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Analysis of Impacts of Window Opening Behavior on Indoor Air Pollutants in Residential Dorms through Deep Neural Network

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Abstract. People spend more than 90% of their time in buildings. The highly stochastic behavior of occupants can alter the pollutants concentration in an indoor space. Many studies have reiterated that window opening is one of the best methods to reduce indoor pollutant concentration. In this study, we analyzed the influence of window opening behavior on indoor pollution parameters (CO_2 and TVOC) in 16 student dorms in Syracuse, NY. The duration of the study encompasses all major seasons of a whole year. We found that the window opening behavior of the living room is triggered by the increased concentration of indoor pollutants. The impact of the window opening on the dilution of the concentration of the indoor pollutants is analyzed using the air exchange rates. We found that the average infiltration air exchange rate is 0.32 h^{-1} and the average air exchange rate during the window opening is 2.20 h^{-1}. The exchange rates are different in different homes; infiltration ACH range from 0.31 - 0.83 h^{-1}, and window opening ACH range from 0.46 - 3.86 h^{-1}. The mean indoor CO_2 concentration for all homes ranges between 458 - 715 ppm, and the mean TVOC concentration is 268 - 1786 ppb. The average error in the loss rate calculated from the mass-balance model and the blower door test is 2.51%. We made a Deep Neural Network model predict the concentration of CO_2 in the indoor space based on the window's state. The DNN model has an RMSE of 7 ppm and a MAPE of 6.66%. The DNN predicts that the exposure during decay events at the window opening is 80.31% lower than during closed state decay.

1 Introduction

People spend about 88-92% of their time indoors [1]. Many field experiments have observed that the concentration of pollutants can reach from two to five times that outdoors [2]. It is estimated that outdoor air pollution will prematurely kill around 6.6 million people annually by 2050 [3]. As the outdoor environment is getting more polluted than ever, it will significantly impact the baseline concentration of indoor pollutants. Exposure to higher levels of pollutants for extended periods might severely affect their health and well-being [4]. Some common health problems caused by more prolonged exposure to pollutants are related to respiratory illness. Several studies have suggested that exposure to ultra-fine particles for a prolonged period can seriously impact the heart and lungs [5]. Other studies have reiterated that exposure to Volatile Organic Compounds (VOC) generated from cigarette smoke and dry-cleaning cloths can cause asthma and bronchial hyper-reactivity [6]. Furthermore, a report from WHO has suggested that low IAQ caused 1.5 million deaths in the year 2000 [7].

To counter these health effects of poor IAQ, the American Society of Heating, Refrigeration and Air Conditioning (ASHRAE) has set guidelines for the minimum indoor ventilation rates, either by mechanical or natural ventilation. The suggested ventilation rates for the residential buildings are set between 0.28 h^{-1} – 0.50 h^{-1} [8]. However, the energy crisis of the 1970s encouraged the government to make homes more air-tight to conserve energy [9]. This shift in government policy made reaching the ventilation rate set by ASHRAE difficult. Also, this policy might have unintended consequences like poor IAQ and increased exposure to indoor air pollutants. Various studies have recently found building components' impact on air exchange rates. A study found that window opening increased the air exchange rates by 1.7 h^{-1} in a house in Virginia and by 2.8 h^{-1} in California [10]. This year-long study was performed using a very stable tracer gas called SF6. The study found that the thermal stack effect was the dominant factor in determining ACH rather than wind. The ACH increased by 0.60 h^{-1} when the indoor-outdoor temperature difference was 30°C, while no significant changes were observed during windy conditions.

Because of the recent devastating global pandemic caused by the outbreak of COVID-19, there has been a spike in the studies related to ventilation requirements in places where people congregate in large numbers. Researchers at Harvard School of Public Health found that opening windows can achieve more than 5 ACH in classrooms. The study found that increasing ACH can

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help to reduce exposure to COVID-19 [11]. Another study in the Netherlands found that increasing ventilation rates to 2.2 h^{-1} and using air cleaners can reduce the aerosol particle concentration by 80-90% [12]. Apart from traditional particle concentration prediction models during decay, a new domain has emerged which uses machine learning (ML) methodologies. Although ML methods lack interpretability, they can provide highly accurate results. For example, new ML models have been used to predict the concentration of CO_2 based on other environmental parameters like VOC, temperature, and moisture. Some studies have included the state of the building components like doors to estimate the concentration of CO_2 during the emission and decay phase. These models have incredibly low RMSE, as close as 6.18 ppm [13]. Furthermore, ASHRAE has released global occupant behavior database that can be used to download data and train the ML models [14].

Some verified studies tried to predict the window's state based on indoor and outdoor weather conditions. Many studies have found that outdoor temperature is the most significant predictor of the window opening. The probability of switching the window's state from 'closed' to 'open' increases with increasing outdoor temperature, and changing the state from 'open' to 'closed' increases with decreasing outdoor temperature [15] [16]. Some studies also found that increased CO_2 levels will trigger a window-opening action [16], while others found a weak correlation between window-opening and indoor pollutants [17]. Most of these studies are predominantly conducted in Asian countries, and we could not find any studies about window opening behavior's impact on IAQ in North American dormitories.

