Improving indoor environmental quality through applying a window controller; a machine learning approach

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Abstract
People spend 90% of their time indoors, and this fact highlights the importance of Indoor Air Quality (IAQ) in living, working, and educational environments. In today's smart buildings, thermal comfort is directly related to indoor air quality and indoor environmental quality (IEQ), which in turn depends on weather conditions such as air velocity, solar heat gain, and relative humidity. IAQ improvement is obtained by different methods of controlling the parameters of the internal conditions in buildings. The effect of IAQ on thermal comfort and occupant's function is undeniably intertwined with one another. This research aims to find the relations between IAQ parameters and occupant's behaviour and preferences using a smart controller for windows. The study attempts to realize the proposed window controller's accuracy and affordability to assess IAQ parameters impacted by occupant's autonomy via availing of one of the most effective deep learning techniques, Artificial Neural Network (ANN). This study is conducted in an educational building.

Key Innovations
• Designing a smart, efficient window controller with better prediction accuracy and speed.
• Personalized window scheduling for each occupant based on their behavioural pattern.
• Creating an affordable, easy-to-use system for traditional buildings with no or insufficient air handling units.
• Applying Artificial Neural Network as a powerful tool for enhancing the controller performance.

Practical Implications
This paper could benefit residential buildings and small-scale tertiary sector buildings with no or insufficient air conditioners to meet IAQ parameters requirement and provide a much more affordable yet accurate window controller for most users and occupants.

Introduction
Dependency on heating, cooling, and air conditioning facilities has led to increased energy use. Almost 50% of the building's energy is used to keep indoor health and thermal comfort parameters stable (Yang, Yan, & Lam, 2014). Simultaneously, acquiring a healthy indoor air quality (IAQ) and improving building energy efficiency, especially tertiary sector buildings with low occupancy interference compared to residential sector, is a significant challenge. Natural ventilation as a non-energy using solution in buildings plays a crucial role in cutting energy consumption. In winter, heating energy is on high demand, mostly when the warm indoor air is replaced by cold outside air due to overheating or bringing fresh air into the building (Santos & Leal, 2012). The indoor comfort temperature in winter is expected to be higher than that of the outside which leads to increased heating energy. Bringing fresh air in and replacing the indoor polluted air, opening windows plays a key role on IAQ and thermal comfort. Window plays a vital role in letting the airflow inside and outside the space. In this research, a novel approach is presented to implement a window controller that interacts with a human a controller for providing IAQ in the building.

Literature review
Window opening patterns and other parameters have been discussed with a predictive model to figure out the effect of the building design in diverse climates in China (Yin, Zhang, Yang, & Wang, 2010). Another study in Shenyang residential buildings suggests that opening windows for less than 10 min with small and reasonable sizes through one-side ventilation helps winter air change rate (Huang, Feng, Li, & Yu, 2014). A research study in Germany investigated the drivers which lead occupants to open or close the windows (Calì, Andersen, Müller, & Olesen, 2016). According to the Covid-19 pandemic, the importance of natural ventilation in buildings has been risen as a practical approach to reduce the virus concentration in indoor spaces. In the wake of Covid-19 limitations, ASHRAE has suggested the air change per hour (Machairas, Tsangrassoulis, & Axarli) value of 6 for offices and classrooms. For Iran, a recent study conducted in the University of Tehran (Mokhtari & Jahangir, 2020) found out that occupant's behavior has a substantial impact on both energy consumption and Covid-19 infection in winter. Moreover, this research also highlights that the higher air change rate in a building will decrease the number of people infected, but on the other hand increases the energy consumption of the building. Also, air change rate of 2.8 per hour has been suggested as an effective value for ACH in educational buildings in Iran.

Machine learning Methods
Different methods have been used for controlling windows toward reaching a better IAQ in buildings.
**Model Predictive Control (MPC) and Reinforced Learning (RL) models among all the conducted models have shown improvement in non-linear systems with uncertain dynamics that require extrapolative and adaptive strategies for control (Yang et al., 2014). Artificial Neural Network (ANN) has been successfully deployed to model the building’s thermal behavior in previous studies (Jafarinejad, Erfani, Fathi, & Shafii, 2019). Among machine learning techniques incorporated in the field of control, ANN is a fast responsive model that benefits from mapping the non-linear structure of both inputs and outputs and is also reliable for real data.**

