Soft Digital Twin for IEQ enabling the COVID risk mitigation in educational spaces

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ABSTRACT

The importance of educational buildings' Indoor Environmental Quality (IEQ) is critically increased due to the COVID-19 pandemic. The need to protect occupants and preserve educational spaces where learning activities could proceed in attendance promotes the development of strategies to monitor and correct the indoor conditions on a real-time basis. The adaptability of building spaces aimed at optimizing comfort and users' health and safety may be connected to a Digital Twin (DT) and a Building Management System (BMS), enabling data collection and diagnostic to trigger corrective actions on indoor air conditions. A soft DT, i.e., one based on a Building Information Model (BIM) with a low Level of Geometry (LOG) coupled with an IoT network, is proposed to collect results from IEQ monitoring in educational spaces. The DT is aimed to measure the CO_2 emissions and Particulate Matter (PM) pollutants, balancing the need for increased ventilation rates to dilute contaminants and thus reduce the infection risk and the control of comfort conditions. Besides the DT, a stand-alone particulate matter sensor has been used to verify the possible inverse influence of the increased ventilation on indoor pollutants coming from outside. This approach enables pupils to learn in a healthy and protected environment.

KEYWORDS

Digital Twin; Indoor Environment Quality; Educational Buildings; Internet of Things; environmental sensors; Building Management System; SARS-CoV-2infection

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INTRODUCTION

The concerning pandemic scenario occurring in 2020, due to coronavirus infection 2019 (COVID-19), has been triggered by a severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [1]. With the intent to react to COVID-19, many countries adopted a mixture of control and mitigation actions to defer significant flows of patients and to smooth the hospitalization rate while protecting the most vulnerable people from the contagion, including aged patients and elderly persons affected by comorbidities. As acknowledged by the CDC, SARS-CoV-2 transmission occurs through three non-exclusive modes of exposure to infectious respiratory fluids. Among these modes, there is the inhalation of contagious small fine droplets and aerosol particles [2]. These tiny particles persist in the air over time and distance, especially in poorly ventilated environments [3]. This evidence led to increasing ventilation rates together with social distancing and intermittent attendance within the indoor environments. However, controlling the most suitable ventilation rate for different buildings uses not always sound like a simple challenge. Although mechanical ventilation can improve the setting's conditions, the possibility of failure due to the maintenance procedures and filter exchange cycles stays as a critical point. In naturally ventilated buildings, the ventilation rate determined by the IEQ standards is frequently disregarded, and increased CO_2 concentrations are detected in many educational facilities. It takes around 4 minutes for the small droplets in the air to be halved with no ventilation, while for mechanical ventilation, the same result in the decrease of respiratory particles could be achieved in 1.4 minutes [4]. In an indoor space with a door and a window opened, the amount is halved after 30s, considerably faster than in the traditional poorly ventilated and unventilated rooms [5]. Hence, a critical approach to dropping the concentrations of indoor air pollutants or contaminants, including any viruses that could be detected in the air, increases the ventilation rate. The CO_2 concentration, which can be used as an indicator of indoor air quality (IAQ), is commonly adopted to estimate the number of people and enhance a healthy indoor environment. Standards provide the thresholds of CO_2 concentration emitted by users breathing in an indoor space, preserving people's wellbeing and attention, and, in educational buildings, the learning performance. CO_2 sensors can support the ventilation procedure and the air change practice showing the level reached by the concentration in the air (number of units of mass of a contaminant per million units of the total mass is measured in ppm, namely part per million).

Good ventilation in classrooms is crucial to reduce concentration and filter out respiratory particles to shrink the infection risk, which is directly related to the vast amount of respiratory particles that are emitted and concentrated in a building room by users' activities such as breathing, talking, singing, coughing and sneezing [6], [7]. Nevertheless, in a cold climate, in the winter period, when the infection risk is higher, opening windows for ventilation, although helpful, can be hardly accepted by users because would lead to an increase of thermal losses for the introduction of outdoor cold air in the heated thermal zones requiring an extensive amount of new additional heating power. Ventilation is to be controlled as well as temperature and relative humidity, which are crucial parameters of users' comfort in buildings and can affect the diffusivity of the contamination risk. Increasing proofs from the investigations highlight how humidity can take part in the persistence of membrane-bound viruses, which is the case of SARS-CoV-2 [8], [9]. Thus, a consistent analysis about IEQ conditions aimed at containing the virus spread has been started monitoring temperature and humidity intertwined with CO_2 concentration, which remains the main parameter for the ventilation rate calculation. Even though the current ventilation standard assumed in healthcare and residential care facilities, based on ASHRAE 170-2017, defines an acceptable range of RH from 20% to 60%, preserving an indoor RH value between 40% and 60% (according to European comfort standards) may limit the spreading and diminish the survival of SARS-CoV-2 in buildings. Concurrently, this range minimizes the risk of mold growth and sustains hydration of the building occupants [10],

