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Comparison of different spatio-temporal strategies for the evacuation of landlocked populations by large-scale agent based simulations

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At a time when the impacts of climate change and increasing urbanization are making risk management more complex, there is an urgent need for tools to better support risk managers. One approach increasingly used in crisis management is preventive mass evacuation. However, implementing this type of strategy in an urban environment where population density can be very high, resulting in high traffic congestion, can be complex. In this paper, we propose an agent-based model to study mass evacuation plans. This model, which is based on classical traffic sub-models, allows considering the impact of mixed and non-normative traffic, as observed in many developing countries, on the effectiveness of evacuation measures. It allows to test and compare, for several tens of thousands of agents, different spatio-temporal evacuation strategies. We illustrate its use with a case study of Phúc Xá district in Hanoi, which is located in a flood-prone landlocked area with a very high population density and only few evacuation points. This case study shows the impact of implementing an evacuation strategy by area or by proximity to area exit points, as well as improving the road network.

Keywords: Agent-based simulation; Evacuation policy; Risk context; Traffic model; Urban area

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1. Introduction

The Sixth IPCC assessment report shows (IPCC 2021) that extreme events such as heavy precipitation and tropical cyclones will increase in the coming decades. Those weather and climate extreme will increase the vulnerabilities of the most densely populated places and unplanned areas, which makes risk and disaster management very complex. When structural solutions (reinforcement of habitats or construction of dams) have not been considered or are insufficient, the rapid and massive evacuation of populations facing the threat of imminent danger is a solution considered in many countries. However, evacuating large numbers of people is always a delicate operation: people (including officials) may not make the most appropriate decisions, emerging congestion during the evacuation may make it difficult to get evacuees to appropriate shelters at the right time, and globally this whole complex procedure is subject to many unplanned circumstances, phenomenon obviously amplified for large populations. All this can increase exposition of evacuees to hazard and the occurrence of incidents. For example, the 55 deaths which occurred during Hurricane Rita in Texas were a consequence of the evacuation process rather than the storm itself (Knabb *et al.* 2006). In such complex and uncertain situations, local governments must therefore prepare systematic evacuation plans that can take into account many factors : number of people to be evacuated, number of buses available to evacuate non-autonomous people, relief routes in the event of disturbed traffic, identification of roads potentially blocked by floods... However, evaluating these plans outside a crisis context is, if not impossible, then very difficult. Indeed, while it is essential to prepare populations and organizations to deal with such events through exercises or educational programs, many aspects cannot be anticipated: secondary effects – also known as cascading disasters (Alexander and Pescaroli 2019) – coming from the primary disaster event such as traffic light shutdown, car accidents or landslides caused by flood may prevent people from leaving the area or communicating; on the same line, individual and collective behaviors such as refusal to evacuate, mass panic or antisocial actions cannot be easily predicted (Vorst 2010) but should be considered key aspects of any evacuation plan.

In this context, as in many other complex social phenomena, computer simulation appears to be an ideal tool to test different solutions in advance for a variety of scenarios, provided of course that it allows to take into account the impact of individual choices on global dynamics. Among the existing approaches, agent-based modeling (ABM) appears to be particularly well adapted to the study of such phenomena, as it is the only one that allows to represent the way in which the heterogeneity of individual behaviors and mobility choices will influence the dynamics of an evacuation. In recent years, many agent-based models have been proposed to simulate the evacuation of populations in risky contexts. Some of these models have focused on pedestrian mobility, others on vehicle mobility. However, very few of them have taken into account the mixed and non-normative traffic that can be observed in many countries where people use a wide range of mobility modes while having a fairly relaxed relationship to legal traffic rules (Dang-Huu *et al.* 2020).

To address this limitation, we propose a new model, part of the ESCAPE framework (Daudé *et al.* 2019), which incorporates a traffic sub-model suitable for representing mixed and non-normative traffic. To illustrate its use, a case study of the Phúc Xá district in Hanoi, Vietnam, is presented. This district, like many others in Vietnam, is built in a flood zone and has a very high population density. This case study is used to present how our model can be used to evaluate the effectiveness of different strategies in

terms of population evacuation time.

