



## AUTOMATED THERMAL COMFORT MONITORING USING IOT TECHNOLOGIES

Carlos Chillón Geck<sup>1</sup>, Thamer Al-Zuriqat<sup>1</sup>, Hayder Alsaad<sup>2</sup>, Conrad Völker<sup>2</sup>, and Kay Smarsly<sup>1</sup>

<sup>1</sup>Hamburg University of Technology, Hamburg, Germany

<sup>2</sup>Bauhaus-Universität Weimar, Weimar, Germany

### Abstract

Thermal comfort is typically assessed either through manual surveys or through sensor data. Automating the manual surveys and the analysis of the sensor data may reduce the risk of information loss, while entailing more accurate thermal comfort assessment. This paper presents the design and implementation of a thermal comfort monitoring system that uses Internet of Things technologies to automatically assess thermal comfort. For validation, thermal comfort indexes are computed and compared with subjectively perceived thermal sensations of building occupants, provided through a digital survey. The results show that the comfort monitoring system continuously and reliably collects and assesses thermal comfort.

### Introduction

Thermal comfort, i.e. subjective satisfaction with the thermal environment, affects the health, well-being, and productivity of building occupants and has become an important area of research in the buildings and construction sector (Lamberti et al., 2020). It is well known that physiological, psychological, and behavioral aspects directly influence the thermal comfort of building occupants (Fanger, 1970). Environmental parameters measured by monitoring systems have been used to calculate thermal comfort indexes, developed based on physiological aspects, such as the predicted mean vote (PMV) or the predicted percentage of dissatisfied (PPD). As a result, the PMV and PPD indexes have been incorporated into thermal comfort standards, e.g. into the ASHRAE Standard 55 (ASHRAE, 2020). However, the PMV index calculates the average feeling of comfort of a group of people sharing an indoor space, but it does not consider every individual separately. Thus, research in the field of thermal comfort has shifted towards personalized thermal comfort, which can only be achieved through controlling the thermal environment by the building occupants (Van Hoof, 2008), adapting to the outdoor and the building conditions (de Dear and Brager, 1998).

Monitoring systems based on the Internet of Things (IoT) have become cost-efficient and reliable (Tomat et al., 2020), particularly in smart home and smart building applications (Peralta Abadía et al., 2022). Due to the growing availability and quality of sensors and microcontrollers, cost-efficient sensor nodes have been used to measure environmental parameters (Kimmeling and Hoffmann, 2019). The environmental parameters measured by monitoring systems have been used to calculate thermal comfort indexes, such as the PMV index, using machine learning (Zang et al., 2019) or by

comparison with high-quality reference sensors (Mthunzi et al., 2019). An indoor environmental quality sensor node has been developed to measure acoustic comfort, air quality, and light levels in addition to thermal comfort (Parkinson et al., 2019). In Demanega et al. (2021), the performance of different indoor air quality hardware components has been comparatively investigated. In addition to monitoring of environmental parameters, personal assessment of thermal comfort has been carried out using thermal comfort surveys in multiple studies, obtaining direct feedback from building occupants (Nicol et al., 2012). Traditionally, thermal comfort surveys are conducted manually, using paper-based questionnaires (McCartney and Fergus Nicol, 2002), and often under controlled conditions (Choi and Yeom, 2017). Although efforts have been made to develop web-based surveys (Graham et al., 2021), survey tools are still expensive and usually not freely available.

Assessing thermal comfort by using either monitoring systems (i.e., environmental data) or only thermal comfort surveys (i.e., building occupant feedback) has several disadvantages. On the one hand, solely collecting environmental data is not sufficient to assess thermal comfort accurately for every building occupant in an indoor space. On the other hand, assessing thermal comfort only through surveys is time-consuming and requires a regular and reliable participation of building occupants. Therefore, a promising solution to solve the aforementioned drawbacks is to combine both methods, i.e. environmental data and building occupant feedback. With advances in sensing, monitoring, and IoT technologies, tools have been made available to incorporate building occupant feedback into thermal comfort assessment (Dragos and Smarsly, 2017). For example, IoT-based mobile applications and digital surveys have been implemented to collect feedback on subjectively perceived thermal sensations and preferences of building occupants (Sanguinetti et al., 2017). In Salamone et al. (2015), a web application has been introduced to record building occupant feedback, while an IoT device monitors environmental parameters. The interaction of building occupants with a voting system has been studied in Sheikh Khan et al. (2021). Despite the efforts to combine feedback systems with environmental monitoring, a fully digitized and automated workflow has not been developed. Integrating both high-quality environmental data and long-term feedback from building occupants would significantly reduce data loss, effort, and cost for thermal comfort assessment.