[11]. The punctual control and management of the IEQ and the ventilation of indoor spaces can support the optimization of specific conditions. For that reason, IEQ monitoring has been planned and installed on an educational case study to provide data to the users in order to activate corrective strategies on temperature, humidity, and ventilation rate related to IEQ based on CO_2 and Particulate matter (PM) concentrations. The proposed approach aims to create a Soft or Quasi Digital Twin (DT) [12], [13], i.e., a building replica featured by a low level of geometrical information, that can gather real-time information from the indoor building spaces and analyse the data to crosscheck indoor air conditions, users' comfort and, last but not least, health hazards. The DT can support the decision-making processes to adapt the building spaces to determined target objectives (e.g., comfort, maintaining the parameters into the standard ranges; health, testing the users and storing the data with correct privacy and effectiveness; safety, minimizing the contamination risk). Risk calculation algorithms are connected to the data collection and delineate the indoor conditions, thus supporting the staff and the users in making decisions about ventilation, window opening, pollution, comfort adaptation, and many more. In the present research, the platform and the IoT infrastructure are described, and the data analysis is extensively reported and discussed to understand how to leverage IEQ data collection for this purpose.

METHODS AND TOOLS

The application of the Soft or Quasi DT approach to monitoring indoor IEQ and users' comfort and health hazard requires the definition of a proper methodology. The first step is defining IEQ parameters to be monitored in the considered indoor environment and defining synthesis performance metrics to be visualized through the Graphical User Interface (GUI). The list of parameters to be visualized from the interface is used as an input for the design of the interface and the identification of sensors to be used and their optimal localization in the environment to be monitored. After the IEQ sensors' installation, the data sets feed the soft DT, to be exploited to monitor the state of the indoor environment. The soft DT architecture is shown in Figure 1. In the proposed architecture, the physical domain, i.e., the school and the IEQ parameters of each room we are interested in monitoring, are acquired by the cyber domain, represented by the soft DT, through an intermediate cyber-physical domain. The cyber-physical domain starts with some electronic devices managing the monitoring parameters coming from the environment and transmit the information to the remote soft DT. The data transmission has been performed using the state-of-the-art Internet of Things (IoT) communication protocols [14]. As mentioned in the previous section, the soft DT limits the complexity of the required informative infrastructure concerning a complete DT solution, like the one in [15], which requires a careful correlation of the data generated by each sensor [16]. The structure of the soft DT is summarized at the top of Figure 1. The data generated by the cyber-physical domain are stored in a database (DB), which stores both the real-time data and any other metadata (e.g., the sensor's ID, the location of sensors, the monitored physical quantity). The data stored in the DB are then presented to the technicians responsible for the school monitoring through an interactive graphical interface. Automatic risk analysis algorithms elaborate the DT data to identify synthesis performance metrics to be presented to the operators. In the considered case, the soft DT infrastructure is hosted in the eLUX data centre, located in the University of Brescia. The part dealing with IEQ data is composed of a InfluxDB instance, a NoSQL DataBase (DB) used to store the sensors data, and a Grafana instance, a framework used to design a real-time dashboard. InfluxDB is a DB optimized to be interfaced to hundreds of thousands of IoT sensors, transmitting parallel data. The DB is interfaced to IoT sensors externally located to the campus of engineering of the University of Brescia through an MQTT broker, which is reachable from the public network. The Grafana framework offers services to easily design web-based dashboards, integrating real-time DB queries, fundamental analytics, and real-time alert system. The more complex analytics are performed by dedicated Python scripts, processing the data stored in the DB in real-time.

