ORIGINAL RESEARCH
https://doi.org/10.4209/aaqr.220079

Aerosol and Air Quality Research

Utilizing Low-cost Mobile Monitoring to Estimate the $PM_{2.5}$ Inhaled Dose in Urban Environment

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Special Issue:
Air Pollution and its Impact in South and Southeast Asia (II)

ABSTRACT

This study has developed a compact, low-cost, and real-time mobile monitoring (MM) device for estimating the $PM_{2.5}$ inhaled dose. The MM device consists of a low-cost $PM_{2.5}$ sensor, temperature and humidity sensor, Wi-Fi module, and microcontroller unit. The MM system (carried on vehicle) has been used to measure $PM_{2.5}$ concentration, geolocation, and meteorological factors during rush hour. To examine repeatability, a new method was proposed to calculate the coefficient of variance of the $PM_{2.5}$ sensor reading. We used several vehicle speeds to evaluate its dependency on the $PM_{2.5}$ sensor reading. A sensor cover was also introduced to prevent the airspeed effect during carried on the vehicle. In this study, mobile monitoring was performing in several areas. The measured $PM_{2.5}$ concentration then used for estimating $PM_{2.5}$ inhaled dose. The Monte Carlo technique was used to introduce the probabilistic of body weight and $PM_{2.5}$ concentration. The result shows that the coefficient of variation of the $PM_{2.5}$ sensor reading was 2% on average in 2 minutes. We found that vehicle speed and sensor cover affects the standard deviation of $PM_{2.5}$ sensor reading. Statistical analysis shows that the on-road area (53 $\mu g\ m^{-3}$) has higher $PM_{2.5}$ concentration than residential area (41 $\mu g\ m^{-3}$). The area around the toll gate where many trucks pass has a higher concentration of $PM_{2.5}$. In addition, low variability on the meteorological factors caused weak relationship with the $PM_{2.5}$ concentration. We found that children were estimated to receive a higher inhaled dose of $PM_{2.5}$ than adults. Therefore, variations in the microenvironment and local pollution sources such as truck and food stalls are dominant factors that affect spatial variation of $PM_{2.5}$. Real-time mobile monitoring can help the government make policy and give warnings to people traveling around polluted areas.

Keywords: Particulate matter, Low-cost sensor, PM sensor, Indonesia

Received: February 15, 2022
Revised: April 20, 2022
Accepted: April 24, 2022

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Publisher:
Taiwan Association for Aerosol Research
ISSN: 1680-8584 print
ISSN: 2071-1409 online

1 INTRODUCTION

Air pollution, including gaseous pollutants and particulate matter, could impact health and the environment (Shi *et al.*, 2018). Particulate matter (PM), especially with a diameter less than 2.5 µm (i.e., $PM_{2.5}$), could carry various toxic substances on its surface (Xing *et al.*, 2016). Moreover, PM can pass through nose hair filtration and deposit inside the lungs, causing damage to other organs through air diffusion (Schraufnagel, 2020; Xing *et al.*, 2016). This damage could develop health problems such as respiratory disease, chronic obstructive pulmonary disease (COPD), lung cancer, and stroke (Lim *et al.*, 2018; Taghizadeh-Hesary and Taghizadeh-Hesary, 2020; Zhang *et al.*, 2018). Meanwhile, there are various sources of PM, such as biomass burning, fossil fuel combustion, and road dust (Lee *et al.*, 2018; Reddington *et al.*, 2021). People's activities in urban areas, such as exercising, cycling, commuting to work, can be exposed to air pollution from vehicles (Alexeeff *et al.*, 2018; Khreis *et al.*, 2017; Lipfert *et al.*, 2006). Prolonged exposure to high PM concentration could increase the mortality risk which related with the health problems (Kim *et al.*, 2018). Urban community faces the risk of high PM exposure in their daily activities.

Based on the risk of PM to our health, air pollution monitoring is needed so that residents can find out or access the latest information about the level of air pollution that occurs. The residents could protect themselves from PM exposure by wearing a mask or reducing activities outside. Effective monitoring can be carried out using several fixed air pollution monitoring stations. Nevertheless, limited funding can limit the provision of fixed monitoring stations. One of the websites providing public access to Bandung air quality information is iqair.com. The Ministry of Environment and Forestry (MoEF) also owns one air pollution monitoring station, which can be accessed from a website (ISPUNet, 2022). The limited number of fixed monitoring stations cannot describe the condition of air pollution throughout the city of Bandung. There are spatial limitations when air pollution in a city is only measured using one monitoring station. The data from fixed station monitoring may not necessarily represent PM concentration at the level of personal exposure since it cannot capture the air quality beyond 500 m (SM *et al.*, 2019). The comparison of mobile and fixed monitoring in California showed that mobile monitoring could reveal black carbon patterns missed by the fixed-site network (Chambliss *et al.*, 2020). Nevertheless, the increase of spatial resolution of measurement to the street level is done at the cost of reduced temporal resolution at a given location (Messier *et al.*, 2018).

Low-cost sensors are used to enhance the spatial and temporal resolution of pollution data since their low price can be implemented in wide areas (Jiao *et al.*, 2016). Air pollution in cities can vary in different locations due to local sources, so a minimum number of monitoring stations is needed to obtain PM distribution. However, not all cities in Indonesia have enough PM monitoring stations. The development of mobile monitoring and air quality monitoring networks solves the limitations of fixed monitoring stations in determining the level of gas pollution and particulate matter in certain areas (deSouza *et al.*, 2020; Li *et al.*, 2018; Liu *et al.*, 2020; Mahajan *et al.*, 2021; Zhou and Lin, 2019). Mobile monitoring can increase the spatial resolution of air pollution measurements at a location or area. The larger data spatial resolution could better describe the variability and exposure received by the community in different microenvironments. Mobile and fixed monitoring could complement each other to better understand the air quality in certain areas. However, it is important to choose between mobile monitoring or a fixed monitoring station based on specific needs and circumstances.

The device on mobile monitoring systems can be carried by vehicle or people. Previous research uses separate instruments to measure different air pollution and location (Kolluru *et al.*, 2019; Li *et al.*, 2018; Liu *et al.*, 2020; Yu *et al.*, 2016). Some studies combined several measurement instruments into one integrated device (Gao *et al.*, 2016; Mazaheri *et al.*, 2018; Sinaga *et al.*, 2020; Wu *et al.*, 2020). However, the effect of vehicle speed and airflow modification are not discussed yet. PM measurement is done by flowing ambient air to the sensor's detection area. Due to relative ambient air movement, the vehicle speed can affect the airflow to the PM sensor. There is no literature about the effect of vehicle speed on the sensor reading.

