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Indoor Air Quality Forecast in Shared Spaces– Predictive Models and Adaptive Design Proposals

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Abstract

The high concentration of air pollutants in indoor environments can have a remarkable adverse impact on health and well-being, cognitive performance and productivity. Indoor air pollutants are especially problematic in naturally ventilated shared spaces such as classrooms and meeting rooms, where human-generated pollutants can rise rapidly. When the inhabitants are exposed to indoor air pollution, recovering from its ramifications takes time and harms their well-being in the long run. In our approach, we seek to predict and prevent such hazardous situations instead of rectifying them after they happen. The prediction and prevention are accomplished through algorithms that can learn from the evolution of air pollutants and other variables to indicate whether or not a high level of pollution is forecast. We present two AI-enabled methods, one providing the forecast for the concentration level of carbon dioxide in the next 5 and 20 minutes with 86% and 92% accuracy. The second algorithm provides predictive indicators about how the CO_2 level will evolve during the upcoming session (meeting or a course) before the session starts. We will discuss design implications and present design proposals on how these methods can inform interactive solutions for preventing high concentrations of indoor air pollutants.

Keywords

Indoor Environmental Qualities, Quantified Buildings, Human-Building Interaction, Indoor Air Quality, Predictive Models

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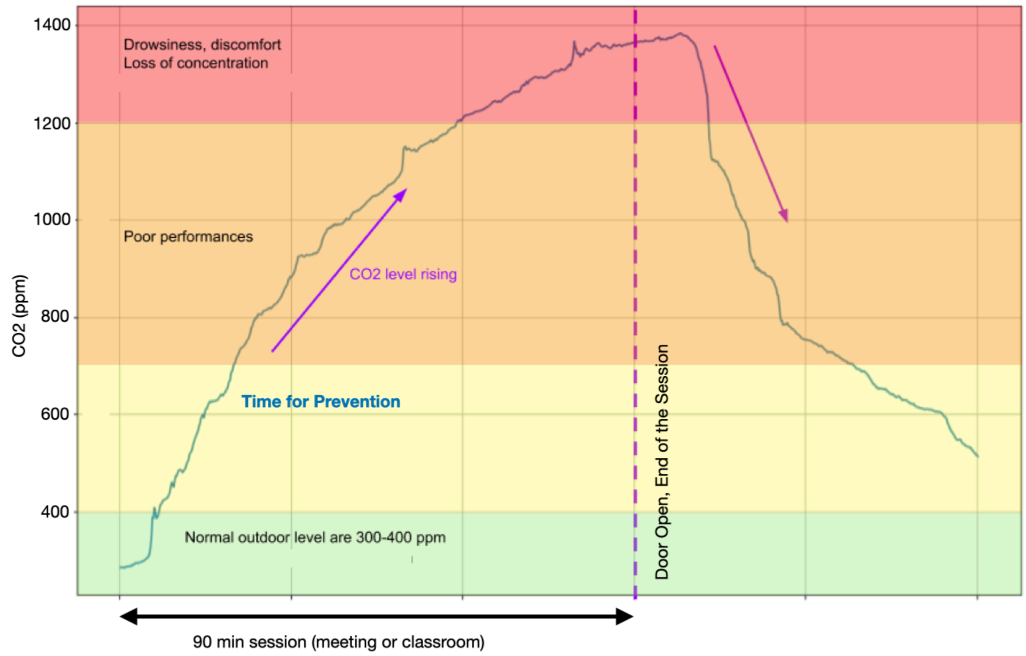


FIGURE 1 The high concentration level of CO_2 in meeting rooms is a common problem with health and productivity adverse consequences.

Introduction and Motivation

Evidence for direct links between exposure to high levels of carbon dioxide concentration and problems such as lethargy, headache, and cardiac arrhythmia, as well as difficulty in retaining attention, concentration, and cognitive performance, have been repeatedly presented in previous studies (e.g. Apte and Erdmann, 2002; Fisk, 2010; Erdmann et al. 2002; Griffiths and Eftekhari, 2008). These health impacts reoccur commonly in shared closed spaces such as open-plan office spaces, conference halls, and classrooms. For example, a recent study of more than 100 schools in Switzerland revealed that students suffer in more than two-thirds of the learning spaces from a high concentration of carbon dioxide (Swiss Federal Office of Public Health, 2016). Research in this area builds on the Indoor Environmental Qualities (IEQ) literature that developed standards and quality norms for an acceptable range of parameters and architectural design guidelines to ensure those norms (e.g. Frontczak and Wargocki, 2011, Burge, 2014, Redlich, 1997). However, it is only recently that studies of comfort in buildings consider the role of humans as active users of buildings.
The new research directions also seek to explore the opportunities that new methods of sensing, actuation techniques, and, more broadly, data science can bring to the problem of indoor air quality (Alavi et al. 2017, Hsu et al. 2018, Meurer et al. 2019). Our research pursues a similar human-centric perspective enabled by data-oriented methods. We examine a novel approach in which the objective is to predict and prevent situations of discomfort rather than rectifying them after they occur. Two reasons motivate this preventive approach: (1) recovering from discomfort exhausts time, and cognitive effort, (2) regular exposure to situations that are even mildly uncomfortable can harm health in the long term.
It is worth noting that carbon dioxide is a common indicator for assessing ventilation efficiency and consequently the overall indoor air quality; particularly, it is a surrogate for the indoor concentration of occupant-generated pollutants. That is why our research focuses on the prediction of CO_2 concentration levels.
In this chapter, we present two methods of forecasting the evolution of carbon dioxide in naturally ventilated indoor environments, evaluate their performance, and conclude with a discussion of how to integrate them in a design solution.

