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PAPER

Assessing metabolic rate and indoor air quality with passive environmental sensors

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The present work introduces the use of environmental sensors to assess indoor air quality (IAQ) in combination with human biometrics. The sensor array included temperature, relative humidity, carbon dioxide, and noise monitors. The array was used in a classroom as well as in a vehicle cabin to assess the carbon dioxide production rate of individuals in a closed ventilation environment. Analysis of carbon dioxide production allowed for the quantification of the average metabolic rate of the group of individuals in the classroom, and for one individual in the vehicle cabin. These results yielded a mere 5% difference from the values assessed using commercial metabolic rate instruments, and averaged values from epidemiological studies. The results presented in this work verify the feasibility of determining an individual's metabolic rate using passive environmental sensors; these same sensors are able to provide a metric of IAQ that helps characterize the safety of the environment in which the individual is present.

1. Introduction

Metabolic activity can have a significant effect on a person's mental and physical health and, as such, the ability to measure metabolic rate is a valuable tool when it is used to assess a person's daily caloric needs [1]. The resting metabolic rate (RMR) is the most useful metric for determining a person's metabolic rate, the measurement and analysis of which is the only way for professionals to properly estimate caloric needs of an individual and to suggest diet and exercise plans that best fit a person's wellness and weight goals [1, 2].

Although epidemiological equations can be used for the calculation of RMR [3], an individual's personal value of RMR is unpredictable and should be directly measured for a more accurate assessment of metabolic activity [4]. The RMR value depends on many physiological parameters and can change depending on a person's stress, diet, and exercise tendencies [2]. Traditional methods of assessing metabolic rate include the use of metabolic carts [1], desk-top instruments [1], hand-held devices [5], and mobile

trackers [6]. These devices are based on the indirect calorimetry method, which assesses the person's oxygen consumption rate (VO_2) only, or in addition to the carbon dioxide emission rate (VCO_2). However, assessing metabolic rate under free living conditions without the burden of actively performing a measurement with an instrument is ideal because it requires little to no effort or time commitment on the part of the individual. Free-living metabolic rate may offer not only information about the resting state (RMR), but also the metabolic rate at different times of the day, periods of the year, and life circumstances, which makes possible the assessment of total energy expenditure (TEE), the key parameter needed for assessment of the individual's true energy expenditure. In this regard, the only Gold Standard for assessment of TEE is the doubly labeled water method [7]. This method uses the decay of isotopes in urine, and determine carbon dioxide production rate to apply the calculation of metabolic rate, assuming a respiratory quotient (RQ) of 0.85 [7]. Although the subject is able to live freely during the testing period of 7–10 d, the method requires urine sample collection at day 1 and at day 7th or 10th. As a

result, it is only able to provide a single integrative metabolic rate value of 7–10 d of life without discrimination of resting, or higher resolution metabolic rate patterns [8]. Furthermore, the method requires of isotope analysis with intensive maintenance, and it is laborious, time consuming and costly (\$1000 isotope dose per test).

Other examples of TEE assessment include calorie/activity trackers (e.g., wrist watches). These devices are based on physical sensors that fail to accurately represent a person's metabolic activity because do not perform indirect calorimetry or isotope-based measures. Instead they use equations based on accelerometer or heart rate parameters and calculated RMR. Even commonly used equations calculating metabolic rate can differ by as much as 900 kcal d^{-1} [4]. Therefore, calorie/activity trackers are not necessarily an accurate approach to monitor TEE or metabolic rate.

In the present work, we present the assessment of metabolic rate under free living conditions, using an inexpensive sensor system that passively assesses the metabolic rate in a period of 20–90 min in conjunction with the simultaneous assessment of an indoor air quality (IAQ) metric. The system includes sensors of carbon dioxide, temperature, relative humidity (RH), noise and occupancy, as well as a mathematical model that determines individual's metabolic rate from produced carbon dioxide (VCO_2) rate.

The system's sensors could be deployed in numerous places of mechanically ventilated buildings, to monitor and adjust IAQ as needed. Today, a majority of people spend approximately 90% of their day indoors, and, as a result, are at risk of developing the signs and symptoms associated with the sick building syndrome (SBS) [9]. The optimization of ventilation system is necessary to minimize the SBS symptoms. Current monitoring methods for ventilation systems offer intermittent sampling, however, the ability to confirm the physical presence of people in a setting and to determine the number of occupants in confined environments allows for unique assessment of the individual's biometrics.

The basis of the present study is the detection and quantification of CO_2 in indoor conditions generated by the human metabolism. Carbon dioxide is already in the atmosphere in concentrations ranging from approximately 350–450 ppm [9, 10] and current atmospheric levels of CO_2 pose little to no health risks. However, high indoor concentrations CO_2 can result in negative health effects. The Occupational Safety and Health Administration has set a 5000 ppm permissible exposure limit as an 8 h total weight average (TWA), and a 30 000 ppm short term exposure limit as a 10 min TWA for CO_2 [11]. Under most common conditions, in non-industrialized indoor settings, such as an office, classroom, and a vehicle, CO_2 concentrations do not exceed 4500 ppm [9, 10]. Recent studies have presented evidence of negative impacts on

cognitive functions for relatively low indoor CO_2 concentrations such as in the range 1000–3000 ppm [12–14]. These levels are below the established exposure limits [15]. It should be noted that CO_2 is used as a surrogate for occupant-related emissions in buildings, which include bio effluents and personal care products [16, 17]. The discomfort affecting these occupants can be serious; those in CO_2 rich environments exhibit upper and lower respiratory tract complications such as dysphonia, dry cough, and asthma. Nervous system complications including headaches and difficulty concentrating are also sign of CO_2 overexposure in addition to skin and eye irritation [18].