Nevertheless, Hapidin *et al.* (2020) found that low-cost PM sensor (Sharp GP2Y) output voltage is affected by airflow drawn to the sampling area. An approach to getting better sensor reading by airflow modification and digital filtering has been discussed (Gao *et al.*, 2016), but they did not discuss the vehicle speed's effect on the sensor reading in detail. Therefore, this study aims to develop a system that simultaneously measures air pollution, meteorological factors, and location. This system is also connected to the internet to see real-time measurement data. This system could further be developed by incorporating more sensors into the device. Moreover, the device's compact size made it easy to carry around. This study will also discuss the effect of vehicle speed and sensor cover modification on $PM_{2.5}$ concentration measurement.

This study designed a portable $PM_{2.5}$ monitoring device using low-cost sensors and GPS to measure particulate matter concentration in urban areas. This study aims to determine: the air pollution level in residential areas and on roads, especially during rush hour, the influence of different spatial characteristics in the area being studied, the dependence of $PM_{2.5}$ sensor reading on vehicle speed as well as sensor cover modification, and estimation of inhaled dose using Monte Carlo technique. The Monte Carlo simulation was started from the measurement data to generate the number distribution. The simulation is conducted to represent various possible cases of inhaled doses from different age groups while participating in different microenvironments. This mobile monitoring system could be potentially equipped with the public transportation system,

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https://doi.org/10.4209/aaqr.220079

which will supply the real-time data of $PM_{2.5}$ measurement. The data could further be processed so that the government could provide information or warnings to the community when they are in an area with particulate matter concentrations that exceed a certain threshold through a smartphone application.

2 METHODS

2.1 Sensor Selection and Monitoring System Development

2.1.1 Sensor selection and testing

The used $PM_{2.5}$ sensor (Model HPMA115S0, Honeywell, United States of America), referred as HPMA, utilizes laser-based sensor to count and detect the particulate matter concentration using light scattering. The HPMA sensor was calibrated using the same aerosol chamber and reference instrument as in previous research, explained in Hapidin *et al.* (2019). Before the HPMA sensor was applied to our mobile monitoring system, we also tested the HPMA sensor inside an aerosol chamber to determine the coefficient of variation (CV) of the sensor (please refer to supplementary information additional notes for the explanation of HPMA sensor selection). Hapidin *et al.* (2019) has characterized several low-cost PM sensors, including HPMA. They found that the coefficient of variation (CV) of HPMA reading is 4%, which fulfills EPA recommendation that the CV of $PM_{2.5}$ measurement is below 10% (U.S. EPA, 2016). Therefore, the HPMA sensor is used in this mobile monitoring system.

The method to determine CV is similar to previous research by Hapidin *et al.* (2019). The air is pumped through a silica gel dryer and HEPA filter. We set the airflow to 5 L m^{-1}. Incense smoke, used as the particle source in this experiment, flowed into the chamber. HPMA sensor measures the concentration of $PM_{2.5}$ inside the chamber. The concentration of $PM_{2.5}$ inside the chamber is varied by controlling the airflow to the system. The air flows to the chamber until the $PM_{2.5}$ concentration drops to a certain value. After the $PM_{2.5}$ concentration defined is obtained, the airflow is stopped. Then, we wait for 2 minutes to stabilize the $PM_{2.5}$ concentration inside the chamber. In the next 2 minutes, after the $PM_{2.5}$ concentration is assumed to be stabilized, the measurement of $PM_{2.5}$ concentration is done. The average and standard deviation to calculate the CV of the sensor are calculated from $PM_{2.5}$ concentration at this time. This practice is repeatedly done for each different $PM_{2.5}$ concentration to get the CV of the sensor in different $PM_{2.5}$ concentrations.

2.1.2 Monitoring system design

Fig. S2 shows a mobile monitoring system diagram for measuring $PM_{2.5}$ concentration. The main components of the measuring instrument are placed in a box with holes to ensure air circulation between the environment and the instrument. The mobile monitoring measurement device consists of a low-cost $PM_{2.5}$ sensor, temperature, relative humidity (RH) sensor, gateway, microcontroller, and power circuit. The HPMA and Asair (Model AM2301, Guangzhou Aosong Electronics Co., Ltd., China) were used as $PM_{2.5}$ and temperature and humidity sensors. HPMA was used due to the reading output was factory calibrated. The HPMA has also been used as a reference sensor to calibrate the mass concentration measurements of PM from other low-cost sensors using a decay test in a chamber (Hapidin *et al.*, 2019). The HPMA measurement principle is discussed in the supplementary information additional notes. Measurement begins with commands from the microcontroller (Model Atmega328P, Atmel, United States of America) to the HPMA and AM2301 sensors every 10 seconds.

The microcontroller was connected to the smartphone via a gateway. The gateway can be a Bluetooth or Wi-Fi module connection. The Wi-Fi module (ESP8266) acts as a gateway that connects the measurement instruments with the smartphone. The mobile hotspot function in the smartphone was activated; thus, the measurement instrument could connect to the smartphone via a Wi-Fi connection. A smartphone application gets measurement data from the microcontroller and the global positioning system (GPS) sensor. The GPS data can be obtained when the smartphone is in a location with enough GPS signals. The data from the GPS are the time and location coordinates (latitude and longitude). When the measurement data, time, and location have been obtained, the data was formatted according to the protocol and sent to the server. Measurement data was also stored on the smartphone's internal storage media as a backup. The data is sent to the server via an internet connection from a smartphone using the HTTP GET method.

The server receives the data and then stores it in the database. Measurement data can be seen in real-time in the form of measurement results vs. time and the data distribution on the map. The measurement data can be downloaded through the website for further processing using geographical information system (GIS) software or other statistical programs.