This paper presents an automated thermal comfort monitoring system that couples environmental data collected by low-cost, yet accurate, wireless sensor nodes

with a digital thermal comfort survey obtaining feedback from building occupants. The system aims to minimize the efforts required for data collection while maximizing the amount of feedback obtained from building occupants. The result is an automated system that continuously monitors thermal comfort and structures the data for further analysis. The remainder of the paper is structured as follows. First, the design and implementation of the automated thermal comfort monitoring system, i.e. the system architecture, hardware and software components, and the digital thermal comfort survey are described. Then, the thermal comfort monitoring system is validated through a field test in an office environment by comparing the PMV index calculated on the sensor nodes with *actual votes*, i.e. subjectively perceived thermal sensations, obtained from the building occupants through the digital survey. Next, the results of the field test are presented and the user-friendliness and performance of the thermal comfort monitoring system are discussed. The paper concludes with a summary of the study and remarks on possible new aspects in the research field of thermal comfort in indoor spaces using automated monitoring systems.

## Design and implementation of an automated thermal comfort monitoring system

The automated thermal comfort monitoring system presented in this paper is based on previous work of the authors, i.e. it utilizes a four-layer IoT architecture (Peralta Abadia et al., 2022) and takes advantage of modern concepts of monitoring (Fitz et al., 2019), embedded systems (Dragos and Smarsly, 2022), and intelligent sensor technologies (Dragos and Smarsly, 2016). The automated thermal comfort monitoring system includes

- the digital thermal comfort survey and
- thermal comfort stations.

The digital thermal comfort survey is designed to be completed by building occupants, while each thermal comfort station consists of a wireless sensor node built from low-cost hardware components. The software applications embedded into the wireless sensor nodes integrate algorithms for real-time sensing, embedded data processing, and IoT connectivity. A key objective of the system is to automate the collection of environmental data and to complement the data with the digital thermal comfort survey to provide an accurate assessment of thermal comfort. In the following subsections, the system architecture of the automated thermal comfort monitoring system is elucidated, followed by a hardware and software description, and the digital thermal comfort survey.

### System architecture

The architecture of the automated thermal comfort monitoring system consists of four layers,

- an application layer,
- a middleware layer,
- a physical layer, and
- a security layer,

which are outlined below. As shown in Figure 1, the building occupants interact with the application layer through a dashboard accessible via a web-based interface. The dashboard provides real-time visualization of environmental data and it comprises the digital thermal comfort survey. The middleware layer contains a mobile server based on a Raspberry Pi, which handles the backend services of the system using the Node-RED development tool, which is a framework that provides visual, flow-based programming for developing the backend logic of the system (OpenJS Foundation, 2023). Node-RED receives feedback from building occupants through the application layer and stores the survey results and environmental data collected by the physical layer.

The physical layer of the automated thermal comfort monitoring system consists of several wireless sensor nodes that collect indoor environmental data, i.e. air temperature, relative humidity (RH), air velocity, and globe temperature. In addition, the wireless sensor nodes have the computing power to process the raw environmental data using embedded algorithms; for example, the PMV and the PPD thermal comfort indexes, which, are calculated on the wireless sensor nodes. The data processed on board is sent to the middleware layer for data storage and visualization using an HTTP communication protocol. Last but not least, the security layer is devised transversely to the other layers and provides authentication services for privacy and security of all layers.

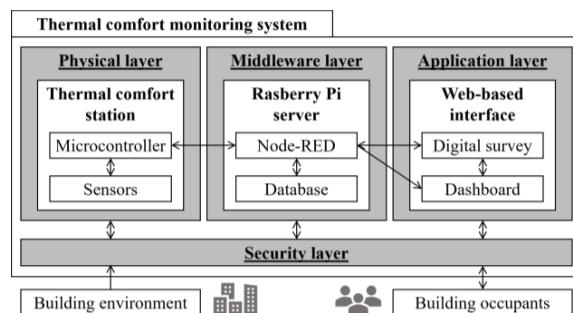


Figure 1: Four-layer IoT architecture of the automated thermal comfort monitoring system

### Hardware components

Several wireless sensor nodes, or *thermal comfort stations*, are part of the automated thermal comfort monitoring system. The thermal comfort stations include three sensors, (1) a combined sensor that measures air temperature and RH, (2) an air velocity sensor, and (3) an air temperature sensor that is installed in a black-painted table-tennis ball to form a globe thermometer used to calculate the MRT.

