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Quantitative estimation of excess mortality for drivers and passengers exposed to particulate matters in long-distance buses

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ABSTRACT

The purpose of this study was to estimate quantitatively the excess mortality for driver/passenger in long-distance buses in terms of long driving time and inhaled particulate matters (PMs) concentrations. This study used an area under the curve (AUC) approach integrating the driving time and a predicted single pulsed PM concentration to estimate the fluctuating PM exposures in long-distance buses. Different peak functions were used to fit a unique fluctuating PM dataset adopted from previous study in Taiwan. We showed that gamma distribution had a best-fitting performance with the minimum values of coefficient of variation (CV) for $PM_{2.5}$ and PM_{10} of 2.9% and 11.7%. The results also indicated that the predicted CV values for $PM_{2.5}$ (5.3%) and PM_{10} (14.0%) from fitted normal distributions were also agreeable compared with the original dataset. The results indicated that the $PM_{2.5}$-associated excess mortality estimates ranged from 0.64 to 1.04 and 4103–6833 individuals per 10^5 population for passengers under short-term and drivers under long-term PM exposures. Moreover, the interquartile ranges of the excess mortality estimate in the proposed model were 2.5–5.6 times less than that in the original dataset. We concluded that our AUC-based model may successfully reduce the variations in PM exposure estimates, and thereby provide more accurate values for improving risk estimation of future excess mortality attributable to traffic-related air pollutants.

1. Introduction

Growing evidence has linked long-term exposure to inhaled traffic-related pollutants with increases in the risk of cardiovascular disease mortality (Chen et al., 2005; Tie et al., 2009; Tsai et al., 2010). Long-term exposure to traffic-related pollutants might also induce lung function decrement and respiratory diseases exacerbations (Suglia et al., 2008; Shankardass et al., 2009). Occupational cohort studies showed that there were higher cancer risks for professional drivers (Hansen et al., 1998; Soll-Johanning et al., 1998; Chen et al., 2005). Significant correlation were obtained between lung cancer and other diseases and traffic-related pollutions in China (Tie et al., 2009), Denmark (Hansen et al., 1998; Soll-Johanning et al., 1998), Korea (Hong et al., 2002), Spain (Perez et al., 2009), Taiwan (Chen et al., 2005; Tsai et al., 2010), and USA (Pope and Dockery, 2006).

The traffic-related pollutants include particulate matters (PM), carbon oxides (CO and CO_2), sulfur oxides (SO_2 and SO_3), nitrogen oxides (NO and NO_2), volatile organic compounds (VOCs), polycyclic aromatic hydrocarbons (PAHs), and bioaerosols (Lee and Jo, 2005; Adar et al., 2008; Rim et al., 2008; Hsu and Huang, 2009). Pope et al. (2002) showed the associations between long-term exposure to the classical pollutants (PM, SO_2, NO_2, and O_3) and adverse health endpoints of respiratory and cardiovascular diseases mortality. However, several time-series and epidemiological studies focused on the health impacts for short-term exposure to air pollutants (Katsouyanni et al., 1995, 2001; Dominici et al., 2006; Rosenlund et al., 2006; Stieb et al., 2009; Strickland et al., 2010; Sicard et al., 2011).

PM characteristics measured from vehicle exhaust or in-cabin include the mass or number concentrations, size distributions, and chemical components, depending on ventilation conditions, indoor and outdoor interactions, driving patterns and vehicle types (Chan, 2003; Chan and Chung, 2003; Huang and Hsu, 2009; Mohammadyan et al., 2009). These affecting factors could cause a fluctuating pattern while monitoring the PM mass concentration

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which was enough to affect the quantifications of PM exposures for drivers, passengers, and even commuters.

Recently, the time-averaged concentration with the range and standard deviation (sd) or real-time concentration can be used to represent the measurements of PM exposure in bus in-cabin (Adar et al., 2008; Kaminsky et al., 2009; Mohammadyan et al., 2009). In practice, the PM time-averaged measurements might have large variations, whereas the monitored data point represents only the value in short moment in the real-time measurements. Therefore, this study proposed an area under the curve (AUC) approach incorporated with a linear combination method (Adar et al., 2008) to overcome the underlying drawback. Adar et al. (2008) indicated that a series continuously monitored data of the fluctuating PM exposure in each journey measured in long-distant buses could be transformed into a single pulsed PM exposure data by using a linear combination method.

For accurately assessing the PM exposure for driver/passenger, this study employed an innovative concept to improve the estimation of PM exposures and associated assessment. The objectives of this study were threefold: (i) to use the AUC approach to improve the PM exposure assessment for driver/passenger, (ii) to develop a single pulse pattern-based estimation model for describing a fluctuating exposure pattern, and (iii) to compare the excess mortality estimates for driver/passenger with current and proposed methods. Our model was validated against an available fluctuating dataset. The excess mortalities for driver and passenger exposed to in-cabin PM in long-distance buses were also estimated. In this study, we considered passengers and drivers as vulnerable persons to assess the excess mortality under short- (daily basis) and long-term (annual basis) PM exposures.