**Indoor air quality factors**

The IAQ factors affecting occupants in a space are mainly temperature, Relative Humidity (RH), Carbon Dioxide, VOCs, Particulate Matter (PM), Formaldehyde, Carbon Monoxide, plus infectious disease concentration. In Figure 1, parameters that trigger the occupant to open the window have been depicted. Other than these factors, eighteen critical variables have a direct or indirect effect on the IAQ of a space, which are named below with respect to their importance; outdoor temperature, wind velocity, outdoor relative humidity, outdoor contaminants concentration, room dimensions, ceiling height, total surface area, infiltration, radiant temperature, surface temperature, indoor relative humidity, volumetric flow rate (natural, mechanical, infiltration), indoor temperature, air density, contaminants generation/deposition/removal rates, number of occupants, exposure time, and air exchange rate (Ma, Aviv, Guo, & Braham, 2021). Outdoor and indoor temperature, along with radiation on the surface are the most influential parameters on thermal comfort alongside RH and CO₂ concentration. RH could affect thermal comfort (ANSI/ASHRAE Standard 55-, 2013; Fanger, 1970; Wolkoff, 2018), IAQ discernment (Fang, Wyon, Clausen, & Fanger, 2004; Rupp, Vásquez, & Lamberts, 2015), occupant well-being (Fang et al., 2004; Wolkoff, 2018), and energy consumption (Wan, Yang, Zhang, & Zhang, 2009; Yang et al., 2014).

**Thermal sensation in human brain**

“Thermal comfort is a condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation” (ANSI/ASHRAE Standard 55-, 2013; Rohles, 2007). The human brain works like a smart thermal sensor and controller. Having perceived feelings of cold or physical display of coldness through shivering or goosebumps, nerves along with hormones serve as neurotransmitters and feedback the control system by developing reactions such as goosebumps, shivering or sweating; the body automatically reacts to negative thermal stimuli. In this research, the human body feedback is used to sense their feeling of discomfort so as to open or close the window.

Ascribed to some accuracy drawbacks of adaptive models (Han et al., 2007; Ioannou, Itard, & Agarwal, 2018; Khan & Pao, 2015), and limitation of the devices and time, instead of measuring other thermal comfort and IAQ factors with sensors, the occupant sense of discomfort or comfort has been chosen as the main parameter of comfort detection, which extends efficiency and accuracy.

Different models for providing the best IAQ condition in a building have been used in control schemes, including support vector machine (S. Chen, Mihara, & Wen, 2018; Shan, Yang, Zhou, & Chang, 2019; Zhao, Lasternas, Lam, Yun, & Loftness, 2014), neural networks (Ayata, Arcakhoğlu, & Yıldız, 2007; Machairas et al., 2014), logistic regression (Daum, Haldi, & Morel, 2011), Gaussian process (Cheung, Schiavon, Gall, Jin, & Nazaroff, 2017). Moreover, reinforcement learning techniques are vastly utilized for providing IAQ within buildings (Appice et al., 2015; Y. Chen, Norford, Samuelson, & Malkawi, 2018). The machine learning techniques’ predictive accuracy in such a control application was reported 17–40% higher than classical adaptive models. Also, the adaptive comfort metric is not accurate when T_{out} is colder than 10 °C and hotter than 33 °C (Halawa & Van Hoof, 2012). Different machine learning methods for window operations have been conducted, including Q-learning, SRASA, or Markov decision processes (MDPs). In another research, Pan et al. (Pan et al., 2019) used the Gaussian distribution model, which resulted in higher prediction accuracy than the logistic regression model. This research uses an ANN algorithm to predict the percentage of window openings.

**Figure 1: Indoor Air Quality (IAQ) features that cause human interaction to open the window.** (Color saturation is based on the importance of the factors which we considered in this research)

**Figure 2: The main Thermal comfort assessment parts in the human brain**

Ascribed to some accuracy drawbacks of adaptive models (Han et al., 2007; Ioannou, Itard, & Agarwal, 2018; Khan & Pao, 2015), and limitation of the devices and time, instead of measuring other thermal comfort and IAQ factors with sensors, the occupant sense of discomfort or comfort has been chosen as the main parameter of comfort detection, which extends efficiency and accuracy.
during the day while the occupants are present in the room at the typical working hour of a tertiary sector building. Since this work is conducted in an educational building and in particular in a room with a limited number of occupants having sedentary activities, the required standards and guidelines for IAQ are sorted out in Table 1 to 2.

