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Simulating the Evacuation of a Subway Station after a Sarin Release

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ABSTRACT

Chemical terrorist attacks in closed areas are a serious threat to national security. In order to deduct the best reponse with regard to treatment and protective measures, simulation is the best tool, either in-silico or as a real-life exercise. The difficulty of the latter is the great number of resources necessary to set up a large-scale realistic exercise while the limitation of the former is that the model needs to be as realistic as possible to draw relevant conclusions. The complexity in designing and running a realistic and large-scale computer simulation model with pedestrian movement and air/gas flows renders studies near-impossible with current computers. To address the complexity issue, agent-based simulation is usually preferred over a Computational Fluid Dynamics (CFD) approach. The aim of this contribution is to present a method to generate a list of victims with both inhaled doses of the chemical warfare agent sarin (NATO designation GB) and traumatic injuries in an emergency subway evacuation scenario. The method couples a simple gas diffusion model with a crowd dynamics model. The interaction of the crowd follows a social force model (SFM) where the overlaps are used to determine a physical injury distribution.

INTRODUCTION

Terrorist attacks on major European cities have been occurring at an alarming rate since the years 2000 (Europol 2021). During these attacks, public transport has been targeted several times. For example, in 2016 the Maelbeek subway station was hit by a suicide bomber as part of a coordinated multi-site terrorist attack which in total lead to 340 injured and 32 dead victims (Lasoen 2017). Another example of a public transport terrorist attack is the 1995 sarin attack in the subway of Tokyo, which led to over 1000 intoxicated victims of which 14 died. The 1995 Tokyo incident is the second recorded incident where the organophosphate compound was used on the general population, following a smaller-scale attack in Matsumoto a year earlier which injured over 500 victims and killed 8 (Olson 1999, Okumura et al 1996). To the best of our knowledge, no other use of sarin in public enclosed areas was recorded in world history.Therefore, it remains of paramount importance for the authorities to be well-coordinated and prepared in the case of chemical disasters. It is difficult and unethical to run experiments in a disaster setting in the real world for obvious reasons. In-silico, there have been a fair amount of studies of chemical agent dispersion in public transport. Smith (Smith et al. 2009) simulated an attack on a bus station and discussed the casualties and procedures. Some studies discuss a chemical attack in a subway evacuation scenario with agent-based modeling (Wan et al. 2014, Zou et al. 2020, Zhang et al. 2020) while others focus on the evacuation (Xu and Chen 2015). Wan includes information knowledge of the presence of the gas to some pedestrians and wind field interaction with the gas source. Their results suggest that the least amount of dead casualties is reached when authorities are aware of the presence of the gas and inform passengers about it. The second factor is given to be a high airflow in the station which helps in mitigating the gas concentration. Zou considers emotion contagion and information spread.The speed of the pedestrian is affected by the gas source. Overall, Zou's model presents more realism than earlier studies and provides modeling-based advise for authorities. Some studies focus solely on the chemical agent diffusion in closed spaces and in particular subway stations with great details using CFD without insisting on the medical aspects of mass casualty incidents and pedestrian dynamics. Endregard (Endregard et al. 2010) and Aalbergsjø (Aalbergsjø and Vik 2016) presented a CFD model in a building, while Camelli (Camelli et al. 2014) and Radusweski (Radusweski and Vianna 2013) consider a subway station. The objective of the literature research was to determine the different techniques used to calculate, on a pedestrian level, the total inhaled dose in the case of an emergency evacuation of a subway station and to use the pedestrian trajectories to establish injury distributions in a logical way. The trajectories are determined via a social force model and the inhaled doses are set via a gaussian puff model. The results will be incorporated in a continuous health state model approach (Benhassine et al. 2022) and used as a method to generate the victims list in our medical disaster simulator, named SIMEDIS (De Rouck et al. 2018, Debacker et al. 2016). Within the simulator, changes in the disaster medical response will be tested to change the outcomes of the generated casualties. For instance, the time at which antidotes can be administered, the decontamination procedures and the evacuation policies from the station to the care facilities.