In a first section, we will present the case study of the Phúc Xá district. Then, in a second section, we review the state of the art regarding agent-based modeling and evacuation in an urban context to highlight some of the shortcomings of existing works. Then, we will present the model that we propose and its application for the Phúc Xá district. The results of the simulations with different scenarios will be presented and discussed. Finally, we will conclude and discuss future perspectives for this work.

2. Evacuation of the Phúc Xá District, Hanoi, Vietnam

Phúc Xá is a district of Hanoi (Vietnam) of about 1 km^2 located in the flood-prone area, highlighted in Figure 1. Despite the fact that this district is declared unbuildable because it is included in the flood area of the river, its density ($17,000 \text{ inhabitants/km}^2$) is one of the most important of Hanoi (the mean population density of Hanoi is around $9,300 \text{ inhabitants/km}^2$). The Red River, which runs alongside the district, is known for its violent floods. The flow of the river has significant seasonal fluctuations. It can drop to $430 \text{ m}^3/\text{s}$ during the dry season but reach $30,000 \text{ m}^3/\text{s}$ during the monsoon season. Since the 1970s, a number of dams have been built to harness the river and produce electricity in China (Yunnan Province) and Vietnam. Among these structures, two present important risks for the districts of Hanoi close to the river, in particular in the case of rupture or sudden discharge: the Hòa Bình dam and the Thác Bà dam.



Figure 1. Map of the Phúc Xá District (OSM data). The red line shows the district border.

One of the specificities of this district is that it is enclosed: to the south, the district is blocked by the Long Biên bridge, to the east by the Red River, to the west by a dike, and

it communicates to the north with another landlocked district. Thus, in case of flooding, the "exit doors" are limited. In practice, only few roads can be used to exit the flood zone. Figure 2 and Figure 3 show these different exits, and for each building respectively the closest exit and the distance to it (using the road network). Apart from these main evacuation routes, a few metal ladders and staircases pass over the dikes and could allow for pedestrian flow, but these are too few and narrow to use for a planned evacuation.

The road data comes from OpenStreetMap and the Building data were digitalized from the cadastral maps provided by the Vietnamese authorities. A comparison with satellite data (Google) allowed us to validate these layers.



Figure 2. For each building, the closest evacuation point (using the road network). The spheres represent the evacuation points.

While there is no recent study on mobility in Hanoi, a 2017 study gives this breakdown on mobilities in Ho Chi Minh City (Hee and Dunn 2017) (second-biggest city in Vietnam): 74% of daily travel is done by motorcycle, 19% by bicycle and 1% by car, 4% by bus, and 2% by Taxi. If mobility has changed since then, with a consequent increase in the use of the car, this distribution is not so far from the current distribution with a significant predominance of the motorcycle. These data disregard displacement on foot, while (Labbé *et al.* 2019) stated that this is not true: in fact, when it comes to go to a nearby place (in the article concerned, to a park) or to take a bus or cab, Vietnamese people mostly go by walk. In a small district like Phúc Xá where the bus must be taken outside the

