Benchmarking thermal performance of buildings and identifying preferred thermal conditions with highly deployable IoT devices

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Abstract. Low cost, network-based, pervasive sensing devices that capture a range of indoor environmental parameters were successfully developed and deployed in two large mechanically ventilated buildings in Sydney and in Wollongong in Australia. The devices could provide information over the internet for the indoor environment of the buildings at high spatial and temporal resolutions and could also capture occupant expressions of preferences for the indoor thermal environment. The paper describes findings from the monitoring data and the real-time occupant responses that were collected between March/2017 and October/2018. The analysis includes records from approximately 1450 real-time expressions of thermal preferences from the occupants of the two buildings and more than 5.5 million time stamp rows that contained sets of indoor environmental quality data. The paper demonstrates a low-cost method for benchmarking buildings with each other and providing the means of communicating the often-unknown occupant requirements to facility managers.

1. Introduction
Indoor environmental quality is closely related to occupants’ comfort, and consequently their well-being and productivity [1]. In commercial buildings, to avoid the decrement in productivity, the monitoring and control of indoor environment, especially the thermal environment when using central heating, ventilation and air conditioning (HVAC) systems is common practice and widely required. However, the control of highly comfortable indoor environments is challenged by the different thermal preferences of occupants, the lack of empowering technologies that allow occupants to communicate their preferences [2], as well as due to the transient occupancy characteristics in some buildings [3]. Consequently, a high-level occupant satisfaction cannot often be achieved because the large HVAC systems of commercial buildings are designed to serve pre-determined “widely acceptable” conditions which do not always guarantee satisfactory thermal conditions [4]. In addition, these systems are often served by a limited number of room sensors that fail to take into account the indoor microclimates (dynamic variations of the indoor conditions locally within a space). Besides, the 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.

Previous relevant studies usually relied on surveys to investigate the thermal preference of occupants and work out potential improvements for system control. However, this method requires excessive efforts to set up the monitoring system for the measurement of indoor conditions, and to collect responses from occupants, which is often costly and time-consuming, but also it brings burden to occupants and the research teams. Low-cost, pervasive wireless real-time sensing of indoor conditions...
and occupant feedback solutions are therefore of great necessity to closely understand and monitor occupant needs and empower people to better choose their preferences or express their opinion [5, 6]. In this study, we demonstrate the application of low cost pervasive sensing and occupant feedback equipment in two mechanically conditioned non-domestic buildings that are located within a similar climate in Australia. We illustrate the opportunity for the plethora of data that could be provided to research teams to better understand the microclimates in these buildings, optimise the controls for the systems serving them, understand the occupant preferences and even compare buildings with each other.

2. Method and equipment
A university building and a large office space of a similar size were instrumented and compared while collecting occupant expressions of dissatisfaction for their thermal environment.

The first space in this study was the office space that was occupied by ARUP in Sydney CBD (Figure 1) up until October 2018. The office floor area was approximately 2700 m$^2$ and included workstations for approximately 375 staff members. The largest part of the office area has an open plan layout. In addition, and as noted in Figure 1, most occupants do not have pre-allocated working desks, but could instead use any of the desks on the south side of the office area (agile office area). The second space of this study was a university building located at the main campus of the University of Wollongong in Australia (Figure 2). This building had a total floor area of 2800 m$^2$ and comprised mainly cellular office spaces that were often shared by two occupants, lab spaces and an open plan office space for postgraduate students.