Social Force Model

Pedestrian dynamics models include the Optimal Steps Model, Gradient Navigation, Cellular Automata (Dietrich et al. 2014) and Social Force Modeling (Helbing and Molnár 1995), see Vermuyten or Zheng for a review (Vermuyten et al. 2016, Zheng et al. 2009). Out of these similar approaches, Wan, Zou and Zhang (Wan et al. 2014, Zou et al. 2020, Zhang et al. 2020) all implement the SFM. This model considers that each pedestrian is attracted to its environment (walls, peers, obstacles) via physical attractive-and-repulsive forces. In addition, each pedestrian has a certain target to reach (a particular exit). The pedestrian can also stay where he is initially. Just like in real-life, pedestrians stay at a certain distance from others and obstacles/walls, and can be attracted by some persons (i.e. family or group members). Each pedestrian is, in essence, a particle obeying Newton laws adapted for human behavior. Several studies have modified the original definition allowing, for instance, for pedestrians to be "stepped" on by other people (Kretz et al 2011). The formulation of the SFM used in this study is from Kleinmeier (Kleinmeier et al. 2019). The primary force driving a pedestrian p towards its destination is

$$\vec{F}_p(t) = \frac{1}{\tau_p}\left(v_p^0 \vec{e}_p - \dot{\vec{x}}_p\right) \qquad (1)$$

$\tau_p$is the pedestrian reaction time, $\vec{e}_p$ is its direction vector. $\vec{v}_p^0$ is the free flow velocity, i.e. the velocity of the pedestrian if there are no obstacles or other agents. $\vec{x}_p$is the pedestrian position at time t.

In addition, obstacles will create a repulsive force as well as other pedestrians (if we neglect attractive groups), thus the force described in equation 1 is the only force acting on the pedestrian only if it can move unhindered. Otherwise, additional forces are added to each pedestrian. The acceleration of the pedestrian follows the following evolution equation:

$$\frac{d\vec{w}_p(t)}{dt} = \vec{F}_p(t) + fluctuation \qquad (2)$$

Where $\vec{w}_p(t)$ is the unrestricted velocity due to the sum of all forces $\vec{F}_p(t)$ acting on pedestrian p. Thus, for each force, attractive or repulsive, equation 2 is solved (more details of the model are given in Helbing and Molnár 1995).This speed can be restricted to a maximum speed from a distribution which is set at the start of the simulation depending on a panic level. The fluctuation term allows for stochastic effects on trajectories to occur and provides more realism. For the implementation of the SFM, we use the open-source Vadere package to implement and calculate these forces and run the evacuation part of the model (Kleinmeier et al. 2019). We use the SFM as it has been reported that it captures effects such as lane formation, bottlenecks, clogging at exits and "faster-is-slower" effects. We also chose this model because of its popularity and its use in similar studies in the literature (Wan et al 2014, Zou et al 2020, Zou et al 2019). As pointed out by Wan, the SFM is usually used for pedestrians in ordinary life. Therefore, other considerations such as stampeding and trampling are not included in the model which are relevant in the case of an emergency evacuation. To still be able to consider these phenomena,we use the interpretation of Sticco (Sticco et al. 2020) that one can define a "compressibility" that each pedestrian can experience when he/she comes in contact with others. This compression is referred to as "overlap" and has relevance when the local density is very high (close to 5 pedestrian/m²). Overlap is expressed in meters and is directly linked to the relative distance between pedestrians. One can use the value of sustained overlap (i.e. successive frames with a high overlap amount) to describe the amount of accumulated constriction that a pedestrian has experienced during the evacuation. Vadere directly calculates the overlaps in the simulation.

Gaussian Puff Model (GPM) for GB

To model chemical agents dispersion, several models are available in the literature depending on the level of realism (See Pirhalla 2020 for a review). Each model has advantages and disadvantages. Microscopic models are defined at the human scale, while macroscopic level models are at the scale of cities. CFD models are considered as the most accurate but are computer-intensive whereas Gaussian Puff (and Plume) models (GPM) provide fast results and are more coarse. Puff models account for a source that diffuses clouds of gas dynamically while the plume model has a constant diffusion rate and does not interact with the air thus we refer to Gaussian Puff Model throughout as GPM. If accurately parameterized and for specific applications, the GPM analytical equations can provide a simple way of linking pedestrian trajectories to inhaled doses. We suppose that GB acts as a source and diffuses in the subway station from its point of origin over time in a continuous manner. We are interested in a 2D formulation since the Vadere evacuation model is two-dimensional. We suppose that everything occurs in a slab of air at head level for all pedestrians. Holzbecher (Holzbecher 2012) provides a 2D solution of the transient transport equation with constant advection in the x direction (we consider that the advection is the wind speed inside the station and that it spreads radially) with diffusion/dispersion of GB. Following these assumptions, at any given time t, the GB content is locally equal to

$$c(x,y,t) = \frac{M}{4\pi t\sqrt{D_x D_y}} exp\left(\frac{-1}{4t}\left(\frac{(x-vt)^2}{D_x} + \frac{y^2}{D_y}\right)\right) \qquad (3)$$

Where *M* is the total mass of GB in Kg.m^{-1}. D_x and D_y are diffusivities in the x and y directions respectively in m².s^{-1}. If the wind speed flows in both directions (within a slab), we would expect that Equation 3 would need to be modified. Based on preliminary CFD and experiments performed on site, we consider that the wind field inside the station is negligible and uniform (v = 0) and therefore neglect advection and only consider diffusion.