An ESP32 microcontroller, type WROOM-32 manages the raw environmental data and sends the data to the middleware layer at regular intervals via Wi-Fi, using the HTTP protocol. As shown in Figure 2, a 3D-printed enclosure protects the hardware components and provides thermal insulation for each component. All components are wired and soldered to a printed circuit board. The

components have been selected based on the following criteria: Low price, low power consumption, accuracy, size, and operability at 5 V. Table 1 presents the values of the criteria for each hardware component.

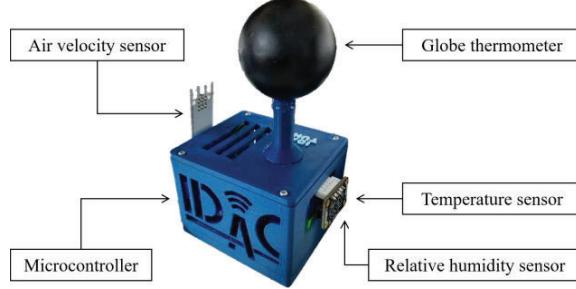


Figure 2: A thermal comfort monitoring station as part of the automated thermal comfort monitoring system

## Software components

The ESP32 microcontroller of the thermal comfort stations embeds software applications designed to collect sensor data, to process it, and to exchange the sensor data with a server. In addition, the software application calculates the PMV and PPD indexes to estimate the average thermal comfort of people in an indoor environment. The algorithms implemented for calculating the PMV index and the PPD index are described in ANSI/ASHRAE (2020). The inputs to calculate the PMV and PPD indexes are the environmental parameters measured by the thermal comfort stations as well as two personal parameters that quantify the clothing and activity (e.g., sitting and writing) of the building occupants. The values of the personal parameters are introduced by the building occupants when filling the digital thermal comfort survey, which allows the system to update the clothing and activity parameters and thus the PMV and PPD indexes. The output of the PMV index corresponds to a value on a 7-point scale of the ASHRAE-55 standard (ASHRAE, 2020), where -3 represents “extreme” cold sensation and +3 represents “extreme” warm sensation, and an index of 0 expresses “neutral” thermal sensation. The PPD index is derived from the PMV value and predicts the percentage of people that would be dissatisfied with the thermal conditions of the environment at a specific point in time. For example, a PPD value of 10 indicates that 10 % of the people are not satisfied with the thermal conditions.

The Node-RED framework, which runs the backend services of the system on the Raspberry Pi, receives the environmental parameters, the PMV index, and the PPD index, and it displays, in real time, the values on visualization dashboards of the application layer hosted in a web interface. At the same time, the building occupants

fill the digital thermal comfort survey, which is displayed on a new dashboard, separate from the visualization dashboards to prevent the current environmental data from influencing the survey responses. The layout of the web interface, which includes the real-time charts and the digital thermal comfort survey, is shown in Figure 3. The digital thermal comfort survey is presented in the following subsection.

## Digital thermal comfort survey

The digital thermal comfort survey is designed to collect the data required for a complete thermal comfort assessment with minimal effort of the building occupants. To collect data with the digital thermal comfort survey, the building occupants obtain a personal link to the web interface (Figure 3). The web interface can be accessed from personal computers or from mobile devices, as long as the device is connected to the local network created by the IoT gateway. Connecting to the IoT gateway requires authentication rights, which adds a layer of security to the system.

The digital thermal comfort survey includes three types of measurements: Personal parameters, subjective measures and behaviors. First, two personal parameters are taken from the data provided by the building occupants, i.e. clothing insulation (CLO) and activity types or metabolic rate (MET), which are required to calculate the PMV and PPD indexes. Second, three subjective measures are integrated, (i) thermal sensation values that describe how the building occupants would rate their feeling on the 7-point thermal sensation scale, (ii) values that indicate how the building occupants rate their own productivity, and (iii) the thermal preference regarding the environment, i.e. warmer, cooler, or non-changing environment. Third, the building occupant behavior is captured in the survey by four further parameters, (i) the state of windows, (ii) the state of shades, which can both be opened or closed, (iii) the use of fans and (iv) the current use of lighting.