2.1.3 Sensor inlet cover and vehicle speed variation

Different sensor inlet cover, 3D printed using PLA filament, is used to test their effect on the $PM_{2.5}$ sensor reading. There are two different sensor covers: type 90 and type 135 cover. The number represents the angle of the sensor cover from the sensor top that covers the sensor inlet. The device is carried on the motorcycle in different average speed variations from 20 to 50 km h^{-1} with different sensor covers. At the beginning and end of each test, the device measures the ambient $PM_{2.5}$ concentration while the motorcycle is not moving. Measurement is done along a road whose length is around 200 to 300 m. The measurement is done on the same road repeatedly in 3 minutes. The road chosen is rarely passed by any other vehicle and is surrounded by grass fields. The evaluation of speed variation to the spatial data resolution is done on different locations with longer roads (1 km per trip). The measurement is done in 1–2 roundtrips on the same road to evaluate the spatial data resolution. Two roundtrips are needed for an average speed of 40 km h^{-1} to get richer data. The effect of different speeds on $PM_{2.5}$ measurement and spatial data resolution will be discussed.

2.2 Research Design

Bandung is the capital city of West Java province, Indonesia, with an area of 167.31 km^2 with an altitude of 768 m. The total population of Bandung in 2019 is 2.5 million people, with a population density of 14,549.88 km^{-2}. The city is congested with many vehicles, including private and public transportation. The main sources of $PM_{2.5}$ in Bandung were transportation (including diesel, gasoline vehicles, and motorcycles), industries, and biomass burning (Lestari and Mauliadi, 2009). Vehicle gas emission such as heavy-duty vehicle becomes a major source of air pollution (de Fatima Andrade *et al.*, 2012; Zhang *et al.*, 2017). The number of vehicles in Bandung reaches 1.7 million units. Moreover, the geographical condition of the city of Bandung, which is in a basin surrounded by volcanic plateaus (Gumilar *et al.*, 2015), allows air pollutants to be trapped.

Areas that pass-through markets, toll gates, and residential areas were selected as sampling routes in the area of interest. The route of the area of interest can be seen in Fig. 1. The area (latitude: –6.958701, longitude: 107.630565) is approximately 3.2 km^2, and the route traveled is 10–11 km. The area of interest can be divided into three specific parts. In Area 1 it is dominated by housing and shops, there is also a school. There is an open field in the middle of Area 1.

Fig. 1. Area of interest.

A traditional market in Area 2 sometimes causes traffic jams on the nearby road. Area 3 is the toll gate area. The red dashed line shows a major road on the sampling route. The solid blue line shows a part of a nearby toll road in the area of interest.

This study focuses on the morning (7:30–9:30 UTC+7) and afternoon (16:00–18:00 UTC+7). In the morning, many people exercise around the open fields in Area 1. The timing is also based on the rush hour so that air pollution on the roads around Area 1 and on the major road which passes the market and toll gates can be observed. Measurements are not taken when the weather is raining. Table S1 shows the weather and data collection time for ten days consists of 9 days and 4 days of measurement in the morning and afternoon, respectively.

Measurement is done by using a motorbike driven at a speed maintained at around 20–50 km h^{-1}. Each data collection takes between 45 and 60 minutes, depending on the traffic conditions on the road. The measuring instrument is placed on the front of the motorbike at about 1 m from the ground. Every 15 seconds, the position, temperature, humidity, and $PM_{2.5}$ concentration data will be measured and sent to the server. After each run of data collection, the weather conditions were recorded. The observer also recorded the events or anthropogenic activity when the $PM_{2.5}$ levels were anomalous during the trip. The anomalous means that in spatial term, the PM level is significantly higher than the surrounding area.

2.3 Dose Estimation

This study hypothesized that exposure magnitudes vary among ages and by microenvironment and commuting time. Particulate matter dose is calculated based on an exposure-dose model (Eq. (1)) (De Oliveira *et al.*, 2012; U.S. EPA, 2002) that considers inhalation rates and body weights. This equation is used since it fulfils the objective of the study. We would like to estimate the inhaled dose of PM for various age groups. The people in each group has a specific inhalation rate and body weights. These two variables are important in estimating the inhaled dose. There was also other alternative in calculating the inhaled dose that used different approach (Borghi *et al.*, 2021).

$$D = \frac{C.IR.FA.FR}{BW} \tag{1}$$

The capital letter D represents the dose (µg kg^{-1} day^{-1}), C is the particulate matter concentration (µg m^{-3}), and IR is the inhalation rate. $PM_{2.5}$ concentration is a generated random number in lognormal distribution with average and standard deviation based on measurement data (Table 1). The inhalation volume used for this study was taken from Makassar, Indonesia, with 0.9 hours of commuting (Patel *et al.*, 2016). FA and FR is the factor of absorption and the factor of retention. These values are assumed as 1 representing the worst-case scenario and potential impact on the community (De Oliveira *et al.*, 2012). BW is the body weight corresponding to the male groups used in this study. The available data for the bodyweight is grouped into the following age categories: 0–5 months, 6–11 months. 12–23 months, 2–3 years, 4–6 years, 7–9 years, 10–12 years, 13–15 years, 16–19 years, 20–39 years, 40–55 years, 56–65 years, 66–75 years, and more than 75 years (Hardinsyah *et al.*, 2012). Values for each age group are estimated as the median age of each group. All variables used for the dose simulation can be seen in Tables S2–S4. Simple software is written in Python to generate the random number with the required distribution for the Monte Carlo simulation. In this simulation, the random values are generated for $PM_{2.5}$

Table 1. Descriptive statistics of measured $PM_{2.5}$ concentration (µg m^{-3}) in the morning and evening in Area 1 and on-road ($p < 0.05$).

Area	Group	n	Mean (µg m^{-3})	Standard Deviation (µg m^{-3})	Median (µg m^{-3})	Min (µg m^{-3})	Max (µg m^{-3})	CV (%)
Area 1	Morning	930	41	15	43	9	71	36
	Afternoon	321	20	5	21	10	31	25
On-road	Morning	853	53	22	52	10	104	41
	Afternoon	388	28	10	27	9	57	35

concentration, body weight, and inhalation rate according to the type of distribution. The random value was extracted from a specific distribution whose parameter is based on measurement data or reference data. The measurement data will provide the mean and standard deviation for the random number distribution. The parameter for generating a random number for BW and IR was based on reference data. The generated set of random sample numbers ($PM_{2.5}$ concentration, body weight, and inhalation rate) is used to calculate the inhaled dose. This process was repeated until we got one million calculations of inhaled dose. The average dose was calculated from one million samples from each age group.