RESULTS AND DISCUSSION

CAD Model of the Subway Station

Based on photographs of a subway station in Brussels, a CAD model has been drawn in Vadere and used as a model for the evacuation simulations. The CAD model is 100 m x 30 m in size which corresponds to only one platform (refer to Fig. 1 for notations). Stairs are modeled as well as access gates. The total number of pedestrians arriving in the metro carriage and inside the station is 986 (The train itself is full and contains 820 passengers). Two simulations are performed, the first one includes 386 pedestrians (320 people stepping out the train and 66 people wanting to step in or who are waiting in the station). The second simulation includes 600 pedestrians exiting the train with the following exit strategy: 33.3% of pedestrians (200 people) spawned in the subway carriage are instructed to exit through A while transiting by B. 33.3% of pedestrians (200 people) are instructed to exit through C while transiting via D. The last 33.3% (200 people) originating from the subway carriage exit through E while transiting via F. Finally, multiple sets (3 or 4 per door) of pedestrians entering the subway carriage start their trajectory from G and end up in H (totaling 66 pedestrians). The bottom left corner of the sketch corresponds to the (0,0) coordinate with x increasing from left to right, and y increasing from the bottom upwards.

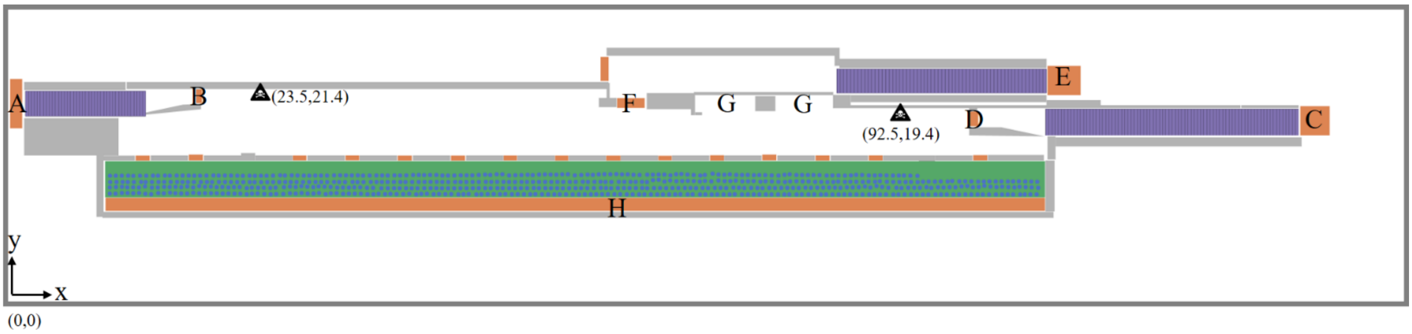

Figure 1 CAD 2D sketch of the subway station within Vadere along with annotations described in the text. The two GB sources used in this model are noted as triangles with their respective coordinates (see table 1)

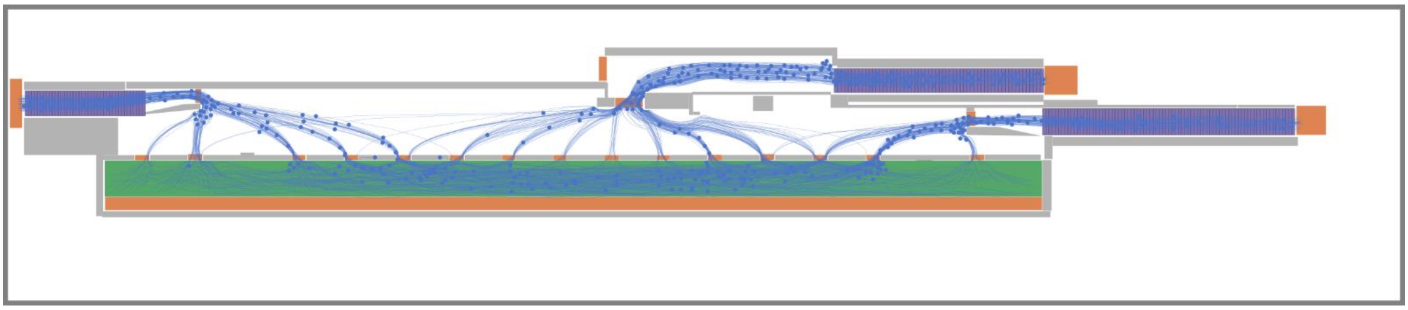

Figure 2 Evacuation trajectories during the second wave evacuation. Each point correspond to a pedestrian.

