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Estimating residential air exchange rates in rural Bangladesh using a near field-far field model

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ABSTRACT

Household air pollution due to solid fuel (biomass) combustion is widely prevalent in rural households in the developing world. Providing adequate ventilation can be a potential method to reduce exposures to residents. Previous cookstove studies in rural areas around the world have estimated the ventilation air changes per hour (ACH) values to be of the order of >20. These studies use a one-compartment model to estimate the ACH from the decay of the pollutant released very near to the cookstove. While the one-box compartmental model is appropriate for estimating exposures farther away from emission sources, a multi-compartment (e.g., a 2-box model) may be more appropriate for distinguishing between exposures of the cook versus other occupants in the house, as well as estimating ventilation rates in the house. In the present study, we use a two-compartment model to estimate the ACH. Field based particulate matter measurements were carried out in 40 Bangladesh rural households in kitchen and living room. The overall Geometric Mean (Geometric Standard Deviation) of ACH across households were found to be 0.43 (4.3) in the kitchen and 0.32 (2.7) in the living room. Obtaining the air changes per hour or ventilation rates from the decay curve of concentrations in the near vicinity of the pollutant source will lead to significant over-estimates. Our findings indicate that there is currently a substantial over-estimate based on using an incorrect model to derive the ACH values.

1. Introduction

Household air pollution (HAP) impacts approximately 41% of the global population [1,2]. The World Health Organization (WHO) estimates that 4.3 million people die every year from exposure to indoor air pollution, with 1.7 million of these deaths occurring in the South-East Asian region alone [3]. In Bangladesh, middle-income and upper-income households in urban areas typically use relatively clean cooking fuels such as liquefied petroleum gas (LPG) or natural gas. However, lower-income households in peri-urban and rural areas rely primarily on biomass fuels [4]. Biomass combustion is one of the major contributors to $PM_{2.5}$ (particulate matter less than 2.5 μm) in Dhaka [5], the second most polluted capital city in the world [6]. In Bangladesh, almost all rural households use biomass as their primary source of cooking energy needs where over 90% of energy is supplied from biomass fuels [7]. WHO guidelines [8] recommend an annual average indoor air quality concentration of below 35 μg/m [3]. However, several indoor air quality studies in Bangladesh rural households report much higher $PM_{2.5}$ concentrations [4,9,10].

The air exchange rate (AER), or the rate at which outdoor air replaces

Abbreviations: ACH, Air Changes Per Hour; AER, Air Exchange Rate; GM, Geometric Mean; GSD, Geometric Standard Deviation; lpm, Liters per minute.

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indoor air typically expressed in air changes per hour (ACH), is a critical parameter for evaluating the quality of ventilation in an environment and commonly used in indoor air exposure models [11] and for designing adequate ventilation strategies. ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers) recommends that homes receive at least 0.35 air changes per hour and not less than approximately 425 L per minute (lpm) per person to provide acceptable indoor air quality [12]. While the Bangladesh National Building Code (BNBC, 2006) recommends ventilation for mechanically ventilated factory buildings, there is no specific regulatory guidance relating to indoor thermal comfort for non-air conditioned spaces [13].

Adequate ventilation to reduce exposure can be a potential solution to the problem of indoor air quality. Begum et al. [4] identified kitchen configuration as a cost-effective measure to lower exposures in their study in rural Bangladesh. Ruth et al. [14] in their study demonstrated that ventilation could make a significant difference to the indoor air quality in cooking environments, reducing carbon monoxide and particulate matter by about 50%. Several factors such as kitchen volume, size and position of windows, location of cookstove in the kitchen/household, overall structure of the kitchen, and ambient and indoor temperatures, influence the pollutant concentrations indoors [9,15].