Both buildings were mechanically conditioned and the HVAC operation settings were similar (7am to 6pm on weekdays), however the exact operation settings were not available to the authors. In terms of climate, Wollongong and Sydney have in general a mild, temperate climate with subtropical elements. The two cities are approximately 68 km apart and their weather conditions are on average very similar. Code for devices with low-cost Arduino sensors linked with Raspberry PI units was developed and the devices were deployed in both buildings at the locations shown by the devices IDs in Figure 1 and Figure 2. Each device had very low power requirements and was set to collect a range of indoor environmental data at 5-minute intervals. The details of the sensors that collected data relevant to this paper are in Table 1. The air temperature, relative humidity and black globe temperature sensors for each device were calibrated over 30 spot measurements over the long period of the study by using a testo 905-T1 thermometer for the air temperature with reported accuracy ±1°C (at -50 to +99.9°C range), a testo 625 for the relative humidity (accuracy ±2.5%, 5 to 95% range), and a testo 480 150mm globe probe that uses a Type K Class 1 thermocouple with ±1.5°C accuracy (0 to +120°C range).

Three push buttons were also added on each device to observe at any time, instant occupant feedback in relation to the indoor environmental conditions. In this way, an expression of dissatisfaction (a mild complaint) or a preference is indirectly logged, and can be compared with the above-mentioned locally collected environmental data from the sensors on each device. Two out of the three buttons were labelled as “Want warmer” and “Want cooler” and were meant to be pressed when the occupants were finding the indoor conditions to be outside their preferred thermal conditions. 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, but the findings from the responses with regard to noise remain outside the scope of this paper. To avoid causing unnecessary burden to the occupants, reminders to press the buttons were not sent and it was left to the occupants’ discretion to express their dissatisfaction with their thermal environment. 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.

All data from the devices were wirelessly sent in a secure SQL database. The data included in this paper cover approximately the same periods for the two buildings. The open plan space dataset records are for the period between 1/Mar/2017 to 11/Oct/2018 (approximately 2.6 million timestamps), and the dataset for the University building is for 1/Apr/2017 to 5/Oct/2018 (approximately 2.9 million timestamps). The difference in the number of timestamps is due to the fact that the University building had 21 devices collecting simultaneous data, while the office space had 18 devices. Figure 1 and Figure
2 also show the device-ID numbers and the locations where the sensing and occupant feedback devices were placed.

The analysis in this paper includes overall statistics and comparisons of the measured data and an overview of the total responses collected as the occupants were pressing the push buttons attached to the sensing devices.

![Plan layout of open plan office space (1st monitored space) and location of devices. Devices 11, 13 and 17 were replaced by 97, 98 and 99 when the north side was converted to an agile workspace.](image1)

**Figure 1.** Plan layout of open plan office space (1st monitored space) and location of devices. Devices 11, 13 and 17 were replaced by 97, 98 and 99 when the north side was converted to an agile workspace.

![Plan layout of the University building (2nd monitored space) and location of devices.](image2)

**Figure 2.** Plan layout of the University building (2nd monitored space) and location of devices.

| Measured Environmental parameter | 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                  |

**Table 1.** Sensor specifications for monitoring and occupant feedback devices.
3. Results

3.1. Benchmarking indoor conditions during operation hours

Prior to analysing the occupant responses, the indoor conditions between two buildings were first compared with frequency histograms, density plots and boxplots. For brevity, only lumped results collected from all devices for each building as a whole are included in this section, however, individual localised analyses are possible with our data collection methodology.

Figure 3 provides an example of the available outputs, in which the indoor air temperature records are plotted. We notice that the office space was most frequently warmer than the University building spaces, but would mostly remain below 26°C for the majority of the typical working periods (typical HVAC operation times were sourced from the Facilities Managers). Table 2 provides a detailed summary output of all measured conditions that have been traditionally associated with thermal comfort in mechanically conditioned buildings, except of the air velocity measurements that remained considerably low during the period of the study. Air velocity measurements were however taken into account in the calculation of the reported PMV values in Table 2. Given the very large datasets, a Welch Two Sample t-test was then undertaken for the mean of all variables listed in Table 2. The t-test showed statistically significant differences between the mean of all variables of Table 2, however, and as it could be intuitively derived, after generating the Coehn’s d values to quantify the effect of these differences it can be noticed that effect is very small for the relative humidity (Table 2).
Figure 3. Frequency histograms, density plot and boxplot analysis of indoor air temperatures in the two buildings (including data only for weekdays from 7am to 6pm).