In this work, we test the feasibility of assessing metabolic rate from carbon dioxide production rate assessed from individual/s in different confined environments, in addition to an IAQ metric and the air exchange rates (ACHs) using environmental sensors.

2. Methods

Two different setting were used to probe the simultaneous assessment of environmental parameters, and biometrics: a classroom and a car cabin.

- Classroom: This allowed to study the concept in a big room, and the assessment of ACH along with the assessment of averaged metabolic rate in the class.
- Car cabin: This allowed the assessment of an individual's metabolic rate value, and characterization of the ACH under conditions of no-ventilation and recirculation mode, typically used in cars to save cooling or heating energy.

2.1. Classroom tests

The classroom environment tests were conducted on the Arizona State University's main campus in Tempe, AZ within the G-wing of the Engineering Center, room number 237 (ECG 237). The subjects for the classroom environment tests were from a set of classes that were conducted at ECG 237: an afternoon class of 18 and a morning class of 30. The ages of the classroom test subjects were from 18 to 30 years old, and both classes have similar population distribution (within 5%) for weight and height, with weights that ranged between 100 and 150 lbs for females, and 130–180 lbs for males, and heights that ranges between 5'5"–5'8" for females, and 5'7"–6'0" for males. The distribution of females and males was: 22% and 78%, respectively in the first class ($n = 19$), and 20% and 80%, respectively in the second class ($n = 30$). The Results from the classroom tests were averaged out among the 18 and 30 respective occupants within each class. Individualized health results for each classroom test subject were not taken. Only an average age, weight, and height with a percentage of gender (which was

~60% for male, and ~40% female) was assessed with no identifiers from the occupants in the room, and used to estimate the expected average metabolic rate using Mifflin-St Jeor epidemiological equation [3].

2.2. Car tests

The vehicle tests were conducted on residential streets within the city of Tempe in a 2007 Toyota Corolla. The car test subject was a healthy 27 year old adult male. The car environment tests portion of the study was approved by the Institutional Review Board of Arizona State University (IRB protocol # 1304009100 for collection of environmental data, and # 1012005855 for collection of metabolic rate data with portable indirect calorimetry technology). The test subject participated voluntarily, providing written consents to participate in the study. All tests for this study were conducted from February to April 2017 by the same driver.

2.3. Sensors and devices

A sensor system was built to conduct the tests. The system consisted of a carbon dioxide sensor (Telaire® 7001 CO₂), a temperature and humidity sensor (HOBO® unit), and a noise and pressure-based sensor to detect occupancy (details below). The sensors were connected to an external data logger. The carbon dioxide sensor was based on a double-beam non-dispersed infrared detector with a detection wavelength of 4.26 μm , CO₂'s strongest absorption band [19, 20]. The sensor measurement range was 0–4000 ppm with measurement resolution of ± 1 ppm. Manufacture specifications report an accuracy of ± 50 ppm or 5% of reading and a repeatability of ± 20 ppm [21]. The reported operating range is from 32 °F to 122 °F and 0% to 95% RH, non-condensing [21]. Calibrations using dilutions of a 5% carbon dioxide gas and pure air were completed before any study tests were conducted to assure the accuracy of the system CO₂ detection levels. The HOBO® unit for temperature and humidity sensing could measure temperature from -4 °F to $+158$ °F and humidity from 0% to 95% RH, non-condensing. The temperature measurement resolution is 0.01 °F and humidity measurement resolution is 0.1% [22].

2.4. Sensors' experimental setup

The experimental setup for the classroom tests involved placing the sensor array in a location within ECG 237 that would provide readings that closely mirrored the average CO₂ concentration of the entire room. In this case, the noise sensor and pressure based sensor for occupancy were not used, and occupancy was assessed via physical person count. Two mid-size, 1 ft diameter fans were placed in the front and back of the room to ensure a well-mixed environment. The sensor was started at 4:00 PM on 20 February, 2017 and collected data the entire night and early morning.

This was done to obtain a more representative CO₂ concentration profile. At about 10:17 AM on 21 February, 2017 the sensor's data logger was stopped and all data was collected.

The experimental setup for the vehicle tests optimized the placement of the CO₂, temperature, and humidity sensors in locations that would give the most accurate representation of the average CO₂ concentration of the entire car volume. The sensor was placed in the front dashboard approximately a meter from the driver. Conditions such as the opening and closing of windows were tracked and varied over a series of tests. The vehicle tests were conducted with the same occupant for all tests and the traffic was not heavy since the tests were performed in highway (60 West to East, and East to West in Phoenix area) at times with low traffic. In addition, testing of single occupancy was corroborated with the noise and pressure-based sensors, which are described in the result and discussion section.

