclusions

Optimal indoor conditions in a large agile open plan office space were identified by using measured indoor conditions and real-time occupant preference responses in a Bayesian ordered logistic regression model. We implemented and compared a series of optimisation scenarios with and without considering the temporal and spatial variations of occupant thermal preferences and of indoor conditions. To compare the importance of the temporal aspects, we designed and evaluated an optimal fixed thermostat setting, an optimal daily profile thermostat setting, and an optimal adaptive thermostat setting. The importance of the spatial aspect was evaluated by zoning the office space and implementing the above three different optimisation scenarios (fixed, daily profile and adaptive) based on the occupant thermal preferences and indoor conditions in individual zones. Two artificial metrics were developed and utilised to assess the impact of these optimisation scenarios when using air temperature and PMV as reference thermostat metrics, respectively.

We found that the Bayesian-based adaptive optimisation algorithm can result into reduced thermal dissatisfaction of occupants when taking the real-time temporal variation of occupant thermal preferences into account. For the non-zoning scenarios, the adaptive optimisation outperformed, in some cases marginally, the cases that had optimal fixed and optimal daily profile thermostat settings. Using the two developed metrics to represent thermal dissatisfaction reductions for temperature and PMV based settings, the adaptive optimisation resulted in the overall reduction of the thermal dissatisfaction of 1.47% and 1.21% respectively, slightly higher than that of the fixed optimal thermostat setting optimisation.

We also found that the occupant thermal dissatisfaction can be further reasonably reduced by taking the spatial deviation of indoor climate into account. The adaptive optimisation algorithm that considers both, the temporal and spatial differences between the occupant thermal preferences, can result in overall occupant thermal dissatisfaction reductions in a zone of up to 5.19% when using the resulted optimal adaptive temperature settings and of up to 5.17% when using the resulted optimal adaptive PMV settings.

### CRediT authorship contribution statement

**Wenyue Lin**: Methodology, Formal analysis, Software, Writing - original draft, Data curation, Investigation. **Kokogiannakis Geor-**
gios: Conceptualization, Funding acquisition, Project administration, Supervision, Data curation, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2020.110536.

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