All the studies mentioned above are either conducted in residential homes or classrooms. As per the literature review, we have not found any indoor air pollutant studies in old residential dorms. This study tries to close this gap by studying eight residential dorms constructed more than fifty years ago. Other studies have primarily relied on local weather station data for the outdoor temperature and wind speeds. This might reduce the efficacy of the data. In this study, we used the outdoor weather data from the weather station inside the university. Also, as per our information, no studies try to quantify the exposure to indoor pollutants inside the residential dorms using machine learning methods that encapsulate the occupant's window opening behavior. This study tries to predict exposure to CO_2 inside a residential dorm using the Deep Neural Network (DNN) model. This DNN model can also quantify the effect of occupants' window opening behavior on exposure to CO_2. Since the concentration of CO_2 and Total Volatile Organic Compound (TVOC) and other pollutants shows a very high correlation, the exposure calculation from this DNN model can also be inferred as the exposure to TVOC. This exposure prediction from the DNN model may be used to calculate the probability of exposure to other airborne diseases like COVID-19 inside the residential dorms.

In this study, we developed the mass balance model using the first-order linear differential equation to calculate the air exchange rates. Also, the validity of the mass balance model was tested using the results obtained from the blower door test. Also, we developed the Deep Neural Network with three hidden layers to accurately predict the concentration of CO_2 during the decay events. This DNN model was then used to calculate the exposure from the CO_2 during closed and window-open conditions.

2 Methods

A brief description of the methods followed is shown in Figure 1. We begin the data acquisition process by collecting the outdoor weather data from the weather station on campus. We also collect the IAQ, thermal, and window operation data from the sensors inside the dorms. We calculate ACH during the window open/close period to determine the pace of pollutant decay. The ACH values are computed using the mass-balance equation for CO_2 decay. To check the validity of the ACH results from the mass balance equation, we compare it with ACH obtained from the blower door test. The blower door test calculates the ACH at 50 Pa induced pressure (ACH_{50}). The ACH_{50} values are converted to ACH values using the Conversion Coefficient (CC). This traditional process of ACH calculation has assumptions that can be measured or unknown in most cases, for example, the structure coefficients. Hence, determining the speed of pollutant decay sometimes has many uncertainties. Thus, we develop the DNN model for estimating CO_2 concentration and exposure during decay, considering weather and window state details as predictors. This marks the transition from a traditional physics-based model to a data-driven based model with measurement.

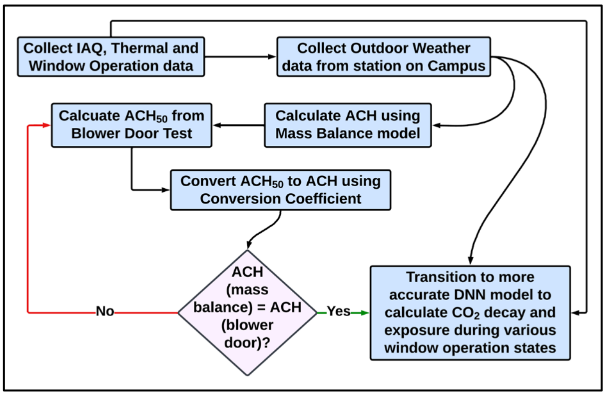

Fig. 1. Methodology Flowchart for ACH calculations

2.1 Location and Climate

The buildings selected for this research are located inside a local university in Syracuse, New York, USA. This location is very close to the border with Canada and has one of the highest snowfall rates in the entire country. The location has hot and humid summers with an average temperature of 27°C and winters with an average temperature of -7°C. Figure 2 shows the monthly average outdoor weather parameters in this location.

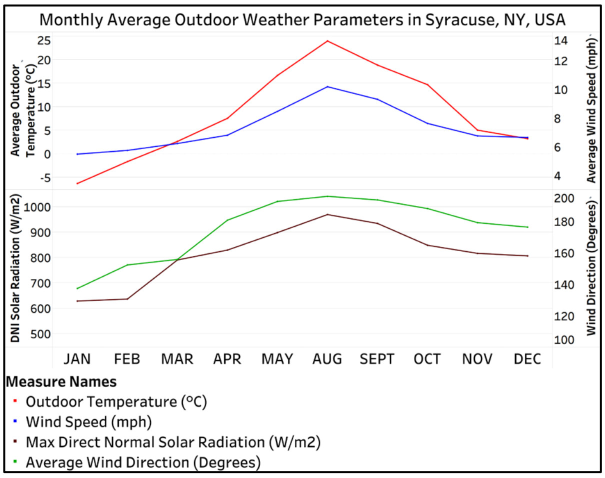

Fig.2. Monthly Average Outdoor Weather Parameters in Syracuse, NY, USA

2.2 Data Acquisition

We studied eight residential dorms at Syracuse University, Syracuse, NY, for this study. The building is equipped with three types of sensors that measure:

a. Occupant Behavior (OB) of window/door openings and closings
b. Indoor air quality and thermal parameters like CO_2, TVOC, Indoor Temperature/ Relative Humidity
c. Power Meter usage for all CTs (Current Transformers) in the building

The outdoor weather sensors inside the university complex measure the outdoor variables. The detailed schematic of the sensor's placement inside the building is shown in Figure 3. The sensors' details, accuracy, and resolution are shown in Table 1.