Table 1- ISO 7730 recommended $T_{opt}$ for occupants doing sedentary activities

<table>
<thead>
<tr>
<th>Season</th>
<th>Clothing insulation</th>
<th>Metabolic rate</th>
<th>Optimal Top (°C)</th>
<th>Top range (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Summer</td>
<td>0.5</td>
<td>1.2</td>
<td>24.5</td>
<td>23-26</td>
</tr>
<tr>
<td>Winter</td>
<td>1.0</td>
<td>1.2</td>
<td>22</td>
<td>20-24</td>
</tr>
</tbody>
</table>

Table 2- ASHRAE 55 recommended $T_{opt}$ for occupants doing sedentary activities at 50% RH and average air velocity less than 0.15 m/s

<table>
<thead>
<tr>
<th>Season</th>
<th>Clothing insulation</th>
<th>Metabolic rate</th>
<th>Optimal Top (°C)</th>
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<td>0.5</td>
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<td>24.5</td>
<td>23-26</td>
</tr>
<tr>
<td>Winter</td>
<td>0.9</td>
<td>1.2</td>
<td>22</td>
<td>20-23.5</td>
</tr>
</tbody>
</table>

Occupant as the critic

Data collection from the environment has always been a challenge; the common process of logging and reading data has been carried out with sensors by applying different sensors in different building scenarios. In recent years the Internet of things has been used for assessing IAQ parameters through connecting a network of things from sensors to actuators (Sepasgozar et al., 2020). However, the challenge of the expenses, maintenance, and calibration process of such sensors have caused some implications while employing them. Many sensors are not yet affordable for collecting data in a building. Reading the sensor data can add to the complexity and raises the expenses which are not cost-effective in tertiary sector buildings. In this research, the challenge of sensor affordability is tackled via low-cost sensors, which required regular calibration that can be concluded as another problem itself (Parkerin, Parkinson, & de Dear, 2019). Given that indoor spaces are diverse, the location of the sensors in buildings interpolating the data still bring some challenges (Jin, Liu, Schiavon, & Spanos, 2018). Based on a review paper conducted by Chojer et al. (Chojer, Branco, Martins, Alvim-Ferraz, & Sousa, 2020), 35 papers out of all the related papers published from 2012 to May 2019 in the following databases of Science Direct, IEEE Xplore, and Scopus were analyzed regarding the advancement on low-cost IAQ devices. The estimated cost of the devices was varied between $54 to $2700 including the maintenance and installation costs, which was mostly neither affordable nor easy to use in the developing countries. The location of temperature sensors in the room is shown in Figure 3. The wholesome description and cost of sensors required in the room to collect ambient data are included in Table 3 and Table 4 respectively, if one was supposed to construct a more elaborate controller.

Figure 3. the placement of applied sensors in the selected room

Table 3: The sensors required in the office room to collect ambient data and their price

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Price per unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waterproof DS18B20 Digital Temperature Sensor</td>
<td>6.9$</td>
</tr>
<tr>
<td>Analog Infrared CO2 Sensor</td>
<td>58$</td>
</tr>
<tr>
<td>I2C Oxygen Sensor</td>
<td>53.9$</td>
</tr>
<tr>
<td>Analog Sound Sensor</td>
<td>4.4$</td>
</tr>
<tr>
<td>Hydrogen Sulphide Gas Sensor</td>
<td>55.4$</td>
</tr>
</tbody>
</table>

Table 4: The accuracy, resolution and frequency of the sensors

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Accuracy</th>
<th>resolution</th>
<th>Data Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waterproof DS18B20 Digital Temperature Sensor</td>
<td>±0.5°C</td>
<td>12 bits</td>
<td>750ms</td>
</tr>
</tbody>
</table>

Last but not least, one of main challenges in terms of asserting the IAQ within a space is to convert the qualitative thermal sensations of the occupant to quantitative feedbacks through a knowledge based rules that can modify the controllers optimal response (Alcalá, Benítez, Casillas, Cordón, & Pérez, 2003). This fastidious task requires a considerable load of sensors and programming. Jayathissa et al. (Jayathissa, Quintana, Abdelrahman, & Miller, 2020) logged human feedback as an instant sensor by developing a smartwatch for individual data collection; the main novelty in their work was to show that even in the absence of IAQ sensors, prediction for comfort-based tendencies can be precise if intensive and sufficient longitudinal data is collected from occupants. Moreover, Porter et al. (Porter, Whitcomb, & Weitzer, 2004) found out that the misrepresentation in responses caused by fatigue while answering the survey can affect the results of the questionnaire. In addition, using questionnaires, such as who to and what to ask, and how to analyze the data will add to the difficulty of the whole process (Heinzlinger, Schiavon, Webster, & Arens, 2013). A large amount of instant feedback from a single person in the room delivers the ability to understand the tendencies for IAQ comfort preferences in order to open or close the window. In this paper, instant human feedback as the reliable and fast responsive sensor to get
the senses of air quality changes in real-time has been considered. The nervous system of a human gathers information of the thermal sensation and converts it into feedbacks to revise the controller’s response. Thereafter, the sensation will play the role of a critic and revise the signal generated by the controller to further train the ANN algorithm and put it in more alignment with the occupant’s preferences.