A limited number of studies in South Asia have quantified the AER in non-mechanically ventilated households using solid fuel for domestic cooking [16–18]. Bhangar [17] in rural west India and Parajuli et al. [16] in rural Nepal estimated ACH from the first order decay rate of the concentration of carbon monoxide (CO) after the conclusion of a cooking event, by assuming that the indoor environment is a homogenous, instantaneously mixed zone, and the effective ventilation rate is first order and invariant with time. This model is referred to as the well-mixed room (WMR) model of a room of volume V (*e.g.*, in m^3) through which the ventilation air flow rate is a constant equal to Q (*e.g.*, in units of m [3]/min). The air entering the room (at a flow rate of Q) has a contaminant concentration of C_{in} (*e.g.*, in units of $\mu g/m^3$). There is also a contaminant source within the room that is generating the particulate contaminant at a constant rate of G (e.g., in units of μg/min). The air flow Q will also remove some of the contaminant from the room. In addition, there might be other routes by which the particulate contaminant may be removed from the room air, gravitational settling, diffusion on to walls, impaction losses, thermophoresis, condensation and evaporation, to name just a few mechanisms. All these loss mechanisms can be combined into one term that denotes a loss rate coefficient k_L (e.g., in units of $\min^{-1}$), *i.e.*, the fractional mass of contaminant in the room removed per minute. Thus, the air flow rate as well as various loss mechanisms are decreasing the amount of contaminant in the room air. The resulting mass balance equation is a differential equation whose solution is given by

$$\boldsymbol{C}(\boldsymbol{t}) = \frac{\boldsymbol{G} + \boldsymbol{C}_{IN}\boldsymbol{Q}}{\boldsymbol{Q} + \boldsymbol{k}_L\boldsymbol{V}}\left(1 - \exp\left(-\frac{\boldsymbol{Q} + \boldsymbol{k}_L\boldsymbol{V}}{\boldsymbol{V}}\boldsymbol{t}\right)\right) + \boldsymbol{C}(0)\exp\left(-\frac{\boldsymbol{Q} + \boldsymbol{k}_L\boldsymbol{V}}{\boldsymbol{V}}\boldsymbol{t}\right) \tag{1}$$

The exponential term $\frac{Q + k_L V}{V}$ is the removal rate of the particles in units of $\min^{-1}$. The term k_L depends on particle size; as particle size increases, k_L increases reflecting the effects of gravitational settling and impaction losses. If we assume that at the start of each cooking event, the indoor air is clean, such that C (0) = 0, then Equation (1) reduces to $C(t) = \frac{G}{Q + k_L V}\left(1 - \exp\left(-\frac{Q + k_L V}{V}t\right)\right)$, which represents the portion of the cooking event when the cookstove is generating aerosol and the concentration in the kitchen and the rest of the indoor environment is increasing.

At the end of the cookstove use period when it is turned off, the concentration starts decreasing with time. This phase of the cooking event is represented by $C(t) = C(0)\exp\left(-\frac{Q + k_L V}{V}t\right)$, where C (0) is the peak concentration reached in the kitchen just before the exponential decrease with time starts. When ln $[C(t)/C\,(t = 0)]$ is plotted against time, a straight line is obtained with a slope of $-\frac{Q + k_L V}{V}$. If we know the value of k_L, or if it can be neglected, then the value of Q/V or the air changes per hour (ACH) can be estimated as $ACH = \frac{Q}{V} \times 60$.

The WMR model gives a reasonable estimate of exposure intensity for individuals who are not positioned close to the emission source. However, spatial monitoring of kitchen indoor environments air indicate that exposure intensity is higher near the cookstove source than at distant points in the kitchen or other rooms [19]. While it is common to use a WMR model for estimation of ACH in rural households, this assumption is only valid for conditions in rooms that are far away from the cookstove source (e.g., living rooms) and not necessarily for the kitchen, especially very close to the cookstove.

A model that accounts for spatial variability in exposure intensity is the so-called near-field far-field (NF-FF) model [20,21]. As opposed to the single zone model with a WMR assumption, the NF-FF conceptually divides the indoor space into two zones (Fig. 1). The conceptual inner zone contains the emission source and its dimensions are representative of the immediate environment of the cook and could potentially be smaller than the physical dimensions of the kitchen. The rest of the house is the conceptual second zone and is representative of conditions in areas farther away in the kitchen as well as other rooms, e.g., the living room. The details of the model are further discussed in the methodology section. The scope of the present study was to determine the AER in typical rural houses of Bangladesh using the NF-FF model, and contrast it with AER obtained using the WMR model.

