On the use of IoT Sensors for Indoor Conditions Assessment and Tuning of Occupancy Rates Models

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***Abstract*— In the last years, the energy savings policies are affecting several aspects of the everyday life, from the introduction of renewables and the use of Electric Vehicles, down to the adoption of more efficient lightening systems. Considering a typical building, one of the most energy consuming plant is the Heating, Ventilation and Air Conditioning (HVAC) system. This consideration is especially true for large public-access buildings, such as schools, universities and public administrations. In these cases, the energy saving of buildings depends on the capability to optimize the behavior of the HVAC. Typically, the HVAC control system is based on static models of the building, which consider an average occupancy rate of each of the rooms. On the contrary, in this research work, a Cognitive Building approach has been considered. The Energy Management System (EMS) is able to control and to regulate the HVAC system, considering an occupancy rate model able to take into consideration user' habits and the indoor air quality (IAQ), provided in near real-time by IoT sensors. This approach has been applied to the eLUX lab building of the campus of the University of Brescia, Italy. Data provided by IAQ sensors (temperature, relative humidity, CO_2) are used to refine the results of occupancy rate models of rooms of this building. The experimental results show as in the 22.15 % of the samples, the CO_2 concentration overcame the 1000 ppm threshold of perception of fresh air and good condition.**

Keywords—Smart City; Cognitive Building; Internet of Thing; Indoor Comfort; Energy Saving; Indoor Air Quality; Sensor Network; Occupancy Rate model.

I. INTRODUCTION

The optimal management of urban assets behind Smart City approach, requires the integration of public and private buildings, destination of large part of urban resources. The Smart City approach requires the integration of communication infrastructure [1] and data storage and analysis systems [2], within the urban infrastructure, including public and private buildings. A building able to learn the user habits and to interact with sensors and plants is known as Cognitive Building. A Cognitive Building is able to optimize its energy consumption, but at the same time, to guarantee the quality of well-being of its inhabitants. Indoor air quality (IAQ) is among the main issues in many types of buildings and it is very important as an influential factor on occupants' health, comfort and work productivity, having also a strong impact on overall energy consumption. In fact, the Heating, Ventilation and Air Conditioning (HVAC) is one of the most energy consuming plant in a building. Many studies about IAQ are carried out in schools, to preserve children from inadequate IAQ because they spent long day-time in their classrooms. Compared to adults, children are particularly sensible to indoor air pollutants due their physical systems. Children could have more problems of infection due to the developing immune system and they have a respiratory system that assure high ventilation rate per their body mass [3]. Studies about IAQ dates to 1800 when extensive investigation on Swedish schools have been carried showing not satisfactory results [4]. Nowadays, the problem of IAQ in schools is confirmed by recent researches and it is affecting both developed such as developing countries. The transversal issue which all the authors underline is not efficient natural ventilation given by thermal gradient driven ventilation and possibility to open the windows which leads to not controlled indoor conditions. This is a main factor for not correct fresh air exchange rates in the classrooms that are consequently connected with unsuitable IAQ and SBS symptoms between uses, i.e. pupils [5]. The learning performance therefore decreases and weaker results occur during the exams with low pass rates evidence [6]. This conditions could be corrected using mechanical ventilation, however the cost is relevant and not always the efficiency and the intensive use of the spaces are supported by this strategy. Typically, the parameter of carbon dioxide CO2 is adopted into detailed analysis on IAQ and ventilation rate [7][8]. CO_2 is also an easily measurable gas [9], through the deployment of dedicated sensors network, as well described in [10]. The target of this research work is to investigate the possibility to integrate IAQ data generated by IoT sensors to improve the estimation of occupancy rate of rooms of buildings, an important parameter considered to regulate the HVAC system. The adoption of IoT architecture for the interconnection of sensors to building management system has been already investigated into [11]. In the paper, that approach has been used to improve the estimation of occupancy rate of traditional probabilistic models. This solution has been applied to estimate occupancy rate of educational laboratories of eLUX lab building of the University of Brescia, which is mainly used for teaching.