2. Materials and methods

2.1. Data acquisition and reanalysis

In order to validate the proposed models, an available dataset, from previous study in Taiwan, was used (Huang and Hsu, 2009). Briefly, the total distance and time spent of one-way trip between Taipei and Tainan Cities were estimated to be 300 km with 4 and 5 h, respectively. According to the results from Huang and Hsu (2009), the sample size of the one-way trip was 30 from August, 2004 to July, 2005. The selected real-time data in our study was on September, 2004, with the trip started at 19:30 from Taipei and ended at 00:30 to Tainan. The meteorological conditions of indoor microenvironment were recorded (temperature: 25.3 ± 2.1 °C and relative humidity: 59.1 ± 5.7%) based on simulation from one-floor roadside house. The recorded results showed that the numbers of passenger in the bus ranged from 2 to 23. Five bus companies, in that two thirds of investigated buses were less than 3 years old and the others were less than 6 years old, were used as the measured buses, except for one bus was 9 years old. The real-time spent of one-way journey depended on many factors including starting time, stop frequency, traffic density, and weather conditions. Although the meteorological conditions in indoor environments, CO_2 level, bus characteristics, and driver and passenger activities were recorded. In parallel, $PM_{2.5}$ and PM_{10} mass concentrations were measured.

Huang and Hsu (2009) used two TSI 8520 DustTrak aerosol monitors (TSI Inc., St. Paul, MN, USA) to determine in-cabin $PM_{2.5}$ and PM_{10} mass concentrations. A well quality assurance/quality control (QA/QC) protocol was also performed. Based on the study design of Huang and Hsu (2009), they calibrated the DustTrak sampler with a Tapered Element Oscillating Microbalance (TEOM) gravimetric sampler plus PM_{10} or $PM_{2.5}$ inlet over a 3-day period. Results showed that the determination coefficients (r^2) between the two samplers were 0.93 and 0.90 for PM_{10} and $PM_{2.5}$. During the sampling period, the sampler was installed in the forward third of the bus with nearly 1.2 m height to take into account homogeneous in-cabin microenvironment and breathing zone sampling.

The average PM_{10} mass concentration were 39.2 ± 26.2 μg m^{-3} with a geometric mean (gm) of 32.9 μg m^{-3} and a geometric standard deviation (gsd) of 1.8. For $PM_{2.5}$, the average mass concentration were 24.4 ± 17.8 μg m^{-3} with a gm of 19.8 μg m^{-3} and a gsd of 1.9 (Huang and Hsu, 2009). These two datasets showed that large variations existed in the in-cabin PM measurements, indicating higher coefficient of variation (CV) values. The CV values of PM_{10} and $PM_{2.5}$ were 66.8 and 73.0% (Huang and Hsu, 2009). Here the reported PM_{10} and $PM_{2.5}$ measurements are referred to as the "Total Mean" settings.

Because there were measured mean values with large variations in in-cabin PM_{10} and $PM_{2.5}$, it is not impossible that the PM exposure may be overestimated or underestimated with large uncertainties in the exposure assessment issues. Huang and Hsu (2009) reported a fluctuating pattern-based PM exposures monitored by real-time samplers on September 15, 2004. They showed 12 peak events occurred in the 5-hour one-way journey. Each event had been categorized by the driver activity.

We designated the sequence of events in the recorded data and synthesized the information for the analyses. Here, we adopted and discussed four categories of peak events defined by Huang and Hsu (2009): (i) door-opened get on, (ii) window opened, (iii) toll station and window opened, and (iv) door-opened get off.

2.2. Model concepts and descriptions

To reduce the large variations from original PM exposure with multi-waves fluctuating pattern, an AUC-based approach for PM exposure model was proposed. An equivalent single pulsed wave was used to represent the fluctuating pattern. The study concept was shown in Fig. 1, representing the original fluctuating waves (Fig. 1A) and designed single pulsed wave (Fig. 1B).

There were four assumptions in our model: (i) all schemes were based on the real exposure pattern, (ii) the source intensity from outdoor to in-cabin was random, (iii) the PM exposure in the whole journey was time-dependent, and (iv) the PM exposure events can be decomposed following a linear combination.

Based on the linear combination concept, the AUC approach for PM exposure can be expressed as,

$$\mathrm{AUC}_{\mathrm{bus}} = \mathrm{AUC}_{\mathrm{background}} + \mathrm{AUC}_{\mathrm{event\text{-}1}} + \ldots + \mathrm{AUC}_{\mathrm{event\text{-}}m}, \quad (1)$$

where AUC_{bus} is the total AUC estimate for PM in the bus, $AUC_{background}$ is the partial AUC estimate for PM under the background level, and $AUC_{event\text{-}1}$ through $AUC_{event\text{-}m}$ are the individual AUC estimate (above background level) for events 1 to m.

Assuming that the measured fluctuating PM exposure (Fig. 1A) may be replaced by a AUC-based single pulsed PM exposure (Fig. 1B), the time-dependent PM concentration for each event i ($C_{t,i}$) and the total AUC (AUC_T) in the whole journey can be expressed as,

$$C_{t,i} = C_{0,i} + i \cdot C_{e_i} \cdot \delta[t - T_i(t_{e_i})], \quad (2)$$

$$\mathrm{AUC}_T = \sum_{t=0}^{T} \sum_{i=1}^{m} C_{t,i} = C_0 T + m \cdot t_e \cdot C_e, \quad (3)$$

where $C_{0,i}$ is the corresponding background PM level to $C_{t,i}$, i, the event occurred number, C_{e_i}, the PM mass concentration above the background level in event i, $\delta[t - T_i(t_{e_i})]$ is the pulsed function occurred at $t = T_i$ with consequent duration t_{e_i} for event i, T, the