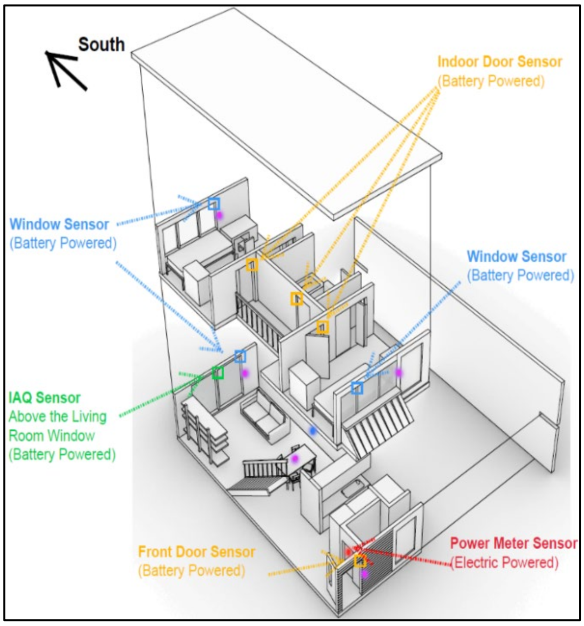

Fig.3. IAQ, Power Meter and Window/Door contact sensors placement inside a dorm

Table 1. Sensor Information

Measure	Sensor Model	Accuracy	Resolution
Window/ Door Status	Netvox (R311A)	NA	NA
Temperature	Milesight (AM107)	0°C to + 70°C (+/- 0.3°C), -20°C to 0°C (+/- 0.6°C)	0.1°C
Humidity	Milesight (AM107)	10% to 90% RH (+/- 3%), below 10% and above 90% RH (+/- 5%)	0.5% RH
CO_2	Milesight (AM107)	±30 ppm or ±3 %of reading	1 ppm
TVOC	Milesight (AM107)	±15 %	1 ppb
Power Usage	ONSET (EG1430 Pro)	NA	1 sec

The measurement accuracy of contact sensors and power meter is not provided by manufacturer. The accuracy of all other sensors is presented in Table 1.

2.3 Calculation of Air Exchanges per Hour

We derived the Air Exchanges per Hour (ACH) by applying the mass balance method and using CO_2 as a tracer gas. Numerous studies have used CO_2 to calculate air infiltration rates because of its very stable and non-reactive nature. First, we separated the decay events that happened in closed conditions. In this scenario, all doors and windows inside the dorm were closed. Then, we separated the decay events when living room windows were opened and all other doors and windows were closed. We focused on living room windows because the IAQ sensor is placed in the living room. After this separation of decay events, the mass balance model was constructed using the first-order linear differential equation as described in the literature [18].

We performed a blower door test during the study to determine the accurate ACH_{50} values for all eight dorms. Since an artificial 50 Pa pressure differential is induced during this study, this air exchange rate is known as ACH_{50} and should not be confused with regular ACH. A study recently published the method of converting the ACH_{50} into ACH using the Conversion Coefficient (CC) derived from the wind and stack effect [19]. Equation 1 shows the process of converting ACH_{50} to the actual ACH value.

$$ACH = \frac{ACH_{50}}{CC} \tag{1}$$

The Conversion Coefficient (CC) is given by Equation 2. n = 2/3 is used as suggested by the model, but this value can range from 2/3 to 1 depending on fan pressurization data.

$$CC = \left(\frac{1}{s}\right)\left(\frac{8}{\rho}\right)^{\frac{1}{2}}\left(\frac{50}{4}\right)^{n} \tag{2}$$

The variable 's' depends on the wind and stack effects and is given by Equation 3.

$$s = (f_w^2 v^2 + f_s^2 |\Delta T|)^n \tag{3}$$

ΔT is the indoor/outdoor temperature difference, and 'v' is the wind speed. The structure coefficients 'f_w' and 'f_s' are obtained from literature and are measured in $\frac{m}{s} K^{\frac{1}{2}}$. Syracuse, NY, lies close to the border of Canada and experiences freezing temperatures for about five months a year. The study showed that the CCs are uniform at freezing temperatures between -40°C and 0°C, as outdoor wind speed has an insignificant impact. Moreover, we have many decay events happening during this freezing temperature range. Thus, to calculate the CC, we examined the decay events at cold temperatures between (-25°C to 0°C). Then we changed the ACH_{50} values obtained from the blower door test to ACH. This ACH value is compared with the value obtained from the mass balance equation. The findings are presented in the results section.