3 RESULTS AND DISCUSSION

3.1 HPMA Sensor Coefficient of Variation

The $PM_{2.5}$ concentration measured in the experiment is depicted in Fig. 2(a). The $PM_{2.5}$ concentration is like a staircase due to varied $PM_{2.5}$ concentrations inside the chamber. CV is calculated using the horizontal part of the data. The calculated CV in each different average $PM_{2.5}$ concentration is depicted in Fig. 2(b). The CV of the sensor is getting lower in increasing the average $PM_{2.5}$ concentration. Overall, the CV of the sensor is below 10%. Using this method, the average CV of the sensor is 2%; this result is lower than the previous result by Hapidin *et al.* (2019). Measurement of CV using this method assumes that the $PM_{2.5}$ concentration decay in the chamber caused by wall deposition is negligible.

Hapidin *et al.* (2019) measure the CV of the HPMA sensor by doing the decay test repeatedly four times. The decay test utilizes a slow decrease in concentration in an aerosol chamber due to clean air circulation. At first, an aerosol source (incense) was used to make aerosols with high concentrations up to saturation in the chamber. Next clean air flows so that the concentration begins to decay. The starting point in this decay is very risky in CV calculations. In addition, clean air control needs to be strictly ensured so that repeated measurements to determine CV can be precise. Differences in flow will cause different decay times. In this study, instead of repeating the decay test, the measurement of CV by our method, as in Fig. 2(a), guaranteed measurement accuracy of CV in certain average $PM_{2.5}$ concentrations. Badura *et al.* (2018) calculate the CV of the sensor by averaging a minute of data of two sensors of the same type in the open environment. They also conduct another method by calculating CV from 1 minute (8%) and 1 hour (6%) data (Badura *et al.*, 2019); as a result, CV depends on time range selection.

3.2 Descriptive Statistics

Table 1 and Fig. S5 shows descriptive statistics and boxplots for Area 1 and road site as differentiated by data collection time. In the morning, the mean $PM_{2.5}$ concentration on the road site (53 $\mu g\ m^{-3}$) was 29% higher than the $PM_{2.5}$ concentration in Area 1 (41 $\mu g\ m^{-3}$). In the afternoon, the $PM_{2.5}$ concentration on road and Area 1 was 28 $\mu g\ m^{-3}$ and 20 $\mu g\ m^{-3}$, respectively, the $PM_{2.5}$ concentration on the road was 37% higher than in Area 1. The maximum value of the measured

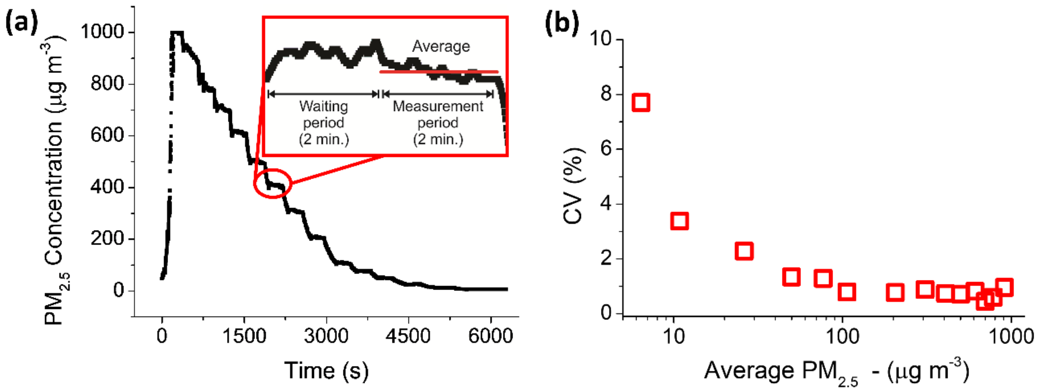

Fig. 2. (a) $PM_{2.5}$ concentration vs. time measured by HPMA sensor; (b) CV of HPMA sensor in different average $PM_{2.5}$ concentration.

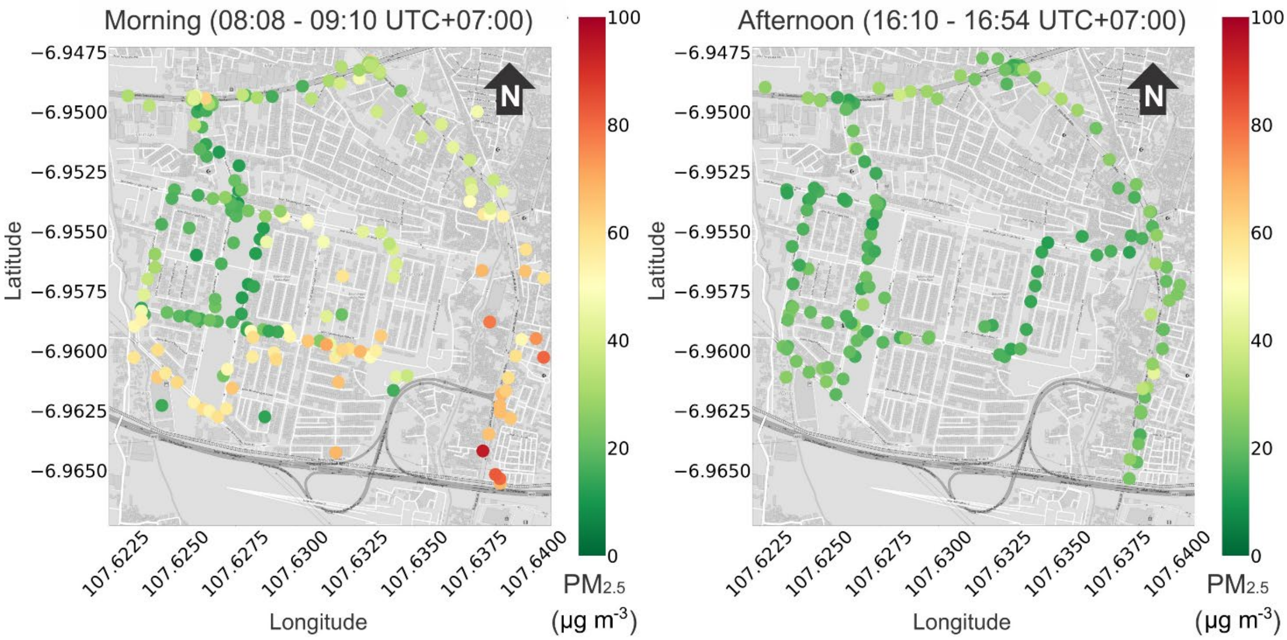

Fig. 3. $PM_{2.5}$ concentration distribution on the area of interest on 2 January 2021.