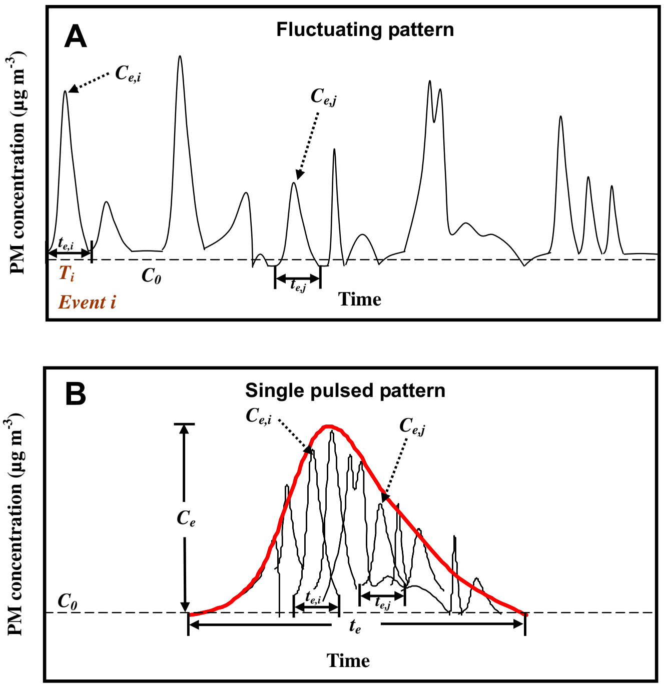

Fig. 1. Schematic concept of this study showing the (A) fluctuating pattern, and (B) single pulsed pattern PM concentrations monitored in long-distance bus. Where C_0 is the background concentration, C_e, the event concentration, t_e, the duration of event, and the small case i and j represent the event numbers.

total time spent in the whole journey, and m, the total number of window/door opened or closed events in the whole journey.

We treated probabilistically the background PM mass concentration (C_0), duration of event (t_e), and event PM mass concentration above the background level (C_e). Therefore, $C_0 \sim \mathrm{Dist}(\mu_{C_0}, \sigma_{C_0})$ is the probability distribution of the background concentration with mean μ_{C_0} and standard deviation (sd) σ_{C_0}. $C_e \sim \mathrm{Dist}(\mu_{C_e}, \sigma_{C_e})$ shows the probability distribution of the event concentration, whereas $t_e \sim \mathrm{Dist}(\mu_{t_e}, \sigma_{t_e})$ shows the probability distribution of the event duration. The probability distributions of C_0, t_e, and C_e were best fitted to the original data from Huang and Hsu (2009).

2.3. Peak functions and parameter optimization

Four peak functions, including normal (N), lognormal (LN), gamma (G), and triangular (T) distributions, were selected,

$$\mathrm{N}(a,b,c,d): y = a + b\exp\left[-0.5\left(\frac{x-c}{d}\right)^2\right], \tag{4}$$

$$\mathrm{LN}(a,b,c,d,e): y = a + b\exp\left[\frac{-\ln 2\left(\ln\left(1+\frac{(x-c)(e^2-1)}{de}\right)\right)^2}{(\ln e)^2}\right], \tag{5}$$

$$\mathrm{G}(a,\ b,\ c,\ d,\ e): y = a + b\exp\left[\frac{-(x-c)}{d}\right]\left[\left(\left(\frac{x-c}{d}\right)+e-1\right)\Big/(e-1)\right]^{e-1}, \tag{6}$$

where the independent variable x is the driving time of each event in the journey (min), the dependent variable y is the real-time monitored PM mass concentration (μg m^{-3}), and a, b, c, d, and e are the fitted parameters. Here, a is defined as an interception, b is a peak height above the background level, c is a location parameter of the peak in x-axis, and d and e can be used to determine the variations.

Triangular distribution function can be expressed as,

$$\mathrm{T}(a,\ b,\ c,\ d)\ : y = \frac{2a}{d-b}\left\{\frac{x-b}{c-b}u[(x-b)(x-c)] + \frac{d-x}{d-c}u[(x-c)(x-d)]\right\}, \tag{7}$$

where a and c represent the peak height and corresponding location parameter arriving the peak height in x-axis, respectively, and b and d are the values of the minimum start time of the event and the maximum stop time of the event in x-axis, respectively. Here, the duration of each event can be calculated as $d - b$. Function $u[(x - x_0)]$ indicates the unit step function. Practically, we used two-step linear fit concept to fit manually the triangular distribution based on Microsoft Excel spreadsheet.

2.4. Data and uncertainty analyses

The model fittings and AUC estimates were performed by TableCurve 2D (Version 5, AISN Software Inc., Mapleton, OR, USA) and Mathematica (Version 5, Wolfram Research Inc., Champaign, IL, USA), respectively. The single pulsed PM exposure estimates for lognormal and gamma distributions may be estimated based on the different occupied proportion (P) and same fitted peak height (H) adopted from normal distribution. The occupied proportion P is an index to represent the fitness magnitude comparing with the best-fit distribution at same fitted peak height H. The occupied proportion P for normal, lognormal, and gamma distributions can be estimated from the "Probability Distribution Calculator" program of Statistica software (Version 6.0, StatSoft Inc., OK, USA).