2.4 DNN architecture for CO_2 decay concentration and exposure prediction

After making a traditional mass balance model to obtain the loss rates, we made a neural network that can predict the concentration of CO_2 based on the window's state. The DNN, also known as Multilayer Perceptron (MLP), has three hidden layers. Six features are used as input for the model: Outdoor Temperature, Indoor Temperature, Outdoor/Indoor Relative Humidity, Indoor TVOC (Total Volatile organic compound), and the state of the window (binary variable). Before inputting the variables into the DNN object, the variables are normalized using the z scores. The mean and Standard deviation of all continuous variables used for Data Normalization are shown in Table 2.

The basic architecture of the model is shown in Figure 4. The DNN architecture is constructed using 'Adam' as an optimizer, 'ReLu' (Rectified Linear Unit) as the inner activation function, and 'MSELoss' as the loss function.

Table 2. Normalization Variables for DNN

Variable	Mean	Standard Deviation
Outdoor Temperature (°C)	4.00	9.39
Indoor Temperature (°C)	21.07	2.14
Outdoor Relative Humidity (%)	70.18	16.54
Indoor Relative Humidity (%)	39.68	14.40
Indoor TVOC (ppb)	1478	3613

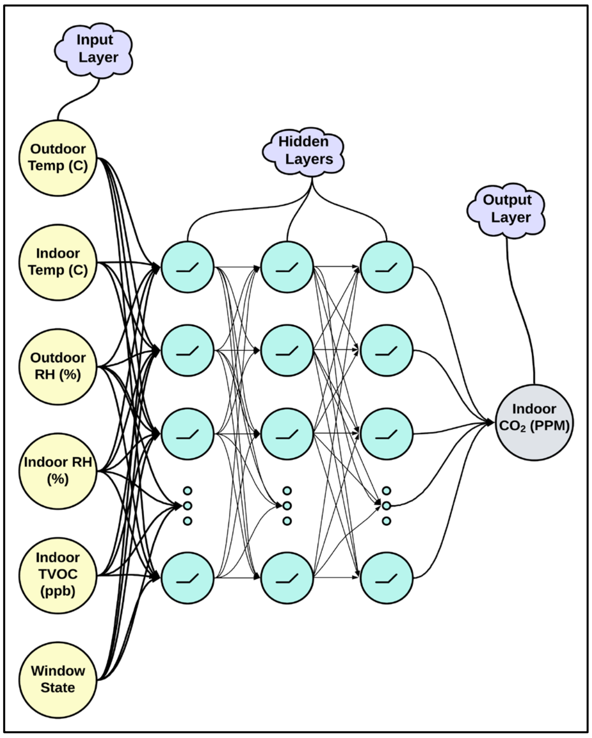

Fig. 4. Architecture of DNN model

The three hidden layered DNN model is trained using the 'torch' package developed by PyTorch. Since we are interested in the decay events and the impact of the window opening on the decay pattern, we neglected the events at which indoor CO_2 concentrations were at least 50 Pa above the outdoor baseline CO_2 concentration. The percentage of these 'uneventful' events was significant, and there is a high chance that the model will heavily depend on if these events are included.

3 Results

The descriptive statistics of all pollutants and duration of window opening during nine months of study for all homes are shown in Table 3. From the mean TVOC concentration, we categorize homes into high, mid, and low occupant activity levels. Homes 341_1, 341_5, and 341_7 are high-activity homes; Home 341_3 is a mid-activity home; and Homes 341_2, 341_4, 341_6, and 341_8 are low-activity homes.

Table 3. Normalization Variables for DNN

HOME ID	Mean CO_2 Conc. (ppm)	Mean TVOC Conc. (ppb)	Duration of Living Room Window Open (hours)
341_1	715	1786	544
341_2	587	444	963
341_3	537	978	644
341_4	608	268	163
341_5	714	1074	1107

HOME ID	Mean CO_2 Conc. (ppm)	Mean TVOC Conc. (ppb)	Duration of Living Room Window Open (hours)
341_6	564	356	413
341_7	458	1452	375
341_8	537	331	701

Based on the solution of the ODE containing natural log term, we can anticipate the CO_2 to follow logarithmic decay once the peak of the emission phase is reached. Figure 5 shows one of such decay events along with the decay start and end time, the mean wind speed, wind direction, and outdoor temperature during decay. After taking the first partial derivative of the CO_2 decay curve with respect to time, the code can find the region of the plot when CO_2 decays continuously. While taking the partial derivative, all other known and unknown parameters aside from time are assumed constant and are substituted by the average values. We investigated 2245 CO_2 decay events in closed and 143 CO_2 decay events in open window conditions.