II. VENTILATION RATE AND IAQ

Different national and international standards provide the equations to calculate the complying ventilation rate for activity in a building with a specific use aimed at maintaining an acceptable IAQ. The ventilation rate is given empirical data

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referred to the number of occupants and related to the net floor surface and building end-uses. The baseline configuration adopted for standard simulation is based on Italian norms [12][13], which include a standard amount or minimum level of outdoor fresh air per person to assure IAQ. Therefore, the air change rate is calculated following the equations:

$$n = \frac{(v_{min} \cdot i_s \cdot A)}{V} \quad (1)$$

$$V_{a,k} = V \cdot n \quad (2)$$

where: n is the number of air changes [h-1]; v_{min} is the external air flow during the use period [m^3/h per person]; i_s is the occupants' density [person/m^2]; A is the zone surface [m^2]; $V_{a,k}$ is the required air flow rate [m^3/h]; V is the net volume of the thermal zone [m^3]. The previous equations are used for deterministic calculation, while, using probabilistic approach, the air change rate depends on the total amount of people staying in a thermal zone for the considered interval time. An acceptable rate of CO_2 (i.e. 1000 ppm) has been stated and consequently the amount of fresh air for each occupant has to be estimated. The variation of CO_2 concentration during time in a thermal zone can is given by the following equation:

$$c = \left(\frac{q}{nV}\right) \cdot \left[1 - \left(\frac{1}{e^{nt}}\right)\right] + (c_0 - c_i) \cdot \left(\frac{1}{e^{nt}}\right) + c_i \quad (3)$$

where: c is concentration of CO_2 [m^3/m^3]; V is the volume of the considered room [m^3]; q is quantity of the CO_2 emitted by people (reference value) [m^3/h]; n is the number of air changes defined for the categories of usage of the room [h-1]; t is the time [h]; c_o is the concentration of CO_2 at the beginning of the analysis t = 0, supposed to be 350 ppm; c_i is the concentration of CO_2 in the inlet pipe, supposed to be 0 m^3/m^3. The people in a room generate a concentration of CO_2 that can be calculated using the equation:

$$q = q_p \cdot n_o \quad (4)$$

where: q is the CO_2 generated by each person in the room (0.05 m^3/h/person) [m^3/h]; n_o is the number of people in the room [-]. Connection between CO_2 concentration and IAQ condition is resumed in Table 1 [14].

TABLE I. IAQ BASED ON CO_2 CONCENTRATION

CO_2 conc. [ppm]	IAQ description	Indoor condition
350-400	Fresh air	Perfect conditions
<600	Almost fresh air	Acceptable conditions
<1000	Upper limit of fresh air	Limit of CO_2 concentration
<1500	Stuffy and not fresh air	Not acceptable
<2000	Weak people can faint and cough	Bad air condition
<10000 ppm	Increase of breath rates, respiratory problems, headaches, nausea	Very bad air condition,

III. THE PROPOSED APPROACH

A. Monitoring and inverse modeling

As mentioned in the previous section, is it possible to calibrate energy models with occupant's behavior through sensor gathered data that are crucial to validate the real occupants' rate during the year and with different period of use of the building (specifically relevant for school buildings). In the presented case study the occupancy rate have been calculated based on people counters installed and CO_2 concentration sensors. These are used for the direct digital control (DDC) of the mechanical ventilation system which allows airflow modulation of the AHUs (air handling units) by means of a stepped or continuous control logics. Moreover, CO_2 sensors can provide detailed information on IAQ, enabling the inverse estimation of the occupants that are using a specific thermal zone. Further inverse modeling strategies are available: for example multiple linear regression models are adopted when influential parameters identification is the goal [15] or when the issue is to gradually calibrate the energy model [16]. Furthermore, it worthy to note that regression approaches are mainly flexible as they can be used in online mode [17] and can perfume different operating modes at the same time by means of statistical ensembles [18] and regression trees [19].

B. Monitoring of the indoor conditions

In the pilot building the installation of the CO_2, temperature and relative humidity (RH) indoors sensors, suggested the possibility to check the IAQ conditions in order to assess the degree of satisfaction. Considering, as reported by ASHRAE [20], that "an acceptable air quality is one for which a substantial majority of people (less than 80%) do not express dissatisfaction" the aim was to check the compliance of indoor condition to users' request of quality for a good learning performance.

This definition is very similar to that provided in the UNI 10339 [21] standard, where the air flow rates, crowding index, indoor and outdoor temperature, relative humidity inside and outside and air velocity in the conventional volume occupied are established. Note that indoor air quality is significantly deteriorated as the temperature and RH increase [22]. The surveys for air quality checks can be carried out with traditional methods (questionnaires) by checking the quantitative values of the parameters of air flow rate of ventilation air, air intake temperature, quantity of CO_2, air temperature, RH as well as a check on the pattern of flow distribution in the environment. In fact, from scientific studies, due to a sufficient supply of air in the environment, inappropriate values of the air intake temperature and disproportionate distribution patterns were detected.