Method

The gap in the reviewed literature is the lack of occupant's preferences as the leading individual factor of IAQ sensation figure that responds as a critic to modify the controller signal in order to open or close the window. In this paper, it has been emphasized on the occupant's role as a human sensor and the focus was on the health factors of IAQ in the rise of the Covid-19 pandemic. Window opening percentage has been measured via applying a window controller that works with ambient sensors and human as a decision-maker, which serves as a critic. This research is conducted in Shiraz, one of the cities located in the southern part of Iran, and in the school of mechanical engineering of Shiraz University. The data was gathered from an office room in the aforementioned building with the maximum capacity of one person as the faculty member and with some visitors considered as guests in our algorithm. In Köppen climate classification Shiraz is classified as a tropical and subtropical steppe climate. The average temperature of this city is 16.85 degrees, and it's maximum and minimum temperatures are 43.2 °C and 4.74 °C, respectively. This research was conducted from late December to mid-January. The last two semesters were attended online as a result of Covid-19 safety protocols for educational buildings. This transition led to some changes in the whole dynamic of the real data collection accompanied by occupants. This transition, along with restrictions, triggered the idea of IAQ assessment with limited people in a room, so that the health and well-being of the occupants will not be compromised and IAQ improvement after the pandemic crisis will be added to such places. The occupant present (working) in the room decides whether the thermal condition is poor or not on the account of his own sense of ambient understanding. At first, an indoor and outdoor temperature sensor for acquiring the environmental data is implemented. This control system uses instant human preferences as inputs to decide the opening percentage of the window in winter. Along with collecting temperature data, the controller picks hour and date from a calendar and uses the historical environmental data instead of applying solar irradiance sensor, which makes the controller more affordable. The hour of the day, for instance, affects the data in a matter of noise detection, temperature, and relative humidity. Since one of the main aim of this paper is to come up with a cost-effective controller no CO2 sensor was incorporated in the control scheme, yet the CO2 concentration of the room was tracked with a TESTO monitoring system, which never exceeded the standard level in the room. It is on the grounds of only one occupant present in the room and the high air infiltration rate of the envelope.

The Covid-19 conditions

Given the Covid-19 safety protocols, every room has to be occupied with one person at a time, and the working hours for staffs differ throughout the day. Due to each window size different from each other, we implemented a micro-switch to control the window by considering humans as a sensor, which in turn reduces the system complexity and initial investment. Occupants ‘thermal sensation in the room determines whether the window should be opened or closed. The window located in the room is a sliding window, and the occupant controls the window opening percentage. This system was examined during winter, but the system is applicable during all seasons, especially in transition seasons when substantial levels of energy saving could be achieved by natural ventilation.

The window controller

The sequence through which the controller operates and is trained is first to consider the IAQ comfort factors based on the occupants’ preferences, the taking energy consumption reduction into consideration. The advantage of this controller is that it doesn't require many sensors, which can lead to a higher reliability and facilitates the implementation of the designed controller and mitigates complex coding compared to the other available window controllers. The ANN control algorithm sends commands, and an ultrasonic distance detection sensor realizes the percentage of the window opening. The controller consists of a processor, a driver, and an actuator. Table 5 enlists every element used with their approximate retail prices. It is worthwhile to mention that the sensor prices are lower in wholesale than in retail.