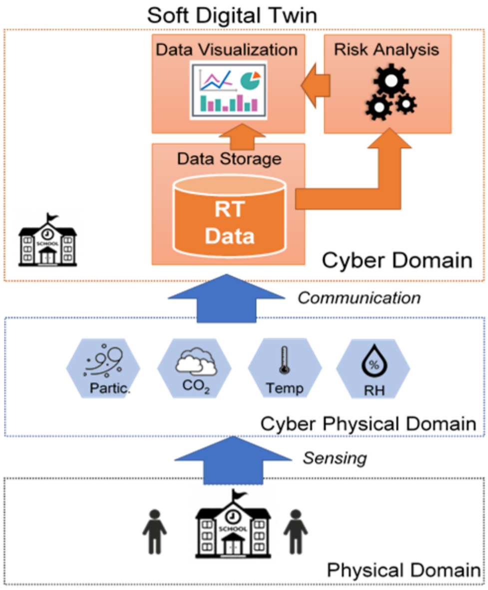

Figure 1. The architecture of the Soft-Digital Twin and its integration into the physical domain.

The building spaces have been sensorized and connected to a data visualization platform, and a test period of 20 days has been investigated to collect enough data about temperature, humidity, and CO_2 concentration in the target building to perform the intended analysis.
In order to control the indoor conditions and to monitor the daily trend of the variables, the sensors have been located across different classrooms, and a network of fourteen multi-purpose sensors have been deployed across the building spaces. The deployed sensor is the SAF TEHNIKA ARANET4, which is an innovative battery-powered stand-alone wireless sensor for monitoring CO_2, temperature, relative humidity, and atmospheric pressure in indoor environments. In Table 1, the sensor specifications are reported.

Table 1. Overview of the variables measured by the Aranet sensors and characteristics

Variable	Unit	Accuracy	Range
Temperature	°C	±0.4	0 - 50
Relative Humidity	%	±3	0% - 85%
Atmospheric Pressure	atm	±0.001	0.3 - 1.1
CO_2	ppm	0-2000: ±50 ppm or 3% of reading 2001-9999 ppm: ±10% of reading	0-9999

Each sensor transmits data every 2 minutes to an ARANET PRO Base Station using a wireless channel (Bluetooth or LoRa). The base station is connected to the Wi-Fi network of the building and pushes the collected data, through an MQTT link over the internet, to an InfluxDB instance hosted in the eLUX Laboratory data centre at the University of Brescia [17], [18]. The use of the MQTT protocol ensures an event-based communication, encrypted with SSL (Secure Socket Layer), without modifying the local firewall configuration and making the deployment easy, scalable and secure without the presence of highly trained ICT personnel. PM was measured using the SPS30 sensor from Sensirion AG connected to an Arduino board and installed in a custom-made 3D printed box. Its measurement principle is based on laser scattering and uses innovative contamination-resistance technology to enable high precision measurements. The PM measure can enhance the information about contamination risk as PM increases the risk of contracting the virus [19]–[21] since the protein that protects the organism from the damage caused by fine dust (precisely PM2.5) is the same one that favours the harmful action of the virus SARSCoV-2. To introduce this measure, a portable and customized PM sensor has been assembled and installed for a testing period of one week in two sample classrooms located in two different sides of the case study-related building, according to two different conditions analysed after the first monitoring campaign of 20 days in all the classrooms. The paper considers three sampled classrooms to represent each level. For the PM measuring, the monitoring campaign has been narrowed to two locations (i.e., street side and garden side) and two levels (i.e., nursery and primary school) where a significant increase of movement could be reported for students in the primary classroom. The nursery classroom lies on the street side, and this could lead to higher PM concentration coming from outside, but the users (the toddlers) are commonly more static, while the primary classroom is located on the garden side but with higher mobility of the students with the possibility to increase the indoor dust movement. The PM movable sensor has been equipped with a customized 3D printed case to protect the assembly in an environment where students might accidentally bump into the monitoring system. The sensor can measure mass concentration in a range from 0 to 1,000 $\mu g/m^3$. The Arduino board collects PM values every 30 seconds.