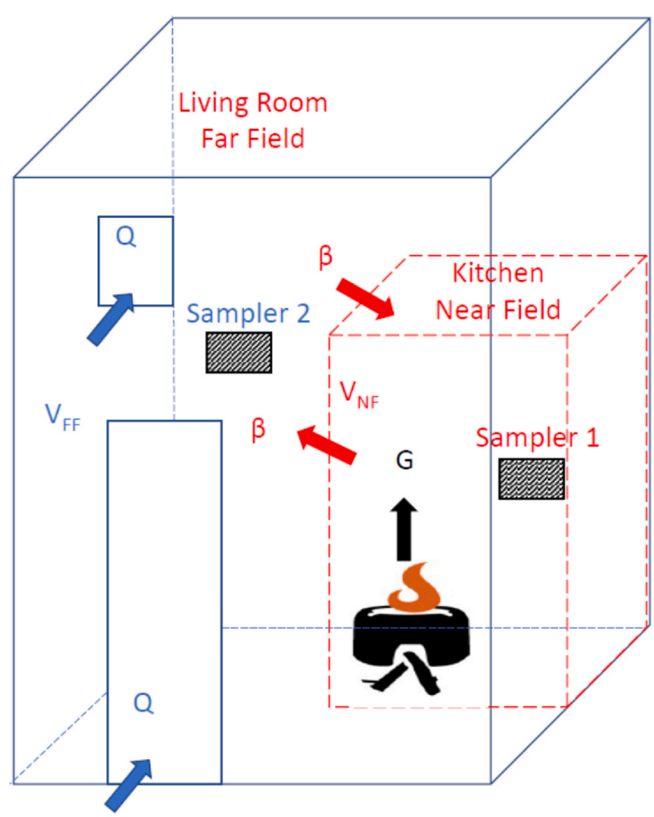

Fig. 1. Schematic representation of residence and the modeling framework.

2. Methodology

2.1. Study design & population

Data used in this analysis come from a longitudinal study of mother-child dyads in northern rural Bangladesh. In 2017, 40 mother-child dyads were enrolled in a study to compare differences in $PM_{2.5}$ exposure and health outcomes between homes that used biomass for cooking and ones that used liquefied petroleum gas (LPG). Recruitment occurred through non-probability, convenience sampling until an equal number of households with each fuel type were enrolled. At the time of

Enrollment, each household completed a questionnaire on physical characteristics of the house, fuel use, family health, and household demographic and socioeconomic characteristics. Each house was visited four to six times over a period of one year to take real-time measurements of $PM_{2.5}$ over a 24-72-h period. Table 1 lists some of the characteristics of the households.

2.2. Air monitoring set up

Personal $PM_{2.5}$ exposure was captured using MicroPEM™ personal exposure monitors (RTI International, Research Triangle Park, NC, USA) as in previous studies [22–24]. The study team placed the real-time nephelometric particle monitors in the kitchen and living room of each household at each study visit as shown in Fig. 1. The nephelometers were placed in a cage hung in the breathing zone of adults in the kitchen area close to the cookstove within 1–2 m. The study team members turned the instruments on and allowed them to run for at least 24 h before returning to the home to and rtrieve the devices. Data were collected continuously during this period at 10 and 20 s intervals. Pictures of typical rural Bangladesh households and 2-D schematic of the setup are provided in the Supplementary Materials.

2.3. Mathematical modelling

In the present study, a NF-FF model was used to estimate the concentration in the kitchen. Methodology similar to Nicas [21] was used to determine the AER. The following expressions describe the decay in contaminant concentration in the two zones (NF-FF) upon cessation of emission.

$$C_N(t) = A\exp(\lambda_1 t) + B\exp(\lambda_2 t) \quad (2)$$

$$C_F(t) = C\exp(\lambda_1 t) + D\exp(\lambda_2 t) \quad (3)$$

where, $C_N(t)$ = time varying concentration in the near field.

$C_F(t)$ = time varying concentration in the far field
λ_1 = air turnover rate in the far field
λ_2 = air turnover rate in the near field

Where A, B, C and D are constants. The full mathematical expressions for A, B, C, D,λ_1 and λ_2 are provided in the Supplementary Materials. The concentration profile is shown by the blue line in Fig. 2, and the decay portion of the profile has two distinct sections in the kitchen measurements. During the initial few minutes, there is a rapid decrease in kitchen near-field concentration $C_N(t)$ governed by the λ_2 parameter. Thereafter, the kitchen near-field concentration exhibits a more gradual decrease governed by the λ_1 parameter. The concentration in the far-field (e.g., living room) shown by the red line behaves similar to a WMR model shown by green line, and the decay is governed by the λ_1 parameter. The λ_2 parameter is approximately equal to the air exchange rate in the near field while the λ_1 parameter is approximately equal to the air exchange rate in the far field [20,21].