The parameters and values set out in the regulations for the use of university classrooms category E.7 are shown in the following Table II.

The Correction factor for ventilation and the Average daily presence factor are defined into the national standard UNI/TS 11300 [23] while the external condition for the location are introduced by UNI 10349:1994 [24].

TABLE II. PARAMETERS FOR DEFINING THE INTERNAL CONDITIONS OF AIR QUALITY AND THERMO-HYGROMETRIC WELLBEING

Parameter	*Unit*	*Value*	
		UNI 10339	DGR 8745
Minimum air flow rate v_{min}	m^3/h p	25.2	21.6
Crowding Index	p/m^2	0.6	0.5
Correction factor for ventilation	-	0.51	
Average daily presence factor	-	8/24	
Internal gains sensible heat	W/m^2	4	
Volumetric perc. of CO_2 conc.	%	0.1	
Acceptable noise levels	dBA	30-40	
System noise levels	dBA	25-30/30-35	
Winter operation			
Dry bulb external temp. T_{bse}	°C	-7	-
External relative humidity UR_e	%	60	-
Dry bulb indoor temperature T_{bsa}	°C	≤20	20
Indoor relative humidity UR_a	%	$35<UR_a<45$	50
Metabolic activity Mr	W/m^2	≥70	-
Thermal res. of clothing Icl	m^2°C/W	≥0.14	-
Air velocity v	m/s	$0.05<v<0.15$	-
Summer operation			
Dry bulb external temp. T_{bse}	°C	32	-
External relative humidity UR_e	%	48	-
Dry bulb indoor temperature T_{bsa}	°C	≥26	26
Indoor relative humidity UR_a	%	$50<UR_a<60$	50
Metabolic activity Mr	W/m^2	≤116	-
Thermal res. of clothing Icl	m^2°C/W	≤0.09	-
Air velocity v	m/s	$0.05<v<0.15$	-

C. The IoT approach

IAQ sensors are typically installed for the control of HVAC system and the information collected from sensors are not available for different application. The IoT paradigm allows to overcame this situation, by the definition of a proper ICT architecture able to virtualize the physical sensors thanks to a proper data model. The ICT architecture provides for the definition of four layers (shown Fig. 1): the device layer, the data layer, the cognitive and the visualization layer. The device layer is the layer of sensors and actuator placed in the field. Each of the device in the field is characterized by a data model used to exchange the data using proper communication protocol. The system is protocol agnostic, i.e. several communication protocol, including the well-known MQTT, web service REST, are supported. The data are collected in databases at the data layer. The data layer includes the run-time data from sensors (Device data DB) as well as information about the building (BIM DB) and about the devices installation and their characteristics (Asset mgt DB). The information available in Device Data DB, can be used by cognitive layer to extract additional data, such as the number of people in a room from CO_2 concentration. The data estimated by the cognitive layer are uploaded in the Device Data, as virtual sensor. The power of the IoT approach relies in the possibility to integrate sensors from different domains, including virtual one.

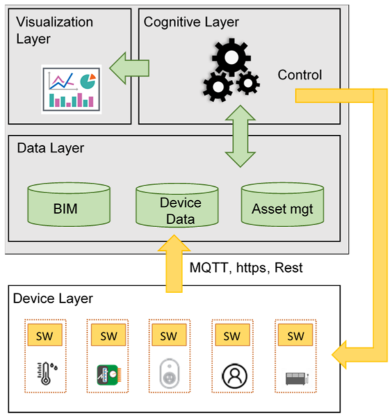

Fig. 1. The reference ICT architecture used for the integration of IoT devices and the estimation of building parameters.

IV. CASE STUDY: ELUX LAB

The eLUX lab building [25][26], the multi-disciplinary research initiative at the University of Brescia is the case study used to demonstrate the potential of refurbishment through smart technologies, of building which consider simultaneously technological and learning matters. The case study is a three floors building (i.e. underground, ground and first floor) used for lectures and computer labs in the ground floor, with a double height atrium. The zones of the building considered during the experiments are reported in Table III. Several sensors are installed in the different zones of the buildings, for different reasons, including the energy monitoring, the automation of the building, security, and many more. The IoT approach followed during the design and the deployment of the sensors network allows the easy integration of sensors, belonging to different application domains. The entire building is covered with more than one hundred sensors. Wireless communication technology are adopted when possible to limit the installation costs of sensors in the existing building. The deployed system takes the benefit of the IoT architecture defined in Fig. 1.