2.5. Modeling

The base development of the model considers prior state of art by the World Health Organization to monitor indoor pollutant concentrations [6], and includes the following assumptions:

- The only source of CO₂ generated is from a room's occupants.
- Once all occupants leave, CO₂ is assumed to decay until equilibrium is reached with the outside baseline value at approximately 350–450 ppm.
- The air is displaced via the room's natural and/or mechanical ventilation systems.

The model considers the following total differential equation for the change in CO₂ concentrations:

$$\frac{d[\text{CO}_2]}{dt} = \frac{d[\text{CO}_2]_{\text{gen}}}{dt} + \frac{d[\text{CO}_2]_{\text{ven}}}{dt}, \quad (1)$$

where $[\text{CO}_2]_{\text{gen}}$ is the carbon dioxide generated by the room's occupant, and $[\text{CO}_2]_{\text{ven}}$ is the carbon dioxide ventilated from the room. Three situations were modeled and measured: (a) *Ventilation and no occupants in the room*, (b) *Ventilation and occupants in the room*, (c) *No ventilation and occupants in the room*.

(a) *Ventilation and no occupants in the room*: In this condition, the generation is assumed to be 0, and the differential equation simplifies to the following:

$$\begin{aligned} \frac{d[\text{CO}_2]_{\text{gen}}}{dt} &= 0 \rightarrow \frac{d[\text{CO}_2]}{dt} = \frac{d[\text{CO}_2]_{\text{ven}}}{dt} \\ \frac{d[\text{CO}_2]}{dt} &= -k_{\text{ven}}[\text{CO}_2]^x, \end{aligned} \quad (2)$$

where k_{ven} is the ACH, and the unknown (x) ventilation order can be determined by plotting the following relationships:

- Zeroth order ventilation: $[\text{CO}_2] = [\text{CO}_2]_i - k_{\text{ven}} t$
- First order ventilation: $\ln[\text{CO}_2] = -k_{\text{ven}} t + \ln [\text{CO}_2]_i$
- Second order ventilation: $\frac{1}{[\text{CO}_2]} = \frac{1}{[\text{CO}_2]_i} + k_{\text{ven}} t$.

As will be discussed in the results section, the first order ventilation rate law yielded the highest R-squared values for all decays. Consequently, the ventilation reaction rate constant (k_{ven}) is equivalent to the ACH, defined here as λ . The first order type of decay validated previous studies conducted by Escombe and Bouhamra *et al* [23, 24]. Therefore, equation (1) is simplified to:

$$\frac{d[\text{CO}_2]}{dt} = -k_{\text{ven}}[\text{CO}_2]^1 = -\lambda[\text{CO}_2]^1. \quad (3)$$

Solving for the indoor CO_2 concentration in an interval where the CO_2 concentration ranges between an initial value $[\text{CO}_2]_i$, and a final value $[\text{CO}_2]$ for all times intervals generates the following analytical expression for $[\text{CO}_2]$:

$$\begin{aligned} \int_{[\text{CO}_2]_i}^{[\text{CO}_2]} \frac{1}{[\text{CO}_2]} d[\text{CO}_2] \\ = - \int_{t_i}^t \lambda dt \rightarrow \ln[\text{CO}_2] - \ln [\text{CO}_2]_i = -\lambda t, \\ \ln[\text{CO}_2] = \ln [\text{CO}_2]_i - \lambda t, \\ [\text{CO}_2] = [\text{CO}_2]_i e^{-\lambda t}. \end{aligned} \quad (4)$$

(b) *Ventilation and occupants in the room*: the second scenario considered the generation of CO_2 from occupants with an ACH different from 0. In this situation, equation (1) can be generically expressed:

$$\frac{d[\text{CO}_2]}{dt} = \frac{d[\text{CO}_2]_{\text{gen}}}{dt} - \lambda[\text{CO}_2] \quad (6)$$

and solved, considering the CO_2 concentration at steady state (S.S.). Making this assumption the differential equation simplifies to the following:

$$\begin{aligned} \text{At S.S.: } 0 &= \frac{d[\text{CO}_2]_{\text{gen}}}{dt} - \lambda[\text{CO}_2] \\ \rightarrow \lambda[\text{CO}_2] &= \frac{d[\text{CO}_2]_{\text{gen}}}{dt}. \end{aligned}$$

$$\text{At S.S. : } \frac{d[\text{CO}_2]_{\text{gen}}}{dt} = \lambda[\text{CO}_2] = \lambda[\text{CO}_2]_{\text{gen}}.$$

Assuming the following boundary condition

$$\text{At } t = 0 \rightarrow [\text{CO}_2] = [\text{CO}_2]_i,$$

where $[\text{CO}_2]_i$ refers to any CO_2 above the baseline atmospheric concentration initially present, and a baseline atmospheric concentration of CO_2 , $[\text{CO}_2]_0$, which is equivalent to 350–450 ppm, the following analytical expression for $[\text{CO}_2]$ is obtained:

$$\begin{aligned} [\text{CO}_2] &= [\text{CO}_2]_0 + [\text{CO}_2]_{\text{gen}}(1 - e^{-\lambda t}) \\ &+ [\text{CO}_2]_i e^{-\lambda t}. \end{aligned} \quad (7)$$

Equation (7) was used to fit the experimental data with units defined as follows: ACH, $\lambda = \text{hour}^{-1}$; initial concentration of carbon dioxide, $[\text{CO}_2]_i = \text{ppm}$, Outdoor CO_2 Concentration, $[\text{CO}_2]_0 = \text{ppm}$; Generated CO_2 , $[\text{CO}_2]_{\text{gen}} = \text{ppm}$; and time, $t = \text{hour}$.