CASE STUDY

A school building in Milan, Northern Italy, has been used as a case study to test the methodology and collect data about the classrooms. The IoT network and the platform are collecting information about n. 14 classrooms to detect critical situations about IEQ and IAQ. Besides this limitation, the approach and results could be replicated for traditional school buildings on the whole national territory. There are 40,000 nationwide operated school buildings in Italy, with an average age of around 52 years; in two out of three cases, these buildings were built more than 40 years ago. In 60.2% of the cases, the construction date of the buildings is before 1976, when the first national energy-saving regulation [22] was issued as well as enforced (this means no mechanical ventilation, lacking envelope, and outdated HVAC system and subsystems). The case study building gets an old square three-floor courtyard building with small windows and a central distribution atrium or hall. The main characteristics of the selected three classrooms are shortly reported in Table 2. They are distributed on the borders with an internal corridor for the distribution; thus, single side ventilation apt to introduce the outdoor air seem viable, and the window and the classrooms doors could be opened. The pandemic situation forced the staff to reduce the mobility of the users in the school spaces to avoid contamination between different groups and to adopt ventilation patterns to increase air changes; therefore, a calculation of the ventilation time for each activity hour has been provided, and an intermittent and a constant ventilation patterns have been tested.

Three classrooms with different levels, ages of the students, location in the building's height, and facing the street and the garden have been equipped with the above-described sensors and used as testbeds for the experimental phase. The specifications of each sample classroom are summarized in Table 2.

RESULTS

During the period from December the 3rd to December the 23rd, around 180.000 data were recorded. The collected data cleaning process and the Exploratory Data Analysis (EDA), made before moving on to the next stage of analysis, produced the following results: a) indoor air temperature, b) relative humidity, and c) CO_2 concentration change during that time frame in the three monitored classrooms.

Table 2. Sensorized spaces in the case study school.

Classrooms	level	n. people	Age	Area	Windows	Window opening	Level	Side
			years	m^2	m^2	min/h		
Quarta A	elementary school	17/19	9-10	55.62	6	13	2nd	garden
M_Arancione	kindergarten	24/26	3-5	51.73	8	8	1st	garden
Mininfanzia	nursery school	24/26	0-3	43.99	7	12	ground	street

Remarkably, some huge peaks of CO_2 concentration and the three classrooms, despite differences in temperature and humidity, have similar CO_2 concentrations during the 20 days when the monitoring campaign was performed (Figure 3).
If only the data recorded during the school operation hours are examined, i.e., from Monday to Friday and from 7 am to 6 pm, the percentage of cases of CO_2 concentration, higher than the thresholds highlighted above, increases considerably. Table 3 shows that in the three classes, the percentage of cases above the first threshold, 600 PPM, is greater than 50%, with peaks above 80% in classroom "Quarta A".
Moreover, in this room, the percentage of cases in which the CO_2 concentration is greater than 1000 ppm, the second threshold, is not negligible, reaching more than 25% of the cases. This depicts a dramatic situation for the primary school students with a critical condition for their learning performance and a higher risk of contamination due to lack of ventilation. The ventilation is manually implemented in the classroom by opening the windows, and the Aranet sensors provide insight with a color code lighting trigged by CO_2 concentration. This configuration should enable a better ventilation pattern; however, the peaks are detected in all the classrooms. The calculation about the ventilation time to increase the standard air change of 2 V/h for educational spaces to 3 V/h has been proposed to the teaching staff, stretching the lecture time to 50 min and ventilating for 8 to 13 min the classroom (Table 3). This was the calculated and suggested pattern, however, the use of sensors should have enhanced this pattern suggesting to open the windows when the CO_2 concentration indicated a detrimental IAQ.
Nonetheless, the sensor alert has been set at 1400 ppm, and critical situations have been recorded. While CO_2 concentration seems an essential parameter of indoor air quality as it affects the cognitive ability of learners to focus attention, temperature and relative humidity cannot be overlooked given their influence on comfort perception. Figure 4 represents these parameters for the three classrooms under consideration between the 4th and the 23rd of December. The period has been narrowed down because of some missing data on the 3rd of December. The X-axis shows the recorded temperature, the Y-axis shows the relative humidity, and each point, corresponding to a record, is coloured according to the CO_2 concentration value, from light green for the lowest concentration to red for the highest. The figures also show, with dotted lines, threshold values for both temperature and relative humidity that define conditions of comfort or discomfort. These threshold values are taken from [19].