TABLE III. DESCRIPTION OF THE ELUX ZONES

Location	***Zone***	***Dimensions***		***Occupants***	
Floor	*Name*	*Area*	*Volume*	*standard*	*actual*
		$[m^2]$	$[m^3]$	*n.*	
-1	MLAB1	152	455	76	56
	MLAB2	208	624	104	82
0	MTA	178	535	89	168
	MTB	177	532	89	168
	Atrium	181	542	90	56
1	M1	337	1012	262	169

The number of the users is defined through a survey on availability of seats in the classroom spaces and referred to the standard number of users that can be calculated based on the crowding index for the use of the space. The use of the spaces is very intense as illustrated in Fig. 2, where the occupancy schedule is provided for the spaces of the building during the week days.

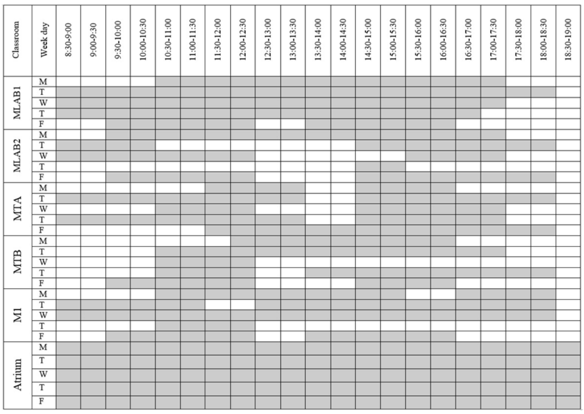

Fig. 2. Occupancy schedule of the eLUX lecture spaces during the working (M to F).

The energy analysis has been verified using deterministic and occupancy levels, however, actually, the use of the building is very intensive nevertheless the actual presence in the classrooms has not been surveyed continuously but just a building survey has been performed at the beginning of the research. The main point was to verify the maximum number of people in the different zones adopted to generate occupancy scenarios based on a triangular distribution (min = 0,3 $n_{o,max}$, mode = 0.6 $n_{o,max}$, max = 1.0 $n_{o,max}$). The simulation scenarios have thus been configured with 60% of people density for the standard simulation while in the probabilistic scenario the profiles have been defined by means of the triangular probability distribution updating in both cases the user dependent parameters [27]. The assumptions about the two simulations are reported in following Table IV.

TABLE IV. STANDARD AND PROBABILISTIC SIMULATION ASSUMPTIONS.

Parameter	*Symbol*	*Unit*	*Standard*	*Probabilistic*
Air change	v_{min}	[m^3/h/p]	21.6	25.5
People density	i_s	[p/m^2]	0.5	Triang. P.D.
CO_2 per occupant	q_p	[m^3/h]	0.05	
CO_2 at t=0	c_0	ppm	350	
CO_2 inlet air	c_I	ppm	0	
CO_2 limit conc.	c_{lim}	ppm	1000	

V. Results

The occupancy scenarios have been used to simulate different indoor conditions and IAQ level adopting standard air change rates (Standard) and evaluating the needed air changes to guarantee an adequate value of CO_2 concentration assumed lower than 1000 ppm (IAQ), according with the previous assumptions. In Table V the ventilation rates are thus summarized considering the number of users in the two scenarios, the need of ventilation and the amount of air changes that can be assured by the AHUs installed. The difference between the ventilation needs for IAQ and for standard requirements and the possibility to provide this ventilation is stressed to show the granularity and weight of the issue in the different building spaces. The negative values in the Gap_{iaq} and $Gap_{standard}$ suggest that the actual AHU cannot support the presence of the actual people attending the classrooms if the occupancy exceeds the standard value, and also in this case, one of the refurbished laboratories in the underground floor is not complying the needed air changes.