Evacuation of the Station and Scenario

Two GB diffusing sources are placed close to the exits: one in the left bin and the other in the right bin. The diffusion starts when the train arrives in the station and continues until the end of the simulation. The evacuation occurs in two waves, and two separate simulation runs. The first wave (first run) is when the GB is in place and diffuses but the pedestrians are unaware of the threat. The train arrives in the station and the doors open. A few pedestrians step into the carriage while others are leaving the station, unaware of the presence of GB. By the end of this first simulation, people become aware that an attack is occurring and start panicking, alarms are rung and remaining pedestrians in the subway carriage are fleeing from the station. This is referred to as wave 2. We suppose that, at the start of the second simulation, there are only people in the carriage and the rest of the station is empty. The evacuation trajectories are used to calculate a total exposure for each pedestrian, but the symptoms are only accounted for when they exit the station. Following Curling's symptoms progressions (Curling et al. 2010), we suppose that there is a delay of 5 minutes justifying the omission of slowing down the pedestrians because of GB effects. This also means that we neglect dynamic progression of symptoms/physiological effects while pedestrians are evacuating the station and that only the total sum of inhaled dose is calculated. The 5 minute window screens such effects but in reality, victims will have accumulated a dose over time. In the second wave, every pedestrian present in the carriage is programmed to flee in the simulator, thus there are no pedestrians coming from G to H for this simulation. The evacuation simulations are set to last 3 minutes (180s) for both waves, which considering the number of pedestrians and the scale of the model (neglecting falling and stampeding) is consistent with timing estimations by subject matter experts. The timestep is set to 0.4s (default value in Vadere's SFM). The trajectories are displayed in Figure 2 for the second wave while Figure 3 shows the number of pedestrians in the station versus time for both waves (the second wave starts after 180s but data are put as a comparison starting both at 0s). The model parameters are detailed in the next section.

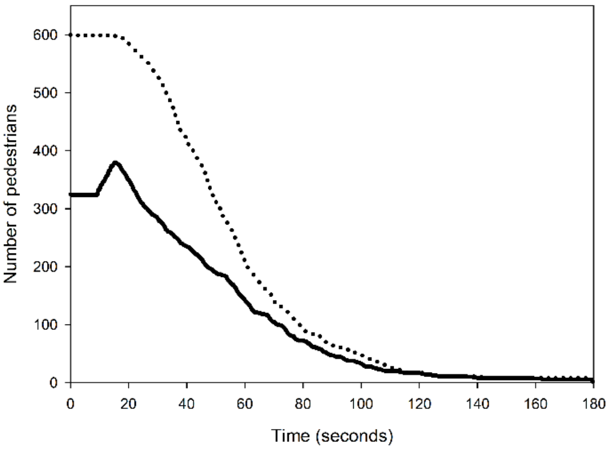

Figure 3 Number of pedestrians for both waves versus time (seconds), each time a pedestrian reaches an exit, it is removed from the simulation. Wave 1, solid line, has a small hump caused by incoming pedestrians that are entering the station. The dashed line represents the number of pedestrians from the second wave.

Model Parameters

GPM parameters were not found for GB in the literature. Both Wan and Zou consider chlorine as an agent with a GPM (Wan et al. 2014, Zou et al. 2020). We cannot justify using the same GPM parameters used for chlorine which is a different chemical species. Instead we propose to adapt the parameters in such a way that the resulting dose distribution is relevant to a mass casualty incident. Concerning SFM parameters, the default values in Vadere were used as no justification for an adaptation was necessary. The parameters of table 1 were used in this study.

Table 1 Model Parameters for the Social Force Model (SFM) and Gaussian Puff Model (GPM).

