Assessing Particulate Matter Dose Through Mobility: An Agent-Based Model Approach in An Urban Context

Abstract. Exposure to particulate matter (PM) is a significant public health issue. Estimates of exposure show the amount of PM in the vicinity, but not how much enters the body through respiration. A calculated dose that considers inhalation rate as a variable can be estimated based on a person's heart rate, providing more context on the effects of activities, microlocations, and personal characteristics. This work presents an agent-based model (ABM) based on the design of the ICARUS project, measuring exposure to PM in an urban context using personal monitors. A simplified virtual (urban) environment was constructed to simulate the behavior of individuals and assess their PM dose. Interactions between agents were based on how they influenced each other on commuting options. Special agents, called "activists," had a higher influence on other agents to opt for walking/cycling. Agents were assigned personal environments (homes), workspaces, and leisure spaces, and had access to 10 different activities. PM concentration and intensity rate were assigned to each activity. PM concentrations were calculated for each activity, and the total dose was calculated for each individual. As outdoor PM concentrations increase, the influence of activists on mobility becomes more important, leading to an increased PM dose for non-activists. The model demonstrates the potential of ABMs in understanding how complex interactions between individuals impact their PM exposure and dose.

Keywords: Particulate matter, inhaled dose, exposure assessment, mobility influence, agent-based model

1 Introduction

A large majority of the urban population in the EU were exposed to levels of particulate matter (PM) above the latest World Health Organization guidelines [1]. Exposure to elevated concentrations of PM is associated with an increased risk of various illnesses and premature death. Exposure is defined as contact between an agent (PM) and a target (person), such as inhalable PM, which is inhaled through the nose and mouth [2]. The mass of PM that enters is the intake dose or simply the dose. Calculating the dose with inhalation rate as a variable can provide more information on the effect of activities, microlocations, indoor/outdoor exposure, and personal characteristics. Inhalation rate, expressed as minute ventilation (amount of air that enters the lungs per minute), can be estimated based on heart rate [3]–[5].

The use of personal monitors in exposure assessment has become more prevalent in recent years. The Horizon 2020 project ICARUS2020 [6] used low-cost personal monitors to measure exposure to PM in an urban context, including the city of Ljubljana, Slovenia [7]. In the scope of the sampling campaign in Ljubljana, 82 participants collected data in two seasons (heating/non-heating). They were equipped with multiple monitors, including a wrist-worn biometric sensor Garmin Vivosmart 3 Smart Activity Tracker, and a personal PM monitor (the PPM) designed for the project. Validation reports showed that these devices provide adequately accurate data [8]–[11].

Determining exposure to PM in urban environments is influenced by various factors, including the time spent outdoors and the type of activity being performed. Vigorous outdoor activities can increase an individual's PM exposure and dose [12], [13]. Walking or cycling in an urban environment is associated with an elevated dose of PM, due to high respiratory rates [14], and proximity to motorized traffic [15]. On average, health benefits of active commuting, due to increased physical activity, outweigh the increased exposure to air pollution and a higher dose of particulate matter [16]. Accurately assessing an individual's dose presents a complex challenge, requiring a multi parameter and multi domain approach. Virtual environments and agent-based models (ABMs) offer a novel approach and a variety of tools to aid in exposure studies.

Studies have demonstrated the use and applicability of ABMs in urban environments, for assessing exposure to particulate matter. Chapizanis et al. [17] developed an ABM, collecting data on the population, urban environment, movement and $PM_{2.5}$ concentrations, informed by personal movement, location and temperature sensors. Emergent behaviour in the ABM influenced PM exposure. A literature review on the same topic in Yang et al. [18] showed a shift towards using portable sensors. ABM research frequently simulates traffic interactions between different entities in urban environments and PM exposure studies [19], [20].

This work describes the construction and testing of an ABM based on the design of the ICARUS project. A simplified environment was constructed to simulate behavior in an urban environment and assess an individual's PM dose. The inputs were based on publicly available population data. Interactions between agents were based on how they influence each other on the commuting option they choose, e.g., opting for cycling or walking, instead of using a car or bus. Special agents, called "activists", had a higher influence on other agents to opt for walking/cycling, instead of using a car or bus.

2 Methodology

An analysis of how interactions between individuals influence commuting choices and impact an individuals' PM dose was conducted in a simulated society, i.e., an ABM. After reviewing tools for building the ABM, NetLogo 6.3 [21] was selected due to its ease of adoption by non-software specialists, interactivity facilitated by the graphical user interface (GUI), and its combination of model description and coding tab in a single interface. A virtual environment was constructed based on population data (and the design of the ICARUS campaign). Agents interacted to influence each other on which commuting option to select.