The data captured by the survey is merged with the environmental data, continuously collected by the thermal comfort stations. All data is automatically stored in a file on the server, which can only be accessed by entering a username and password. One file is created for each thermal comfort station, adding new data in a new line of the file. A timestamp is added for each new row of data in the file, creating times series datasets that synchronize the environmental data with the survey results. The datasets may be exported and analyzed for further processing and analysis. In the following section, the field validation test devised to determine the user-friendliness and performance of the thermal comfort monitoring system and the analysis of the data collected during the test are described.

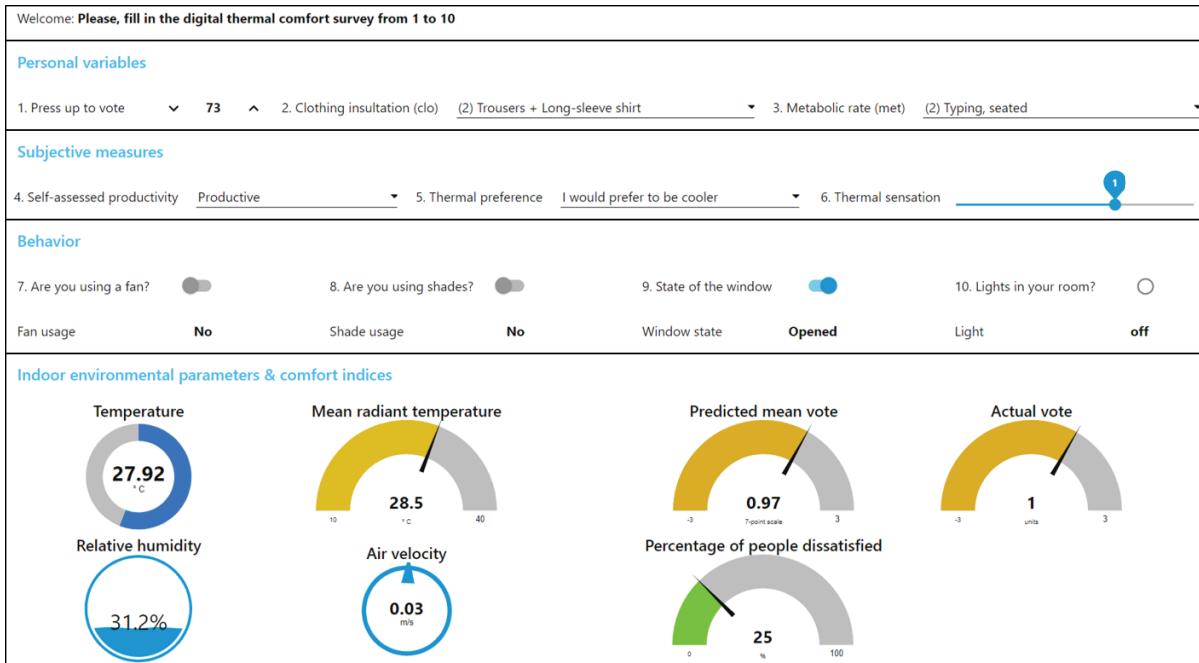


Figure 3: Dashboard of the web interface, including real-time charts of thermal comfort parameters and the digital thermal comfort survey in one window

## Field validation test

To validate the user-friendliness and performance of the automated thermal comfort monitoring system, a field validation test is conducted in an office environment using (1) environmental parameters measured by the thermal comfort stations and (2) feedback received from the building occupants entered through the digital survey. First, the results of the field test and the data collection are statistically analyzed. Next, the PMV index calculated on the sensor nodes is compared with the actual thermal sensation votes, or actual votes, of the building occupants, to assess the suitability of the PMV model. Finally, the state of the window (opened and closed) in the office environment is related to the air temperature values, to validate the capability of capturing the interaction of the building occupants with the building environment.

### Test setup

Five thermal comfort stations are calibrated in a climate chamber and then placed in five offices to measure environmental parameters at 5-second intervals. In addition, each person taking part in the field test is assigned a dashboard to complete the digital survey. An IoT gateway establishes a secure local network, in which the thermal comfort stations and the server are interconnected. The location of the thermal comfort stations in the office environment as well as the server and the IoT gateway are shown in Figure 4.