2.5.1. Assessment of IAQ and metabolic rate

In environments where occupants are coming in and out and leave an empty room, the ACH was determined with experimental decay values by taking the natural logarithm of the CO_2 concentration and plotting it against the time at which the decay began. The slope of the line corresponded to an ACH value. The ACH value, denoted as $\lambda (\text{hour}^{-1})$, along with the room's volume (V) is related to the ventilation rate (Q) via the following equation [23]:

$$Q = \lambda * V. \quad (8)$$

The ventilation rate is needed to solve the generated CO_2 ($[\text{CO}_2]_{\text{gen}}$) [25]

$$\begin{aligned} [\text{CO}_2]_{\text{gen}} &= \frac{\text{CO}_2 \text{ source generation rate}}{\text{Room ventilation rate}} \\ &* 10^6 \text{ ppm} = \frac{\dot{P}}{Q} (\text{ppm}). \end{aligned} \quad (9)$$

Plotting experiment values from the classroom and vehicle tests, and extracting known values of λ , V , $[\text{CO}_2]_0$, and $[\text{CO}_2]_i$, the value of $\dot{P}$ was fitted and empirically determined after completing a series of iterations. In this particular work, the Excel *What-if-analysis Goal Seek* function was used to determine values of $\dot{P}$ that produced the smallest percent error between the experimentally obtained CO_2 concentrations and values obtained via the developed model (equation (7)).

Understanding the phenomena of cellular respiration has allowed for the development of a model that directly relates metabolic rate to consumed O_2 (VO_2) rate and produced CO_2 (VCO_2) rate by a living being. This relationship was developed by physiologist Weir [26]:

$$\begin{aligned} \text{Metabolic Rate} (\text{kcal d}^{-1}) &= [3.941(\text{VO}_2 (\text{l min}^{-1})) \\ &+ 1.11(\text{VCO}_2 (\text{l min}^{-1}))] * 1.440. \end{aligned} \quad (10)$$

In the absence of VO_2 rate readings, such as in the double labeled water method [8], the concept of RQ can be used to relate VCO_2 to VO_2 [27]. RQ is the ratio of the produced carbon dioxide rate (VCO_2) and consumed oxygen rate (VO_2) of a person:

$$\text{RQ} = \frac{\text{VCO}_2}{\text{VO}_2}. \quad (11)$$

The RQ can be implemented into the Weir equation giving the following relationship between metabolic rate, and VCO_2 [27]:

Figure 1. Temperature, relative humidity, and CO₂ concentrations versus time within room ECG 237 for classroom test taken on 20–21 February from 4:06 PM to 10:17 AM. The left y-axis corresponds the CO₂ concentration in ppm, while the right y-axis corresponds the temperature in °F and relative humidity in %. Measurements were updated every 30 s. ‘Decay #1’ starts at 4:06 PM and ends at 4:22 PM. ‘Decay 2’ occurs from 5:38 PM to 6:22 PM, and ‘Decay 3’ occurs from 9:39 AM to 10:16 AM. ‘Growth 1’ starts at 4:22 PM and ends at 5:38 PM, and ‘Growth 2’ starts at 8:35 AM to 9:39 AM.

$$\text{Metabolic Rate (kcal d}^{-1}\text{)} = [3.941(\text{VCO}_2 \text{ (ml min}^{-1}\text{)} \\ * \text{RQ} + 1.11(\text{VCO}_2 \text{ (ml min}^{-1}\text{)})] * 1.440. \quad (12)$$

The RQ is typically in the range of 0.67–1.2 and depends on the specific substrate undergoing cellular respiration [27]. However, studies have found the weighted average of RQ to be 0.86 [28]. Inputting this value into the Weir equation provides a simplified metabolic rate calculation:

$$\text{Metabolic Rate (kcal d}^{-1}\text{)} = 8.19(\text{VCO}_2 \text{ (ml min}^{-1}\text{)}). \quad (13)$$

Using the developed Weir equation and the described-above mathematical model, the VCO₂ will be able to be quantified via passive environmental CO₂ sensors and used to determine a person’s metabolic rate or the average metabolic rate in a group of a room’s occupants. It is worthy to mention that, this is another important contribution by the present model that has not been reported before.