2.5. Excess mortality model and adjust factors

The excess mortality (EM, ind) can be calculated as (Tainio et al., 2005),

$$\mathrm{EM}_j = M_j \times \left(e^{\beta_j \Delta E} - 1\right), \tag{8}$$

where M is the background mortality (ind), β represents the $PM_{2.5}$ exposure-mortality coefficient (% per 10 μg m^{-3}) (Pope and Dockery, 2006), ΔE is the excess $PM_{2.5}$ exposure (μg m^{-3}), and indices $j = 1$ and 2 represent the short- (daily basis) and long-term (annual basis) exposures.

For background mortality M, we adopted the background epidemiological data in Taiwan during 2009 (Taiwan DOH, 2010) for estimating the disease-specific excess mortality induced by $PM_{2.5}$ exposure. The daily mortalities for all causes, cardiovascular disease (CVD), and respiratory disease (RD) are 390 (standard mortality ratio (SMR): 1.28 per 10^5 population), 41 (SMR: 0.11 per 10^5 population), and 14 (SMR: 0.04 per 10^5 population) individuals, whereas annual mortalities for all cause, CVD, and lung cancer (LC) are 142 240 (SMR: 466.7 per 10^5 population), 15 093 (SMR: 47.7 per 10^5 population), and 7951 (SMR: 25.3 per 10^5 population) individuals. Here we did not calculate and show the SMR values for daily mortality because the values were 2–3 orders of magnitudes lower than the annual data.

We treated the dose-response range as the 1- to 99-percentile for estimating the excess mortality. In addition, two adjusted factors were used based on real exposure duration of 5 h in each journey: one for passenger subgroup ($5/24 = 0.208$) and the other for driver subgroup ($(10/24) \times (250/365) = 0.285$). We assumed that the working hours of bus driver subgroup were at least 10 h per day, 250 days per year, for over 10 years. Here the adjusted factors of 0.208 and 0.285 were used to reasonably represent the daily (short-term) and annually (long-term) exposure settings for passengers and drivers.

3. Results and discussion

3.1. Events classifications and characteristics

Table 1 shows the data extraction and reanalysis for all events in a long-distance bus. The mass concentrations of $PM_{2.5}$ and PM_{10} under background situations were estimated to be 10.2 ± 1.5 and 33.5 ± 10.1 μg m^{-3}. The event mass concentrations of $PM_{2.5}$ and PM_{10} were estimated to be 126.88 ± 41.06 and 164.75 ± 56.27 μg m^{-3}. The event concentrations of $PM_{2.5}$ and PM_{10} were nearly 12 and 5 times higher than that in background, respectively. The duration of occurred events was 0.21 ± 0.04 h ranging from 0.10 to 0.32 h. The starting and ending points were defined to be the two minimums in each event.

Fig. 2 shows the different event categories of $PM_{2.5}$ and PM_{10} mass concentrations and duration. There were highest mean $PM_{2.5}$ and PM_{10} mass concentrations during the "Door-opened get off", followed by "Window opened", "Toll station and window opened", and "Door-opened get on" events. We found that higher variations of $PM_{2.5}$ and PM_{10} mass concentrations occurred in the "Door-opened get on" and "Window opened" events. Their CV values were greater than 50%, showing that the traditional calculations of PM exposures for driver/passenger might not be accurate and could cause uncertainties in risk assessment.

3.2. Fitted distribution functions

Table 2 summarizes the best fitted parameters for four selected representative events using normal, lognormal, and gamma distribution functions. The gamma distributions ($r^2 = 0.92$–0.99) was fitted better than normal distributions ($r^2 = 0.87$–0.98). The fitted peak heights H (summation of parameters a and b) of events #5, #7, #9, and #12 for normal distribution are estimated as 199.3, 254.7, 92.0, and 287.3 μg m^{-3} (Table 2). The occurred times of peak events could be determined by parameter c, showing no significant difference. The occurred times of peak events in events #5, #7, #9, and #12 for normal distribution are estimated to 21 h 12 min, 21 h 48 min, 23 h 00 min, and 00 h 06 min. The variations of fitted distributions can be calculated by parameters d and e.

To compare the fitted distributions, we used event #5 and three selected distribution functions (Fig. 3). The same observation for hours and minutes of events #5 started at 21 h 04 min, peaked at 21 h 10 min, and ended at 21 h 21 min. (Table 2 and Fig. 3). The fitted peak heights H of events #5 for normal, lognormal, and gamma distributions were 199.3, 197.8, and 197.4 μg m^{-3}.

3.3. AUC model

Fig. 4 shows the mass basis AUCs for $PM_{2.5}$ and PM_{10} estimated by using triangular distribution function for selected 12 events in

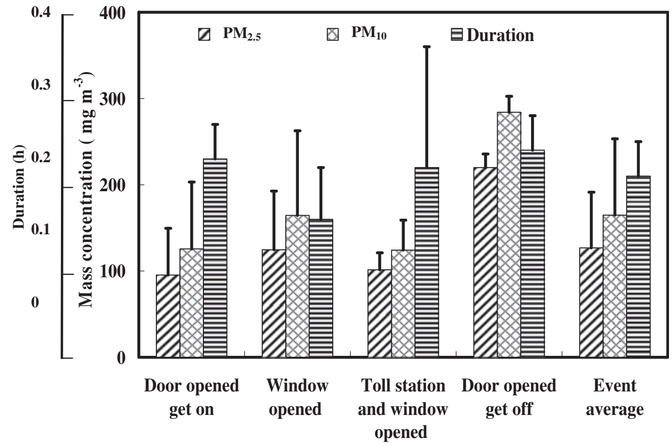

Fig. 2. Different event categories of $PM_{2.5}$ and PM_{10} in mass concentrations and duration.