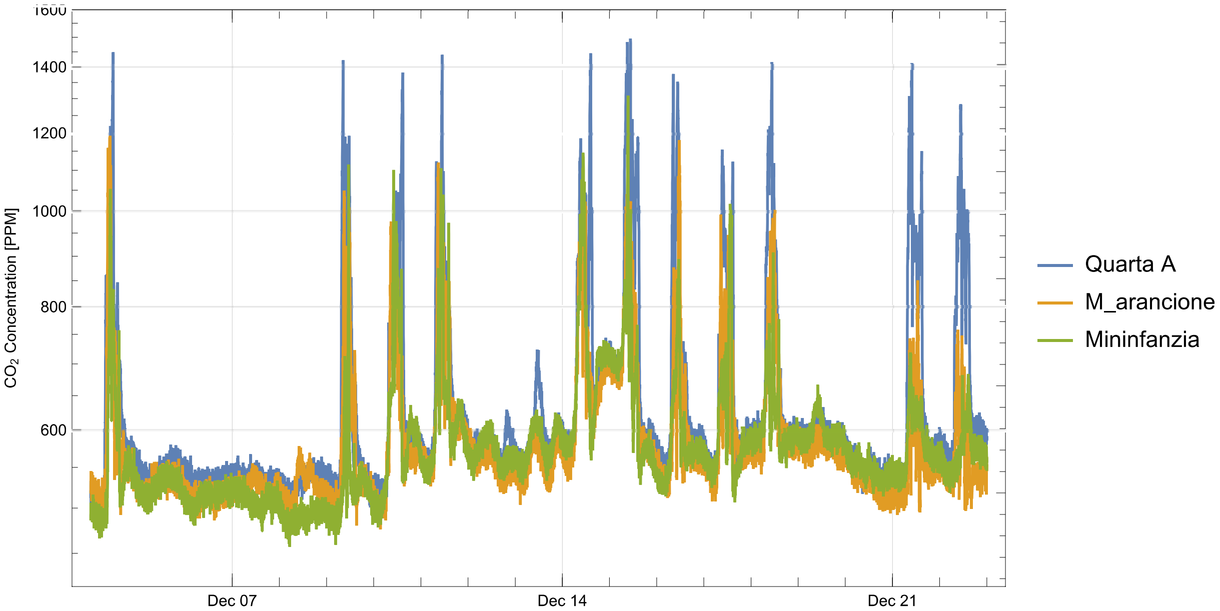

Figure 3. The collected CO_2 concentration [ppm, in logarithmic scale].

Table 3. Percentage of recorded CO_2 concentrations above the 600 PPM and 1000 PPM thresholds during the working hours.

thresholds	Quarta A	M_Arancione	Mininfanzia
> 600 ppm	82.11%	68.57%	54.87%
> 1000 ppm	25.44%	3.07%	2.39%

According to a recurring pattern in Italian school buildings, the activities performed within the three classrooms under examination change on an hourly basis. For this reason, it may be interesting to analyse the average comfort conditions on an hourly basis, excluding holidays, when the school is not used and limiting the analysis to the hours of the day when there is the presence of people in the classrooms that is from 7 am to 6 pm. The analysis of comfort conditions inside the classrooms was accomplished using the recorded temperature, relative humidity, and CO_2 concentration. The IEQ metrics, combining the three recorded parameters and the graphical methodology to represent the comfort conditions, have been developed by the authors in [23, 24]. This methodology combines IEQ and IAQ data defining a comfort conditions classification based on T, RH, and CO2 threshold values. As shown in Table 2, these threshold values allow defining 27 volumes in Cartesian space T, RH, and CO2 that are here called comfort conditions from C1, the best, to C27, the worst. Condition C1 is characterized by temperature between 20°C and 22°C, relative humidity between 30% and 35%, and CO_2 less than 600 PPM, i.e., the optimal winter conditions for a heated indoor environment. The average condition, C13 describes a room where an issue is perceived; however, the condition is not strongly critical: i.e., the temperature is below 20°C (a little bit cold), the relative humidity is lower than 30% (dry air perceived), and CO_2 concentration is between 600 and 1000 ppm. Eventually, condition C27, the worst, is reached when the temperature is above 22°C, relative humidity above 45%, and CO_2 concentration above 1000 PPM.
The comfort conditions computed using the hourly average values of temperature, relative humidity, and CO_2 concentrations are shown in the carpet plots of Figure 5 together with the hourly average CO_2 concentration. In row a) there are the two plots depicting classroom “Quarta A” CO_2 concentration (left column) and comfort conditions (right column), in row b) the ones for classroom “M_Arancione” and in row c) the ones for classroom “Mininfanzia”.