Table 2. Summary statistics of indoor conditions and calculated PMV for weekdays (7am-6pm)

|                            | Agile open plan office (N = 875,405) | University building (N = 988,048) |
|-----------------------------|--------------------------------------|----------------------------------|
| Air Temperature (°C)        |                                       |                                  |
| Min, Max                    | 12.4, 29.7                           | 12.1, 29.3                       |
| Mean (sd)                   | 23.6 ± 1.28                          | 22.5 ± 1.11                      |
| Median (IQR)                | 23.7 (22.9, 24.5)                    | 22.5 (21.9, 23.1)                |
| Relative Humidity (%)       |                                       |                                  |
| Min, Max                    | 24.7, 82.8                           | 11.3, 98.5                       |
| Mean (sd)                   | 53.5 ± 10.3                          | 54.0 ± 13.1                      |
| Median (IQR)                | 55.2 (45.3, 61.6)                    | 54.5 (43.4, 64.2)                |
| MRT (°C)                    |                                       |                                  |
| Min, Max                    | 12.7, 37.9                           | 7.4, 38.7                        |
| Mean (sd)                   | 24.4 ± 1.37                          | 23.2 ± 1.58                      |
| Median (IQR)                | 24.6 (23.6, 25.3)                    | 23.2 (22.2, 24.2)                |
| PMV (CLO= 0.9, MET= 1.1)    |                                       |                                  |
| Min, Max                    | -4.55, 1.59                          | -5.57, 1.87                      |
| Mean (sd)                   | -0.26 ± 0.52                         | -0.63 ± 0.48                     |
| Median (IQR)                | -0.17 (-0.48, 0.07)                  | -0.60 (-0.88, -0.34)             |

3.2. Occupant expressions of dissatisfaction for the thermal conditions
We only illustrate here the overall responses that have been plotted in Figure 4. The responses were compared with the air temperature and the measured PMV at the time of the response. To avoid double counting, we have removed the push button presses that were recorded within the same hour from the same device.
Figure 4. Occupant expressions of preferences (push buttons in real-time) for “want warmer” and “want cooler” conditions in relation to indoor air temperature (graph on the left) and PMV (two graphs on the right). Responses recorded from all devices for the whole measurement period.

An overall of 814 “want warmer/cooler” real-time responses were gathered from the devices at the University building and 640 from the open plan office building. There were 481 “Want Warmer” responses from the occupants of the University building, as opposed to only 263 responses for the open plan space, which indicates a higher dissatisfaction of the occupants of the University building due to the occurrence of perceived cold conditions. However, the “Want Cooler” responses from the open plan office were slightly higher than those at the University building (377 as opposed to 333, respectively), which indicates that the occupants of this densely occupied open plan office were experiencing conditions that were perceived as more frequently warmer than the occupants of the other building. In terms of individual locations, device 48 recorded the highest number of “Want Warmer” push button presses (N=103) for the University building, and device 28 (N=21) for the open plan space (refer to Figure 1 and Figure 2 for locations). For “Want Cooler”, the highest number of responses were collected by devices 22 (N=33, but with other devices collecting only slightly less responses), and by devices 5 and 41 for the University building (equally N=52), (Figure 1 and Figure 2).

4. Conclusions
We have demonstrated the application of a method that uses low-cost, internet-enabled highly deployable devices with a set of sensors for capturing indoor conditions and the thermal preferences of occupants in two mechanically conditioned buildings. The plethora of the available data that are collected with such devices provides myriads opportunities of analysing and benchmarking the indoor environmental quality of spaces at high temporal and spatial resolutions and linking in real-time the measured parameters with the diversified preferences of occupants in large spaces. Sample overall results and findings were provided in this paper from data collected for approximately 1.5 years. However, the equipment used in this study offers the possibility to analyse in detail individual responses and microclimates that are left out of this paper and will compose the material of future work.

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