$PM_{2.5}$ concentration (ignoring anomalous data) was on the morning days, which are 104 µg m^{-3} on the road and 71 µg m^{-3} in Area 1. The higher value of the measured $PM_{2.5}$ on the road was due to truck fumes close to the measuring instrument. We also observed visible truck fumes and the drastic increase in $PM_{2.5}$ measurement. Several other factors were also observed to cause a significant increase in measured $PM_{2.5}$ concentration: the smoke from biomass combustion, food stalls on the side of the road, and the old or poorly maintained vehicles emitting thicker smoke. In addition, due to traffic activities in the morning, $PM_{2.5}$ measured in the morning was much higher than $PM_{2.5}$ concentration measured in the afternoon for both locations, as shown in Fig. 3.

The CV of each data category in Table 1 was calculated to determine the spatial variability in Area 1 and on-road sites. The CV value of the afternoon is lower than that of the morning. In the different research areas, CV on the road is greater than the CV in Area 1. $PM_{2.5}$ concentration data from fixed stations can cause discrepancies in personal $PM_{2.5}$ exposure, especially in the microenvironment, due to its large spatial variation.

PM monitoring for a longer period (23 months) using filter-based measurement has been done in Institut Teknologi Bandung (ITB), Bandung, Indonesia (Snider *et al.*, 2016), which results in 31.4 µg m^{-3} in average for $PM_{2.5}$. An urban forest near ITB made its environment like the residential area in this study. A recent study of personal monitoring in Bandung shows that the 30 minutes average $PM_{2.5}$ exposure on the road, home, and home exterior is between 25–50 µg m^{-3} (Sinaga *et al.*, 2020). These two previous studies show good agreement for $PM_{2.5}$ measurement using mobile monitoring. An environment with appropriate tree characteristics could remove the PM_{10} up to 57% of the total particulate emission on the street (Ortolani and Vitale, 2016).

According to Sinaga *et al.* (2020), the mode of transport that showed the highest $PM_{2.5}$ exposure are bicycles, motorcycles, and walking. Using proper gear such as a mask for a cyclist can reduce the risk of $PM_{2.5}$ exposure, especially when passing a major road with many vehicles or trucks. Some roads indeed have bicycle lanes, but it is common to see a motorcycle or cars get in the bicycle lane daily, especially when there is a traffic jam. The cyclist or pedestrian could get higher exposure to $PM_{2.5}$ when vehicles are in front of them as the smoke is probably inhaled directly. This case is similar to when the mobile monitoring device detects a significant increase of $PM_{2.5}$ measurement while the vehicle carrying the device is near a truck's exhaust.

3.3 Spatial Data Distribution

Python, QGIS process the data, and SAGA GIS (QGIS, 2020; SAGA, 2020) was used to map the $PM_{2.5}$ concentration. The measurement data was grouped by Area 1 as a residential area; Areas 2 and 3 are grouped with on-road measurement since the road passes through the two areas. Each circle scattered on the map of the area of interest at a certain time describes the $PM_{2.5}$ concentration. Some points appear to have deviated from the path that should have been possible due to poor GPS signals resulting in less GPS accuracy.

In Fig. 3, there is a clear spatial variation of $PM_{2.5}$ in the morning, while in the afternoon, the variation in the value is significant. The air pollution is quite high in the area of the major road that passes through Areas 2 and 3. Along these roads are offices, shops, markets, and toll gates. The shops along the main road are relatively more crowded than those in Area 1, which tend to be dominated by houses. The air pollution mapping can help identify the sources of hotspots in Area 1 and on roads. In Area 1, the concentration of $PM_{2.5}$ in the southern area of Area 1 is measured as a relatively higher concentration of pollution compared to areas in the north (Fig. 3).

Distance from each measurement point to the road was calculated using the nearest feature in QGIS to get the $PM_{2.5}$ concentration vs. the nearest distance to the road (Fig. S6). Grouped data by the time show the decreasing trend of the maximum value measured with increasing distance from the road. The result is by Mazaheri *et al.* (2018), which found that the concentration of $PM_{2.5}$ at less than 50 m from the road was higher than 10 $\mu g\ m^{-3}$ (concentration is generally in Brisbane). At a larger distance, Mazaheri *et al.* (2018) also found that the mean value of the measured PM was lower than the PM concentration near the road, which agreed with the exponential decay model of the distance (Ling *et al.*, 2020). $PM_{2.5}$ concentration in the afternoon has a lower average than in the morning. Lower traffic activities in the afternoon probably cause this; for example, the traditional market in Area 2 opens only in the morning. In this study, the decrease in the mean value of $PM_{2.5}$ was not as noticeable as the decrease in the maximum value of the measured $PM_{2.5}$ concentration. Yu *et al.* (2016) found that the concentration of $PM_{2.5}$ measured against distance using mobile monitoring did not show a declining pattern with distance from the road, which can happen when there are many local $PM_{2.5}$ sources in areas far from the road.

Higher $PM_{2.5}$ concentration near the road or other sources can consider in designing a city. Public spaces such as gardens or sports fields can be built within a certain distance to reduce the risk of $PM_{2.5}$ exposure when doing the activity outside. Planting a suitable plant in the garden or around the city can help absorb particulate matter (Shao *et al.*, 2019). Different types of plants, leaf morphology, and season affect the particle retention by the plants (Zhou *et al.*, 2020). The community should consider choosing a place or a route with minimum risk of exposure to $PM_{2.5}$ to prevent risk of PM exposure.

Wu *et al.* (2020) found that the hot spot of $PM_{2.5}$ in the research of taxi-based mobile monitoring are congested intersections, bus stops, or high emission corridors. An interesting hot spot source such as congested intersections is similarly found in this study. Although it is not the intersection, the road with moderate or even heavy congestion shows a higher $PM_{2.5}$ concentration based on general observation. The congestion usually happens at the market in Area 2 is caused by the vehicle parked on the road's side. Public transportation waiting for passengers around the market sometimes causes more severe congestion. The result of mobile monitoring measurement in the city of Cambridge found that the fine particles tended to concentrate along heavily trafficked roads (deSouza *et al.*, 2020). Thus, there may be a relationship between the number of traffic, average speed, or vehicle types with the $PM_{2.5}$ emission on the road.