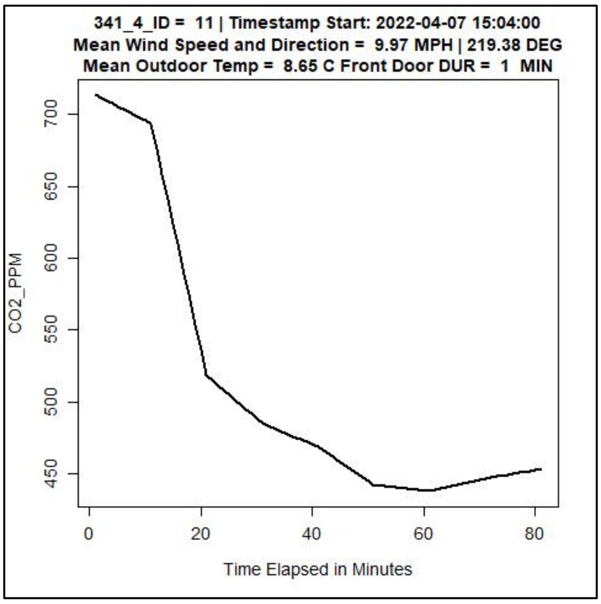

Fig. 5. The sample decay curve of CO_2 with respect to the time elapsed in minutes

Figure 6 shows the normalized CO_2 concentration with respect to the time elapsed in hours. The slope of this figure will give ACH.

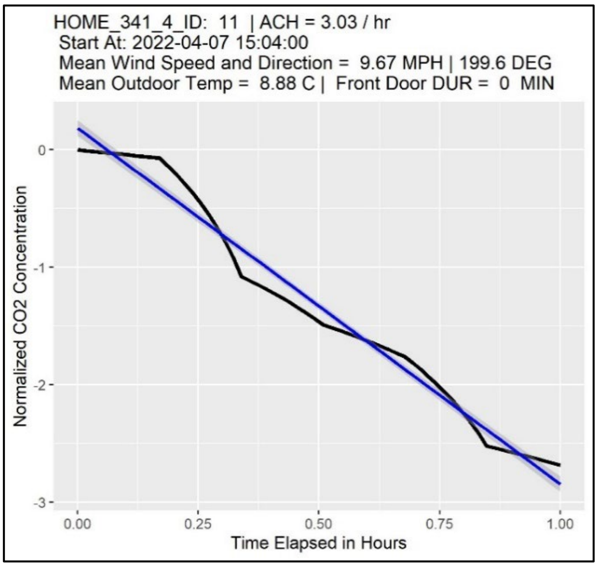

Fig. 6. The normalized CO_2 concentration with respect to the time elapsed in hours.

Using the mass balance model explained in the methodology, we calculated the ACH for all eight residential dorms, as shown in Table 4. These homes' average infiltration air exchange rate is 0.32 h^{-1}, and the average rate during the window opening is 2.20 h^{-1}. Thus, window opening increased the infiltration rate by 387.63% on average. The detailed ACH for all homes and the corresponding percentage increase is shown in Table 4.

Table 4. Percentage Difference of ACH during window opening as compared to infiltration rates at all homes

Home ID	Window State	Average ACH	Percentage Difference
341_1	CLOSED	0.34	32.57%
	OPEN	0.46	
341_2	CLOSED	0.35	296.65%
	OPEN	1.39	
341_3	CLOSED	0.42	NA
	OPEN	NA	
341_4	CLOSED	0.37	731.32%
	OPEN	3.07	
341_5	CLOSED	0.31	793.51%
	OPEN	2.74	
341_6	CLOSED	0.57	392.69%
	OPEN	2.83	
341_7	CLOSED	0.83	363.64%
	OPEN	3.86	
341_8	CLOSED	0.40	153.27%
	OPEN	1.02	

Based on these results from Table 4, a question might be raised about the discrepancy in the ACH value during window opening. In some homes, the average ACH during window opening can reach up to 3.86 h^{-1}, while in one home, it is 0.46 h^{-1}. There might be two reasons for this significant difference. Either the factors affecting the wind and stack effect are different during window opening activity at all homes, or the surface area of the window opening is different. We found that the average indoor–outdoor temperature difference and the wind speed during the window opening show slight variations, as shown in Figure 7 and Figure 8.

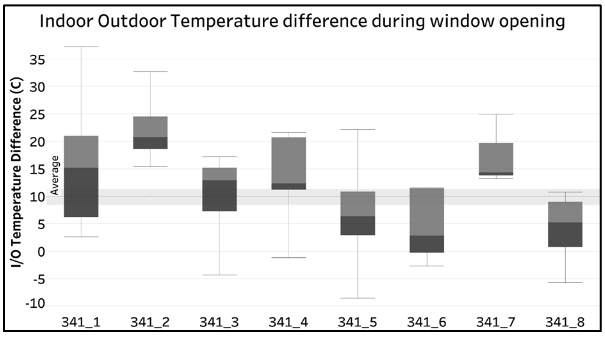

Fig. 7. Indoor Outdoor Temperature differences during window opening (average shown with 95% CI)

The higher indoor–outdoor temperature difference in Figure 7 shows that the occupants tend to open the window during freezing outdoor temperatures. If this metric is close to zero, the window openings occur mainly during transition season.