The slope of the decay indicative of the losses were determined by plotting ln $[C(t)/C\ (t=0)]$ versus time. While, living room decay visually has one slope, the kitchen concentration decay can be seen to have a fast decay and a slower decay period, and will result in two slopes. The smaller of the two slopes (slower decay period) corresponds to the slope of the decay obtained from the living room and can be considered to correspond to the ACH for the entire residence. Ideally, these two slopes (i.e., the slope from the living room and the slope of the more gradual decay portion in the kitchen) would be identical (as shown in Fig. 2).

Decay losses in a room are a function of both ACH and particle losses. Particle losses are a function of their diameter. The count median diameter (CMD) of particles emitted from cookstoves was assumed to be approximately 30–40 nm [25] and was used to determine the particle decay rate $k_d = 0.15$ [26]. The ACH values were therefore calculated by subtracting this assumed particle decay rate from the slope values.

Table 1
Household Characteristics by Fuel type.

	Liquified Petroleum Gas (LPG)	Biomass
Number of Households	20	20
Average Number of Rooms	4.2 (SD: 3.4)	4.0 (SD:1.5)
Average Square Feet of Kitchen	189.2 (SD: 79.2)	128.83 (SD: 90.6)
Geometric Mean PM 2.5 μg/m3 Kitchen	55.5 (GSD: 1.4)	109.8 (GSD: 1.5)
Geometric Mean 2.5 μg/m3 Living Room	51.6 (GSD: 1.4)	60.1 (GSD: 1.4)

3. Results and discussion

Table 2 shows the ACH values calculated for each household in the kitchen and living room. A lognormal distribution was fit to the ACH values estimated from data obtained in the kitchens and the living rooms for 20 LPG and 20 biomass-using homes as shown in Fig. 3 and geometric mean (GM) and geometric standard deviation (GSD) were estimated. In the present study, the overall GM (GSD) across households using both kinds of fuels was found to be 0.43 (4.3) from data obtained from monitors in the kitchen and 0.32 (2.7) from data obtained from monitors in the living room. The GM (GSD) for biomass-using residences were 0.5 (4.4) for the kitchen and 0.29 (2.7) for the living room. The GM (GSD) for LPG-using residences were 0.37 (4.4) for the kitchen and 0.35 (2.9) for the living room. The high variability in GSD is likely due to variability in household characteristics.

Usage of LPG is typically linked to better socio-economic livelihood structure [27]. Weaver et al. [28] in their study identified that compared with poorly ventilated homes, better ventilated homes were larger, their residents wealthier and less likely to use biomass fuel. However, ACH comparison of biomass and LPG in kitchen and living room in the present study indicate no statistically significant difference ($p > 0.05$). The present values obtained using the NF-FF model are more representative of the ventilation conditions in rural Bangladesh households. The ACH range obtained from the present study in Bangladesh, a low or medium income country are comparable with the values of 0.4–0.7 seen in residential US houses, a high income country [29].

Many cookstove-based studies assumed a WMR model in their estimation of ventilation rate and reported high ACH values in rural households. Bhangar (2006) [17] measured carbon monoxide concentrations in rural Indian households continuously for 5 days as 1-min time weighted averages (TWA). The monitors were located close to the stove (1 m horizontal and 1.5 m vertical distance away from the stove) and in proximity to the breathing zone of the cook. In these experiments, a mixture of dung and kerosene was allowed to burn in a brazier for 20–30 min to allow CO levels to reach a high level, and then the brazier was removed. Assuming a well-mixed room model, the natural log of CO concentration levels following the removal of the brazier were plotted against time, and the slope estimated from the first 4–8 min was the air exchange rate. This study estimated air exchange rates of 7–27 ACH. Similar values were reported by Brant et al. [30], but these values were