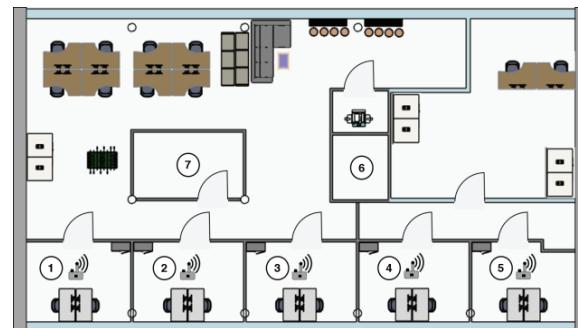


Figure 4: Setup of the field test: (1) to (5) comfort stations, (6) IoT gateway, (7) server

### Results and discussion of the field validation test

During the field validation test, a total of 14,880 measurements of the environmental parameters have been collected over a one-month period, and the building occupants have voted 260 times. In addition, outdoor temperature, rainfall, and solar energy have been obtained from external sources. Using descriptive statistics, Table 1 summarizes the results of the data collection for all thermal comfort parameters, including minimum, mean, and maximum values as well as the standard deviation (SD). The averages of the PMV index and the averages of actual vote values, both expressed in the ASHRAE 7-point scale, are highlighted.

Table 1: Descriptive statistics for the thermal comfort stations

Variable	Min.	Mean	Max.	SD
Air temp (°C)	23.95	27.15	29.43	1.65
RH (%)	23.30	27.82	33.25	5.94
MRT (°C)	10.84	26.82	35.13	2.66
Air vel. (m/s)	0.03	0.07	1.21	0.17
MET (met)	1.10	1.12	1.14	0.07
CLO (clo)	0.75	0.76	0.81	0.15
PMV (-)	<b>-1.62</b>	<b>0.72</b>	<b>2.64</b>	<b>0.68</b>
AV (-)	<b>0.41</b>	<b>0.71</b>	<b>0.91</b>	<b>0.60</b>

The actual votes quantify the subjective thermal sensations on the 7-point-scale that the building occupants have entered via the digital thermal comfort survey. As can be seen from Table 1, the mean value of the PMV index, taken from the sensor node calculations, is 0.72 and the mean value of the actual votes, taken from the building occupant feedback, is 0.71. The difference of  $\delta_{Mean} = 0.01$  indicates that the PMV index, calculated on the wireless sensor nodes, accurately estimates the actual votes, entered through the digital survey by the building occupants. On the other hand, the average of the minimum values of the PMV index is -1.62 and the average of the minimum values of the actual votes is 0.41 ( $\delta_{Min} = 2.03$ ); the average of the maximum values of the PMV index is 2.64 and the average of the maximum values of the actual votes is 0.91 ( $\delta_{Max} = 1.73$ ). It can be concluded that the PMV index, for the conditions in this study, serves as a good model as long as the thermal sensation is close to 0 (i.e. neutral thermal sensation), but the PMV index does not estimate well at extreme thermal sensations (i.e. values closer to -3 and +3).

To assess the suitability of the PMV model for each building occupant, the PMV index and the actual votes are examined in more detail. Figure 5 shows the daily averages of the PMV index (blue) and the actual votes (orange) of one building occupant (here comfort station CS01) for a two-week observation period.

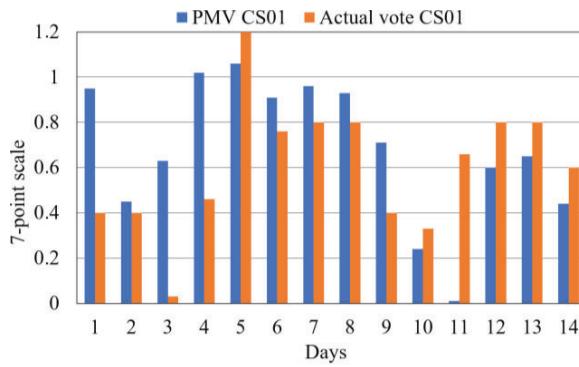


Figure 5: Comparison of the PMV index (blue) and the actual votes (orange) of one building occupant for comfort station CS01

In addition to study the suitability of the PMV index, the data collected from the digital survey is analyzed. Figure 6 shows the air temperatures measured by the thermal comfort stations (CS01 ... CS05) over the course of a regular working day. By opening the windows in the room where CS04 is placed, the air temperature drops significantly. When the windows are closed, the temperature rises accordingly, which is characterized by the dips and peaks in Figure 6. Similar dips and peaks, attributed to opening and closing the windows, are observed for all thermal comfort stations. In conclusion, the thermal comfort monitoring system proposed in this paper serves as a technical basis to collecting and visualizing environmental data, for screening the interaction of building occupants with the environment, and for identifying the personal behavior of each building occupant. Moreover, knowledge on window, shades, and light states may be used to further investigate the efficiency of HVAC systems or to, for example, send alerts when rooms have not been ventilated for defined time periods, e.g. to comply with Covid-19 regulations.