3.4 Effect of Speed and Sensor Cover on $PM_{2.5}$ Sensor Reading

Several experiments with different average speeds of vehicles have been attempted to figure out the dependency of the vehicle speed on the sensor reading. The results of this subject are shown in Fig. 4. There is a dependency on sensor readings at different vehicle average speeds. The vehicle speed affects mainly the standard deviation of the sensor. The vehicle's speed can affect relative airflow around the sensor, which could disturb the sensor reading and internal airflow of the sensor. The amount of $PM_{2.5}$ entering the detection area increases along with the increased airflow, which results in a higher $PM_{2.5}$ sensor reading.

We have added a cover on the sensor to cancel the speed effect on the sensor reading. There are two types of sensor cover that we used, which are type 90 and 135. This sensor cover type is based on the angle covering the sensor inlet, as shown in Fig. 4; type 90 covers 90 degrees from the top of the sensor, while type 135 covers the inlet 135 degrees from the top of the sensor.

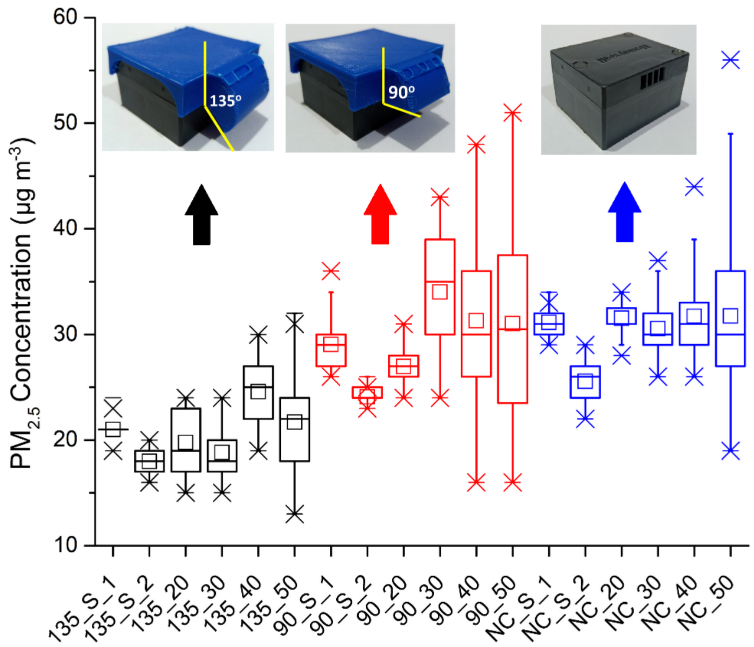

Fig. 4. HPMA sensor reading in different cover types and vehicle speed variation.

However, in general, the variation of the cover type used does not significantly affect the average reading from the sensor; only at a relatively high speed, the measured $PM_{2.5}$ concentration is higher than when the vehicle was at rest. Nevertheless, using different inlet covers, the type 135 cover reduces the standard deviation of $PM_{2.5}$ measurement.

Data is labeled according to X_Y where X is cover variation: no cover (NC), type 90 (90), and type 135 (135); Y is speed variation: stationary condition before (S_1) and after (S_2), speed variation 20, 30, 40, and 50 km h^{-1}. The distribution of measurement data with a type 135 cover tends to be smaller than that of a sensor without a cover and type 90. The use of a cover tends to reduce the standard deviation of the measurement of $PM_{2.5}$ concentration with increasing speed (Fig. S3). There is still an increase in standard deviation with type 135 cover, but the increment is lower than the type 90 cover. Comparing a type 90 cover to no cover sensor almost does not affect the standard deviation of the sensor. Type 90 cover cannot reduce the relative airflow to the sensor caused by moving vehicles. Even though using a cover to modify the airflow on the sensor, the increasing speed still affects the increase in the standard deviation of the measurement. The sensor standard deviation decreases the most when using the type 135 cover. The maximum measured value when the sensor uses type 135 is about 1.5 times greater than the average value at rest. The maximum concentration measured is almost 1.8 times greater than the average value at rest if the sensor cover is not used.

3.4.1 Speed effect on spatial data

The experiments on vehicle speed variation to determine its effect on $PM_{2.5}$ sensor location reading were carried out sequentially for each variation. In this experiment, it was assumed that during the experiment (~1 h), the $PM_{2.5}$ concentration did not change because there was only low traffic in the area. Visualization of $PM_{2.5}$ concentration measurement data (Fig. 5) with different speeds showed a difference in the number of points that represent measurement points. The spatial resolution is higher when using a lower speed because more data is sent along the route. High spatial resolution can also be achieved using a higher speed by taking several measurements over the same area. Another approach to maintaining high spatial resolution at high speed is adjusting the measurement interval of the device.

Nevertheless, the ability of smartphone GPS to get exact locations can be an additional problem. The measurement interval may be limited by how fast the GPS can get to the measurement location. Further development of this study can include location estimation of several $PM_{2.5}$ data measured between 2 GPS coordinates. The results are shown in Figs. 5(a–c) are measurement