2.1 Environment

The environment consisted of a grid of personal (homes), work, and leisure spaces. Each individual was randomly assigned an empty home patch, surrounded with 8 patches representing different activities/rooms (excluding work and leisure). All households consisted of only one individual. There were the same number of home patches as agents, and 1/10 of this number of work and leisure patches. After being assigned a home patch, surrounded with activity patches, individuals randomly chose one work patch and one leisure patch. The latter changed at each step, simulating the individual choosing a different leisure activity/location each time. Their assigned work patch did not change in the same run. All the patches that the individual had access to represented 10 different activities, selected based on the data collected in the ICARUS project. These activities were: smoking, cooking, cleaning, playing, resting, car-bus (driving a car, riding a bus), working, sleeping, sports_out (sporting activities outdoors, leisure activity), and foot-bike (walking or cycling). The number of individuals in the simulation, share of each gender, the average age of the population, and the share of smokers was set in the Graphic User Interface (GUI). Individuals were probabilistically assigned a body weight and a baseline inhalation rate, based on information obtained from the EPA Exposure Handbook [22].

Each room/activity was probabilistically assigned a $PM_{2.5}$ (in this work labelled as PM) concentration every time that the individual performed that activity. All mean PM values and standard deviations could be set in the GUI. For the purpose of this experiment the mean PM concentrations for each room/activity were collected from published research, with an associated standard deviation. Each individual was probabilistically assigned a baseline minute ventilation (inhaled air per minute), based on their gender and age [22]. This value (in m^3/min) corresponded with a Metabolic Equivalent of Task (M.E.T.) of 1, which is the M.E.T. during sleeping or resting. Minute ventilation linearly increases with an increasing M.E.T. value, when activities become more strenuous. Each activity has a range of M.E.T., depending on the vigor involved [23]. Accordingly, based on the activity/room, an intensity rate was assigned, corresponding with the M.E.T. or how physically intensive the activity is [22]. Minute ventilation during a specific activity is calculated by multiplying the baseline minute ventilation with the intensity rate.

Outdoor PM concentrations, which set the PM exposure level for leisure and walking/cycling, were set in the GUI. For this experiment the $PM_{2.5}$ data was collected from the Bežigrad governmental air quality monitoring station in Ljubljana, Slovenia, operated by the Slovenian Environmental Agency. Infiltration factors of outdoor air were not included in the ABM.

The PM dose was calculated using i) the minute ventilation ($\dot{V}_E$), ii) the intensity of the current activity (int_{act}), and iii) the PM pollution level at that activity ($c_{PM_{2.5}}$), shown in Equation (1):

$$intake\ dose\ per\ kg\ of\ body\ weight = \frac{\dot{V}_E * int_{act} * c_{PM_{2.5}}}{body - weight} \qquad (1)$$

Share of smokers, average age, and share of each gender in the simulated population, in this specific scenario, based on the ICARUS campaign, were determined using population data for Slovenia. In the ICARUS campaign individuals collected data for up to 7 days per season. The same limit was applied in the ABM. As the decisions in this model were based on a predetermined set of probabilities for activities, each tick/step was considered as an iteration. The model ran for 368 hours with 168 hours used as the simulation result. The first 200 hours were discarded to eliminate the initial transient period or "burn-in" phase, where the system is still stabilizing and reaching equilibrium. High fluctuations of the inhaled dose were observed in the first 200 hours, most probably attributed to the burn-in phase.

Fig. 1 shows a virtual spatial representation of the ABM. Sliders for different settings are placed on the left side of the interface. Buttons (placed below the sliders) setup the model, e.g., create the patches, agents and their properties, and start the simulation.