Table 1
Data extraction for all events in a long-distance bus on September 15, 2004.

Event	No.	$PM_{2.5}$ (μg m^{-3})	PM_{10} (μg m^{-3})	Duration (h)
Original data from Huang and Hsu (2009)				
Door opened get on	#1	128.63	185.74	0.25
Door opened get on	#2	67.62	83.27	0.19
Window opened	#3	66.23	76.24	0.20
Window opened	#4	65.46	84.54	0.11
Door opened get on	#5	151.36	195.64	0.27
Toll station and window opened	#6	115.38	148.71	0.32
Window opened	#7	185.80	266.22	0.23
Door opened get on	#8	33.73	38.11	0.21
Toll station and window opened	#9	87.26	99.78	0.12
window opened	#10	181.14	230.74	0.10
Door opened get off	#11	208.84	270.96	0.21
Door opened get off	#12	231.08	297.11	0.27

[a]Mean (standard deviation).

Table 2
Best fitted parameters estimated for four selected representative events by using triangular, normal, lognormal, and gamma distribution functions.

Fitted peak Functions	Best fitted parameters					r^2
	a	b	c	d	e	
Door-opened get on (#5)						
Triangular	196.38	21.08	21.15	21.35	–	0.89[a]
Normal	33.55	165.72	21.17	0.05	–	0.92
Lognormal	12.97	184.84	21.15	0.13	1.64	0.99
Gamma	21.30	176.08	21.15	0.03	3.88	0.99
Window opened (#7)						
Triangular	266.39	21.78	21.84	22.02	–	0.87[a]
Normal	54.80	199.85	21.85	0.02	–	0.87
Lognormal	41.45	200.06	21.84	0.06	2.06	0.96
Gamma	59.99	186.97	21.84	0.02	1.62	0.92
Toll station and window opened (#9)						
Triangular	99.98	22.94	22.98	23.06	–	0.84[a]
Normal	33.93	58.08	22.98	0.02	–	0.96
Lognormal	32.21	59.15	22.98	0.04	1.26	0.97
Gamma	32.46	58.80	22.98	0.01	13.33	0.97
Door-opened get off (#12)						
Triangular	297.52	0.02	0.10	0.21	–	0.90[a]
Normal	21.29	266.03	0.10	0.03	–	0.98
Lognormal	16.46	270.22	0.10	0.08	1.27	0.99
Gamma	17.26	268.71	0.10	0.01	11.62	0.99

[a] The calculated coefficients of determination (r^2) of triangular distribution are computed manually based on Microsoft Excel spreadsheet by using two-step linear fit concept.

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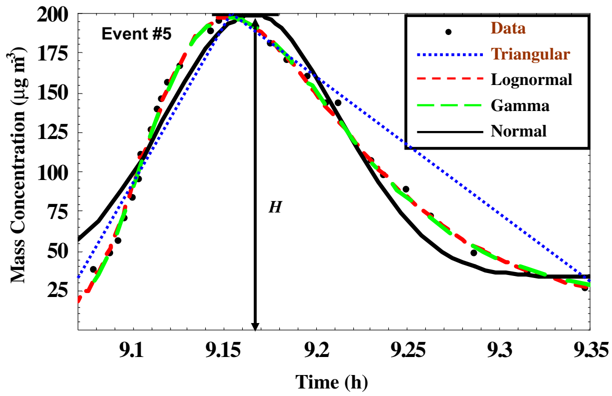

Fig. 3. The relationships among data and triangular, normal, lognormal, and gamma fitting distribution functions to the PM_{10} data of event #5. The peak height (H) can be obtained from data fitting with different distributions.

the long journey. In the "Door-opened get on" category, the AUCs of $PM_{2.5}$ and PM_{10} ranged from 0.02 to 15.91 and 0.48–21.89 μg h m^{-3}. In the "Window opened" category, the AUCs of $PM_{2.5}$ and PM_{10} ranged from 1.76 to 17.51 and 2.81–26.76 μg h m^{-3}. The estimated AUCs for $PM_{2.5}$ in "Toll station and window opened" and "Door-opened get off" categories ranged from 3.23 to 13.10 and 18.41–26.67 μg h m^{-3}. The estimated AUCs for PM_{10} in "Toll station and window opened" and "Door-opened get off" categories ranged from 3.98 to 18.43 and 24.93–35.59 μg h m^{-3}.

Fig. 5 shows a mass basis AUC comparison using four selected distribution functions for four event categories (events #5, #7, #9, and #12). The AUCs of mass basis PM_{10} under four selected distribution functions were estimated: 21.89–29.05, 18.18–26.76, 3.98–6.45, and 27.09–35.59 μg h m^{-3}, in "Door-opened get on", "Window opened", "Toll station and window opened", and "Door-opened get off" categories. The results showed that the AUC estimates in "Door-opened get on" ($p = 0.024$), "Toll station and window opened" ($p < 0.001$), and "Door-opened get off" ($p = 0.044$) categories from triangular distribution were significantly different contrary to the other three distributions.