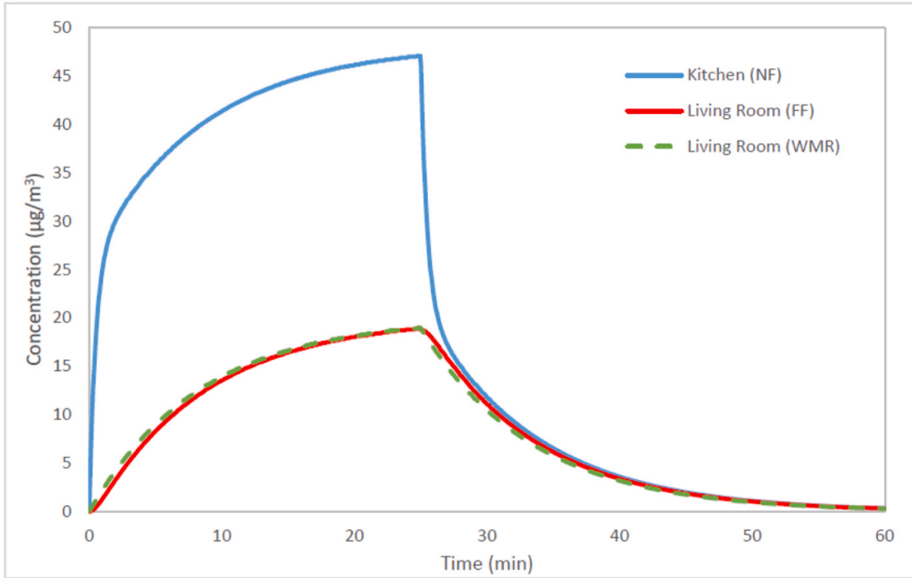

Fig. 2. Example profile of $PM_{2.5}$ concentration (μg/m^3) in the near field e.g. (kitchen) and the far field (e.g., living room), as predicted by the near field/far field model and the well-mixed room model.

Table 2
ACH values for 40 households. Blank values indicate data is missing.

S.No.	Fuel Type	Kitchen	Living Room
1.	Biomass	2.66	–
2.	Biomass	0.41	0.02
3.	Biomass	0.35	0.36
4.	Biomass	0.00	0.15
5.	Biomass	1.50	0.18
6.	Biomass	0.74	0.37
7.	Biomass	1.01	–
8.	Biomass	0.40	0.51
9.	Biomass	0.16	0.60
10.	Biomass	0.05	–
11.	Biomass	0.76	1.01
12.	Biomass	0.78	–
13.	Biomass	5.49	0.33
14.	Biomass	0.32	0.19
15.	Biomass	0.16	–
16.	Biomass	0.22	0.18
17.	Biomass	6.59	–
18.	Biomass	–	0.70
19.	Biomass	0.02	0.81
20.	Biomass	0.59	0.18
21.	LPG	2.11	0.62
22.	LPG	–	0.00
23.	LPG	1.44	0.15
24.	LPG	0.08	–
25.	LPG	0.58	0.16
26.	LPG	2.33	1.02
27.	LPG	0.74	0.51
28.	LPG	2.92	0.10
29.	LPG	0.17	–
30.	LPG	0.00	0.05
31.	LPG	1.17	0.77
32.	LPG	0.02	0.20
33.	LPG	0.06	1.28
34.	LPG	0.16	0.41
35.	LPG	0.50	0.59
36.	LPG	–	0.06
37.	LPG	–	0.21
38.	LPG	0.57	1.29
39.	LPG	0.09	0.63
40.	LPG	0.14	0.92

also obtained when the monitor was placed close to the stove. McCracken and Smith (1988) first used this method for estimating AER using CO decay curves. An analysis of Fig. 1 in their paper shows the same feature: a rapid decay followed by a slower decay (see Supplementary Materials). Assuming a WMR model, the slope of the faster decay period would yield an AER of ~15 ACH, while the slower decay portion yields an AER of ~1 ACH. Parajuli et al. [16] measured CO concentrations using a CO T82 data logger at 1-min intervals and also used the same approach as Bhangar [17] to obtain much lower air exchange rates in the range 0.67–2.67 [15] in rural Nepali houses. They report placing the monitors in the kitchen although they don't mention placing the monitors close to the stoves in the range 0.67–2.67 [15], and this could possibly explain the lower ACH values. Johnson et al. (2011) proposed a probabilistic modeling framework and they assumed a mean ACH value of 25 (range: 3–60) [18] based on results from Brant et al. [30] and Bhangar [17]. They found significant discrepancies between model predictions and measurements and attributed it correctly to the limitations of the one-box WMR model. Most emission measurements in cookstove studies are carried out closer to the cookstove location < 1 m from the source [31], and if a one-box model assumption is made to determine the ACH from the steep portion of the decay this will result in over-estimation of AER. While these are recent studies, these insights date back to at least to the 1980s when Davidson et al. [32] used a one-compartment model and found that modeling results did not match measured levels well. They attributed the discrepancies between calculated and measured concentrations to uncertainties in the model input data, especially the emission factors and air exchange rates, and recognized that the one-compartment model neglects problems of imperfect mixing, non-steady-state conditions, and indoor loss rates from deposition and chemical reactions. Most studies are appropriately focused on estimating exposures of the primary cook who is in close proximity to the stove, and the exposure monitor is placed either on the body of the cook or in close proximity to the stove. While the one-box compartmental model is appropriate for estimating exposures farther away from emission sources, a multi-compartment (e.g., a 2-box model) may be more appropriate for distinguishing between exposures of the cook versus other occupants in the house, as well as estimating ventilation rates in the house. Obtaining the air changes per hour or ventilation rates from the decay curve of concentrations in the near vicinity of the pollutant source will lead to significant over-estimates.