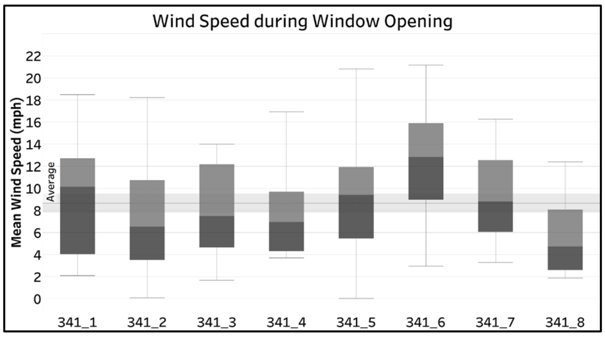

Fig. 8. Wind Speed during window opening (average shown with 95% CI)

Unlike I/O temperature variations of all homes compared to overall average (SD = 5.92°C) shown by Figure 7, there is no significant variations (SD = 1.70 mph) in the wind speed during window opening as shown by Figure 8. Thus, thermal stack effect might have greater impact on ACH during window opening. The air exchange rate due to window opening also depends on the area of the windows opened. The actual information about the degree of the window opening is not available, but it can be inferred from the ACH values. We can observe that the end units have the lowest ACH during the window opening. Since end units have a higher surface area in contact with the outdoors, it might be possible that occupants leave a lesser surface area of the window open as the impact of the outdoor environment is highest in these two apartments than in the central units. The box plot in Figure 9 shows the difference in the ACH when windows are opened and closed in some apartments.

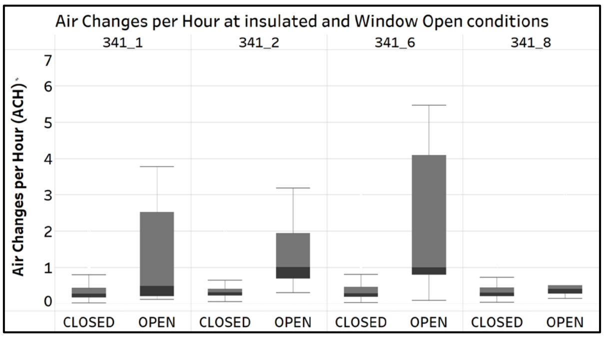

Fig. 9. Air Changes per Hour (ACH) during window open and closed conditions for some homes

We test the validity of the mass balance model from the ACH_{50} values obtained from the blower door test. During the summer of 2021, a professional team conducted the blower door test. The test reveals that the average ACH_{50} value for all eight apartments is 3.26 h^{-1}. The methodology section explains that the CC value should be obtained at freezing temperatures below 0°C. The CC values for all decay events below 0°C are shown in Figure 10.

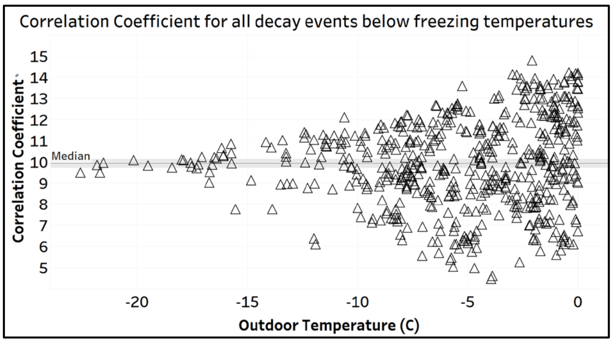

Fig. 10. The Conversion Coefficient (CC) of all the decay event at the Sub-zero temperatures

From equations 2 and 3, we can observe that CC is also the function of outdoor wind speed. Figure 11 shows the correlation between CC and mean wind speed. The color legend in Figure 11 shows the correlation coefficient at various outdoor temperatures. We can observe that the CC values are more stable at freezing temperatures (blue region). The median overall CC value at all outdoor temperature ranges is 10.82, and the median CC value at outdoor temperatures below O°C is 9.92.

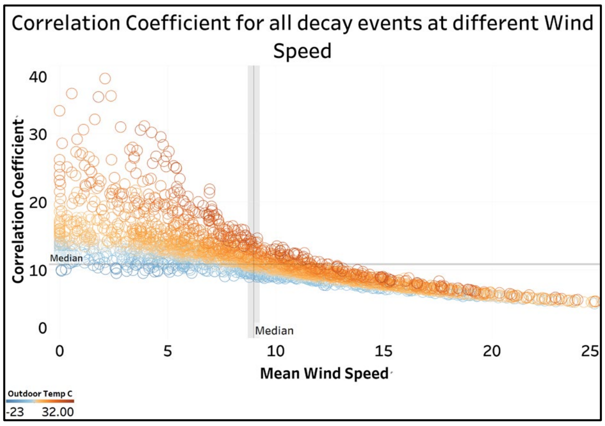

Fig. 11. The Conversion Coefficient (CC) of all the decay events at various wind speeds.

Since the median CC value for the freezing temperature is 9.92, the ACH from the blower door test during freezing temperature is 0.33 h^{-1}. Also, the median ACH from the mass balance model at freezing temperature is 0.32 h^{-1}, as shown in Figure 12. Thus, the error between the ACH calculated by the mass balance model and the blower door test is 2.51%. This provides validity to the results obtained during window opening for the mass balance model.