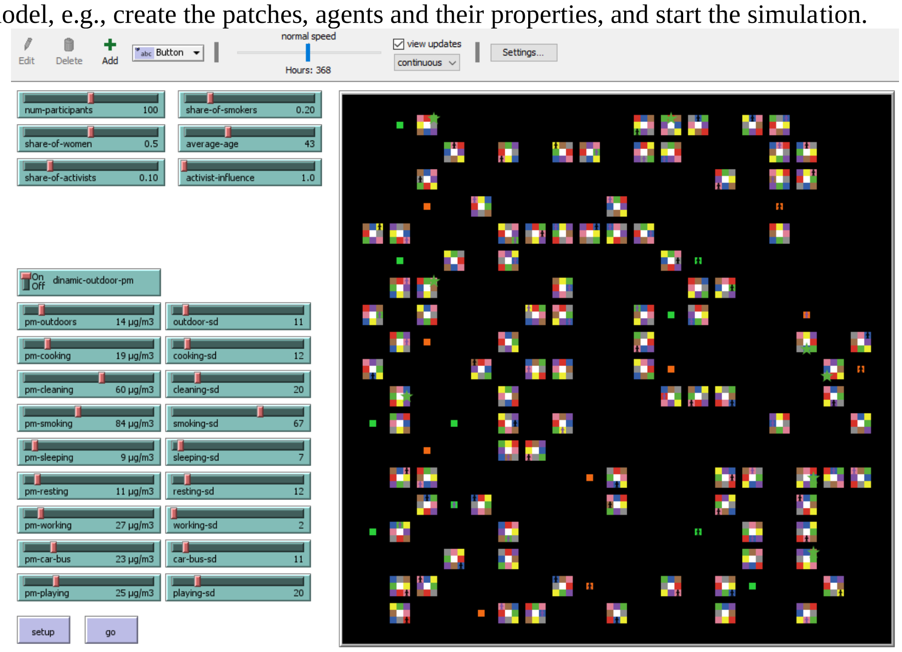

Fig. 1. Virtual spatial representation of the PM exposure and dose ABM with the initial setting, at 368 hours in the NetLogo GUI.

2.2 Interactions

This simulated environment includes single person households, with agents coming in contact with other agents only on leisure and work patches. Walking and cycling play an important role in this assessment due to the associated elevated minute ventilation, influencing the dose. Therefore, the agents in this model influence decisions of other agents related to walking/cycling. Human behavior and opinions are, among others, driven by interactions with other individuals, in particular by two major attractors: (1) the expert effect, with highly confident individuals, and (2) the majority effect, a critical mass of people sharing similar opinions [24]. Studying these interactions could provide valuable insights into how the dynamics of mutual influence, the significance of interaction points, and the emergence of collective behavior influences PM exposure and dose.

Special agents, called “activists”, prompt other agents to reduce their probability of choosing a car/bus to commute, opting for walking/cycling. Two settings in the model GUI determine the initial influence of activists: (1) share-of-activists, determines the number of agents labeled as activists, and (2) activist-influence, determining how persuasive the activists are. Share of activists can range from 0 to 50 % of the population, and their influence from 1.0 to 2.0. All agents that are labeled as activists receive a random value of influence between 1 and 10, all non-activist agents begin their life with an influence level of 0.1. Whenever an agent is in a same place with another agent (on leisure/sports and work/office patches) they "are influenced", and the influence variable value increases. If the second agent is an activist, the first agent receives their full influence value (mb_{inf}^{act}), multiplied by activist-influence (act_{inf}), which is added to their prior mobility influence (mb_{inf}), as shown in Equation (2)

$$mb_{\mathrm{inf}}(new) = mb_{inf}(existing) + \left(mb_{inf}^{act} * act_{inf}\right) \tag{2}$$

When the other agent is a non-activist, they receive only 1/3 of the influence ($mb_{inf}^{non-act}$), added to their existing mobility influence (mb_{inf}) (Equation (3)):

$$mb_{\mathrm{inf}}(new) = mb_{inf}(existing) + \left(\frac{mb_{inf}^{non-act}}{3}\right) \tag{3}$$

Each hour all non-activists that have >1.1 influence lose 1 influence, as their interest falls. If they have influence between 0.1 and 1.1, they lose the appropriate amount to get back to 0.1. In this way the model attempts to reflect how individuals can lose interest with time, due to memory decay, changing circumstances, new experiences replacing prior ones, or reaching an influence saturation point. If the agents would not lose influence, the model would not function well, as the influence would keep increasing exponentially or quickly reach a set upper limit. An exception is after they randomly meet an activist at a leisure or work space. In this case, the activist influences their behavior, and they lose their influence more slowly. This corresponds with activists being more persuasive, having better arguments, and being generally verse in the methods to influence others. The rate is determined (Equation (4)) by the number of hours that have passed (h) since the last meeting, multiplied by activist-influence (act_{inf}). A baseline value of 6 hours is set, which can increase to 12 hours when the activist-influence (which can be set in the GUI between 1.0 and 2.0) is set to 2.0. If an agent comes in contact with an activist, their mobility influence will decrease by 1/6 in the first hour, 1/5 the second, 1/4 the third, and so on, until the (h) drops to 1. This diminishing influence reduction follows the notion that activists have a higher power of persuasion, thus having a longer influence on individuals. For the model to work, the agents have to keep losing the influence, and 1/n value has been determined as a "good compromise". The agent will resume losing their mobility influence at the rate of 1 per hour after the next encounter with a non-activist agent.

$$mb_{\mathrm{inf}}(new) = mb_{inf}(existing) - \left(\frac{1}{h * act_{inf}}\right) \tag{4}$$

Activists cannot gain or lose influence, and the minimum and maximum values of influence for any non-activist agent are 0.1 and 10, respectively.