3.4. Model predictions and comparisons

Table 3 shows the comparisons among single pulsed mass basis AUC estimates for $PM_{2.5}$ and PM_{10} computed from four selected

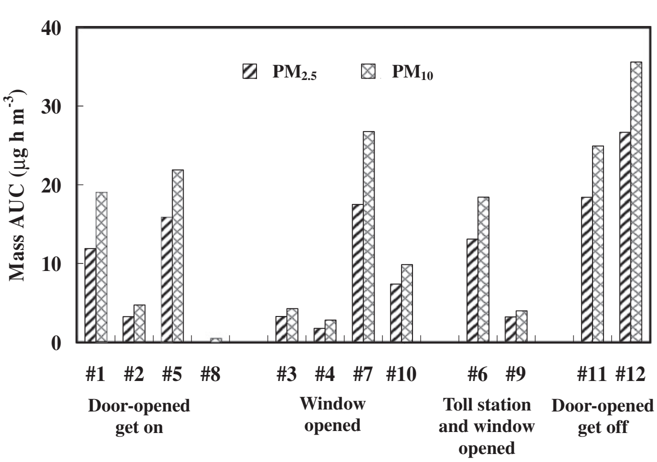

Fig. 4. Mass basis AUC for $PM_{2.5}$ and PM_{10} estimated using triangular distribution function for selected 12 events in the long-distance travel.

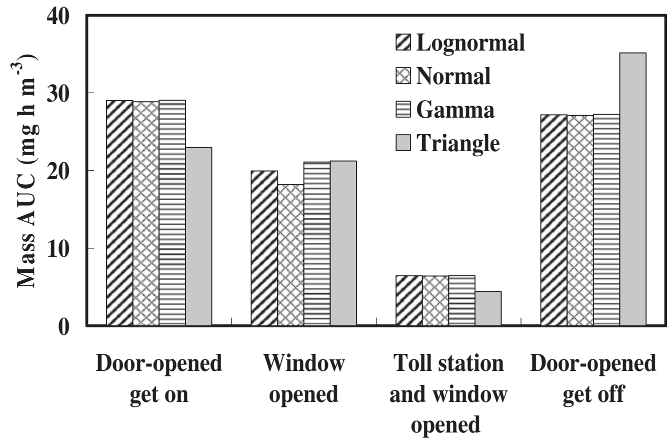

Fig. 5. $PM_{2.5}$ mass basis AUC comparison using four selected distribution functions for four event categories of events #5, #7, #9, and #12.

distribution functions with the adopted values. All predicted results have been normalized with their corresponding CV values. For $PM_{2.5}$, the estimated CVs of their AUCs were 73.0, 18.5, 5.3, 5.0, and 2.9% in "Total Mean", "Triangular", "Normal', "Lognormal", and "Gamma" distribution settings. However, CVs of 66.8, 22.4, 14.0, 14.0, and 11.7% were obtained in "Total Mean" and the selected four distribution settings aforementioned for PM_{10}.

Results showed that the gamma distribution had a better performance with minimum CV values of 2.9% and 11.7% for $PM_{2.5}$ and PM_{10}. The occupied proportion P values for normal, lognormal, and gamma distributions in $PM_{2.5}$ were 0.972, 0.975, and 1.0, whereas in PM_{10} we obtained 0.967, 0.967, and, 1.0. The predicted CV values for $PM_{2.5}$ and PM_{10} based on normal distribution were 5.3% and 14.0%, which were much less than the original "Total Mean" and "Triangular" settings.

3.5. Excess mortality estimates

Fig. 6 shows the excess mortality risk assessment of $PM_{2.5}$ exposure for passenger and driver. The $PM_{2.5}$ AUC estimates of "Total Mean" and "Normal Distribution" (the accepted scenario) were 122.0 ± 89.0 and 123.0 ± 6.5 h μg m^{-3}. The 5 h-averaged AUC-based $PM_{2.5}$ exposure were 24.4 ± 17.8 and 24.6 ± 1.3 μg m^{-3}. By accounting for the background $PM_{2.5}$ (10.2 ± 1.5 μg m^{-3}), the excess $PM_{2.5}$ exposure level can be 14.2 ± 17.8 and 14.4 ± 1.5 μg m^{-3} for "Total Mean" and "Normal Distribution" settings.

Table 3
Modeled AUC estimates and their related statistics of $PM_{2.5}$ and PM_{10} with four selected peak functions.

	Mean AUC (h μg m^{-3})		Standard deviation (h μg m^{-3})		Coefficient of variation (%)	
	$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}
Total Mean[a]	122.0	196.0	89.0	131.0	73.0	66.8
Peak functions						
Triangle	185.1	292.7	34.2	65.7	18.5	22.4
Normal	123.1	209.7	6.5	29.3	5.3	14.0
Lognormal	123.4	209.9	6.2	29.4	5.0	14.0
Gamma	125.9	214.2	3.7	25.0	2.9	11.7

[a] Values were obtained by using the average exposure concentrations (including $PM_{2.5}$ and PM_{10}) adopted from Huang and Hsu (2009) multiplied by exposure duration of 5-hour.