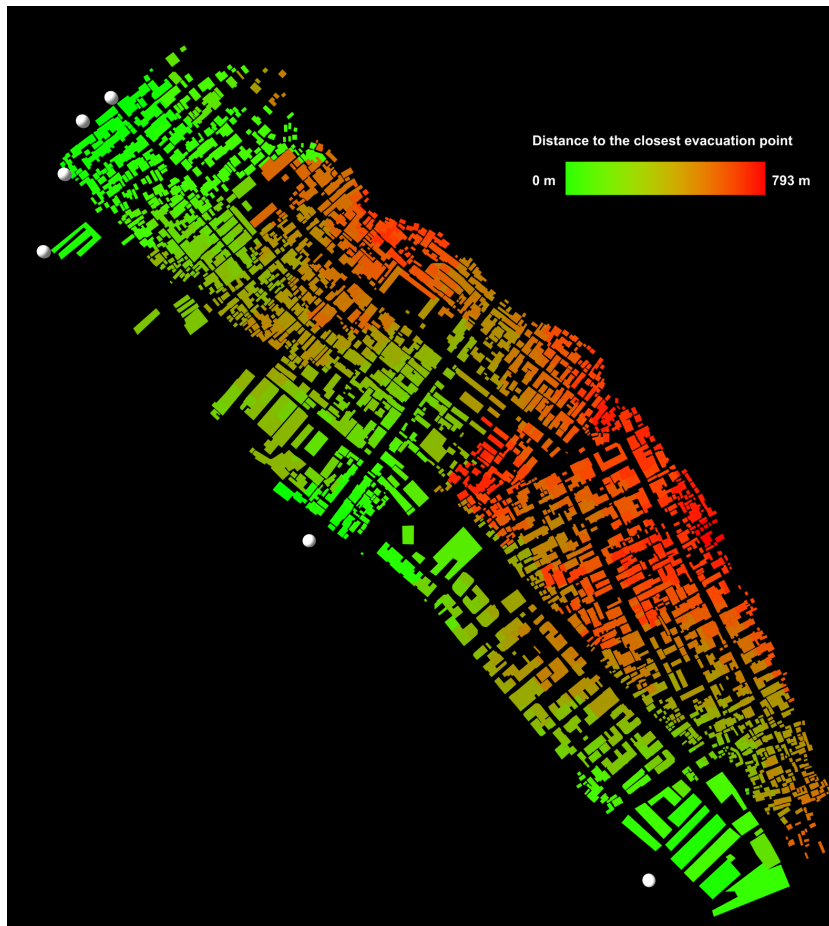


Figure 3. Distance (using the road) between the building and the evacuation points. the greener the building, the closer it is to an evacuation point. The redder it is, the farther it is. The white spheres represent the evacuation points.

district (the nearest bus stations are located on the main road behind the dike in the west), a significant part of the population which does not have a motorcycle, bicycle or car (difficult to park in the district) moves on foot. A characteristic of most roads in Vietnam and all roads in Phúc Xá is that there are no sidewalks and when there are, they are rarely usable by pedestrians because they are obstructed by motorcycles or other things. Therefore, pedestrians must walk on the road with other vehicles.

In terms of crisis management, there is no specific plan for this district (nor for any district in Hanoi), nor any awareness of the risks by the inhabitants, except a habit of regular flooding caused by heavy rainfall in Hanoi.

3. Related works

As mentioned in the introduction, individual decisions can have an important collective impact in massive population displacements, thus making agent-based modeling particularly well suited to the study of evacuation in a disaster context and therefore many models can be found in the relevant scientific literature. To have a more global view of the existing models, we have carried out a systematic review. We follow a classical

methodology based on the following process: (1) Identification of the target: article presenting a model dealing with evacuation simulation in urban territory, (2) Search in online databases: use of the keywords "Agent based model evacuation urban" on Scopus (128 documents), (3) Selection of documents: to ensure the relevance of the analyzed article. This last step was based on the following conditions: (i) we only consider articles from journals and conferences, (ii) we only consider articles written in English, (iii) we only consider in this state-of-the-art articles from 2017 and newer; we assume that they have already taken advantage of older models. Based on these constraints, 36 articles were collected. Of these articles, 9 were removed because they did not present an agent-based model or did not provide enough information about the model (short articles).

Tables A1, A2, A3, A4 present the list of articles and the corresponding references. To classify them, we defined several categories: *evacuation* for articles presenting an evacuation model; *mobility model* for articles presenting a new mobility model or an improvement of an existing model (typically, a new social force model); *behavioral model* for articles focusing on people's behavior in a crisis context (actions they performed during the crisis); *large-scale model* for articles presenting new methods for evacuation of large populations. An article may belong to more than one category: for example, Makinoshima *et al.* (2018) presents an evacuation model, but much of the article is devoted to presenting and testing a parallelization strategy for the calculation. For each article, we also noted the hazard involved (if any), whether its dynamics are simulated or only used as input or context, the territory involved, the number of agents simulated (when multiple experiments are performed, we just noted the highest value), how mobility is modeled, and the type of strategies or scenarios tested.