(c) *No ventilation and occupants in the room:* the third testing scenario considered the generation of CO₂ from occupants, and no ventilation (ACH = λ = 0). In this condition, the generation from occupant/s can be considered zero order since the constant production of CO₂ is intrinsic from the person as far as the person is living, and produced from consumed food and energy storage (person’s glycogen, fat, proteins) [29, 30]. Note that this is another important contribution by the present model that has not been associated before. Therefore, equation (1) can be generically expressed as

$$\frac{d[\text{CO}_2]}{dt} = k_{\text{gen}}[\text{CO}_2]^0 \quad (14)$$

and solved as follows:

$$[\text{CO}_2] = k_{\text{gen}}t + S, \quad (15)$$

where S can be considered as follows from the boundary condition:

$$\text{At } t = 0 \rightarrow [\text{CO}_2] = S = [\text{CO}_2]_0 + [\text{CO}_2]_i$$

with $[\text{CO}_2]_0$, the baseline concentration based on CO₂ atmospheric concentration, and $[\text{CO}_2]_i$ additional CO₂ concentration from a remaining source. Therefore, the following analytical expression for $[\text{CO}_2]$ is applicable:

$$[\text{CO}_2] = k_{\text{gen}}t + [\text{CO}_2]_0 + [\text{CO}_2]_i \quad (16)$$

with k_{gen} (ppm min⁻¹), ppm could be defined as ml of exhaled CO₂/l of exhaled air volume = ml of exhaled CO₂/dm³ exhaled air volume, k_{gen} (ppm/min) × V (room volume) (dm³) = VCO₂ (ml CO₂/min), and VCO₂ can be directly applied to equation (13) to assess metabolic rate.

3. Results

3.1. Classroom tests

In order to determine the CO₂ generation rate from a group of individuals in a classroom, the classroom ACH was evaluated first. It is worthy to mention that the use of the generated carbon dioxide from a room’s occupants to determine ACH is an advantage since: (1) it avoids the assessment of leakage functions, and mechanical ventilation airflow rates, (2) CO₂ is a chemically inert, and non-toxic gas, and (3) the release of CO₂ concentrations from a room’s occupants cause indoor concentrations to be greater than outdoor concentrations resulting in an outdoor-indoor concentration gradient [31]. Once all occupants of a room leave, the indoor CO₂ concentrations decline until outdoor and indoor concentrations reach equilibrium and this decay can be used to determine the room’s ACH [28].

The classroom test was conducted on 20 February, 2017 from 4:06 PM to 10:17 AM in the next day.

Figure 1 shows the raw CO_2 concentrations, RH, and temperature versus time. The data show variable fluctuations of growth and decay with a long period of relatively constant concentrations.

As it can be observed in figure 1, the sensor's data logging started in the middle of a decay, labeled as 'decay #1'. The decline in CO_2 levels continued until approximately 4:22 PM where there was a reversed CO_2 level growing trend labeled 'growth #1'. Growth #1 was a clear indicator that the room gained occupants as the scheduled class time was approached. Concentrations rose until a plateau value was obtained at about 4:52 PM. The plateau showed that steady-state CO_2 concentration was reached, and that the difference between the CO_2 being produced and the ventilation rate was approximately zero. The plateau continued until 5:38 PM which corresponded to the course's dismissal time. A decay, labeled 'decay #2', took place until the indoor CO_2 concentration matched outside levels. The baseline value was attained at about 6:22 PM and was determined to be at about 436 ppm. A growth in concentration, labeled 'growth #2', occurred at 8:35 am where the CO_2 levels rose rapidly, and reached quasi-S.S.. At 9:39 AM the last observed decay, 'decay #3', occurred. Growth #2 and decay #3 corresponded to the arrival and dismissal of the morning class.

Figures 2(A)–(C) shows data of CO_2 levels corresponding to decay #1, #2, and #3 from figure 1, as Ln CO_2 (ppm) versus time. The linear behavior between $\text{Ln}[\text{CO}_2]$ and time, indicated that the ventilation rate has a first order behavior, and followed equation (4). Therefore, a linear fitting was performed to determine the ACH values, which rendered R^2 coefficients between 0.95 and 0.96. Table 1 summarizes the findings.

Table 1. ACH values from classroom tests.

λ	Classroom's air change rate (h^{-1})
Decay #1	1.68
Decay #2	1.10
Decay #3	0.90

It is worth to notice that the decay #1 was a period where the classroom had no occupants and the door remained open with ventilation supported by fans as described in the experimental section. On the contrary, decay #2 had no occupants also, but the classroom door was close with ventilation supported by fans. On the other hand, decay #3 had the classroom door closed, fans were off but there were 3 occupants. The higher ACH value resulting from decay #1 with respect to decay #2 may be due to the fact of having the door open versus closed. In addition, the fact of having slightly lower value in decay #3 versus decay #2 could be attributed to the fans off and 3 occupants concurrently producing CO_2 in the room. It is worth noticing that equation (4) was used for decay #3, and it was assumed the contributions of 3 occupants left in the room after the presence of 30 occupants was not significant.

Figures 3(A), (B) shows the curves of periods for growth #1 and growth #2 from figure 1. In this case, fittings of the CO_2 levels to equation (7) from the model were performed. The fitted parameter was the CO_2 source generation rate $[\text{CO}_2]_{\text{gen}}$, and the parameter $\dot{P}$ (in units of ppm h^{-1}) was obtained by applying equation (9), using λ , $[\text{CO}_2]_i$, $[\text{CO}_2]_o$, and Q (room ventilation rate) = V (room volume) $\times \lambda$ as known parameters. Since the number of occupants in the room for growth #1 and #2 was known, an averaged carbon dioxide production rate, VCO_2 per occupant

Figure 3. Graphical representation of the CO₂ concentration (ppm) versus time. The fitted parameter is [CO₂]_{gen} (CO₂ source generation rate) value for: (A) 'Growth #1' that occurred from 4:25 to 4:45 PM, where 18 room occupants were present. (B) 'Growth #2' that occurred from 8:51 to 9:39 AM, where 30 room occupants were present.