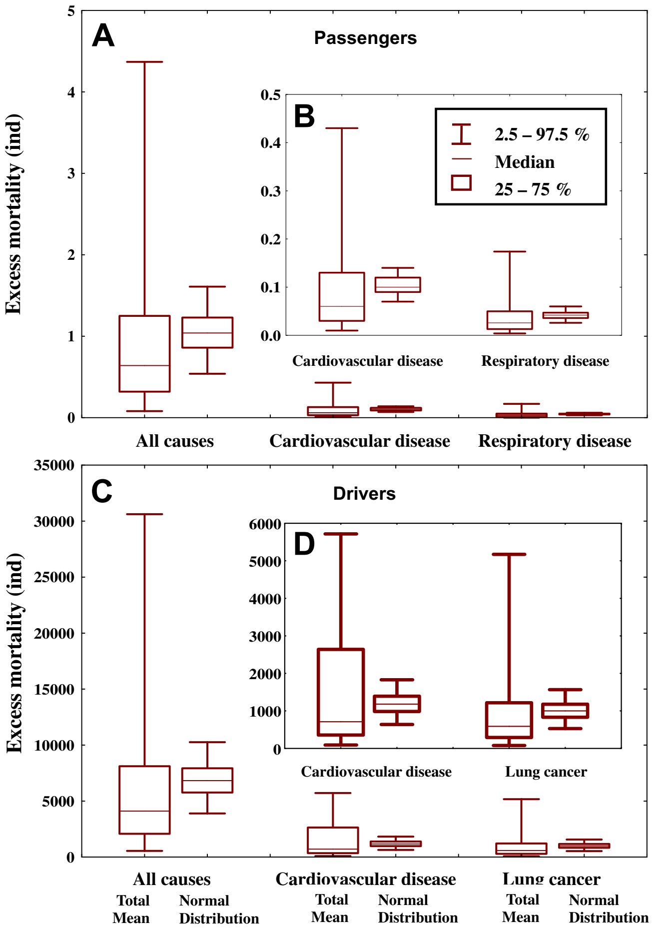

Fig. 6. Excess mortality estimates due to excess $PM_{2.5}$ exposure for (A, B) passengers and (C, D) drivers under "Total Mean" and "Normal Distribution" settings. For annually basis long-term scenario, the excess mortalities due to all causes, cardiovascular and lung cancer were considered (A, C), however the all causes, cardiovascular disease, and respiratory disease associated mortalities were concerned in the daily basis short-term scenario (B, D).

The daily excess mortality for passenger (adjusted to 5 h-averaged exposure) were 0.64 (95% CI: 0.08–4.37), 0.06 (0.01–0.43), and 0.03 (<0.01–0.17) individuals in "Total Mean" setting, whereas 1.04 (0.54–1.61), 0.10 (0.07–0.14), and 0.04 (0.04–0.06) individuals in "Normal Distribution" setting for all cause, CVD, and RD. However, the adjusted excess mortality for driver under long-term exposure were 4103 (555–30 624), 712 (92–5718), and 589 (77–5174) individuals in "Total Mean" setting, whereas 6833 (3897–10 259), 1180 (640–1831), and 1001 (531–1566) individuals were estimated in "Normal Distribution" setting for all cause, CVD, and LC, respectively. That is to say, the SMR estimates for driver were 13.5 (1.8–100.4), 2.2 (0.3–18.1), and 1.9 (0.2–16.5) per 10^5 population in "Total Mean" setting, however nearly 22.4 (12.8–33.6), 3.7 (2.0–5.8), and 3.2 (1.7–5.0) per 10^5 population were obtained in "Normal Distribution" setting for all cause, CVD, and LC, respectively. Our results indicated that the median values of disease-specific excess mortalities in our fitted normal distribution were 1.3–1.7 times higher contrary to the original dataset in the "Total Mean" setting.

On the other hand, nearly 2 orders of magnitude between the upper and lower bounds of 95% CI associated with the excess mortality estimates in "Total Mean" setting were found, whereas only 2–3 times of those estimates were found in "Normal Distribution" setting. The interquartile range (IQR) of the excess mortality values in our predicted model were 2.5–5.6 times less than that in the original dataset, showing that our predicted model could successfully reduce the variations in estimates.

3.6. Data reanalysis and PM exposure

The aim of this paper was to evaluate a single trip-based PM exposure in a long-distance bus with "door-open get on" and "door-open get off" events occurred in different locations (or cities). According to the original data (Huang and Hsu, 2009), the drivers and passengers get on the bus at Taipei city (including 2 bus stops, events #1 and #2) and the final destination is Tainan city (including 2 bus stops, events #11 and #12). Because the time spent on single trip was nearly 5 h, there would be one or two 5- to 10-min breaks for restroom or store in the intermediate station or rest area in highway. At the same time, new passengers might be carried after the breaks in the long-distance bus (events #5 and #8 in this study). Therefore, the possible factors contributing to the great differences may due in part to numbers of passengers, PM in stations or stops, engine status, resident times, and the behaviors of passengers (Adar et al., 2008; Keogh et al., 2010; Zuurbier et al., 2010).

Aerosol fine fraction (ratio of $PM_{2.5}$ to PM_{10}) might be a useful factor to compare the measurement and estimation. In the original data set (Huang and Hsu, 2009), the fine fraction of total measured mean PM was 62.2% ($n = 173$, 24.4/39.2) with large variations (~70%), yet the ones computed by journey basis were 61 ± 14%. The fine fraction values with lesser and greater than 8 times of window opened were 57 ± 14% ($n = 20$) and 69 ± 9% ($n = 10$) (Huang and Hsu, 2009). For event analysis, the fine fractions were 76.6, 78.2, 82.6, and 77.5%, respectively, for "Door-opened get on", "window opened" ($n = 4$), "Toll station and window opened" ($n = 2$), and "Door-opened get off" ($n = 2$) categories. However, the fine fractions were 67.9, 69.9, 76.2, and 74.4% under the AUC-based approach with triangular distribution for above mentioned four categories.