SFM		**GPM**	
Pedestrian body potential	2.1 N	$\frac{M}{4\pi\sqrt{D_x D_y}}$	2.5
Pedestrian recognition distance	0.4 m	D_x	2.0833
Obstacle body potential	2.1 N	D_y	2.0833
Obstacle repulsion strength	1.0 N	First GB source (x,y) in meters	(23.5,21.4)
Pedestrian radius	0.3 m	Second GB source (x,y) in meters	(92.5, 19.4)
Mean pedestrian speed (first wave/second wave)	1.34/ 1.5 m/s	Wave 1 number of pedestrians	386
Maximum pedestrian speed (first wave/second wave)	2.2/ 3.0 m/s	Wave 2 number of pedestrians	600

We varied the plume parameters in order to obtain a distribution of inhaled doses which are classified in specific ranges. These dose ranges are set in such a way that there is a maximum dose of 30 mg.min/m³ which is deadly (Curling et al. 2010). Depending on dose thresholds, 6 different injury profiles (IP) are categorized in the NATO AMedP-8(C) publication (see table 2 for ranges).

Table 2 GB dose ranges adapted from Curling et al 2010.

mg-min/m³	IP1	IP2	IP3	IP4	IP5	IP6
Dosage lower bound	0.2	1	6.5	12	25	30
Dosage upper bound	1	6.5	12	25	30	>30

Each profile includes symptom progressions. While we assume for this model that there is no interaction between evacuation speed and symptoms due to the delayed onset and low concentrations, it remains a theoretical possibility. However, these considerations were deemed beyond the scope of this study which aims at providing a list of victims with an injury distribution.

Inhaled Doses Distribution

To calculate the total inhaled dose (or toxic load), the position and distance from each GB source are computed for each pedestrian versus time with equation 3 where x and y are replaced with the position of the pedestrian. Since each trajectory point is spaced by 0.4 s, we obtain the total dose by a sum (or discrete integral) of the accumulated doses. An adaptation to the dose ranges was applied for the civilian population in the subway station because the ranges were originally calibrated for soldiers. For the first wave, the plume parameters are chosen to result in a repartition of profiles (for 386 victims) characteristic of similar mass casualty incidents. This entails having some critically intoxicated victims but not too many as it would result in a very high number of dead casualties. On the other side of the spectrum having only mildly injured victims would result in 0 casualties. We varied following parameters to determine the injury profile repartitions:

$$\begin{cases} a = \dfrac{M}{4\pi\sqrt{D_x D_y}} \\ b = \dfrac{1}{4D_x} \end{cases}$$

The a parameter can be physically interpreted as a coupling between the total quantity of GB and the speed at which the GB will evaporate into the air.The b parameter is related to the vector form of release both of which can be supposed to be tailored to accomplish the resulting injury profile repartitions.We suppose that the diffusion is homogeneous in the x and y directions ($D_x = D_y$), allowing Eq. 3 to be rewritten as

$$c(x,y,t) = \frac{a}{t} exp\left(\frac{-b}{t}(x^2 + y^2)\right) \qquad (4)$$

It is not our intent to find accurate experimental values for GB diffusion in the subway station but rather to model the resulting distribution of doses and couple these with the trajectories computed by Vadere. Table 3 and table 4 contain the resulting injury profile distributions depending on multiple *a* and *b* combinations (IP0 in the tables corresponds to asymptomatic exposure).

Table 3 Wave 1 Plume Parameters and consequence on injury profile numbers.

(a;b)	IP0	IP1	IP2	IP3	IP4	IP5	IP6
(2.2;0.1)	67	2	48	30	143	54	42
(2.2;0.12)	66	16	60	56	173	8	7
(2;0.12)	66	17	12	67	160	7	3
(2;0.05)	61	2	1	13	30	8	271
(2:0.1)	65	2	55	33	169	37	25
(2;0.2)	118	45	154	64	5	0	0
(2.5;0.12)	66	13	59	39	170	26	13

In terms of the aforementioned considerations, the retained values for the first wave are *a* =2.5 and *b*=0.12. For the second wave, we can expect that the GB reservoir will have been partially depleted while keeping the same diffusion rate. We assumed *a*=1.2 and *b*=0.12 in equation 4.

Table 4 Wave 2 Plume Parameters and consequence on injury profile numbers.

(a;b)	IP0	IP1	IP2	IP3	IP4	IP5	IP6
(1.4;0.12)	106	65	145	139	141	3	1
(1.6;0.12)	102	58	142	110	176	8	4
(1.2;0.12)	111	67	155	179	87	0	1

For the second wave of pedestrians, speed values are adapted to reflect this behavior. The GPM allows determining the total inhaled dose received by the victims but there is an additional step taken to include traumatic injuries, since we expect that the surge of panic will increase the chance for some victims to fall and suffocate increasing their odds of having additional injuries. This is described in the next section.