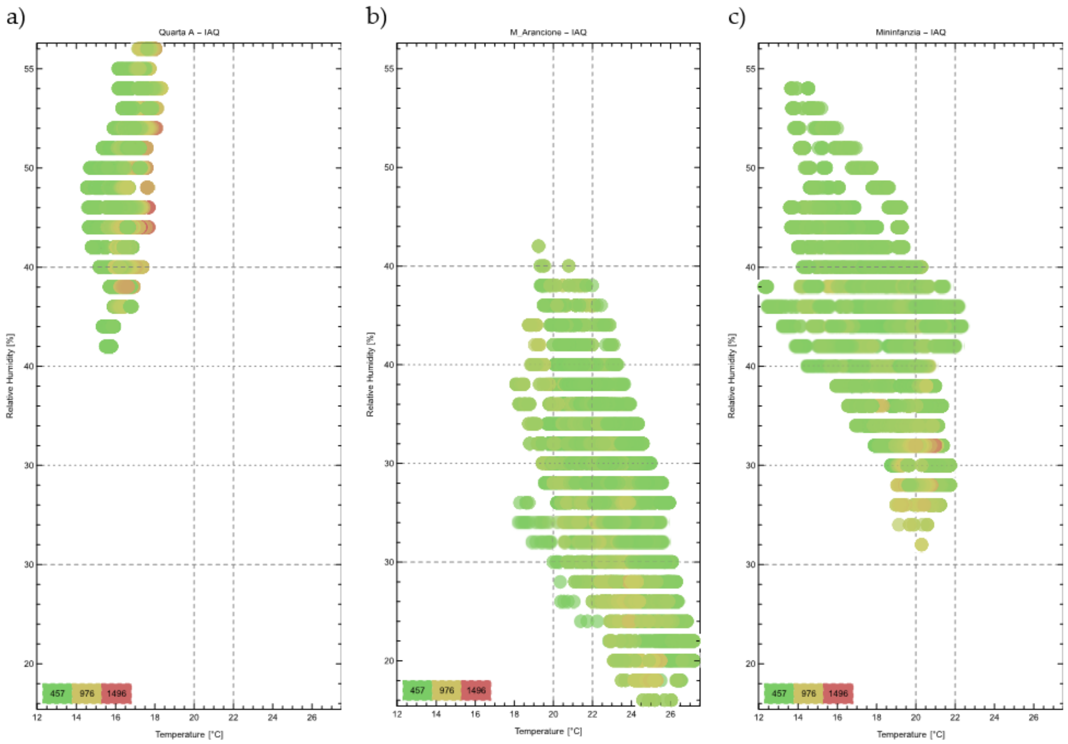

Figure 4. T, RH and CO2 measured for a) classroom “Quarta A”; b) classroom “M_Arancione” and c) classroom “Mininfanzia”. In each plot, there is the recorded temperature [°C] on the X axes, and on the Y axes, the relative humidity [%]. Points are coloured according to the CO2 values, light green the lower values, red the higher.

Table 5. Temperature, relative humidity, and CO_2 concentration thresholds used to define indoor comfort conditions.

Parameter	Measure unit	Limit L1	Limit L2
Indoor air temperature	°C	20	22
CO_2 concentration	PPM	600	1000
Minimum relative humidity	%	30	35
Maximum relative humidity	%	40	45

In each carpet plot, the X axis is used for the hours of the day, from 7 am to 6 pm, and the Y axis for the 11 working days encompassed from December the 4th to December the 23rd. Dark gray squares stand for best comfort conditions and lowest CO2 concentrations hours, while light gray depicts worst conditions and higher CO_2 concentrations. The carpet plots of Figure 5 show that classroom “Quarta A” is the one with the worst comfort conditions during the period of analysis while the better is room “Mininfanzia”, even if also this room has some light gray squares, i.e., in some hours of the days during December 2020 the comfort conditions were considerably poor. Moreover, in then classroom “Quarta A” the comfort condition is below or equal to C13, the average, nearly 56% of the working hours while in classroom “M_Arancione” 53% of the times and in the room “Mininfanzia” a little bit more than 97%, being the best classroom as regards to comfort conditions. A more in-depth analysis of comfort conditions within classrooms can be performed using Figure 6 that displays a dashboard of comfort and health conditions based on the comfort thresholds (Table 5).