Overall, the maximum interval ranged from 76.6 to 82.6% for event peak measurements, followed by 67.9–76.2% based on AUC-based approaches ($n = 12$), 62.2% (~70% variation, $n = 173$) for all measured data, and 61 ± 14% ($n = 30$) for journey-based exposures. There was smallest variation but with highest aerosol fine fraction occurred in event peak measurement setting due to only accounting the maximum peak concentration. However, the estimated aerosol fine fraction with our proposed model almost fell within the range calculated by using journey-based exposures.

3.7. Model limitations

Our study indicated that the proposed AUC-based models can obviously improve the uncertainty of exposure assessment. The CV value was a useful indicator to examine the improvement of the uncertainty associated mean value estimates. The proposed methods have some limitations. First, the model is based on the PM exposure events decomposed as a linear combination. Although the proposed assumption had been validated, the linear combination of every peak could not be represented by a single peak function (or distribution). To resolve this problem, we performed the specific peak function by curve fitting technology and selected four representative peak functions to validate the assumption.

We firstly assumed the original data from Huang and Hsu (2009) is a triangle distribution. The mass AUC estimates were the basis for comparing with other selected distributions and/or

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original "Total Mean" setting. However, the results showed that the gamma distribution is the best fitted distribution. We selected a simplest basis (triangular distribution) as control setting not a perfect but complex setting (gamma distribution). However, we used the occupied proportion P as an index to depict the differences among normal, lognormal, and gamma distributions. The occupied proportion P also influence the mass AUC and CV estimates.

Second, the proposed method still needed to be validated with further monitoring data. Unfortunately, only limited published data were available (Huang and Hsu, 2009; Zuurbier et al., 2010). Therefore, the measurements of in-cabin PM exposure should be included in the future work. Third, the well-designated monitoring devices with integrate curve method to estimate accurately the PM exposure levels are already available but expensive. The used method may provide an alternative tool that is capable of estimating the in-cabin PM exposures with acceptable level based on the data from general monitoring devices.

3.8. Excess mortality assessment

The disease-specific excess mortality assessments were strongly based on the background mortality data, $PM_{2.5}$-mortality coefficient, and $PM_{2.5}$ level. The results were overestimated because the background epidemiological data of $PM_{2.5}$ exposure (Taiwan DOH, 2010) we used are higher values contrary to the Helsinki study (Tainio et al., 2005). The estimated daily excess mortality for passenger in our study were lower than the observed daily mortality of 13 (3–32) for CVD and 4 (0–20) individuals for RD in Barcelona, Spain (Perez et al., 2009) because the observed mortality was caused by multiple pollutants (e.g. $PM_{10-2.5}$, $PM_{2.5-1}$, PM_1, O_3, and NO_2).

Our results showed that the driver subgroups had 3–4 orders of magnitude higher in excess mortality risk than that for passenger of all causes and CVD. For excess mortality of lung cancer (similar to CVD), our results were consistent with the studies in Demark (Hansen et al., 1998; Soll-Johanning et al., 1998). Meanwhile, our excess mortality estimates for driver depended strongly on the $PM_{2.5}$-mortality coefficient (β) adopted from Pope and Dockery (2006) indicated that the range of coefficients (β) for all causes, CVD, and RD were 0.4–1.4, 0.6–1.1, and 0.6–1.4% per 10 $\mu g\ m^{-3}$ $PM_{2.5}$ exposure under daily short-term scenario. On the other hand, those for all cause, CVD, and LC were 6–17, 9–28, and 14–44% per 10 $\mu g\ m^{-3}$ $PM_{2.5}$ exposure under long-term scenario. Moreover, β values used in the present study might cause the annual excess mortality to be overestimated. Soll-Johanning et al. (1998) showed that the observed all causes and lung cancers for bus drivers and tramway employees cohort in Demark had a positive correlation with duration of employment.

4. Conclusions

This study provided a parsimonious approach to reduce the associated uncertainties for monitored PM levels. The CV value can be used to examine and to compare the appropriated models with different distributions. Results showed that the estimated CV values (%) for single-pulsed PM exposures based on the "Normal", "Lognormal", and "Gamma" distributions were agreeable compared with the original "Total Mean" and "Triangular" settings. Furthermore, the disease-specific excess mortality assessments due to $PM_{2.5}$ exposure indicated that the predicted median values in "Normal Distribution" setting were 1.3–1.7 times higher than that estimated from original dataset in "Total Mean" setting. Meanwhile, nearly 2 order of magnitude between the upper and lower bounds of 95% CI associated with the excess mortality estimates in "Total Mean" setting were found, whereas only 2–3 times of those estimates were found in "Normal Distribution" setting. The IQR of the excess mortality values, however, were 2.5–5.6 times less than that in the original dataset. Therefore, our study indicated that more accurate estimates of the PM level can be obtained by the proposed model. Consequently, the uncertainties of the risk estimates can be reduced on assessing human health effects posed by PMs in the real situations.

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