Exponential pattern recognition for deriving air change rates from CO_2 data

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***Abstract*—A novel procedure for automated determination of air change rates from measured indoor CO_2 concentrations is proposed. The suggested approach builds upon a new algorithm to detect exponential build-up and decay patterns in CO_2 concentration time series. The feasibility of the concept is proved with a test run on synthetic data that shows a good reproduction of the previously defined air change distribution. The demonstration continues with test runs on CO_2 datasets measured in the kitchen and the sleeping room of two residential buildings. The derived air change rates were within the expected distributions and ranges in both cases when natural or mechanical ventilation was used.**

Keywords—air change rate; tracer gas; exponential pattern recognition; indoor air quality; ventilation, concentration decay

I. Introduction

In industrial nations, buildings are responsible for 20 to 40 % of the total energy consumption. In the EU and in the USA the energy demand of buildings is above industry and transportations [1]. Hence, the efficiency improvement of Heating, Ventilation and Air Conditioning (HVAC) systems is substantial to reduce the primary energy consumption and the greenhouse gas emissions.

The energy loss by transmission through the building envelope is successively reduced due to stricter building regulations and design specifications for insulation. Consequently, the share of the energy losses caused by ventilation increased in the recent years and the demand of intelligent monitoring systems arose. For quantification of the natural or mechanical ventilation losses usually the air change rate is used. According to (1) the air change or exchange rate n in 1/h is defined as the ratio of the supply air flow rate $\dot{V}_{sup}$ in m^3/h to the volume of the related zone or room V_R in m^3 and describes how often the volume is exchanged with fresh air within one hour by natural and/or mechanical ventilation.

$$n = \dot{V}_{sup}/V_R \tag{1}$$

On the one hand, a continuous and sufficient air exchange, especially in occupied buildings, is important to ensure a satisfying indoor air quality, which is declined by various interior pollutions like emissions from humans, furniture or building materials. On the other hand, an increased air exchange above an adequate hygienic level causes unnecessary energy consumption of the building, since the ambient air needs to be conditioned to comfortable values and transported or distributed by the HVAC systems.

Under defined boundary conditions like constant pressure differences, the tightness of the building envelope and therefore the air change by infiltration is constant and can be quantified e.g. by blower door tests. In practice, the occurring air change rates are subject to strong fluctuations depending on the changing overall conditions, like wind speed and direction, temperature differences between in- and outdoor and different kinds of manual window ventilations. In [2] the air change rates derived from experiments in a test room comprise four orders of magnitude from 10^{-1} to 10^{2} 1/h if various window ventilation modes from closed, tilted, wide open to cross ventilation are applied. The air change rate is of course not only influenced by natural ventilation. In fact, if appropriated systems are installed, the supplying and exhausting air flow rates are predominantly defined by the mechanical ventilation. The mentioned factors together with a varying user behavior lead to a unique distribution of air change rates for each building. The experimental study of [3] investigated the air change rates in an occupied town house over one year, collecting 4656 samples with a median value equal to 0.49 1/h. The strongest influences on the air change were open windows and the use of an attic fan resulting in the skewed distribution to higher air change rates in Fig. 1 in which unequally divided percentiles are plotted. A log-normal distribution, as proposed by the authors, is added.

Determining realistic air change rate distributions on the spot helps considerably to further improve control and monitoring strategies of HVAC components. The data sets could be used in holistic energy management systems for automatic fault detection of ventilation systems or in model predictive control applications to predict the demand of heating and cooling energy. The ongoing innovations in the sensor industry and wireless data transmission make it possible to meet the technical requirements for a continuous, distributed and cost effective monitoring of the air quality inside the smart buildings of the future. The huge amount of data delivered by the sensors encapsulates valuable information about the building performance, yet the operators must first master the challenge to extract the relevant information.