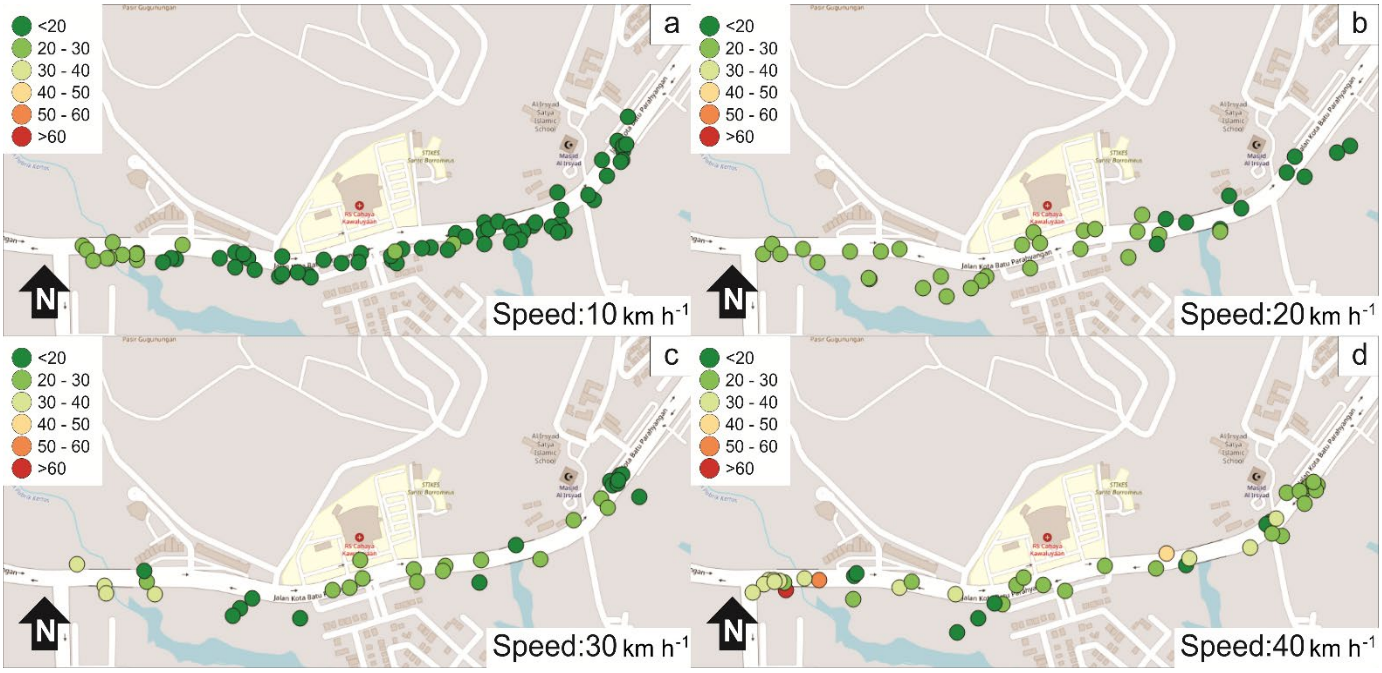

Fig. 5. Spatial resolution with vehicle speed variation: (a) 10 km h^{-1}, (b) 20 km h^{-1}, (c) 30 km h^{-1}, (d) 40 km h^{-1}.

data for 2 trips, while Fig. 5(d) is the result of 4 trips. Practically, measurements at medium speed (20–30 km h^{-1}) can produce a good resolution of spatial measurements in only 1 roundtrip.

The distance from each measurement point to the origin (–6.866415, 107.468764) can be calculated from the experiment. The origin point at the T-junction was in the lower-left area in Fig. 5. The distance of each point is measured by summing up the distance between the points to the origin of the measurement. The $PM_{2.5}$ concentration measurements were then plotted against the measurement distance from the T-junction (Fig. S4). The graph shows a similar pattern of the measured $PM_{2.5}$ concentration with different speeds. In this case, the $PM_{2.5}$ concentration tends to be higher at a distance closer to the T-junction, then decreases with increasing distance. At the T-junction, traffic lights may cause a buildup of vehicles around the area. The accumulation of these vehicles is one source of $PM_{2.5}$, which causes the concentration of $PM_{2.5}$ in the area to be higher than in areas further from that point.

Measurement data at higher speeds (40 km h^{-1}) are more irregular than those at lower speeds. This may be related to previous tests that showed an effect of speed on the $PM_{2.5}$ concentration readings. The standard deviation of the data tends to increase when the vehicle's speed increases. Nevertheless, the effect of vehicle speed on sensor reading and spatial data distribution was rather a qualitative approach. As the mobile monitoring device will be used mainly outdoors, the results could give a general description of how the vehicle speed could affect the sensor reading and data distribution. Detailed effect of vehicle speed on sensor reading could be done in a controlled laboratory-scale experiment.

3.5 Correlation with Meteorological Factors

The Spearman correlation (Table 2) between temperature and humidity meteorological factors was varied based on the time of collection (morning and evening) and area (Area 1 and on-road). The average temperature and humidity in the dataset are 31°C and 82%, respectively. With a standard deviation of 2°C and 12% for temperature and humidity, respectively, the coefficient calculation only includes data set with humidity values below the maximum limit value of the AM2301 sensor. The correlation between temperature and humidity is negative and relatively strong in all categories. The negative correlation coefficient shows that the humidity decreases when the temperature increases or vice versa. A weak to moderate correlation occurs between meteorological factors and $PM_{2.5}$ concentrations. The correlation of temperature with $PM_{2.5}$ concentration is weak and has a positive value, except in the afternoon. The *p*-values (Table S5)

Table 2. Spearman correlation between $PM_{2.5}$ concentration, relative humidity, and temperature.

Morning	Temperature	RH	$PM_{2.5}$
Temperature	1	–0.61	0.41
RH	–0.61	1	0.07
$PM_{2.5}$	0.41	0.07	1
Afternoon	Temperature	RH	$PM_{2.5}$
Temperature	1	–0.98	–0.34
RH	–0.98	1	0.39
$PM_{2.5}$	–0.34	0.39	1
Area 1	Temperature	RH	$PM_{2.5}$
Temperature	1	–0.36	0.33
RH	–0.36	1	0.46
$PM_{2.5}$	0.33	0.46	1
On road	Temperature	RH	$PM_{2.5}$
Temperature	1	–0.82	0.24
RH	–0.82	1	0.03
$PM_{2.5}$	0.24	0.03	1

of the $PM_{2.5}$ and temperature correlations show a significant correlation. On the other hand, the correlation between humidity and $PM_{2.5}$ concentration is only significant and is classified as weak or moderate in the afternoon and Area 1. The correlation, which is classified as weak or moderate, may be due to the variation of meteorological factors in the measurement time range not too large.

We found a relatively weak correlation between the $PM_{2.5}$ concentration and the meteorological factors in the measurement timeframe. This weak correlation was probably due to less variable meteorological conditions, which have a similar result to the $PM_{2.5}$ measurement on the vehicle in the winter season (Kolluru *et al.*, 2019). Kolluru *et al.* (2019) utilize EPAM-5000 to experiment longer, about 5–6 hours, and the route is 200 km. The EPAM-5000 was brought by car with open windows, closed windows, and buses, different from the one used in this work. Local or mobile sources that produce $PM_{2.5}$ are more common along major roads than roads in residential areas.