Real-Time Forecast

The primary source of carbon dioxide indoors is human respiration, and thus its concentration is directly related to the number of people in a room. Nevertheless, the level of CO_2 in the air is also affected by many other variables such as room size, ventilation rate, relative humidity, and outdoor air quality (e.g. Fang et al. 1998). Since measuring all of these parameters entails heavy instrumentation of the environment and its inhabitants, we aim to develop a prediction model that can function independently of their variations. More precisely, the goal is to develop and compare real-time prediction algorithms that can indicate whether or not the CO_2 level in a room will exceed a threshold solely based on previous measurements of carbon dioxide in the same office.

We can predict the level of carbon dioxide in office space by determining the likelihood L that after a time interval Delta T the concentration of carbon dioxide molecules in the air will exceed a value V. To do so, we examined Autoregressive (AR) and Autoregressive Integrated Moving Average (ARIMA) on CO_2 measurements collected in shared office spaces and meeting rooms. We can gather the data by sensing systems that we have developed in collaboration with an industrial partner (see Figure 2), logging the concentration of air pollutants every five seconds. In addition, we examined Long Short-Term Memory (LSTM) – a recurrent neural network architecture – in which the problem was formulated as multiple parallel input and multi-step output case. To evaluate and compare the performance of the models, we consider two parameters: (1) the accuracy of prediction verified by the actual values and (2) the time required for training the model.

FIGURE 2 Two sensing devices that we developed for recording the concentration of various indoor air pollutants. Connected to these devices, smartwatch and phone applications are provided to make available the live prediction of indoor air quality..

We computed the accuracy of a prediction based on the percentage of predicted values that fall within the confidence interval around the actual value with the confidence interval fixed to 30 ppm, based on the technical error range of the sensor. The model's overall accuracy is the average accuracy of all instances of prediction executed on one day of data (four devices, 12 times prediction per hour, 10 hours, and excluding the last 20 minutes). We used a sliding window to test the AR and ARIMA models: an observation buffer to build the model to predict the CO_2 concentration in the next Delta T minutes.

We tested combinations of observation buffer sizes of 10 and 20 minutes and Delta T of 5, 10, and 15 minutes. In all performed tests, the Autoregressive (AR) model outperformed the other methods, both in terms of accuracy and in training time. Using AR and a buffer size 20 minutes, we have achieved 97.66% accuracy of prediction for Delta T = 5 minutes and 87.51% for Delta T = 20 minutes.

Pre-session Prediction

This section explores the opportunities to predict the evolution of air quality much more in advance: before a meeting (or a classroom session) starts. Instead of predicting the value of CO_2 concentration level, the objective is to predict how the CO_2 level will evolve during the upcoming session based on parameters such as the size of the room, number of participants, outdoor weather, time of the day, and so forth. In the first step, applying hierarchical clustering on the data collected from more than 1000 meeting sessions in 26 meeting rooms , we distinguished seven patterns of evolution of CO_2. Each pattern is identified by the initial value and the coefficient of the rise during the first and second half of the session. The data used in this part were collected using CO_2 sensors developed by an industrial partner, installed on the meeting room desks, logging CO_2 values every 10 seconds during five months. More than 300 employees in a naturally ventilated building used the meeting rooms of various sizes during sessions of typically around one hour long.

In the second step, we search for a combination of external parameters that can suggest which of the seven patterns will occur in the upcoming session. This has been accomplished using Linear Discriminant Analysis (LDA) on a list of parameters including size of the room, number of occupants, indoor conditions (temperature, humidity, light, etc.), outdoor conditions (temperature, humidity, luminosity, wind speed, etc.), time of the day, as well as the concentration level of indoor air pollutants before the session.