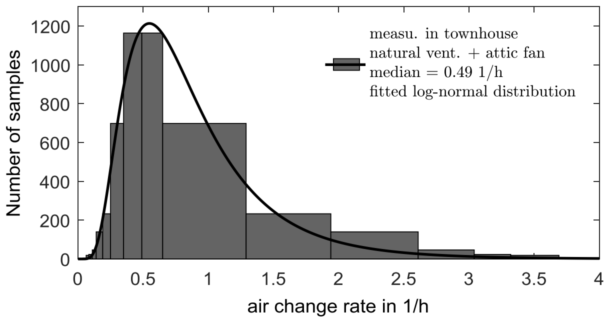

Fig. 1. Distribution of air change rates in an occupied residential townhouse derived during a one-year experiment with 4656 samples done by [3].

In this paper, a novel procedure for automatically determining the air change rates from measurements of the CO_2 concentration in occupied rooms is proposed. This procedure builds upon a new algorithm for detecting segments in the measured data with exponential behavior. The resulting method enables the stand-alone statistical evaluation of air change rates to further improve HVAC efficiency. Finally, it opens up new possibilities as statistical tool for scientific investigations of air change rate distributions.

II. Determining the Air Change Rate from CO_2 Data

The air change rate within a room or a single zone is usually determined from tracer gas measurements. Thereby a certain amount of tracer gas is released into the room and the tracer gas dilution is examined. According to the relevant ASTM (American Society for Testing and Materials) standard [4] three main methods exist for the determination of the air change rate using tracer gases: the concentration decay method, the constant injection method and the constant concentration method.

A. Underlying physical model and assumptions

For each method the underlying model is based on the mass balance equation of the tracer gas in a closed volume as given by (2) for a constant tracer gas density. The defined volume rates $\dot{V}$ in m³/h and tracer gas concentrations C per m³ for the supply and exhaust air stream as well as a tracer gas source S inside the volume, in m³/h, define the tracer gas concentration C_R in the room volume V_R in m³ over the time t in h.

$$\dot{V}_{sup} \cdot C_{sup} - \dot{V}_{exh} \cdot C_{exh} + S \; = V_R \cdot dC_R/dt \tag{2}$$

Under the assumptions that (i) $\dot{V}_{sup} = \dot{V}_{exh}$, (ii) the tracer gas is ideally mixed inside the balance room, and (iii) the tracer gas is chemically stable and inert, as claimed in [5], (2) can be further simplified resulting in the ordinary differential equation (3) for C_R.

$$\dot{V}_{sup}/V_R \left(C_{sup} - C_R\right) + S/V_R = dC_R/dt \tag{3}$$

Assuming that the initial tracer gas concentration C_R at time $t = 0$ is equal to the value $C_{R,0}$, the tracer gas concentration C_R at time t given in (4) is obtained by integrating (3).

$$C_R(t) = C_{sup} + S/\dot{V}_{sup} + \\ +\left(C_{R,0} - C_{sup} - S/\dot{V}_{sup}\right) \exp\left(-\left(\dot{V}_{sup}/V_R\right) \cdot t\right) \tag{4}$$

The sign of the coefficient $B = \left(C_{R,0} - C_{sup} - S/\dot{V}_{sup}\right)$ in front of the exponential term defines whether a transient event increases (-) or decreases (+) the tracer gas concentration. The resulting equilibrium concentration C_{Equ} is given by $C_{sup} + S/\dot{V}_{sup}$. Furthermore, taking the definition of the air change rate from (1) into account, (4) can be shortened to (5) with only three parameters left.

$$C_R(t) = C_{Equ} + B \cdot \exp(-n \cdot t) \tag{5}$$

In the established tracer gas concentration decay method as described in [4], the air change rate n is calculated based on an exponential concentration decrease characterized in (5) by the difference between the logarithms of two measured tracer gas concentrations divided by the time period in between and assuming $C_{Equ} = 0$.

B. Usage of CO_2 as a tracer gas

The European standard describing tracer gas dilution methods [6] lists six commonly used tracer gases for the determination of the airflow rate in buildings - carbon dioxide (CO_2), helium, ethylene, sulfur hexafluoride (SF_6), nitrous oxide (N_2O) and halogenated hydrocarbons like perfluoro carbons (PFCs). Besides the previously mentioned non-reactivity of the tracer gas, [7] quoted additional requirements for tracer gases like non-toxic and non-allergenic, non-flammable or explosive and not harmful to the environment. The high global warming potential of SF_6, PFCs and N_2O is to be noted. Furthermore, the concentration of tracer gas in the ambient air should be low compared to the attainable indoor concentrations and the tracer gas should be detectable with adequate accuracy in a cost-effective way.