These incorrect estimates, will in turn, affect other estimates.

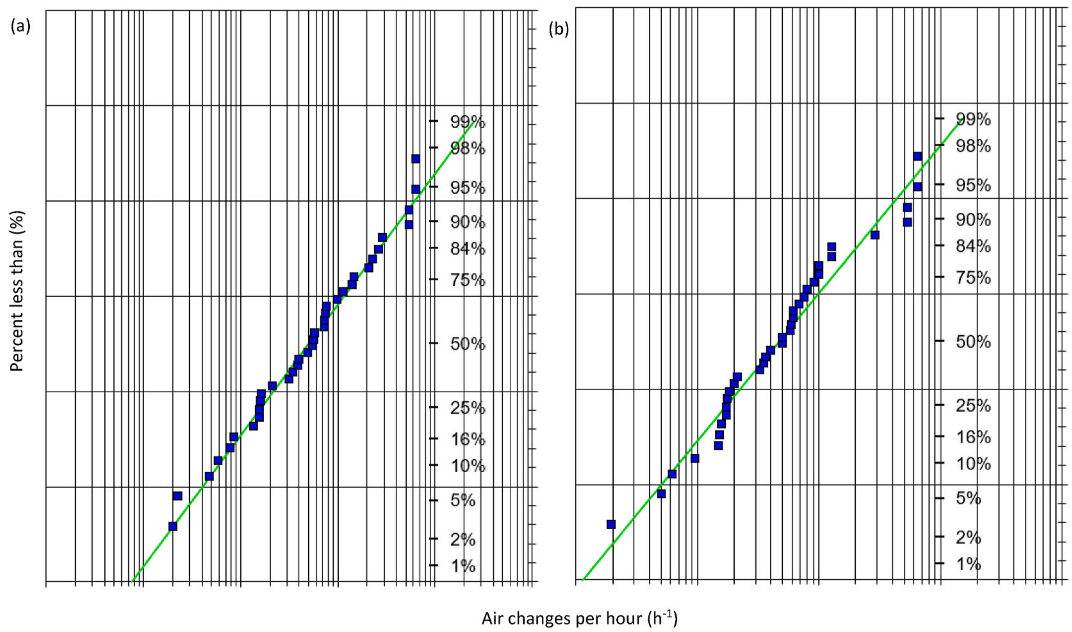

Fig. 3. Log Probability Plot and Least-Squares Best-Fit line of ACH's in (a) Kitchen (b) Living Room.

Johnson et al. [18] using a WMR model estimated only 4% of the homes, even under idealized conditions, would meet the WHO interim annual $PM_{2.5}$ guideline of 35 μg/m [3]. They suggested a target PM2.5 emission rate of 1.75 mg/min that would result in at least 60% and at best 100% of the homes meeting WHO guidelines [8]. These estimates need to be re-evaluated given the findings of this work that using the NF-FF model would be a more appropriate approach in the estimation of AER. It is reasonable to expect that this re-evaluation will lead to even more stringent targets for emission rates. Ventilation rates, typically obtained from decay experiments, need to be grounded in correct models so that the estimates are accurate.

4. Conclusions

The findings of the present study indicate that the two-compartment NF-FF model is a better representation of concentrations of pollutants emitted by cookstoves near the source and leads to better estimates of the air exchange rates than the one-compartment WMR model. Assuming a one-compartment model leads to unrealistically high estimates of air changes per hour. Many extant studies likely measured AER at locations close to the cookstove source using the steeper part of the decay curve, leading to high AERs. We recommend that a two-compartment model be used and the slower, second part of the decay curve of the pollutant be used for the determination of AER, when the measuring instrument is placed closer to the source. The revised methodology can be used by WHO to determine the ACH and thus devise the emission rate targets for cookstoves.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2021.108325.