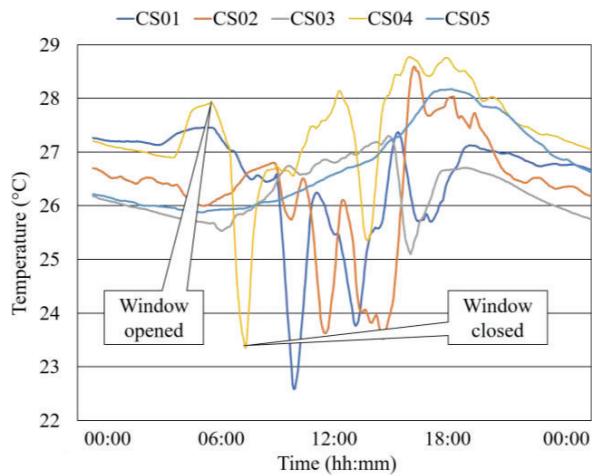


Figure 6: Air temperature recorded during one day with dips and peaks, attributed to the window states (opened/closed)

## Summary and conclusions

This paper has presented an automated thermal comfort monitoring system, which builds upon a four-layer IoT architecture, on cost-efficient hardware components, and on embedded software applications. The system attempts to minimize the data collection effort while maximizing the amount of feedback received from building occupants, continuously monitoring thermal comfort and automatically structuring thermal comfort data for further analysis. The automated thermal comfort monitoring system, which includes thermal comfort stations and a digital survey, has proven to increase data collection over time. Moreover, automating data collection reduces errors known from traditional paper-based surveys, caused by manual data processing and data integration.

A field test has been conducted to validate the user-friendliness and performance of the automated thermal comfort monitoring system by looking at the number of times the building occupants have voted and by testing the

suitability of the PMV index for the studied environment, respectively. The results of the field test show that the automated thermal comfort monitoring system continuously and reliably collects thermal comfort data over long periods of time. The digital survey has been filled 260 times by five building occupants, corroborating the user-friendliness of the system. The system may support research in the field of thermal comfort by further exploring the interactions between people and buildings and the well-being of the building occupants. Furthermore, the system is able to prove the suitability of thermal comfort models, such as the PMV model, by comparing the results of the models with actual votes provided by building occupants through the digital thermal comfort survey. The building occupant behavior is also captured in the survey by means of four parameters, (i) the state of windows, (ii) the state of shades, (iii) the current use of fans, and (iv) the current use of lighting.

This paper has exemplarily presented results from a one-month study of the thermal comfort monitoring system; however, the system is designed to continuously record and analyze data over an extended period of time. Further results obtained from this ongoing study are expected to be presented in the future. In addition, in future work the automated thermal comfort monitoring system may be used in conjunction with control systems, such as humidifiers, HVAC systems, and automatic shades, via actuators to expand the potential in building automation. Furthermore, lightning, noise, and air quality sensors may be added to monitor the overall comfort of building occupants in indoor spaces.

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## References

ASHRAE, 2020. ASHRAE Standard 55-2020. Thermal Environmental Conditions for Human Occupancy. American Society of Heating, Refrigerating and Air-Conditioning Engineers, USA.

Choi, J.-H. & Yeom, D. (2017). Study of data-driven thermal sensation prediction model as a function of local body skin temperatures in a built environment. *Building and Environment*, 121, pp. 130–147.

de Dear, R. & Brager, G.S. (1998). Developing an adaptive model of thermal comfort and preference. *ASHRAE Transactions*, 104(1), pp. 145–167.

Demanega, I., Mujan, I., Singer, B.C., Andelković, A.S., Babich, F. & Licina, D. (2021). Performance assessment of low-cost environmental monitors and single sensors under variable indoor air quality and thermal conditions. *Building and Environment*, 187, 107415.