TABLE V. VENTILATION OF THE CLASSROOMS

Location	*Zone*	*Air changes*				
Floor	Name	AHU	IAQ	Gap_{iaq}	Standard	$Gap_{standard}$
		[m^3/h]				
-1	MLAB1	5000	1427	3573	1639	3361
	MLAB2	2000	2786	-786	2246	-246
0	MTA	2000	4281	-2281	1925	75
	MTB	2000	4281	-2281	1917	83
	Atrium	5500	1903	3597	1952	3548
1	M1	5500	6677	-1177	3645	1855

A. Building level: predictive model

As shown in Fig. 3, the simulation of CO_2 concentration into the building reached high level of discomfort (e.g. drowsiness and smell) and mainly in MTA, MTB and M1 where lectures are intensely programmed and spaces have not been refurbished. Acceptable IAQ is predicted in the atrium, because of a lower people density, and in the underground floor Labs (MLAB1) due to updating of the AHUs (2010). In all the learning spaces of the pilot building, a reduced IAQ can be predicted (and fully confirmed by users' feedbacks and interviews when occupancy is intensive. These conditions are not allowing the best learning performance of the students and thus retrofit or tuning strategies should be implemented.

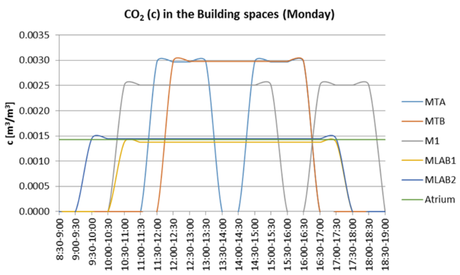

Fig. 3. CO_2 concentration (estimated) into the different eLUX spaces in a representative day (Monday).

B. Test space MLAB2:predictive model vs data monitoring

As specific example, MLAB2, a computer lab, is adopted to understand how the estimation of IAQ could be verified through the sensors and how the measured level of CO_2, indoor temperature and RH can provide crucial insights to calculate the presence of people into the building spaces. For this purposes, MLAB2, and the rest of the classrooms of eLUX lab building, has been equipped with Siegenia Sensoair CO2 and VOC sensor and Everspring ST814 temperature and RH sensor. Both the sensors support Z-wave communication protocol and are interconnected with the rest of the monitoring system through a dedicated gateway (See Fig. 1 for more detail about the communication architecture). In Fig. 4**,** the estimation of CO_2 for the lab MLAB2 are plotted. IAQ is not optimal because of the 1000 ppm limit is overcome when 60% of occupancy is in the space due to educational schedule. A maximum value of about 1445 ppm is measured in MLAB2 when the occupancy is quite high near to the perception of stuffy and not fresh air. The data acquisition allows to tune the predictive model and to understand the indoor air quality condition. As further results, it is possible to estimate the occupancy rate and validate the data coming from the people counter sensor.

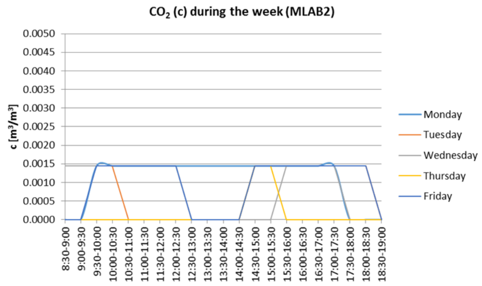

Fig. 4. CO_2 concentration in MLAB2 during the week.

The building spaces are equipped with sensor [28] to measure thermos-hygrometric indoor condition and IAQ. In Fig. 5, Fig. 6 and Fig. 7, respectively, the cumulative distribution of the recorded values of CO2 concentration, indoor temperature and RH are plotted for three months of data monitoring campaign (the whole period considered, 10 October 2017-10 January 2018). The value collected by the sensors showed that the standard comfort conditions (represented by dotted lines in Fig. 5, Fig 6 and Fig. 7) in the indoor space are not constantly into the range defined in Table 1.

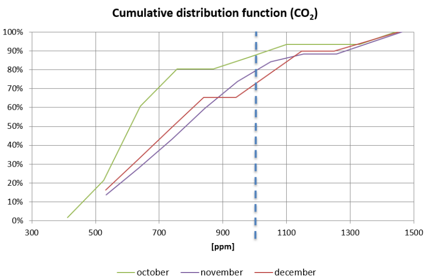

Fig. 5. Cumulative curve of CO2 concentration based on data recorded during the experimental period (october 2017-first days of january 2018).

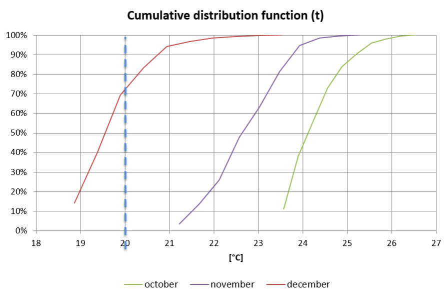

Fig. 6. Cumulative curve of indoor temperature based on data recorded during the experimental period (october 2017-first days of january 2018).