Table 2. CO₂ source generation rate and metabolic rate calculation parameters from classroom tests.

Variables ^a	Growth #1	Growth #2
Air exchange rate— λ	1.10 h ⁻¹	0.90 h ⁻¹
Room volume	9720 ft ³ = 262 440 dm ³	9720 ft ³ = 262 440 dm ³
Room ventilation rate— $Q (\lambda \times V)$	~9720 ft ³ h ⁻¹	~9720 ft ³ h ⁻¹
Initial + Outside CO ₂ Concentration—[CO ₂] _i + [CO ₂] _o	616 ppm	509 ppm
CO ₂ source generation rate—[CO ₂] _{gen}	410 000 ppm h ⁻¹ occupant	450 000 ppm h ⁻¹ occupant
Fitting percent error	6%	6%
Metabolic rate calculation parameters ^b		
[CO ₂] _{max}	~771 ppm	~1216 ppm
σ —# of room occupants	18	30
VCO ₂	184 ml min ⁻¹	174 ml min ⁻¹
Metabolic rate	1511 kcal d ⁻¹	1422 kcal d ⁻¹

^a Known and fitted parameters using equation (7).

^b Metabolic rate calculation parameters, using $\frac{\dot{P}}{Q} = \frac{VCO_2}{\sigma \times Q}$ and equation (13).

was calculated, using the following expression:

$$\frac{\dot{P}}{Q} = \frac{VCO_2}{\sigma \times Q} \quad (17)$$

followed by the estimation of an average metabolic rate per person in the room. Table 2 summarizes the findings. The average metabolic rate values were 1511 (± 150) and 1422 (± 140) kcal d⁻¹, which was in coincidence with the level of metabolic rate estimated from the Mifflin-St Jeor equation considering average age, average height, average weight, and gender percentage distribution. Although the results did not allow to assess individuals' metabolic rate values, the use of the model to assess metabolic rate from environmental CO₂ detection (particularly equations (7), (9), and (17)) was proven to be functioning. As consequence, the car tests were performed, hypothesizing that CO₂ level detectable changes and the model would make possible to assess metabolic rate from the driver.

3.2. Vehicle tests

A total of four vehicle tests were conducted. Three of them were performed between the months of March

and April 2017, and the final test took place in September 2017. Table 3 shows a summary of the dates of the 3 first tests as well as the testing conditions. These tests were assessed on three consecutive dates where outside temperature and humidity were in a narrow range of 75–83 °F, and 25%–30% RH, respectively. In all tests, the integrated sensor data in the car seat were used to assure two main points, number of persons in the car, and whether the person/s was/were talking. The integrated pressure sensor in the seats indicated the presence of one person in all tests, while the noise sensor indicated that the driver of the car was talking while driving.

Figure 4(A) shows a schematic representation of the pressure-based sensor indicating the number of occupants in the car. The occupancy sensor is located on each seat of the car, and has two fractions that allow detecting object presence and movement. The movement is important to discriminate between unanimated objects (e.g. bags) on the seat, and a person. Figures 4(B), (C) shows a typical trace of sensor signal for both sensor components, which enables discrimination of object

Figure 4. (A) Schematic representation of the occupancy sensor. The pressure-based sensor has two fractions that allow to detect object presence and movement from a person. Back (B) and front (C) sensor signal for detection of an object and a person.

Figure 5. Temperature, relative humidity (RH), and CO₂ concentrations versus time within a 2007 Toyota Corolla while driving in testing conditions shown in table 3. The left y-axis corresponds to the CO₂ concentration in ppm, while the right y-axis corresponds to the temperature in °F and relative humidity in %. Measurements were updated every 30 s. (A) Car test #1 taken on 11 March, 2017 from 9:33 PM to 10:22 PM. (B) Car test #2 taken on 12 March, 2017 from 9:34 PM to 10:09 PM. (C) Car test #3 taken on 12 March, 2017 from 9:35 PM to 10:15 PM.

Table 3. Vehicle tests' testing conditions^a.

Date	11/March/2017	12/March/2017	13/March/2017
Time of test	9:33 PM–10:22 PM	9:34 PM–10:09 PM	9:35 PM–10:12 PM
Location of sensor	Front middle dashboard	Front middle dashboard	Front middle dashboard
Year, make and model of vehicle	2007 Toyota Corolla	2007 Toyota Corolla	2007 Toyota Corolla
Number of occupants	1 occupant	1 occupant	1 occupant
Occupant conditions	Talking through the duration of the experiment	Talking through the duration of the experiment	Talking through the duration of the experiment
Testing environment	Windows closed and No Circulation (recirculation)	Windows closed and No Circulation (recirculation)	Windows opened
Car environment	Residential streets	Residential streets	Residential streets

^a Tests shown in figure 5.