Dragos, K. & Smarsly, K. (2022). An embedded physics-based modeling concept for wireless structural health monitoring. In: Proceedings of the Eighth International Conference on Structural Engineering, Mechanics and Computation (SEMC 2022). Cape Town, South Africa, 09/05/2022.

Dragos, K. & Smarsly, K., (2017). Decentralized infrastructure health monitoring using embedded computing in wireless sensor networks. In: Sextos, A. & Manolis, G. D. (eds.). *Dynamic Response of Infrastructure to Environmentally Induced Loads*, pp. 183-201. Cham, Switzerland: Springer International Publishing AG.

Dragos, K. & Smarsly, K. (2016). A hybrid system identification methodology for wireless structural health monitoring systems based on dynamic substructuring. In: Proceedings of the SPIE Smart Structures/NDE Conference: Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems. Las Vegas, NV, USA, 03/24/2016.

Fanger, P.O., 1970. Thermal comfort. Analysis and applications in environmental engineering. McGraw Hill Company, New York, USA.

Fitz, T., Theiler, M. & Smarsly, K. (2019). A metamodel for cyber-physical systems. *Advanced Engineering Informatics*, 41, 100930.

Graham, L.T., Parkinson, T., Schiavon, S., 2021. Lessons learned from 20 years of CBE's occupant surveys. *Building & Cities* 2(1), pp. 166–184.

Kimmling, M. & Hoffmann, S. (2019). Behaglichkeitsmonitoring – flächendeckend und kostengünstig mit der Sensorstation CoMoS. *Bauphysik*, 41(2), pp. 111–119.

Lamberti, G., Fantozzi, F. & Salvadori, G. (2020). Thermal comfort in educational buildings: Future directions regarding the impact of environmental conditions on students' health and performance. In: 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe). Madrid, Spain, 06/09/2020.

McCartney, K.J. & Fergus Nicol, J. (2002). Developing an adaptive control algorithm for Europe. *Energy and Buildings*, Special Issue on Thermal Comfort Standards, 34(6), pp. 623–635.

Mthunzi, M., Alsaad, H., Voelker, C. & Smarsly, K., (2019). An ultra-low-cost thermal comfort monitoring station. In: *Bauphysiktage* in Weimar: Weimar, Germany, 09/25/2019.

Nicol, F., Humphreys, M., Roaf, S., (2012). *Adaptive thermal comfort: Principles and practice*, 1st ed. Routledge, London, UK.

OpenJS Foundation, (2023). Node-RED [WWW Document]. URL: <https://nodered.org> (accessed 6.15.22).

Parkinson, T., Parkinson, A. & de Dear, R. (2019). Continuous IEQ monitoring system: Context and development. *Building and Environment*, 149, pp. 15–25.

Peralta Abadía, J.J., Walther, C., Osman, A. & Smarsly, K. (2022). A systematic survey of Internet of Things frameworks for smart city applications. *Sustainable Cities & Society*, 83, 103949.

Salamone, F., Belussi, L., Danza, L., Ghellere, M. & Meroni, I. (2015). Design and Development of nEMoS, an All-in-One, Low-Cost, Web-Connected and 3D-Printed Device for Environmental Analysis. *Sensors*, 15(6), pp. 13012–13027.

Sanguinetti, A., Pritoni, M., Salmon, K., Meier, A. & Morejohn, J. (2017). Upscaling participatory thermal sensing: Lessons from an interdisciplinary case study at University of California for improving campus efficiency and comfort. *Energy Research & Social Science*, 32, pp. 44–54.

Sheikh Khan, D., Kolarik, J. & Weitzmann, P. (2021). Occupants' Interaction with an Occupant Voting System for Thermal and Indoor Air Quality Feedback – Case Studies in Office Spaces. *Frontiers in Built Environment*, 7, 643630.

Tomat, V., Ramallo-González, A.P. & Skarmeta Gómez, A.F. (2020). A Comprehensive Survey about Thermal Comfort under the IoT Paradigm: Is Crowdsensing the New Horizon? *Sensors* 20(16), 4647.

Van Hoof, J. (2008). Forty years of Fanger's model of thermal comfort: comfort for all? *Indoor Air*, 18(3), pp. 182–201.

Zang, M., Xing, Z. & Tan, Y. (2019). IoT-based personal thermal comfort control for livable environment. *International Journal of Distributed Sensor Networks*, 15(7), 1550147719865506