CO_2 as a tracer gas fulfills most of the required characteristics while reaching typical indoor concentrations below a few thousand ppmv. Additionally, it has a property other tracer gases do not have, namely, it is naturally generated through metabolic production by humans in occupied rooms. In [8], the CO_2 emission per person is considered to be between 15 and 180 l/h, depending on the degree of activity. Hence, a synthetic tracer gas injection is not necessary if limiting parameters are taken into account.

For instance, [9] notes that the standardized tracer gas concentration decay method with single measurements assumes that no source of tracer gas is within the building envelope, requiring an unoccupied building while measuring. Additionally, the tracer gas concentration should be uniform without local gradients, which may be difficult to achieve in buildings with both occupied and unoccupied areas. Due to the varying CO_2 emissions by humans, a predefined injection rate can also not be guaranteed when occupant-generated CO_2 is used as a tracer gas, making methods based on constant tracer gas concentration inapplicable, if high accuracy is required. Therefore, the authors in [2] recommend to derive the air change rate from CO_2 time series with statistical evaluation of exponential patterns by linear or non-linear regression analysis:

- In the linear regression approach, the source term S needs to be zero while a CO_2 decay curve is measured continuously. After subtracting the measured or estimated outdoor CO_2 concentration from the indoor concentration C_R, (4) can be logarithmised to a linear relation and the air change rate n can be identified as the gradient in a linear regression.

- The non-linear regression approach requires a constant, possibly zero, source term S and a constant supply air flow $\dot{V}_{sup}$ and concentration C_{sup}. The equation (5) is adjusted by non-linear regression (iterative curve fitting) to make it agree with the experimental data, which can consist of either decay or build-up curves. This approach enables deriving both the air change rate n and the equilibrium concentration C_{Equ}.

Examples for both approaches can be found in the literature: [2], [10] and [11] calculated multiple air change rates by linear regression, whereas [2], [12], [13] and [14] used direct data fitting with an exponential function. The authors in [2], [11] and [13] derived the air change rate from both CO_2 and SF_6 concentration measurements and compared the results. In [14], the results were compared with defined air change rates in a climate chamber. In all cases, the validations suggest that the air change rates derived from the statistical evaluations of the CO_2 concentration curves were good approximations.

C. Proposal of statistical evaluation by automatic detection

In the previously mentioned tracer gas studies the air change rates were determined in dedicated experimental investigations in which the CO_2 concentration was measured over a defined time period (e.g. a few days) with distinct build-up and decay phases. The statistical evaluation, in particular the selection of appropriate CO_2 data sections with exponential shape, was done manually for each experimental run.

In Fig. 2, a CO_2 concentration time series over one week, measured in a residential single-family house, with a sample rate of 0.2 S/min, is displayed. The experimental data was originally recorded for passive indoor air quality monitoring and not for the purpose of air change studies. Nevertheless, multiple time periods with exponential shapes, mainly decay behavior, can be observed in the measured data. Assuming that the supply air flow and concentration as well as the number of occupants in the room remained constant during these time periods, the air change rates can be determined by fitting (5) to the individual exponential sections. Due to overall fluctuations of the influencing conditions, the assessment of air change rates needs a long-term observation of the CO_2 concentrations, leading to possibly many exponential sections in the CO_2 curve. Identifying the exponential sections for analysis requires an automatic detection tool, since the traditional manual detection is not feasible for big data series.

In the following, a novel algorithm for detecting exponential build-up and decay patterns in indoor CO_2 concentration data series is proposed. This procedure is the main technical contribution of the current paper and provides the basis for automatic derivation of air change rates from measured CO_2 concentration data.

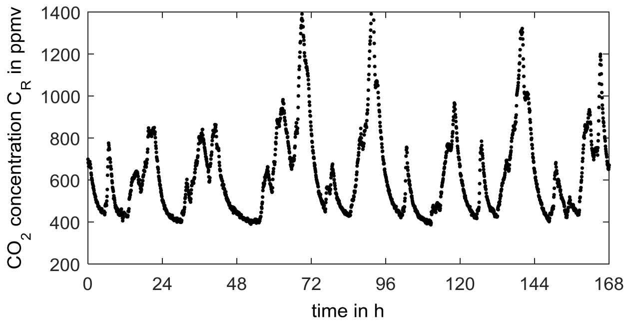

Fig. 2. Examplary CO_2 data in residential home shows exponential behaviour.