The mobility influence value affects the probability of the agent choosing a means of transport. A higher value increases the probability of selecting cycling/walking versus using a car/bus. Each agent is assigned a probability for both activities based on population data and their age and gender. Their baseline probability for choosing the foot/bike (p_{fb}) or car/bus (p_{cb}) activities is modified ($p_{fb(m)}$, $p_{cb(m)}$) based on the agent's mobility influence (mb_{inf}) at time of choosing as evident in Equation (5) and Equation (6).

$$p_{fb(m)} = (p_{fb} + p_{cb}) * \left(\left(\frac{p_{fb}}{p_{fb} + p_{cb}}\right) + \left(1 - \left(\frac{p_{fb}}{p_{fb} + p_{cb}}\right)\right) * \left(\frac{mb_{\text{inf}}}{10}\right)\right) \tag{5}$$

$$p_{cb(m)} = (p_{fb} + p_{cb}) - p_{fb(m)} \tag{6}$$

Agents select an activity based on the modified probabilities and end their turn for that hour. The Behavior Space tool is used to iterate the model multiple times by simultaneously varying the share-of-activists, activist-influence and pm-outdoors variables. To observe the behavior of the modified ABM, the share-of-activists was varied from 0 to 0.5 by increments of 0.1, activist-influence was varied from 1.0 to 2.0 by increments of 0.1, and pm-outdoors was varied from 5 $\mu g/m^3$ to 105 $\mu g/m^3$ (maximum hourly value of $PM_{2.5}$ recorded in Ljubljana in 2022), by increments of 10 $\mu g/m^3$. Each combination of the aforementioned variables was repeated 10 times with a time limit of 168 hours. Runs were measured with several reporters, providing results of the cumulative dose of all agents, of agents by gender and age, respectively, and if the agent was an activist or not. The results were exported to a csv file and analyzed in R [25], and plots were constructed using the ggplot package [26].

3 Results and discussion

Results were aggregated for different populations based on the share of activists, shown in **Fig. 2**. Expectedly, the mean cumulative dose of all non-activist agents increased linearly with an increased outdoor PM. While concentrations remained low (< 15 µg/m3), all populations experienced a similar mean dose. However, the lines in **Fig. *2*** begin to diverge as PM concentrations increase. Activists influence agents to reduce their time in the car/bus and opt for cycling or walking, which increases their time outdoors, increasing their exposure. Cycling and walking are more vigorous activities with an increased minute ventilation and PM dose. As the outdoor pollution increases, the mobility influence becomes a more important factor. Moreover, as the share of activists increases, the higher the mean mobility influence in the non-activist population.

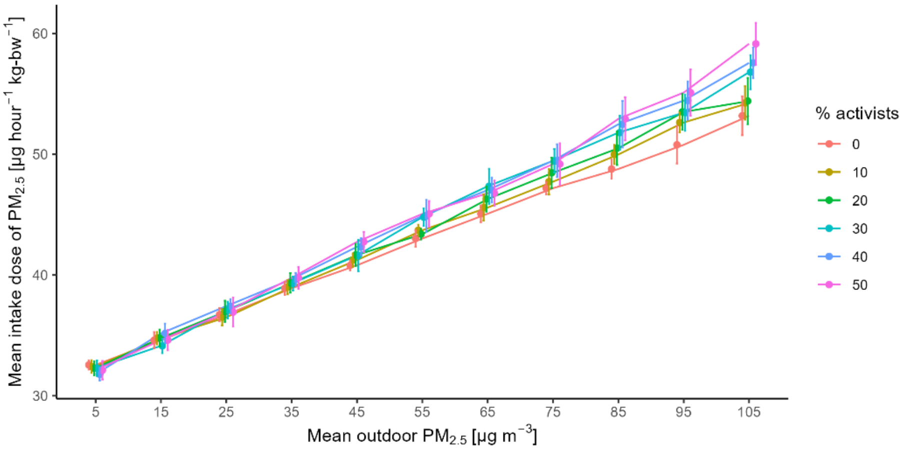

Fig. 2. Mean PM dose of all agents at increasing levels of outdoor PM, grouped by the percentage of population that are activists. Each point is showing a calculated standard deviation.