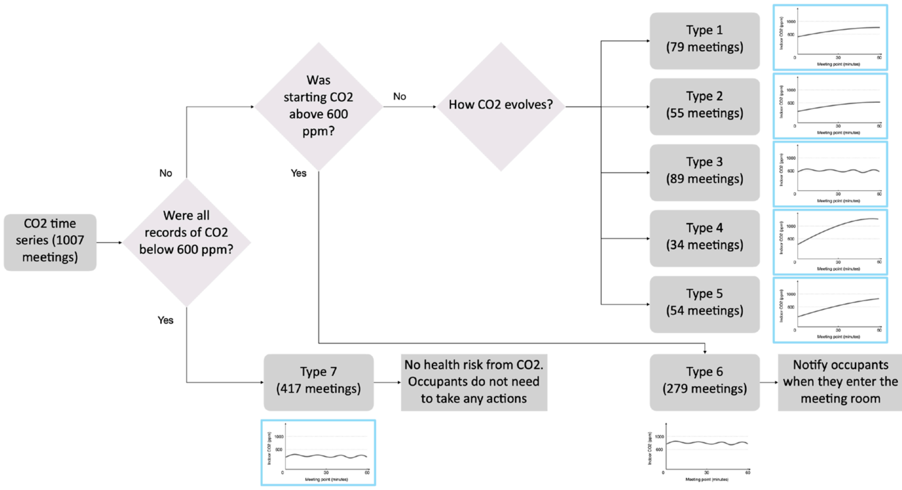
The results suggest certain indications – in the form of a combination of external parameters – that can specify which of the seven patterns of CO_2 evolution is most likely to occur in the upcoming session (Zhong et al. 2021). This can be particularly helpful in social situations when interrupting the session (meeting or lecture) to deal with environmental qualities that can harm productivity or may not be appropriate. In the next section, we describe how the coupling of the two predictive methods informs a design solution that can unobtrusively integrate into the social context of shared spaces.

From Prediction to Prevention: An Interactive Design Proposal

Once a high concentration of air pollutants is forecasted, it needs to be communicated with the users to take preventive action (e.g. opening a window). However, such notifications, particularly in cooperative work situations, can disrupt the workflow and eventually be counterproductive and substantially reduce the adoptability of the solution. Building on the two predictive algorithms presented in the last sections, the design solution that we develop seeks to find the right moment to notify the users to minimise the interruption cost and maximise the long-term impact. Figure 3 demonstrates how the interaction with the users is intelligently determined before and during a cooperative work or learning session. In a nutshell: depending on the likelihood that the level of CO_2 passes the healthy threshold during the upcoming session, the users would be made aware of the prediction and the solution that can prevent the hazardous situation (operating one of the room openings for how long). In cases where the pre-session prediction does not provide an adequately high level of certainty, the real-time prediction provides notifications through various modalities, including ambient interfaces. The decision on whether or not the users should be notified before the session is informed by:

A the predictive models that anticipate the risk of high levels of CO_2 pollution in the upcoming session (i.e. the pattern of evolution of CO_2), and
B the design of the notification system during the session, informed by the predictive models (AR) that with high accuracy estimated the level of CO_2 in the next 5 to 20 minutes.

1. Classifying the pattern of CO2 Evolution



2. Determining external indicators for each pattern

Feature	Test	p-value
indoor_co2	ANOVA	< 2.2E-16***
co2_last_5min_slope	ANOVA	0.04067*
occupancy_calendar	ANOVA	< 2.2E-16***
attendee_diff	ANOVA	3.185e-14 ***
snow_1h	ANOVA	0.03336 *
Gaz(i)	ANOVA	4.826e-06 ***
Light(i)	ANOVA	0.003428 **
room_size	ANOVA	.033e-05 ***
Hour of the day	ANOVA	0.01064 *
Day of the week	ANOVA	0.003742 **
floor	χ^2	0.001499 **
is_a_meeting_bf	χ^2	0.004498 **
Win facing	χ^2	0.0009995 ***

3. Interaction style based on social and physical context

FIGURE 3 When a high level of CO_2 is forecasted, the design solution determines whether or not to notify the users. The notification can occur before or during the session. That depends on the predicted evolution pattern of CO_2 among the seven patterns.

Conclusion

This contribution presents a preventive approach to the problem of poor indoor air quality in shared spaces. The broad objective is to predict the situations where the concentration of air pollutants, particularly carbon dioxide, may harm the well-being or cognitive performance of the occupants and inform them through interaction mechanisms that minimise the disruption caused by the awareness/notification system.
To that end, we have developed a predictive model that can, with very high accuracy, indicate whether or not the level of CO_2 would be higher than a certain threshold in 5 minutes. Furthermore, a second predictive model can specify before a collaborative session starts the pattern of evolution of CO2 during that session. Combining these two algorithms enabled a solution that can notify the users when action is needed while reducing the interruption costs.

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