We constructed the DNN model for calculating the concentration of CO_2 during the decay phases only. The DNN was trained using the actual data obtained from the test site. The variables used for creating the model are Indoor Temperature, Outdoor Temperature, Indoor Relative Humidity, Outdoor Relative Humidity, Total Volatile Organic Compound (TVOC), and Window State. The trained model has a testing RMSE (Root Mean Square Error) of 7 ppm and MAPE of 6.66%. After training and testing the model, we dumped the model into a 'pickle' type object for its reusability. Then the model was applied to other decay events, and the decay pattern was observed.

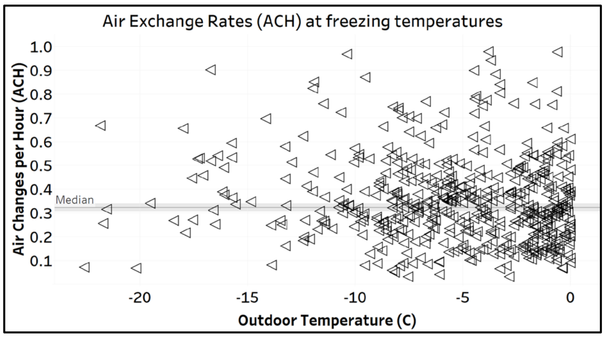

Fig. 12. Air Exchange Rates at Sub-zero temperatures

We constructed the DNN model for calculating the concentration of CO_2 during the decay phases only. The DNN was trained using the actual data obtained from the test site. The variables used for creating the model are Indoor Temperature, Outdoor Temperature, Indoor Relative Humidity, Outdoor Relative Humidity, Total Volatile Organic Compound (TVOC), and Window State. The trained model has a testing RMSE (Root Mean Square Error) of 7 ppm and MAPE of 6.66%. After training and testing the model, we dumped the model into a 'pickle' type object for its reusability. Then the model was applied to other decay events, and the decay pattern was observed.

Figure 13 shows the actual vs. predicted CO_2 concentration in the living room. The reason for such a low RMSE might be the inclusion of the TVOC data. The data analysis revealed that the indoor TVOC has the second highest correlation with CO_2 (*Pearson Coefficient = 0.11*) after the window's state (*Point Biserial Correlation = -0.15*). Also, indoor and outdoor temperatures were included in the model to encompass the thermal stack effect. Since there is lush vegetation outside the apartments, wind speed plays a minor role in this model. Hence, to avoid the overfitting of the model, the wind speed was neglected. The significant negative correlation of indoor pollutants with window state shows that window opening reduces indoor pollutants.

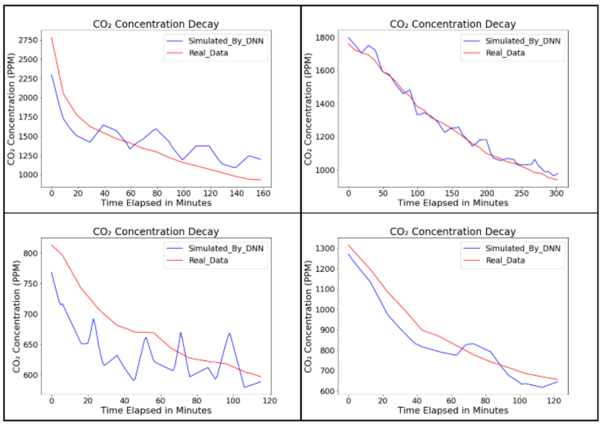

Fig. 13 Actual Vs. predicted CO_2 Concentration Decay

We tested the model in other decay events which were not included in the dataset used for training the main model. The average RMSE of the DNN model from these decay events is 7.09 ppm and 6.71 ppm, respectively. Similarly, the average and median MAPE of the DNN model from these decay events is 6.93% and 6.02%, respectively. We calculated the exposure to the pollutants using the 'trapz' function inside the 'NumPy' library in Python. The DNN model predicts that the average exposure from CO_2 during the decay events when windows were closed is 3140 ppm.hr. Also, the model predicts the average exposure from the CO_2 during the decay events when the windows are open is 618 ppm.hr. Thus, the DNN model predicts that the average exposure from CO_2 during the window opening events is 80.31% lower than the average exposure from CO_2 during the window closed events. Since TVOC and CO_2 have the second highest correlations after the window's state, the same pollutant decay and exposure analogy can be derived for indoor TVOC concentration.

4 Conclusion

The decay rate calculations found that window opening can increase the decay rate by as low as 32% to 793%. The average decay rate during closed conditions is 0.32 h^{-1}, and the average decay rate during window opening is 2.20 h^{-1}. The validity of the decay rate obtained from the mass-balance equation was tested by comparing it with the values obtained from the blower door test. For this comparison, we calculated the Correlation Coefficient (CC) value of 9.92. The error between the ACH decay rate obtained from these two models is 2.51%. We also trained a DNN model for estimating the decay of CO_2 using six variables obtained from sensors. The RMSE and MAPE of the model are 7 ppm and 6.66%, respectively. The DNN model was used to calculate the exposure to CO_2 during the decay events when the window was open and closed. At window state ‘open,’ the average exposure is 618 ppm.hr, and at window state ‘close,’ the average exposure is 3140 ppm.hr. Thus, window openings can reduce the exposure to CO_2 by 80.31%.