Mobility model: these papers present an innovation in terms of mobility modeling. Two papers in this category (Prédhumeau *et al.* 2021, Hesham and Wainer 2021) deal with pedestrian mobility: their objective is to propose an improved model to simulate pedestrian behavior. A last paper is Haghpanah *et al.* (2021), which proposes a real application for evacuation, but focuses on the comparison of mobility models.

Behavior model: these articles focus on the behavior of people in the face of the crisis: evacuation is usually one of the possible strategies, but the model also proposes other behaviors (e.g. staying at home, informing others, etc.). Taillandier *et al.* (2021) is a good example of a model where the focus is more on the behavior of people in a flood context: the behavior is modeled using a BDI architecture with many actions that people can undertake among which evacuation. Another example is Bernardini *et al.* (2017) which focuses on video analysis to extract a behavioral model. In Yang *et al.* (2018), the agents representing the household do not move, the model focuses only on their behaviors. Other works like Battagazzorre *et al.* (2021) and Parikh *et al.* (2017) propose different actions for the agents, but focus more on the movement of the population. In this case, they belong to both categories (*evacuation model* and *behavioral model*).

Large-scale model: these articles propose methods to allow large-scale simulation. Both the proposed method (coupling of models / parallelization) and the number of simulated agents differ (from 25,869 to 10 million). Thus, some of these articles propose to couple a macro/meso model with a micro model (agent-based model) to be able to carry out scenarios with a large population. Other works like Makinoshima *et al.* (2018),

Battegazzorre *et al.* (2021), Wijerathne *et al.* (2018) use parallel computing. Finally, Parikh *et al.* (2017) uses a simple routing model to be able to simulate a large population.

Evacuation model: the largest category is that of articles that present an actual evacuation model (22 articles). An important first observation is that most of the models propose to incorporate only one mode of travel. In 13 of the articles, only walking trips are considered and in 5 models, only driving trips are considered. Note that one paper focuses on evacuation using urban air mobility systems, and human mobility is not considered West and Sherry (2020). Therefore, only 3 models in this category propose to simulate both car and pedestrian mobility. Thus, Aguilar *et al.* (2019) propose to represent both pedestrian and car traffic using a model based on the calculation of a collision-free velocity along a graph. Few details are given about the precise calculation of this velocity and the model used. Haghpanah *et al.* (2021) uses two different models for cars and pedestrians: for cars, a simple version of the car tracking model is used; for pedestrians, two bug navigation algorithms coming from robotics are tested. Two types of interactions are considered between pedestrians and cars: at intersections without traffic lights, pedestrians have the right to cross streets before vehicles; in addition, if sidewalks are crowded, pedestrians can use the road and cars must stop to let pedestrians pass. Daudé *et al.* (2019) propose also to use two mobility models: a social force model for pedestrians and a model derived from the intelligent driver model for cars (and buses). However, no information is given about the interaction between the car and the pedestrian. Returning to pedestrian models, several types of mobility models are used, but most of the works relies on social force models, cellular automata models, optimal reciprocal collision avoidance models, or on a simple calculation of the agent's speed as a function of its characteristics or density. As far as car traffic is concerned, apart from simple models, most of the works are based on classical traffic models (Transim, Sumo, Matisse, etc.). Another remark is that the hazard is rarely modeled, except for flooding. Sometimes, the impact of the hazard (area affected, impact on the building) is taken as input. Concerning the type of scenarios and strategies tested with the model, they can be of different types: hazard scenarios (Battegazzorre *et al.* 2021, Veeraswamy *et al.* 2018), different parameters for the population – e.g. density/number (Li *et al.* 2019, Wang *et al.* 2020, Nakasaka *et al.* 2020), psychological/physical characteristics (Yamazaki *et al.* 2017, Wang *et al.* 2020, West and Sherry 2020), knowledge of the shelters (Sun *et al.* 2021), information/communication (Parikh *et al.* 2017) or car use (Aguilar *et al.* 2019, Kim and Cho 2020) – group composition (Pan *et al.* 2021) or evaluation of different policies (Kim *et al.* 2017, Yin *et al.* 2020, Bianchin and Pasqualetti 2020, Oh *et al.* 2021, Al-Zinati and Zalila-Wenkstern 2018). Regarding the latter type, Bianchin and Pasqualetti (2020) proposes to optimize the duration of traffic lights to minimize congestion. Yin *et al.* (2020) are interested in the optimization of the evacuation plan: how to minimize the evacuation time by assigning a specific exit to each agent. Oh *et al.* (2021) study the impact of staged evacuation by introducing a delay between the evacuation processes of different areas. Al-Zinati and Zalila-Wenkstern (2018) are also interested in zoning strategies, but test as well the impact of a route reversal. Finally, Yin *et al.* (2020), whose main contribution concerns the use of cell phone data to improve the efficiency of evacuation model exploration, tests different scenarios among which different departure time, phasing and road policies.