Fig. *3* shows an increased activist influence impacting non-activist agents in the modified ABM. In this figure, share of activists is set at 10%. As evident in **Fig. *3***, the mean dose is similar between the populations and begins to slowly diverge as concentrations of PM increase. Populations with more influential activists increase their mean dose faster than populations with less influential activists. The greatest contrast can be observed when PM levels exceed 95 μg/m^3, though the difference is small with high overlap when standard deviations and considered. However, at the highest outdoor value, the group with 2.0 activist influence doesn't show the highest mean exposure, which may be attributed to the stochastic nature of the ABM. Although 10 iterations/runs produce more reliable outcomes, they can still produce extreme values that influence the final result.

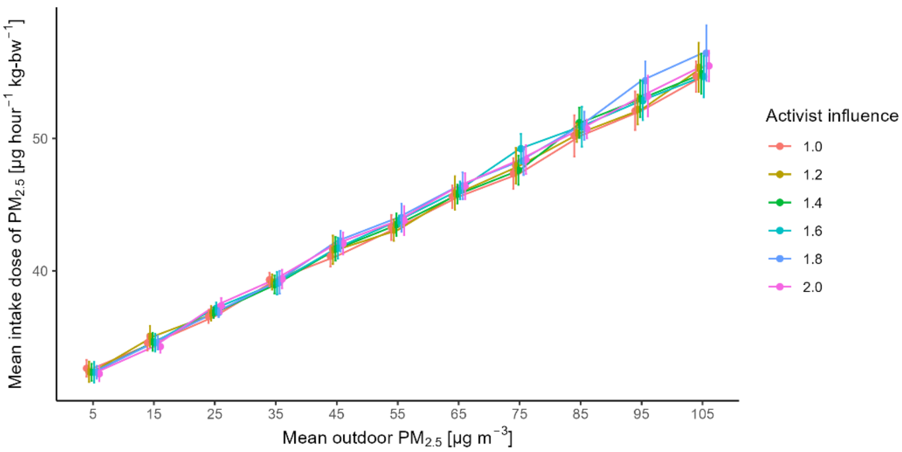

Fig. 3. Mean PM dose of all agents at increasing levels of outdoor PM concentrations, grouped by activist influence. Each point is showing a calculated standard deviation.

This model shows how interactions between individuals can influence an individual's dose of PM. While it represents only one simplified interaction, influencing one specific activity, it does show the power of agent-based models and their ability to gain insight into otherwise difficult to assess phenomena.

4 Conclusions and future work

Given the inherent challenges in determining accurate PM exposure or inhaled dose estimates using traditional approaches or measurements, which are hindered by the dynamic nature of human movement and activities, our research took an alternative path. Recognizing the potential of agent-based modeling (ABM) to address these limitations, we adopted this approach to examine the impact of individual interactions on commuting choices and subsequent PM dose. By constructing a virtual indoor and outdoor urban environment and simulating interactions among 100 agents, we obtained valuable insights. While ABM showcased promising advantages, it is important to acknowledge its limitations as well. With this in mind, our findings demonstrated that activists played a less significant role in lower PM levels, as all populations reported similar mean doses. However, as outdoor PM concentrations increased, a higher proportion of activists resulted in elevated doses. Additionally, we observed a similar, albeit less pronounced, trend with increased influence of activists on non-activist agents.

Currently, the agents in the model do not have a "memory" and select the next activity based on predetermined probabilities for daily activities. A further development of this model would allow agents to adapt and learn based on their prior results with a "memory length" variable. Such a feature would allow the user to control how many prior activities influence the agent's probabilities for their next action. Individual's generally do not have real-time data about their personal exposure to PM. An updated model would implement an option to have a share of agents that are willing to change their behavior if they see that another strategy would reduce their dose. Gaining, losing, and transferring influence in the model are rough estimates that are designed in a way to make the model function properly. Future work should tune these variables based on real-world data. Furthermore, the outcomes of the model can be validated using the ICARUS data, to a degree. In the scope of an ongoing Horizon 2020 project, URBANOME [27], an urban living lab (ULL) will be set up in Ljubljana. This ULL will set up and assess how cyclists perceive the urban environment, and how their commute impacts their exposure and wellbeing. Further development of the ABM and validation of the current model is possible through an analysis of the cyclists' decision-making, and the paths they choose.

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