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[32] C.I. Davidson, et al., Indoor and outdoor air pollution in the himalayas, Environ. Sci. Technol. 20 (1986) 561–567.

Further reading

[1] P. Wilkinson, et al., Public health benefits of strategies to reduce greenhouse-gas emissions: household energy,, Lancet 374 (2009) 1917–1929.

Supplementary Information

Figure SI 1: Picture from field sampling: (a) kitchen near field (b) kitchen far field (c) living room (d) typical Bangladeshi rural house

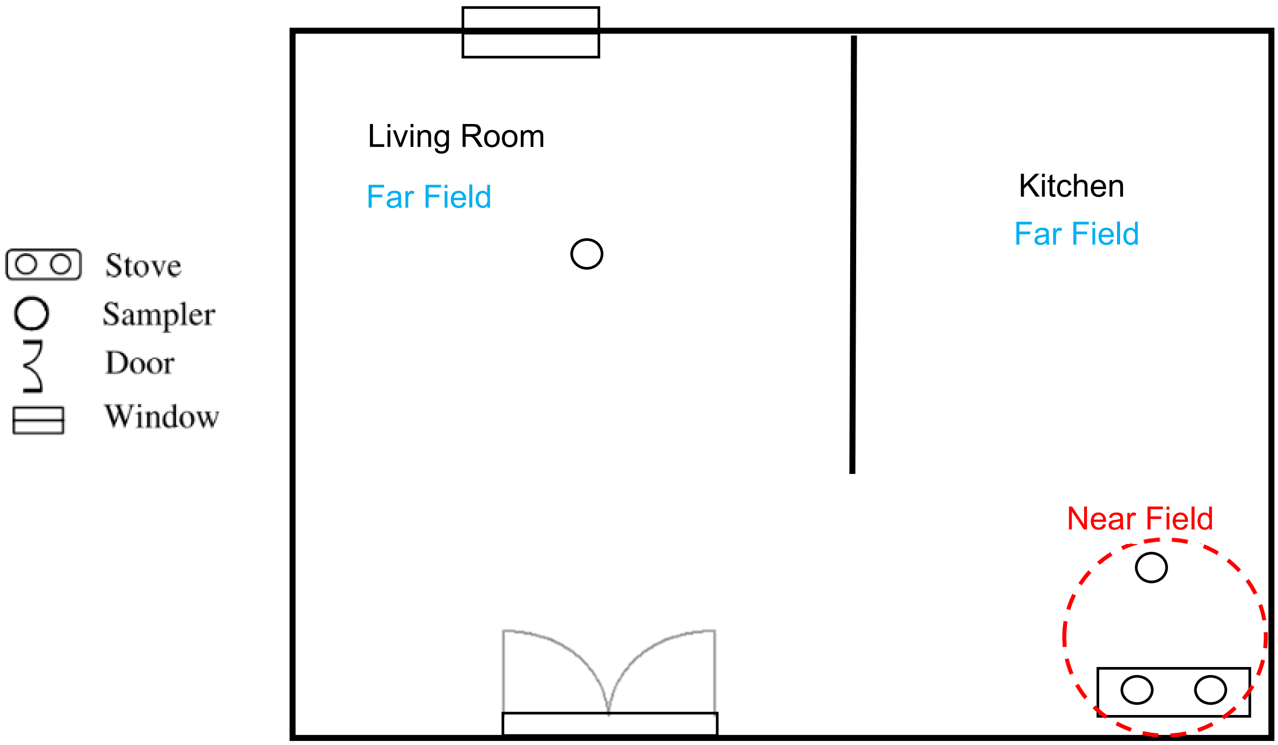

Figure SI-2: 2D-Schematic representation of typical sampling setup

Mathematical expressions of the NF-FF model

$$C_N(t) = A\exp(\lambda_1 t) + B\exp(\lambda_2 t)$$

$$C_F(t) = C\exp(\lambda_1 t) + D\exp(\lambda_2 t)$$

Where, $A = \frac{\beta(C_{F,0} - C_{N,0}) - \lambda_2 . V_N . C_{N,0}}{V_N(\lambda_1 - \lambda_2)}$;

$B = \frac{\beta(C_{N,0} - C_{F,0}) - \lambda_1 . V_N . C_{N,0}}{V_N(\lambda_1 - \lambda_2)}$;