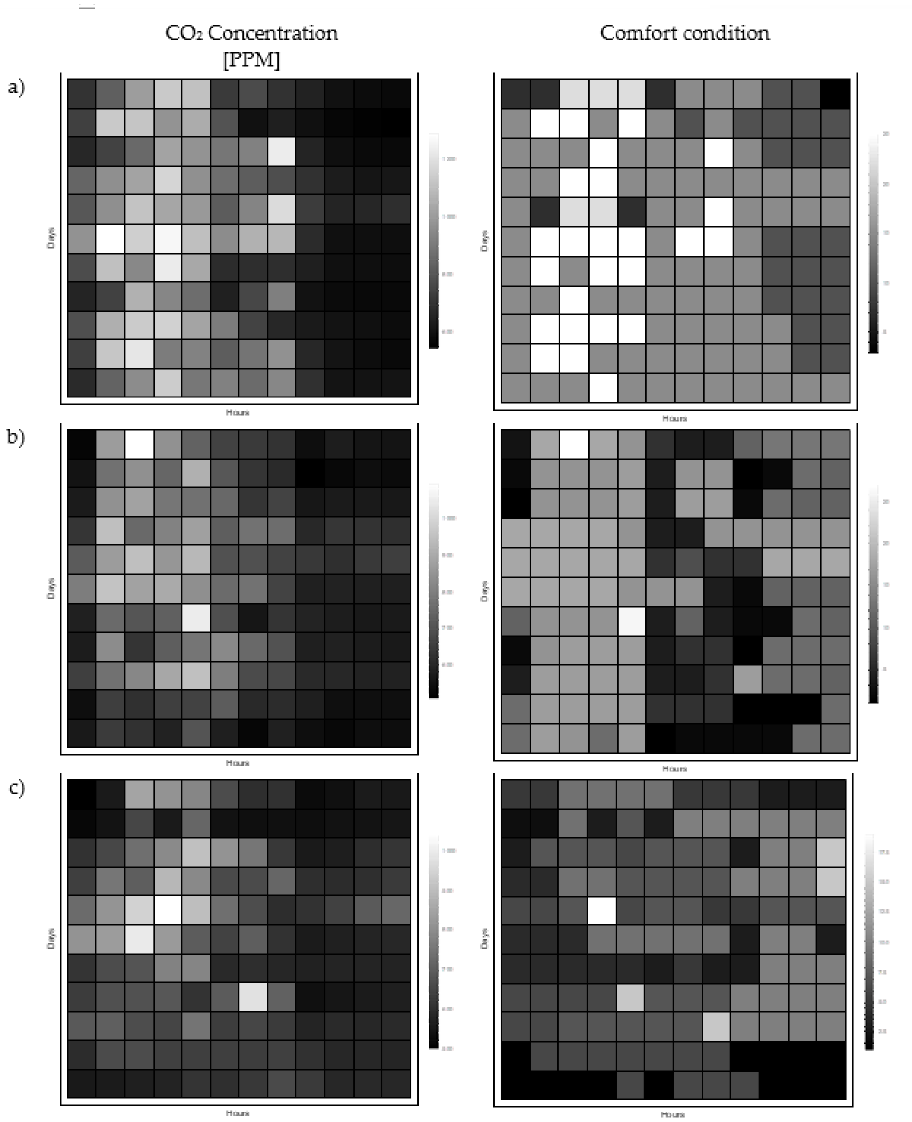

Figure 5. Hourly average CO_2 concentration [ppm] (left column) and comfort condition (right column) for classrooms a) “Quarta A”, b) “M_Arancione” and c) “Mininfanzia”. On the vertical axes of each plot there are the eleven working days encompassed in the period of analysis, on the horizontal axis the twelve working hours of the school, from 7 am to 6 pm.