The recorded data of RH showed a very dry indoor environment with the 75% of the data with a value below 35% and a 4% of hours over the 45%. Thereby the conditions are strongly not compliant with the required value of the comfort parameters. The temperature inside the space is for the 27 % of the recorded data under 20 °C. It should be noted as the observation interval includes Christmas breaks period, when the HVAC plant is off because the building is closed. The 68 % of the monitored data shows temperature over the threshold of 20 °C due to the high internal gains (i.e. people, computers, lighting).

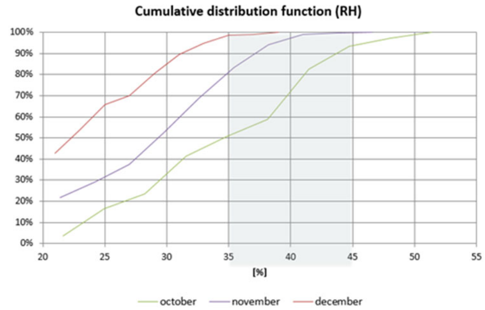

Fig. 7. Cumulative curve of indoor RH based on data recorded during the experimental period (october 2017-first days of january 2018).

The 22.15 % of the data collected by the CO_2 sensor overcame the 1000 ppm threshold of perception of fresh air and good condition for empower learning performance of the students. Again, it should be noted as the observation interval include days when the building is closed. Focusing more in detail on a current Monday in the University of Brescia Smart campus, more than 50 % of the records are over the 1000 ppm - reaching 1500 ppm - during the lecture hours. The number of people in MLAB2, estimated from CO_2 concentration data during one day (10[th] October 2017) has been shown.

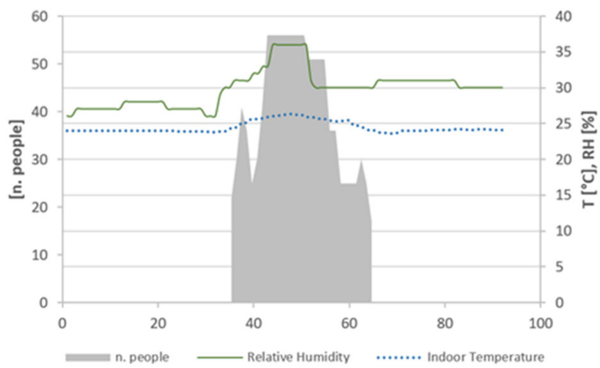

Fig. 8. Sample day (10th October 2017) in which temperaure and RH are recorded and n. people estimated from CO_2 concentration in the MLAB2.

In Fig. 8, it is possible to check how the people occupancy increases the RH measured into the space, which is mostly dry (RH <35%) in the 91 % of the recorded hours and the temperature, although, in the computer lab, the temperature is over the 20 °C also during the night (100 % hours t > 20 °C). The estimated number of people, obtained from CO_2 data concentration, could be useful to confirm a rate of occupancy in the MLAB2 of about 60% that is an average rate of attendance to the lectures.

VI. CONCLUSION

The present study verifies the IAQ using CO_2 concentration as a main parameter and, in combination with temperature and RH sensors, highlights the capability of IoT architecture to exploit the use of sensors data for different application domains. In details, IAQ sensors are used to improve (in near real time) the estimation of occupancy rates in the classrooms of a pilot building. The indoor conditions are strongly affected by the refurbishment introduced into the different spaces of the building. Nevertheless, in the best scenario (i.e. refurbished computer labs), discrepancy between comfort values for comfort indoor conditions and monitored data frequently occurs (CO_2 concentration > 1000 ppm with 60% of occupancy rate). Not to mention the other existing spaces, where predictive models of IAQ during operational period forecast CO_2 concentration around 3000 ppm, with possible cough and faints events for weakest subjects. The data analysis on monitored data about indoor conditions can firstly improve the strategic view of the building management, secondly it could suggest possible interventions (e.g. automation of ventilation strategies and fan operation schedule related to lecture schedule) and, last but not least, it could increase possible energy savings, comfort indoor and learning performance of the users. The situation in existing educational buildings can be very critical when intense rate of occupancy is allowed. A further step towards cognitive solutions is to connect actuators of HVAC plant and to promote customized real-time strategies tailored on actual attendance rate to the lectures. Internationally, the research on occupancy monitoring is oriented to CO_2 concentration sensors which are more accurate and fitting the needs of scheduled indoor spaces.

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