$C = \frac{(\lambda_1 . V_N + \beta)[\beta(C_{F,0} - C_{N,0}) - (\lambda_2 . V_N . C_{N,0})]}{V_N(\lambda_1 - \lambda_2)}$;

$D = \frac{(\lambda_2 . V_N + \beta)[\beta(C_{N,0} - C_{F,0}) - \lambda_1 . V_N . C_{N,0}]}{V_N(\lambda_1 - \lambda_2)}$;

$$\lambda_1 = 0.5\left[-\left[\frac{\beta.V_F + V_N(\beta + Q)}{V_N + V_F}\right] + \sqrt{\left[\frac{\beta.V_F + V_N(\beta + Q)}{V_N + V_F}\right]^2 - 4\left[\frac{\beta.Q}{V_N.V_F}\right]}\right]$$

$$\lambda_2 = 0.5\left[-\left[\frac{\beta.V_F + V_N(\beta + Q)}{V_N + V_F}\right] - \sqrt{\left[\frac{\beta.V_F + V_N(\beta + Q)}{V_N + V_F}\right]^2 - 4\left[\frac{\beta.Q}{V_N.V_F}\right]}\right]$$

Where, V_N and V_F: the near-field and far-field volumes, respectively (m^3)

C_N and C_F: the near-field and far-field concentrations respectively (mg/m^3)

β: air flow rate (m^3/min) between the near and far fields

Q: room supply air rate (m^3/min)

λ_1 = air turnover rate in the far field

λ_2 = air turnover rate in the near field

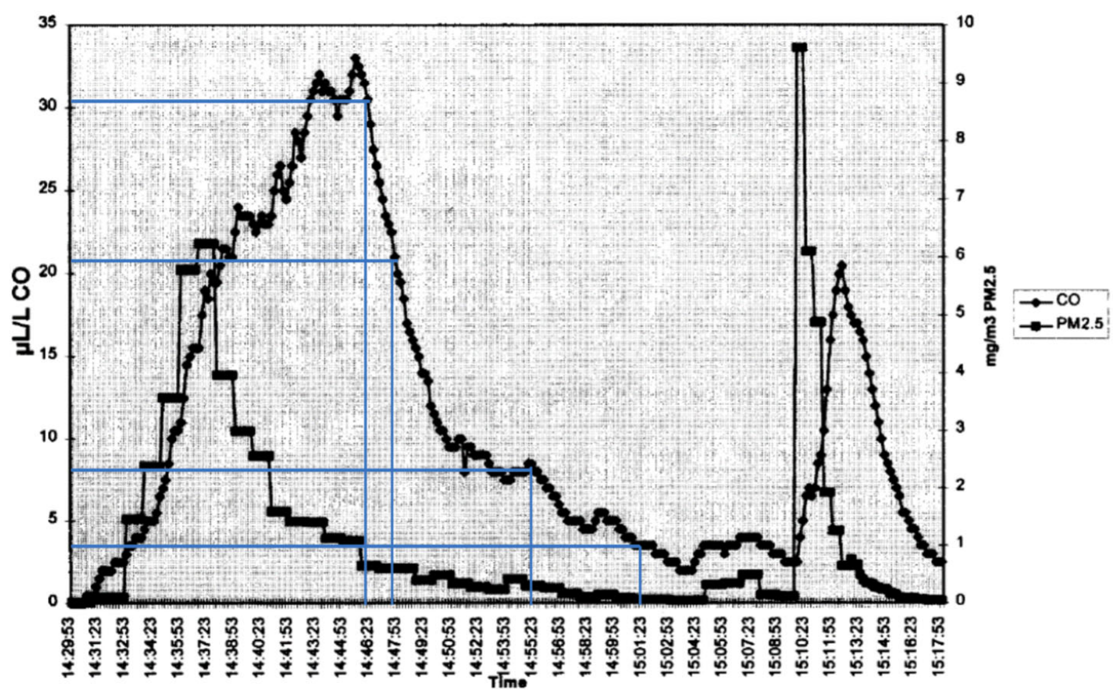

Figure SI 3: Concentration time series plot adapted from McCracken and Smith [1] used to estimate the air exchange rate.

McCracken and Smith

t	C		
0	30.2	slope (fast decay)=	14.91555751
90	20.8		
0	8	Slope (slow decay)	0.980829253
3600	3		

References

1. McCracken, J. P. & Smith, K. R. Emissions and efficiency of improved woodburning cookstoves in highland Guatemala. *Environ. Int.* **24**, 739–747 (1998).