Table 5- The window controller devices and their price

<table>
<thead>
<tr>
<th>Controller device</th>
<th>Number</th>
<th>Price per unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mega2560 Arduino</td>
<td>1</td>
<td>24.95$</td>
</tr>
<tr>
<td>PC</td>
<td>1</td>
<td>&gt;150$</td>
</tr>
<tr>
<td>Waterproof DS18B20 Digital Temperature Sensor</td>
<td>2</td>
<td>6.95$</td>
</tr>
<tr>
<td>Micro-switch</td>
<td>2</td>
<td>1.55$</td>
</tr>
<tr>
<td>Analog Ultrasonic Sensor</td>
<td>1</td>
<td>4.95$</td>
</tr>
<tr>
<td>Counter sensor</td>
<td>2</td>
<td>15.99$</td>
</tr>
</tbody>
</table>

The controller has a reset switch that can return the statements when the Covid-19 restrictions are over in order to self-train itself and at the same time save multiple data. Three main scenarios as the current statement are defined. First, when the faculty member is out of the room and the window stay closed. Second scenario is when the faculty member is in the room whereas no guests is in the room. Third scenario is for the time when both the faculty member and the guest are in the room at the same time and the window must be opened. The three scenarios stated above are depicted in MATLAB in Figure 5 below.
Figure 5: The scenarios for window controller operation

This controller can also personalize occupant's patterns for up to three people and practice each pattern individually. Furthermore, this operable window controller is applicable to any window and is especially suitable for spaces where they are poorly conditioned or serviced by non-efficient air distributors. The window control system introduced in this paper is suitable for residential, office, and small commercial buildings. This controller cannot be used for spaces with special needs such as hospitals, because of a minimum number of sensors. By adding extra features to upgrade the system's complexity, this can be placed in more complexed buildings.

Considering the importance of outdoor noise and its indirect impact on the IAQ conditions, sound sensors should be used in certain places such as studios and hospitals or crowded urban areas. In buildings such as hospitals, air pollution should be considered as well, and more accurate complex sensors should be installed in addition to sound sensors to close the windows when outside conditions are adverse. Nevertheless, the impact of the closed window should be closely monitored in terms of increased air pollutants within the space. As mentioned earlier, this controller is mostly designed for spaces that are not capable of providing fresh air, such as buildings that only have a full-return-air system and lack fresh air supply systems. The designed controller works with a minimum number of sensors with fewer limitations on the sensor's location, more convenient installation by inexpert people, higher performance and better accessibility to the controller. In order to develop this controller in the future, sensors can be set up to detect continuous and irritating environmental noises such as construction work noise, which can be trained and added to the proposed algorithm for window operation. A temperature sensor is installed outside and another inside, along with two counter sensors to count the number of guests apart from the faculty member. The priority of opening and closing windows in the current pandemic situation has been given to Covid-19 safety protocols. Henceforth, for maximum air circulation in the space, windows should be open most of the time, and somewhat comfort and energy consumption should be sacrificed for this matter. Initially, the controller is trained in terms of energy consumption, which means if the outdoor air temperature is higher in the cold season of the year, the window opens and vice versa, when the temperature is colder in the hot season, it will command the windows to open. The personal preference of occupants in the room is taken into account in this controller. This means when the occupant is present, his personal preferences of thermal comfort become a higher priority, which is prioritized by coefficients of each parameter. Non-continuous data such as the momentary presence or short sounds are removed from the controller training system over a long period of time. Therefore, at the beginning of the office hour, the thermal comfort band of the occupant determines the opening and closing status of the window. Moreover, when the user is not present or temporarily leaves the space, the window would be closed for security reasons.

ANN training set

ANN's main inputs are the indoor temperature, outdoor temperature, the counter sensor, and the exact date and hour of the year. The main person residing in the room is a faculty member, and other persons paying a visit, who are mostly students are called guests. The importance of another person's presence in the room according to the Covid-19 protocols and the necessity of opening the window makes this a priority factor. In case of the guests' presence in the room, the window opens under any circumstances. Sequential options of the ANN algorithm training are listed below

2. Occupant's thermal comfort preferences

In the beginning, the algorithm is trained for the faculty member as the main resident and solely personalizes the data for the faculty member. Then in the second stage, data will be trained for the faculty member plus temporary presence of guests. The controller is located in one of the professors’ offices in the school of mechanical engineering at Shiraz University, where its window is located westwards and is exposed to direct irradiance. The street is located on the east side, and the building is located at a distance of 69 meters from the street. The building is far from the noise of the streets and the outside environmental factors such as air pollution, which resulted in fast training of the ANN model. The room windows are faced toward the west, which resulted in high-temperature concentration that is widely discussed in results’ section during afternoon up until evening. In the neural network training algorithm, the windows receive commands to be completely closed (0%) or fully open (100%). The ANN algorithm is written in MATLAB and has been implemented from December 26 to January 13.