III. EXPONENTIAL PATTERN RECOGNITION

Briefly, the proposed algorithm fits the simplified exponential model in (5) to the experimental data sets by using non-linear regression with iterative calculation of the model parameters. The main challenge that the algorithm addresses is the automatic detection of time segments with exponential build-ups and decays in which the curve fitting determines the requested air change rate n and the parameters C_{Equ} and B. The crucial ingredient of the algorithm is the method that assesses the quality of a fit, i.e. the measure of how well the data represents an exponential behavior according to (5). In the following, the established coefficient of determination R^2 - a function of the residual sum of squares (RSS) and the total sum of squared errors (TSS) as shown in (6) - is used to measure the goodness of fit.

$$R^2 = 1 - (RSS/TSS) \tag{6}$$

A. Algorithm formulation

The algorithm for automatic detection of sections with exponential behavior checks iteratively the entire CO_2 concentration data set. The first iteration starts with the first data point in the CO_2 data set. An iteration k, $k > 1$, starts at the data point where the previous iteration $k-1$ ended, that is, the sections analyzed by two consecutive iterations are adjacent. At each iteration, a section with exponential behavior is returned, if one is found; otherwise, the end of the data set is reached and the algorithm terminates. Given a data set of CO_2 concentrations, the i[th] data point is denoted by (t_i, y_i), where y_i is the CO_2 concentration value at time t_i. The coefficient of determination R^2 corresponding to the data points from the interval $[i{:}j]$ ranging from i to j, $i < j$, is denoted by $R^2[i{:}j]$. A predefined minimal fit length f_{min} (made dimensionless by the sample rate) and a minimal coefficient of determination R^2_{min} are set. To identify segments that match exponential behavior, the algorithm checks iteratively the entire CO_2 concentration data set by performing three consecutive steps to (I) search for a promising match, (II) optimizing the start time of the match and (III) optimizing its fit length.

I) THE SEARCH FOR A PROMISING MATCH

The algorithm searches the data set and looks for time intervals $[i: i + f_{min}]$ such that $R^2[i: i + f_{min}] \geq R^2_{min}$. If such a candidate is found, the algorithm moves to the step II of the iteration; otherwise, the end of the data set must have been reached and the algorithm terminates.

II) OPTIMIZING THE START TIME

The segment $[i: i + f_{min}]$ such that $R^2[i: i + f_{min}] \geq R^2_{min}$ found in step I matches in a satisfactory manner an exponential shape. However, the starting point i of the match may not be optimal. Step II attempts to optimize the starting point by shifting it forward along the measured data set until the stopping criteria $R^2[i: i + f_{min}] > R^2[i + 1: i + 1 + f_{min}]$ holds. Finally, the algorithm selects the starting point of the fit with the highest R^2 and moves to step III.

III) OPTIMIZING THE FIT LENGTH

Step III starts from $[i: i + f_0]$ with $f_0 = f_{min}$ and iteratively extends the fit length to $f_k = f_{k-1}+1$, $k = 1, 2, \ldots$, as long as the variation of R^2 between two consecutive steps remains within a predefined boundary ΔR^2_{max}, that is, as long as $R^2[i: i + f_{k-1}] - R^2[i: i + f_k] \leq \Delta R^2_{max}$ holds. The final fit length is then obtained by backtracking to the last best value, setting the final f_k at the last local maximum in the R^2 sequence. For a robust detection of the stop criteria, the sensibility for the R^2 decrease is adjusted to the current fit length so that, for a larger amount of data, a single outlier has minor impact on the total goodness of fit. $\Delta R^2_{max}(f_k)$ is therefore obtained by linear interpolation between two predefined values ΔR^2_{high} and ΔR^2_{low} at specified fit lengths f_1 and f_2 according to Fig. 3.