Setting of Traumatic Injuries based on Overlaps

The implemented SFM outputs overlaps (in meters) or oversteps between pedestrians at each frame for each person who was constricted by peers. The values represent the amount of frames for which pedestrians were overlapping one another and are expected to increase the odds that the victim will sustain traumatic injuries. Victims were sorted both by total inhaled dose and total amount of cumulative overlap during the evacuation. Then, the victims with total overlap above a certain threshold were given up to 3 traumatic injuries ranked by order of severity. Then, based on the number of injuries, a sub-percentage of victims were assigned lethal injuries, reflecting the small chance that the traumatic injuries may be severe enough to be life-threatening. This method allows obtaining a victim list of the event based on a physical trajectory rather than assigned at random. Each time pedestrians come close to each other (essentially at bottlenecks which are access gates and the base of the stairs) there is an increase in overlap. After the end of the evacuation, the total number of overlaps per pedestrian is calculated and used to set an "overlap score" which we correlate with the number of injuries that a victim has (Figure 4). Only the second wave overlaps were used to set traumatic injuries because we supposed that in the first wave only chemical injuries were possible.

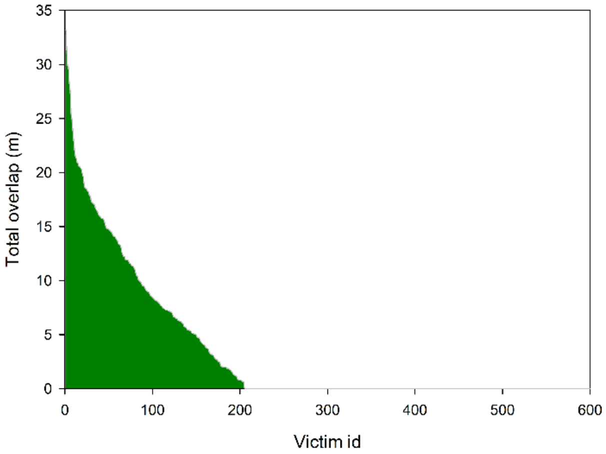

Figure 4 cumulative value of overlaps from the second wave of the evacuation for each victim (the x axis is a victim id, unique for each pedestrian).

The setting of the traumatic injuries is done with the model of Benhassine et al (Benhassine et al 2022). Victims with an overlap score higher than 25 m are given 3 traumatic injuries. If the overlap score is between 10 and 25, 2 physical injuries are given. If the overlap score is between 5 and 10, only one physical injury is set. The severity of the injuries given and the proportion of lethal injuries is as follows: if 3 injuries are present there is a 4.5% chance that a lethal injury is present. 2 injuries present a 3% chance of having a lethal injury while if only 1 injury is present there is 1.5% chance that the injury is lethal. The justification for these numbers are beyond the scope of this contribution but were set by subject matter experts and is a modeling assumption.

CONCLUSION

The evacuation simulation presented in this contribution allowed us to establish a list of victims with both inhaled doses and traumatic injuries based on the trajectories calculated with an open-source crowd simulation package. Because of specific features of the evacuation scenario, the simulation was divided in two separate runs (or waves). The first wave consisted of an evacuation under normal circumstances where the pedestrians were unaware they were being exposed to GB. The second wave consisted of an emergency evacuation of a panicked crowd. To set the total inhaled doses, a simple gaussian puff model was used. This approach is straight-forward but has limitations. The parameters of the gaussian plume were not fitted to experimental or CFD data but rather adapted to result in a distribution of injury profiles that is relevant to a mass casualty incident. Small group cohesion was neglected as well as pedestrians' perception and psychology which are beyond the scope of this study. To assign traumatic injuries, the overlaps defined in the Vadere SFM formulation were used. Based on thresholds, a number of traumatic injuries were assigned to the victims who experienced the greatest amount of collisions in the second wave of evacuation.

FUTURE RESEARCH

The method to setup inhaled doses and traumatic injuries presented in this contribution will be used to create a victims list in the SIMEDIS simulator (De Rouck et al. 2018). Based on the list, we will use our continuous victim model (Benhassine et al 2022) to create victims health state progressions. The results will be presented in a future paper on the evaluation and optimization of medical response in the case of a chemical attack in an urban setting. Future research could involve other chemical agents and locations as well as incorporate the interaction between trajectories and chemical exposure.

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