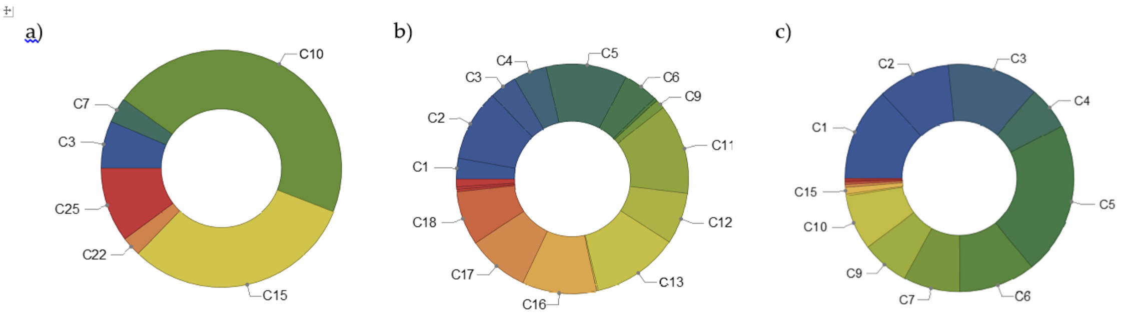

Figure 6. Comfort conditions in a) classroom “Quarta”, b) classroom “M_Arancione”, c) classroom “Mininfanzia”. The comfort condition numbered from C1 (best) to C27 (worst).

It shows the comfort conditions measured in the three classrooms during the school's opening hours in December 2020. Figure 6 shows that there are two most recurrent conditions in the classroom "Quarta A", C10 and C15, recorded 5,328 and 3,602 times, respectively. A third condition, C25, one of the worst, occurs 1,173 times. The classroom "M_Arancione" has a much greater variety of conditions, with 3 of them appearing more than 1,000 times during the analysis period. Similarly, in the classroom "Mininfanzia" five conditions appear more than 1,000 times, but the comfort is on average better.

DISCUSSION AND CONCLUSION

The IEQ data collection acts as the fundamental step to provide customised and tuned strategies that could be implemented in real-time as the indoor environment changes with users' interaction. The case study has been exploited to extensively show how it is possible to leverage data on IEQ and IAQ to organize dashboards, visualize data and provide data analytics aimed at understanding IEQ changings during the day and, thus, improving critical IEQ conditions, even with regards to COVID-19 contagion risk, with real-time mitigation actions. The research shapes and figures out a soft digital twin, which exploits the collected data in order to shape information and trigger some procedures and corrective strategies in an adaptive indoor environment, either fully automated or based on mutual interaction between users and the built-environment. The case study proved that such a challenge is viable, showing how to improve IEQ conditions through data acquisition via IoT sensors and knowledge extraction via the bespoke software application. The soft digital twin enables school staff, pupils, and facility managers to prevent and correct uncomfortable and unhealthy classroom conditions. For example, the ventilation time required for providing air changes for improving pollution dilution for a specific indoor space is related, in the soft digital twin, to the outdoor air temperature and the CO_2 concentration in the enclosed rooms is related to the number and age of users and activities also fluctuating during the day. The possibility to gather the information and process them through algorithms and models to identify critical parameters, such as when harsh situations are detected, could support the decision-making process. Furthermore, the building management helps the staff and users to make optimal use of the interior space by triggering conditions and actions for a more comfortable and safer environment. In the present case study, a decisive engagement of the pupils in the classrooms has been promoted by the interaction with some LEDs of the IEQ sensors. The teaching staff and the students collaborated actively in checking the conditions and promoting the corrective actions (i.e., opening windows and doors, starting recesses, wearing hotter clothing, …). The dashboards and analytics provided are intended to support a soft DT based on interactive floorplans or on Business Intelligence (BI) dashboard that can boost multiple purposes through data visualization and processing. Noteworthy, the current vision on DTs underlines that a DT can also disentangle problems that can be solved by a kind of DT with a higher degree of complexity. For example, an As-Built DT can support any business case supported by a building services DT in a sort of backward capability. Different categories of DTs are emerging with variable degrees of complexity, and to maintain the trade-off between benefit and complexity, the business cases must be linked to the simplest DT that can adequately support them. These simpler soft DTs fit the goal of offering an up-to-date visual representation of the physical asset, embedded with static and dynamic data [25, 26], with easy deployment, low costs and short time of realization. The deployed platform for data gathering has been directly used for data analytics, getting geometrical information from a low level of a detailed BIM model. In the case study, the most critical situation is related to the higher level of education with students up to 10 years of age because of their movement in the classroom, higher rate of breath and CO_2 emission, and extended educational schedule. Corrective actions have been performed at all levels, and the active engagement could be reported for the Quarta_A classroom.

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