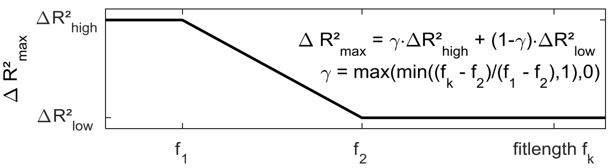

Fig. 3. Adjustment of ΔR^2_{max} over fitlength f_k between predefined constants.

To illustrate the developed method for step III, Fig. 4 depicts on the left y-axis a part of the CO_2 data from Fig. 2 with an automatically detected exponential fit on the grey background. The sequence of the corresponding R^2-values is given on the right y-axis by the black continuous line starting after the predefined minimal fit length, here f_{min} = 3 h. The R^2 behavior seen in Fig. 4 is typical for most of the detected fits. When the fit length exceeds the acceptable exponential shape, R^2 deteriorates drastically compared to rather small previous fluctuations. This sharp drop triggers the stop criteria of the algorithm in step III.

B. Specification of parameters, pre- and post-processing

To apply the algorithm, several predefined constants have to be set manually by the user. However, the performance of the algorithm is not affected significantly if values from specific ranges are chosen. For example, the parameters f_{min} and R^2_{min} give just the initial values of a detected match, which are iteratively extended or improved in most of the cases. Since the shapes of exponential patterns in indoor CO_2 datasets are typically within similar ranges, the values for f_{min} and R^2_{min}, as well as for the constants ΔR^2_{high} and ΔR^2_{low} at the fit lengths f_1 and f_2 do not necessarily need an individual adjustment for different data sets. The authors recommend the parameter setting from Table I and II, used for test runs on three different datasets.

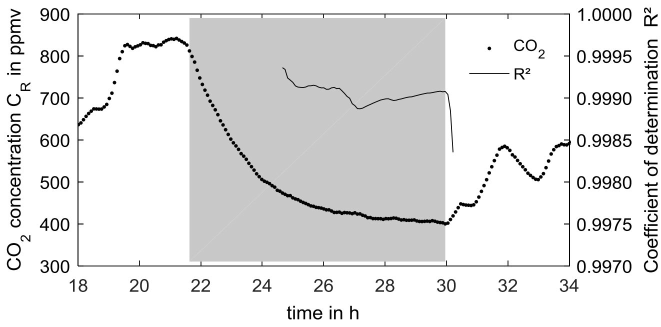

Fig. 4. Left y-axis: Section of the CO_2 data from Fig. 2 with an automatically detected exponential fit. Right y-axis: results of R^2 values computed in step III.

In order to further improve the detection quality, the original dataset can be first filtered to reduce noise as it was done in the example shown in Fig. 4. The noise suppression facilitates the detection for the stop criteria in step II and III, since the R^2 trends are smoothed. To support the fitting process and reduce the calculation time, custom initial values, considering well-known physical ranges, can be set for the optimization of the parameters in (5). Furthermore, the coefficients can also be restricted by predefined bounds. For instance, in the case that only exponential curves with steady state concentrations near the ambient air level are of interest, C_{Equ} can be bound to a specific ambient air concentration. In addition, the coefficient B can be bounded between 0 and +∞ for exclusive recognition of decay curves. On the other hand, if B is predefined with a negative sign, only build-up curves will be detected (assuming negative exponents). The parameter restrictions can also be done in a post-processing procedure to check the validity of each exponential fit. For example, fits with insufficient fit lengths or unphysical values for the air change rate or the equilibrium concentration can be automatically rejected in the final results.

IV. PROOF OF CONCEPT

To demonstrate the feasibility of the proposed automatic determination of air change rates in CO_2 datasets by exponential pattern recognition, the algorithm is tested on both synthetically generated CO_2 data and real CO_2 data from two experimental investigations in residential buildings. In the present study, the computational environment of MATLAB R2016a is used. The curve fitting is performed by invoking the '*fit*' function with the '*NonlinearLeastSquare*' method and the '*Trust-Region*' optimization.