Figure 6. Graphical representation of the CO₂ concentration versus time. The fitted parameter is k_{gen} to assess CO₂ source generation rate from equation (16) for: (A) ‘Growth #1’ that occurred from 9:33 to 9:49 PM in car test #1, (B) ‘Growth #2’ that occurred from 9:59 to 10:10 PM in car test #1, (C) ‘Growth #3’ that occurred from 9:35 to 9:57 PM in car test #2.

Table 4. CO₂ source generation rate and metabolic rate from car tests with one occupant ($\sigma = 1$).

Metabolic rate valuation	Growth #1	Growth #2	Growth #3	Average (SD)
Outside + initial CO ₂ concentration—[CO ₂] _o + [CO ₂] _i	735 ppm	1557 ppm	1744 ppm	n/a
$k_{\text{gen}} = [\text{CO}_2]/h$	5350 ppm h ⁻¹	3454 ppm h ⁻¹	4348 ppm h ⁻¹	4384 (948) ppm h ⁻¹
R^2 —regression coefficient	0.895	0.995	0.940	n/a
Fitting percent error (average absolute error for each data point)	6.1%	0.9%	3.3%	n/a
Car volume	90.3 ft ³ /2438 dm ³	90.3 ft ³ /2438 dm ³	90.3 ft ³ /2438 dm ³	90.3 ft ³ /2438 dm ³
VCO ₂ (with $t = 60$ min)				176 (35) ml min ⁻¹
Estimated metabolic rate				1433 (285) kcal d ⁻¹
Measured metabolic rate (Breezing™)				1510 kcal d ⁻¹
Difference error				5%

from a person. The sensors were tested in the lab and later integrated in a car. Along this line, figures 5(A)–(C) shows the CO₂ levels, temperature and RH versus time recorded during test #1, #2, and #3, respectively, while a single occupant was present in the car.

The raw results for the vehicle test #1 and #2, where windows were close and ventilation was shut-off, show alternating growths and decays of CO₂ levels. The growths are due to generation of CO₂, and periods of CO₂ decay are observed due to the automatic activation of the ventilation system of the car. It is interesting to notice that in case of test #1, the ventilation powered on automatically for about 10 min after 15 min of having been driving, even though air conditioning setting was manually set to a level of zero. In the same run, the ventilation system automatically turned on again ~12 min later. In the case of test #2, the automatic ventilation system turns on ~24 min after the car was started. We have named ‘decay #1’ and ‘decay #2’ to the decay periods observed in the car test #1, and ‘decay #3’ to the decay period observed in the car test #2. These CO₂ decay periods occurred while the driver was still inside the car, and therefore, there was a significant generation of CO₂ source. As a consequence, equation (4) cannot longer been applied to assess ACH. The ACH must be assessed using

equation (7), once the CO₂ source generation rate ([CO₂]_{gen}) is determined. Along this line, [CO₂]_{gen} can be determined from the growth CO₂ level periods, assuming the ACH is negligible, and therefore equation (16) is applied. It is worth to notice that, in the case of equation (16), [CO₂]_{gen} is determined as k_{gen} (with convenient conversion units, ppm h⁻¹).

Figures 6(A)–(C) show the fitting to equation (16) to the growths from car test #1 and #2, which has been named ‘growth #1’ and ‘growth #2’ for the car test #1 (figure 4(A)), and ‘growth 3’ for the car test #2 (figure 4(B)). Table 4 shows a summary of the calculation of metabolic rate, resulting from the analysis.

With the empirically determined k_{gen} (ppm min⁻¹) from car test #1 and #2, which rendered an average of 4383 ppm h⁻¹ or 73.1 ppm min⁻¹. VCO₂ (ml CO₂/min) was determined with the following procedure: VCO₂ (ml CO₂/min) = k_{gen} (ppm min⁻¹) × V (room volume) (2438 dm³) = 176.3 ml CO₂/min, and VCO₂ can be directly applied to equation (13) to assess metabolic rate, which rendered a value of 1433 kcal d⁻¹.

Using the k_{gen} determined before, the ACH for the automatic ventilation in the car was assessed. Figures 7(A)–(C) shows the fitting of decay #1, decay #2, and decay #3 for car test #1 and #2, respectively, using the equation (7), and table 5 summarizes the

results, indicating that the average ventilation rate is $(9.6 \pm 0.9) \text{ h}^{-1}$ as well as other parameters resulting from the fitting results from experimental values to the model. For first time, the automatic ventilation rate of a car at recirculation conditions (AC max mode—ventilation system shut-off conditions) has been assessed. This mode of ventilation is set in the cars to avoid excessive build up of CO₂ [32]

The third vehicle test was conducted on 11 March, 2017 from 9:35 PM to 10:12 PM. The testing conditions are noted on table 3. The CO₂ concentrations versus time are graphically displayed in figure 7(D), as well as the corresponding fitting to equation (7), utilizing an averaged k_{gen} of 4384 ppm h^{-1} assessed from the driver under no ventilation conditions. As it can be observed in table 5, the ACH was $\sim 69.5 \text{ h}^{-1}$, which is ~ 7 times higher than at closed window and recirculation condition due to the fact the windows were opened.