Several studies show that relative humidity affects $PM_{2.5}$ sensor performance. There are four mechanisms suggested (Budde *et al.*, 2013) that affect sensor performance: hygroscopic growth on the particulate matter (Crilley *et al.*, 2018); change in the refractive index of the particulate matter; moisture on the electrical components in the sensor, which can lead to reading failure (Wang *et al.*, 2015) and scattering LED light by moisture itself in extreme RH (Jayaratne *et al.*, 2018). HPMA has been investigated by Zou *et al.* (2021). interestingly, as a result, there is no significant correlation between temperature (15–40°C) and humidity (10–90%) to the sensor output. Nevertheless, RH still affects the relative $PM_{2.5}$ sensor response. In this study, the temperature probably affects the $PM_{2.5}$ concentration measurement since temperature affects the surrounding environment, not the particle itself, such as a dry environment that causes more particles in the air. Qiu *et al.* (2013) found that PM_{10} concentration in the cool and dry season in Hongkong is lower than in other seasons in their study. The hospital emergency admission for ischemic heart disease (IHD) also correlated with cool and dry seasons (Qiu *et al.*, 2013). Besides urban areas, the $PM_{2.5}$ and PM_{10} concentrations around the mining zone are higher in dry weather (Yadav and Jain, 2020). Yadav and Jain (2020) also discover that PM concentration is lower due to light precipitation during wet weather. Dry weather may cause reduced PM weight, staying longer in the air. The $PM_{2.5}$ concentration measured by mobile monitoring devices in this study has a weak correlation with meteorological factors such as temperature and RH. Thus, the variance of $PM_{2.5}$ concentration is mostly caused by the difference in microenvironment and pollution source.

3.6 Estimated $PM_{2.5}$ Inhaled Dose

$PM_{2.5}$ dose is the particulate matter that gets into the human body. The dose is calculated by

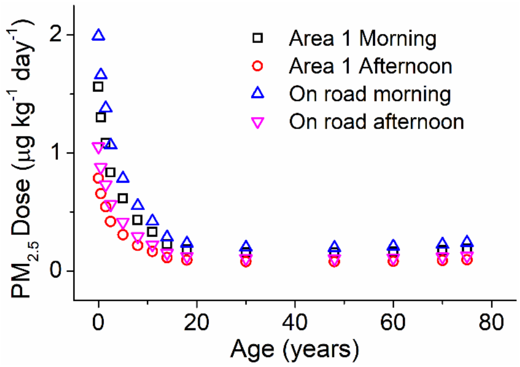

Fig. 6. $PM_{2.5}$ exposure per area and time group at 50th percentile.

Eq. (1) with several parameters such as $PM_{2.5}$ concentration, inhalation rate, body weight, and absorption and retention factors. The result of the simulation is depicted in Fig. 6. This simulation can give $PM_{2.5}$ dose exposure to the community while doing activities at different times and locations. At the 50th percentile for each age group, the children below five years old had an average dose of $PM_{2.5}$ that was approximately 3 to 6 times that of other age groups. Both morning groups in different microenvironments have higher estimated $PM_{2.5}$ doses than the afternoon groups. The average of the adolescents and young adult Indonesian $PM_{2.5}$ dose per group of Area 1 morning - afternoon and on-road morning-afternoon were 0.17, 0.089, 0.22, 0.12 µg kg^{-1} day^{-1}, respectively. The result from this study is higher than the daily commute in Makassar (0.11 µg kg^{-1} day^{-1}) (Patel *et al.*, 2016). The higher dose is most probably due to higher values of $PM_{2.5}$ concentration than in the previous study in Makassar, which can be caused by an increasing number of vehicles and differences in demographics between the cities.

From the average dose of adolescence and young adult for commuting time, the highest potential dose happens on-road in the morning. The mode of transport with vehicles that allows free air circulation within the environment, such as motorcycles, a car with open windows, public transportation, and bus (Goel *et al.*, 2015; Kolluru *et al.*, 2019; Patel *et al.*, 2016; Qiu *et al.*, 2017) gives higher exposure dose. The proper mask can be used (Patel *et al.*, 2016) to reduce the risk of $PM_{2.5}$ exposure. If the daily commute time is changed to the other activities such as exercising, the best time and area to exercise in this study is in Area 1 in the afternoon. Exercising in highly concentrated $PM_{2.5}$ areas, such as on the side of a major road, for a very long time can increase the potential risk of particulate matter exposure.

Furthermore, the exposure to $PM_{2.5}$ decreases as the age increases until around 30 years old. The older groups almost have the same dose value. This is because the average body weight value used for the age groups larger than 30 is almost identical. Despite a lower dose for the elderly, it is still recommended to minimize outdoor exposure to $PM_{2.5}$, especially for the elderly with cardiopulmonary problems (Xing *et al.*, 2016). The younger child gets a higher dose of particulate matter caused by the children's weight.

The data collected by the mobile monitoring devices can be seen directly from the website. These data can be used to make a smartphone application that shares the $PM_{2.5}$ data and the potential dose of the person when they are passing a certain area. Using this mobile application, the community can take precautionary measures when going by open windows vehicles, on a bicycle, or on foot to reduce the potential risk of $PM_{2.5}$ exposure.

4 CONCLUSIONS

This study conducted the design of mobile monitoring system to study the PM levels in an urban area. In addition, the inhaled dose was also estimated by a computer simulation. Several other aspects, such as vehicle speed effect on sensor reading and the PM relation with meteorological factors, are also studied. Results acquired that the coefficient of the HPMA sensor is 2% which is adequate for PM monitoring purposes. In general, the high PM level in this study occurs on the road (53.39 µg m^{-3}), mainly coming from vehicles. Other sources such as biomass burning and dust roads can contribute to the high PM levels. The measurement of mobile monitoring could be used to estimate inhaled doses. Mobile monitoring problems, such as instability of the PM sensor reading, were solved by adding a cover to the sensor inlet. A 135 degrees sensor cover could reduce the standard deviation in PM measurement while the vehicle is moving. Moreover, the Monte Carlo technique introduced the probability concept to the simulation in estimating the inhaled doses. The simulation shows that children get more inhaled doses of PM than other age groups. Further development is needed to optimize the system and make an integrated monitoring and informative system about the air pollution levels and their effect on health.

DISCLAIMER

The authors declare no competing interests.

ACKNOWLEDGMENTS

This work was financially supported by the Applied Research (*Penelitian Terapan*) Grant from the Ministry of Education, Culture, Research and Technology, the Republic of Indonesia, in the fiscal year 2020–2022.

SUPPLEMENTARY MATERIAL

Supplementary material for this article can be found in the online version at https://doi.org/10.4209/aaqr.220079

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