In summary, many models exist, but few are really adapted to our case study. The study

of evacuation in Hanoi requires to be able to consider different types of mobility (at least cars and pedestrians) and their interaction. Moreover, as in many places in Vietnam, there are no sidewalks: pedestrians, cars and motorcycles use the same space. Finally, the way people drive in Vietnam is very different from most developed countries: while people tend to respect driving on the right, many other driving rules like the notion of priority, passing on the left or to respect driving speed limitations are more loosely followed. If the population's size, about 20,000 people, requires attention to the model chosen to simulate mobility, it does not require a very specific large-scale modeling strategy. Since our goal is to focus on the spatio-temporal impacts of evacuation's strategies rather than investigating the impact of people's behavior in the face of flooding, we can use a simple behavioral model: when the alert signal is triggered, people leave without having to think about the relevance of evacuating. Similarly, as we are in a preventive evacuation context, we do not need, as most of these works, to model the dynamics of the flood. In terms of tested strategies, we can draw on the strategies tested previously regarding zoning, i.e. introducing a delay between the evacuation processes of different zones.

Our model take advantage of an existing framework (Daudé *et al.* 2019). ESCAPE integrates several mobility models, and in particular a lane-based traffic model - each vehicle moves on one lane of a road and can change lane at any time (Taillandier 2014). One of the strengths of this mobility model, in addition to being adapted to large-scale simulations with tens of thousands of vehicles, is that it can consider non-normative driving: drivers may or may not respect traffic rules, e.g. they may decide not to stop at a red light, not to respect right/left priorities, to overtake using left/right lanes, etc. However, it does not model vehicles of different widths, and it is based on simple ad hoc acceleration and lane change models. An ESCAPE application for the Phúc Xá district had already been proposed (Chapuis *et al.* 2019a), but this one mainly focused in the coupling between a flooding software (HEC-RAS) and a simple mobility model (with pedestrians and motorbikes). Our proposal is therefore to use ESCAPE as a basis but to enrich it to make it suitable for our context. Like ESCAPE, our model is implemented with the GAMA open-source agent-based simulation platform (Taillandier *et al.* 2019). This platform provides a complete modeling and simulation development environment for building agent-based simulations. Many models dedicated to evacuation have already been implemented using this platform (e.g. Valette *et al.* (2018), Le *et al.* (2017), Anh *et al.* (2011)). The model and all data used for the experiments are available on Open-ABM¹.

4. Model proposed

4.1. Hypotheses

We pose the following hypotheses on the evacuation model:

- (1) people evacuate as soon as they receive the order to evacuate.
- (2) people are familiar with the district in which they live and therefore know all the possible routes and paths.
- (3) people use the same means of transport as usual, and may be several in a car or on a motorcycle. Since there is no bus station in the district and ordering a cab

¹for reasons of anonymity, we do not give for the moment the link to the model on OpenABM, but the model (and all the data) can be downloaded from this temporary link: <https://drive.google.com/file/d/1g-qUrt10EVajk8kZ1Be9ZHJWgL533JB/view?usp=sharing>

- takes time, people who usually use the bus or cab walk to the exit of the district.
- (4) pedestrians do not use sidewalks, but walk on the road with other vehicles
 - (5) people evacuate by the nearest exit (by the roads).
 - (6) to go to this exit, people use the shortest route (minimization of the distance by the roads).
 - (7) at the crossroads, people can see if the road is congested and possibly choose a new exit and/or a new path. Whether people choose to question their path depends on how close they are to the exit they are trying to reach: the closer a person is to the exit, the less likely she/he will question her/his path.
 - (8) if an inextricable traffic jam appears, it is the most mobile people who will try to unblock it (by stepping back).