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References

[1] N. E. Klepeis *et al.*, “The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants,” *J Expo Sci Environ Epidemiol*, vol. 11, no. 3, pp. 231–252, Jul. 2001, doi: 10.1038/sj.jea.7500165.
[2] M. H. Sherman, “ASHRAE’s First Residential Ventilation Standard,” p. 9.
[3] E. E. van der Wall, “Air pollution: 6.6 million premature deaths in 2050!,” *Neth Heart J*, vol. 23, no. 12, pp. 557–558, Dec. 2015, doi: 10.1007/s12471-015-0763-9.
[4] X. Zheng *et al.*, “Association between Air Pollutants and Asthma Emergency Room Visits and Hospital Admissions in Time Series Studies: A Systematic Review and Meta-Analysis,” *PLoS ONE*, vol. 10, no. 9, p. e0138146, Sep. 2015, doi: 10.1371/journal.pone.0138146.
[5] World Health Organization, Ed., *Who guidelines for indoor air quality: selected pollutants*. Copenhagen: WHO, 2010.
[6] A. T. Hodgson, A. F. Rudd, D. Beal, and S. Chandra, “Volatile organic compound concentrations and emission rates in new manufactured and site-built houses,” *Indoor Air*, vol. 10, no. 3, pp. 178–192, Sep. 2000, doi: 10.1034/j.1600-0668.2000.010003178.x.
[7] World Health Organization, “Indoor air pollution : national burden of disease estimates,” World Health Organization, WHO/SDE/PHE/07.01 rev, 2007. Accessed: Sep. 30, 2022. [Online]. Available: https://apps.who.int/iris/handle/10665/69651
[8] M. H. Sherman and A. T. Hodgson, “Formaldehyde as a basis for residential ventilation rates,” *Indoor Air*, vol. 14, no. 1, pp. 2–8, Feb. 2004, doi: 10.1046/j.1600-0668.2003.00188.x.
[9] A. M. Papadopoulos, “Energy Cost and its Impact on Regulating Building Energy Behaviour,” in *Advances in Building Energy Research*, Routledge, 2007.
[10] C. Howard-Reed, L. Wallace, and W. Ott, “The Effect of Opening Windows on Air Change Rates in Two Homes,” *Journal of the Air & Waste Management Association (1995)*, vol. 52, pp. 147–59, Mar. 2002, doi: 10.1080/10473289.2002.10470775.
[11] “Harvard-Healthy-Buildings-program-How-to-assess-classroom-ventilation-10-30-2020-EN_R1.8.pdf.” Accessed: Oct. 01, 2022. [Online]. Available: https://schools.forhealth.org/wp-content/uploads/sites/19/2021/01/Harvard-Healthy-Buildings-program-How-to-assess-classroom-ventilation-10-30-2020-EN_R1.8.pdf
[12] B. Blocken *et al.*, “Ventilation and air cleaning to limit aerosol particle concentrations in a gym during the COVID-19 pandemic,” *Building and Environment*, vol. 193, p. 107659, Apr. 2021, doi: 10.1016/j.buildenv.2021.107659.
[13] R. Mäkynen, “Carbon dioxide level prediction for indoor air using neural networks,” 2020.
[14] B. Dong *et al.*, “A Global Building Occupant Behavior Database,” *Sci Data*, vol. 9, no. 1, Art. no. 1, Jun. 2022, doi: 10.1038/s41597-022-01475-3.
[15] H. B. Rijal, P. Tuohy, M. A. Humphreys, J. F. Nicol, A. Samuel, and J. Clarke, “Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings,” *Energy and Buildings*, vol. 39, no. 7, pp. 823–836, Jul. 2007, doi: 10.1016/j.enbuild.2007.02.003.
[16] R. Andersen, B. W. Olesen, and J. Toftum, *Modelling window opening behaviour in Danish dwellings*, vol. 2. 2011.
[17] F. Stazi, F. Naspi, G. Ulpiani, and C. Di Perna, “Indoor air quality and thermal comfort optimization in classrooms developing an automatic system for windows opening and closing,” *Energy and Buildings*, vol. 139, pp. 732–746, Mar. 2017, doi: 10.1016/j.enbuild.2017.01.017.
[18] S. Batterman, “Review and Extension of CO2-Based Methods to Determine Ventilation Rates with Application to School Classrooms,” *Int J Environ Res Public Health*, vol. 14, no. 2, p. 145, Feb. 2017, doi: 10.3390/ijerph14020145.
[19] Y. Ji, L. Duanmu, and S. Hu, “Study on the conversion coefficient between ACH50 and ACH in typical zones of public buildings,” *Energy and Built Environment*, Mar. 2022, doi: 10.1016/j.enbenv.2022.02.010.