In order to assure that the ACH is null in a closed ventilation setup and that there is no CO₂ generation

being introduced in the car cabin from the car's combustion engine, a fourth test was performed as a control experiment with the car engine on, and the ventilation system closed. Figure 8 shows the parameters of temperature, humidity and carbon dioxide levels. Temperature and humidity were similar to the previous car tests, and the carbon dioxide levels did not change significantly from the baseline level recorded right before the car test.

4. Discussion

The present work explored a new method of tracking the metabolic activity of individuals in confined environments using a sensor array to measure exhalation rate of CO₂ and subsequent modeling the individual's metabolic rate using the Weir equation. The model also allowed for the assessment of an IAQ metric of a room or vehicle in addition to the quantification of the metabolic rate of an individual or

Table 5. CO₂ source generation rate and calculation parameters from car tests (car volume = 90.3 ft³/2438 dm³) with one occupant.

Variables	Decay #1	Decay #2	Decay #3	Decay #1, #2, and #3 Average (SD)	Decay #4
Conditions	Windows closed and recirculation on	Windows open			
Air exchange rate— λ	9.4 h ⁻¹	10.5 h ⁻¹	8.8 h ⁻¹	9.6 ± 0.8 h ⁻¹	69.5 h ⁻¹
Room ventilation rate—Q	22 132 dm ³ h ⁻¹	24 690 dm ³ h ⁻¹	20 734 dm ³ h ⁻¹		163 234 dm ³ h ⁻¹
Initial [CO ₂] _i	1220	1473	1540		425
[CO ₂] _{max}	1956	2208	3283		894
Baseline concentration—	735 ppm	735 ppm	1744 ppm		469 ppm
Average absolute error for each data point	1.2%	1.3%	2.2%		6.3%
R ²	0.9985	0.9857	0.8685		0.8856
Average percentage significance of [1 − exp(−λt)] term	20%	22%	33%		~0%
Average percentage significance of [exp(−λt)] term	80%	78%	67%		~100%

group. Experimental results from the classroom test show that the average metabolic rate from the two classes taken was 1511 kcal d^{-1} and 1422 kcal d^{-1} which are within $\sim 5\%$ of the 1500 kcal d^{-1} average expected for the group of students [6]. The classroom scenario validates the accuracy of model and techniques employed to determine the CO₂ source generation rate. The vehicle tests yielded metabolic rate average of $1433 \text{ kcal yr}^{-1}$ with a 5% error with respect to a reading from a validated mobile indirect calorimeter (Breezing[®]), which assessed a metabolic rate of 1510 kcal d^{-1} . The good accuracy indicated that the assessment of metabolic rate via the passive environmental sensor array is feasible and worthy of further exploration in larger population studies in the future. It is important to note that 5% discrepancy is acceptable level for clinical relevant evaluation. It is also important to notice that the variability between assessments was relatively large ($\sim 20\%$), given the subject may have faced different metabolic rates set up by free-living conditions factors. The variability of a person's metabolic rate can be originated from numerous environmental factors such as daily stress, sleep, diet, medications, physical activity, and even exposure to chemicals, pollutant and weather factors. In this regard, the assessment of metabolic rate measurements under free-living conditions is valuable to observe daily variability, as well as to average higher resolution measures to assess more representative metabolic rate values. In this regard, the present method uses proven validity in a previous study performed under controlled conditions. The previous study probed that the assessment of metabolic rate from prolonged testing carbon dioxide production rate in intubated patients is a good surrogate and replacement of more expensive assessment performed with Gold Standard Indirect Calorimetry Instrument Parvo Medics [28].

On the other hand, it is important to emphasize that the method does not compete as alternative of common calorie/activity trackers (e.g., wrist-watches). These devices are based on physical sensors that fail to accurately represent a person's metabolic activity because do not perform indirect calorimetry measures. Instead, they use a calculated metabolic rate. As mentioned before, even the author of one of the most commonly equations calculating metabolic rate, acknowledged that equation-based predictive metabolic rates could differ by as much as 900 kcal d^{-1} [4]. Therefore, calorie/activity trackers are not necessary an accurate approach to monitor metabolic rate.

In addition, the present study has revealed that indoor CO₂ concentrations can reach and exceed 1000 ppm with several students in the classroom. Concentrations in vehicle settings reached levels as high as 3000 ppm and rarely dipped below 600 ppm. Drivers subjected to these conditions for extended periods of time may experience fatigue, drowsiness, and loss of focus [33].

With the ability to determine the CO₂ generation rate of an individual(s), a ventilation system could realistically forecast CO₂ concentrations in a closed environment and accordingly adjust the rate of ventilation to prevent CO₂ build-up. Based on the levels predicted, ventilation systems could be activated to raise ACH values by increasing supply of outdoor air entering the specific indoor space.

5. Conclusion

We have proposed a new methodology that leverages a substantial amount of data that can be taken passively, and averaged overtime to tune more accurately the biometrics for the individuals. The sensing technology is robust, and relies on multiple sensors for carbon dioxide, temperature, humidity, sound, and occupancy; as well as on models that are fundamentally based on strong studies of IAQ and metabolic rate assessments.

This new indirect calorimetry based on environmental sensor technologies is expected to reduce the fabrication cost, increasing feasibility and number of applications.

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