A. Test run with synthetic data

A synthetic dataset, over a time period of ten years, is generated by a finite difference simulation of the differential equation for C_R stated in (3). To include random phenomena, several random numbers are used to create a distributed occupancy profile and alternating air change rates. The probability that the room is occupied by 0/1/2 persons is set to 0.5/0.3/0.2. The occupation duration is normally distributed with mean 8/6/4 hours and a standard deviation of 2 hours each. One person emits 17 l/h CO_2 into a room of volume V_R = 50 m³. The air change rate varies every 24 hours and is normal distributed with a mean value μ of 0.8 1/h and a standard deviation σ of 0.1 1/h. The CO_2 concentration in the supply air is set to C_{sup} = 400 ppmv. To imitate a random error in the CO_2 dataset with a sample rate of 0.2 S/min, the simulation result is artificially normal distributed with a standard deviation σ of 50/3 ppmv. This means that 99.73 % of the data is within the error interval $\pm$50 ppmv, which is a typical error for common CO_2 measuring instruments. In Table I the applied parameter setting for the exponential pattern recognition algorithm is listed. The coefficients were restricted during the fitting to the stated upper and lower bounds for exclusive determination of decay curves. No additional post-processing was done.

TABLE I. PARAMETER SETTING FOR TEST RUN WITH SYNTHETIC DATA

	C_{Equ} in ppmv	B	n in 1/h
Lower bound	0	0	0
Upper bound	5000	+Inf	100
Initial value	400	0	1
R^2_{min}	f_{min} in h	$\Delta R^2_{high}(f_1 = 3\text{ h})$	$\Delta R^2_{low}(f_2 = 10\text{ h})$
0.99	3	0.001	0.0001

Before applying the curve-fitting algorithm, the data was smoothed by a central moving average filter with a total extent of five data points. Over the artificially generated ten-year period, the algorithm detects 3756 exponential decay curves. The obtained distribution of air change rates is plotted in histogram form in Fig. 5. The probability density function for the normal distribution calculated from the sample mean $\bar{x}$ and the sample standard deviation s of the derived air change rates (continuous line) and the probability function of the original normal distribution (dashed line) used to generate the synthetic data are depicted in Fig. 5 as well.

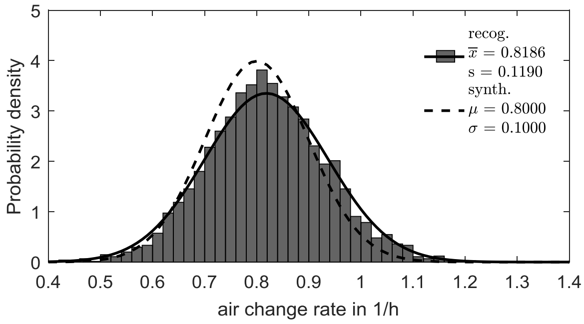

Fig. 5. Distribution of 3756 air change rates (recog.) automatically derived from the synthetic CO_2 data generated by a normal distributed air change.

The calculated distribution turns out to be a good approximation of the original distribution, confirmed also when comparing the statistical coefficients, i.e. mean value and standard deviation, of the two distributions.

B. Test runs with experimental data

For the test runs on real data, indoor CO_2 concentration measurements in two residential buildings located in Austria were used. The first building is a single-family house that is natural ventilated through leakages in the building envelope; additionally, it can be ventilated manually by window ventilation. An infrared CO_2 sensor was placed in a central position in the kitchen, which is connected to the living room resulting in a total zone volume of 161 m³. The second measurement was done in an apartment equipped with a mechanical supply and exhaust airflow system. This time, an infrared CO_2 sensor was placed in a sleeping room with a room volume of 39 m³. In both experiments, the specified measurement uncertainty of the installed CO_2 sensors was ±50 ppmv without any indication of the error distribution. In the naturally ventilated single-family house, the CO_2 concentration was measured continuously over a three month winter period with a sample rate 0.2 S/min. In the mechanically ventilated apartment, the measurement lasted for four and a half months in the summer period with a sample rate of 0.1 S/min. The same parameter setting for the exponential pattern recognition, listed in Table II, was used in both experiments. The coefficients were restricted to focus on exponential decay curves with an equilibrium CO_2 concentration of the ambient air between 350 and 450 ppmv. Except for smoothing the data with the previously mentioned moving average filter, no additional pre- or post-processing was done.