In the following sections we describe the model following the ODD protocol (Grimm *et al.* 2020).

4.2. Overview

4.2.1. Purpose and patterns

The objective of the model is to test the impact of spatio-temporal evacuation policy on the evacuation time at the scale of a district (several thousand agents). This allows considering the different types of mobility that can be found in Vietnam (car, motorcycle, bicycle, pedestrian) as well as the rules of the road in this country. We evaluate our model by its ability to reproduce two patterns.

Pattern 1: generation of traffic jams – when a large population seeks to evacuate, it will generate traffic jams that will slow down the evacuation.

Pattern 2: interest of the evacuation by zone – not evacuating everyone at the same time greatly limits traffic jams and therefore the time spent on the roads by people, which is particularly important because the roads are often areas at risk for the populations.

4.2.2. Entities, state variables, and scales

Figure 4 presents the UML class diagram of the model. The model is composed of several types of entities. Concerning the environment, this one is composed of *Roads*. Each *Road* is characterized by linear oriented geometries (polyline) with a number of lanes and speed limitation. Each *Road* is linked to each of its ends by an *Intersection*. A *Road* can be linked to a reverse *Road* (i.e. with reversed geometries). If a reverse *Road* is defined, it means that a *Moving agent* can use it to overtake another *Moving agent*. In addition, *Building* are located in the environment with a given geometry (polygon) and is linked to an *Intersection* (the closest *Intersection*). Finally, *Evacuation points* are located in the environment and are linked to an *Intersection* (the closest *Intersection*).

The main active agents are *Moving agents* which represents an abstract class of agents. There are four types of them: *Cars*, *Motorbike*, *Bicycles* and *Pedestrians*. These agents share the same attributes. First, a *Moving agent* has a home (a *Building*), a preferred evacuation point and a departure time. They are also characterized by physical attributes: a length, a maximal speed, a maximal acceleration, and a number of lanes occupied. In-

deed, our mobility model is based on extending the usual notion of lane: each *Moving agent* will occupy one or more lanes according to its width. This means that a car will occupy more lanes than a motorcycle or a pedestrian. *Moving agents* are also characterized by several attributes linked to the way they are driving and moving, and linked to two sub-models we are using to compute the vehicle speed (Intelligent Driver Model – IRM Treiber *et al.* (2000) – and lane-change (Minimizing Overall Braking deceleration Induced by Lane changes – MOBIL Kesting *et al.* (2007)). First, the *Moving agents* have a speed coefficient that defines if they tend to move above or below the speed limit (a value of 1.0 means that the desired speed is the speed limit, if the max speed of the agent allows it). Concerning the IDM model, 3 additional attributes are defined: the maximal deceleration, the minimum spacing, i.e. the minimal distance from the car in the front, and the desired headway time, i.e. the minimum possible time to the vehicle in front. For the MOBIL model, 3 additional attributes are defined: the politeness factor (0.0, a purely selfish behavior; 1.0 a very polite behavior), the maximum safe deceleration, and a minimal acceleration gain threshold to avoid lane-change triggered by marginal advantages. Two last attributes characterizing *Moving Agents* are their propensity to use reverse *Roads* if necessary: a probability to use these and a maximum number of lanes that the agent will be able to use on it. In addition to these static attributes, *Moving agents* have some dynamic attributes: they are characterized by a location in the space (x-y coordinate), they can be located on a specific lane of a road, and have a speed and an acceleration. Finally, they can memorize a list of congested roads - they will be able to change their path according to this knowledge.

Concerning the timescale, a simulation step represent 0.5s, which is the most suitable simulation step for the IDM model. Overall micro-traffic simulations need to be as precise as possible due to the very sensitive nature of the modeled phenomenon, like collision avoidance or stop-and-go traffic jam.