Results

Three main scenarios, had happened as follows. The first scenario was when the resident occupant (faculty member) was not present in the room; therefore, no guests were allowed to be in the room, which led to closed windows all the time due to security restrictions. Figure

% This script calculates the window opening percentage
faculty member = input ('occupant’s presence based on sensor');
if faculty member == 0
    Window opening percentage = 0
elseif faculty member == 1
    if guest == 0
        date = input ()
        hour = input ()
        indoor temperature = input ()
        ambient temperature = input ()
calculate window opening percentage
    else
        faculty member >= 1
        if guest = 1
            Window opening percentage = 1
end

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6(a), 6(b), and 6(c) are a sample to depict the first scenario results. The horizontal axis shows hours of the day, left vertical axis shows indoor and ambient (outdoor) temperature fluctuations, and the right vertical axis shows the window opening percentage differed between 0 to 100%. As evident from Figure 6(a), on December 26, nobody has entered the room, so the window was closed all day. Considering the west-faced façade, the outside ambient sensor caught the highest air temperature from 14:00 PM to 16:30 PM. The indoor temperature is around 15 °C, which is below the comfort band for winter when no occupant is in the room the whole day. The same situation happened in Figure 6(b) on December 29 and 30, when due to security restrictions window was not opened (showed by the thick black line, which here is at 0 = completely closed). The second scenario accounts for the time when the faculty member is present in the room, but no guests (students) were present during the day. In this scenario as the sensors are logging the IAQ data every second (date, hour, indoor and outdoor temperature), the occupant feedbacks his decisions whether he is satisfied with the indoor air quality or not, which in return helps the control command to open or keep the window closed. In this instant, the faculty member has felt comfortable during his presence in the room. Therefore, his comfort was in concurrence with the controller’s command and the window remained closed up until 4 PM, the time he leaves his office. The CO₂ concentration for one person didn’t exceed over 800 ppm and remained in the comfort band as logged with a TESTO device due to improper airtightness. Occupant’s presence has been divided into two parts in two days, January 13 from 9:30 to 1, and January 7 from 18:00 to 21:30. Throughout these times, the outside temperature was lower than the indoor temperature, so the controller command aligned with occupants’ preference not to open the window (Figure 7(a) and Figure 7(b)). The third scenario shown in figure 8 is for the time when both the faculty member and guest(s) (could be more than 1) are present in the room, and for Covid-19 safety protocols, which is prioritized over all comfort consideration, the window was opened the whole time of their presence.

Figure 6: The temperature data collected from indoor and ambient (outdoor) temperature sensors during 6(a). December 26. 6(b). December 29 and December 30th and 6(c) on January 1 while the faculty member was absent

Figure 7: The window is closed during the occupant’s presence as he preferences to keep it closed due to lower outside temperature both on January 7 7(a) and January 13 7(b)

Figure 8: Faculty member and guest are present from 14:00 to 18:00 in the room, so for Covid-19 safety Protocols, the window opened during their stay

Conclusion

The ANN algorithm is trained based on the behaviour of individuals to capture the window opening pattern of the occupants in the room. IAQ inputs gathered from sensors and historical data were added to the training set by including date and time and the occupant’s comfort preferences (faculty member). In this work according to Covid-19 implications all the preferences of occupant’s thermal comfort were prioritised based on the health protocols. Three main scenarios affecting the window
operation have been considered in this research and the ANN model successfully detected the patterns and saved it as a base model for personalized application of the controller. The occupant will have his own pattern of window opening schedule in their room and factors of IAQ can be added or removed and the training algorithm can update itself during occupant’s presence or any changes in their preferences. The results convey the effective performance and learning process of the controller and algorithm, respectively. This affordable and fair-performing controller for windows can be easily applied to traditional residential buildings, educational and office buildings. The Covid-19 implications enormously affected the learning process and preferences of the window opening in this experiment. The controller correctly detects the occupant’s situation and can be applied to any room dedicated to this faculty member since it can remember the trained data and personalize it for other spaces. This paper is a part of an ongoing project which will consider circumstances with different number of occupants in post-Covid-19. Also, other IAQ factors such as relative humidity will be measured for more accurate results. In this paper, indoor RH percentages have not exceeded the comfort band, so it hasn’t been put into the algorithm as a critical input. For future studies, short temporary changes affecting IAQ will be considered. In this paper, only continuous persistence changes in IAQ over time have been taken into account.

References