TABLE II. PARAMETER SETTING FOR TEST RUNS WITH EXPERIM. DATA

	C_{Equ} in ppmv	B	n in 1/h
Lower bound	350	-Inf	0
Upper bound	450	+Inf	100
Initial value	400	0	1
R^2_{min}	f_{min} in h	$\Delta R^2_{high}(f_1 = 3\text{ h})$	$\Delta R^2_{low}(f_2 = 10\text{ h})$
0.99	3	0.001	0.0001

The results from both testruns are displayed by overlapping histograms in Fig. 6. The probability density functions for a normal respectively log-normal distribution calculated from the sample means and the sample standard deviations of the derived air change rates are shown by the continuous lines.

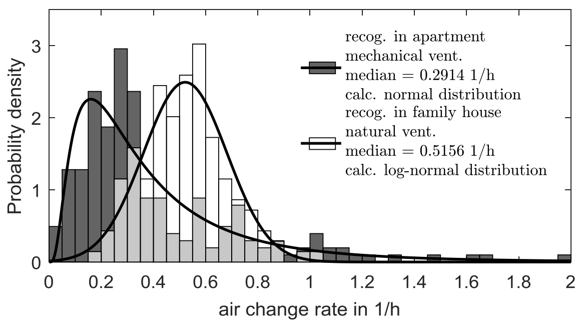

Fig. 6. Distribution of automatically derived air change rates from CO_2 data in the kitchen of a naturally ventilated single-family house (139 counts) and in the sleeping room of a mechanically ventilated apartment (204 counts).

For the naturally ventilated single-family house, plotted in white colored bars, the 139 detected air change rates correspond to a symmetric normal distribution with a total arithmetic mean of 0.5216 1/h and a median value equal to 0.5156 1/h, which are typical values for a naturally ventilated building.

In the monitored sleeping room of the apartment, 204 air change rate values were recognized and plotted with grey colored bars in Fig. 6. In contrast to the naturally ventilated family house, the air change rate distribution in the mechanically ventilated apartment is skewed to the right and the arithmetic mean of 0.4133 1/h as well as the median value of 0.2914 1/h is lower, but still in an expected range. The skewed distribution towards higher air change rates, which is close to a log-normal distribution, has also been discovered by [3], based on one-year measurements in a town house (cf. Fig. 1). In the experimental study the air change rates increased in the summer months due to a temperature controlled attic fan and window ventilation by the occupants. Since the CO_2 measurements in the family house took place in the winter period, manual window ventilation with higher air change is not to be expected. This seasonal effect may explain the symmetric distribution of air change rates in the single-family house.

Note that in case of a multi-zonal building, air may enter from an adjacent zone. The inter-zonal air flows often do have CO_2 concentrations above ambient air level, so that a single-zone mass balance model like (2) leads to an air change rate based on an equivalent outdoor airflow as mentioned in [11].

V. CONCLUSION AND FUTURE WORK

A novel procedure for automatic determination of air change rates from CO_2 concentrations measured in indoor occupied rooms was proposed. The method builds upon a new algorithm for detecting exponential build-up and decay patterns in CO_2 time series. The feasibility of the concept was first proved with a test run on synthetic data that shows a good reproduction of the predefined air change distribution used to generate the synthetic data. Further demonstration includes the test runs on real CO_2 datasets measured in the kitchen and the sleeping room of two residential buildings. The derived air change rates were within typical expected ranges in both cases, when mechanical or natural ventilation was used.

The promising results suggest a continuation of the research on further improvements of the algorithm for an even more robust and precise detection of exponential sections. Additional self-adapting strategies would reduce the number of parameters which need to be set manually. The determination of very high air change rates when only fits with short lengths are available also presents a future challenge. Moreover, the performance of the method should be assessed with extended experimental data.

The use case for automatic detection of air change rates can further improve ventilation control strategies and substantially reduce the efforts in air change investigations. Furthermore, the evaluation of automatically detected equilibrium concentrations may enable conclusions on the current occupancy or provide new calibration strategies for CO_2 sensors used in environments that rarely reach ambient CO_2 concentrations. In principle, the concept of exponential fitting can be adopted to every physical process based on a simple balance equation, addressing a huge field of technical applications.

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