4.2.3. Process overview and scheduling

The only acting agents are the *Moving agents*, i.e. *Cars*, *Motorbikes*, *Bicycles* and *Pedestrians*. At each simulation step, they will carry out 3 main behaviors:

- (1) if the current time is higher than the departure time, the agent chooses an evacuation point and the path along the road to reach it.
- (2) if the agent has a path, follow the path.
- (3) if the agent cross by a high road density (i.e. traffic jam), evacuation point and the path to it might be reconsidered.

For the first behavior, the agent will choose the closest evacuation point to its current position using the road network. To compute the distance and the shortest path, the agent considers the traffic jams it knows: it will favor roads without traffic jams if possible. More precisely, to compute the shortest path, the agent uses a directed weighted graph representation of the road network: each road represents an arc. The weight of each arc corresponds to the perimeter of the road. If the agent has the belief that there is a traffic jam on the road, it multiplies the weight of the arc by a penalty factor. This factor corresponds to the maximum possible length of a path, arbitrarily chosen so to exclude it from potential evacuation track.

The agent's knowledge about traffic jams is empty at the beginning of the simulation and is updated each time the agent arrives at an intersection: for all roads connected to this intersection, the agent will update whether the road is congested or not depending on the density of vehicles on the road. If the density is higher than a certain threshold tj_a specific to each agent, it is considered as congested. The density of vehicles on the

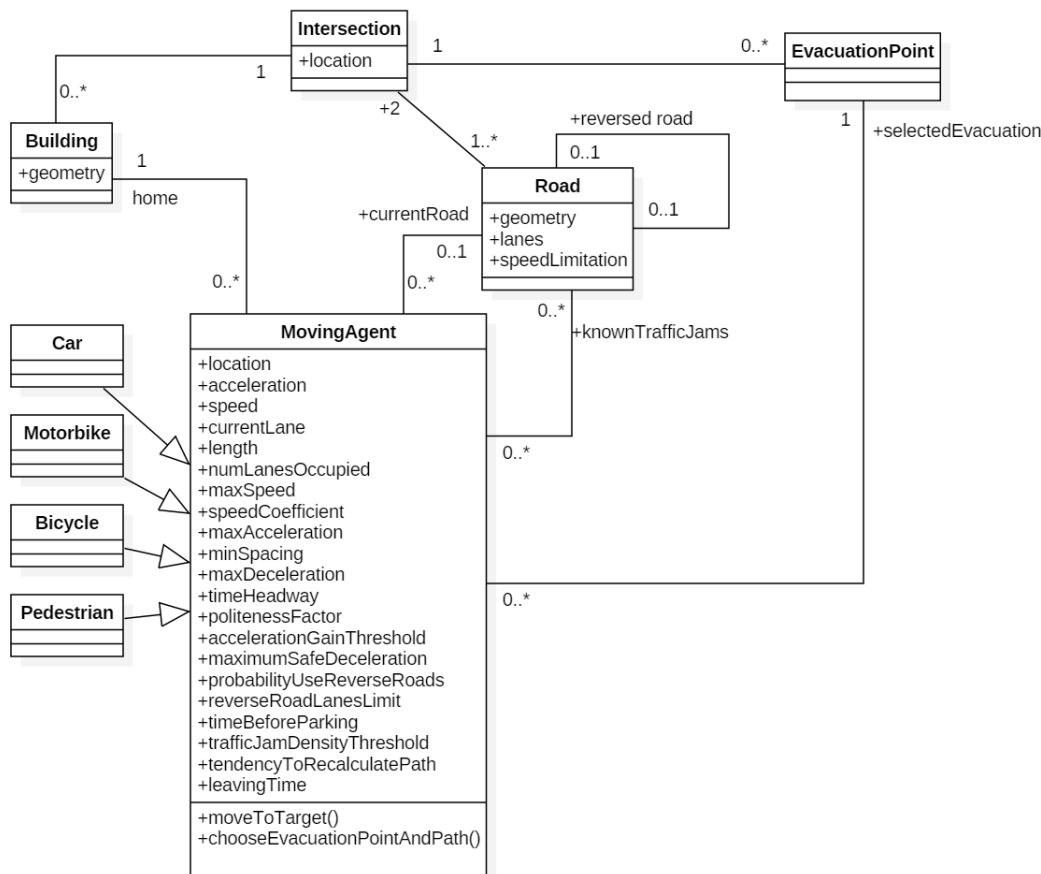


Figure 4. UML class diagram of the model

road r is computed following equation 1 below:

$$density(r) = \frac{\sum_{a \in r_a} l_a}{p_r \times n_r} \quad (1)$$

with r_a the list of *Moving agents* on the road r ; l_a the length of the *Moving agent* a ; p_r the perimeter¹ of road r ; n_r the number of lanes of road r . The NBA* algorithm is used to compute the shortest path Pijls and Post (2009). NBA* is a generalized version of bidirectional A*, which is particularly efficient in a context where each agent makes shortest-path calculations based on its own weights. This feature is particularly important in our context, because agents elicit shortest path during simulation updating their knowledge (weight) on road congestion.

Concerning the second behavior, the agent moves toward the evacuation point, by following the path defined. On a microscopic scale, the agent first calculates a desired speed which depends on the speed limit on the road, its speed coefficient and its maximum speed. From this desired speed, it defines, using the MOBIL and IDM models, a lane to move on and a speed/acceleration on this lane according to other *Moving agents*. These two models are based on the notion of leading and backward agents. The calculation of

¹Which is actually a length given that *Roads* are represented as lines

these agents includes the number of lanes occupied by the vehicles (attribute num_L_a of agent a): for example, a car can be the leading vehicle for 2 motorcycles on 2 different lanes. More information about the IDM and MOBIL models are given in the Details section 4.4.

When an agent arrives at an intersection, it first updates its knowledge about traffic jams (see previous paragraph), then it defines whether it wants to continue on its path or not. Third behavior is akin to the agent recognition of overcrowded roads, and triggers the re-evaluation of target and path: recalculating an evacuation point and its path depends on the distance to the evacuation point and to a random draw. More precisely, the probability for an agent a to recalculate its evacuation point and path is:

$$proba_{recalculate}(a) = k_a \times d(a, a_{ep}) \quad (2)$$

with $d(a, a_{ep})$ the distance between agent a and its current selected evacuation point a_{ep} ; k_a the tendency for agent a to recalculate the path. An agent who recalculates its evacuation point will recalculate the distance to all evacuation points thinking about its knowledge about traffic jams and choose the fastest way. This process may well lead to keeping the same evacuation point or even the same path if no other path is better.

Finally, after moving, the *Moving agents* can, if necessary, make a specific maneuver to let another vehicle pass to avoid complete blockages. More precisely, we integrated the following rule: if a vehicle is blocked (speed of zero) on a reverse road and if the vehicle in front of it (which is in the opposite direction) has the same size or a bigger size, then after a certain time (defined by the attribute $time_p_a$ of the agent a), the agent will park, i.e. it does everything it can to go back on the normal road (not the reverse one) even if this violates the minimum distances to other agents - this corresponds to the classic maneuvers in Vietnam where motorcycles will stick together to let a car pass.

4.3. Design Concepts

4.3.1. Emergence

Due to the capacity limits of the roads and the interactions between the moving agents, traffic jams will emerge from the simulation. This is a classical result, well described by the fundamental diagram of two-phase traffic (Geroliminis and Daganzo 2008). When the number of vehicles on a road is very small, interaction between these vehicles is close to zero. Each agent can therefore ride at the maximum speed it wants, without being disturbed by the presence of other vehicles. As the number of cars increases, the interaction between vehicles also increases, which has the effect of reducing the speed of the vehicles. As a result, the average speed on the road decreases regarding the number of vehicles.

4.3.2. Adaptation

There are several levels of adaptation. The first level concerns microscopic traffic movement: the speed of the *Moving agents* is adapted to the speed of other *Moving agents* and to the road infrastructure. The second level concerns the mesoscopic scale of path selection and change: agents are able, if they perceive traffic jams, to question their destination and the path followed. The third is that an agent may temporarily use a reverse traffic lane to avoid or escape a blockage on the regular lane he is following.

4.3.3. Sensing

Moving agents have perception capabilities: they can perceive the *Moving agents* on the same road as them to define their speed of travel. Also, when they arrive at intersections, they can perceive traffic jams and thus adapt their behavior.

4.3.4. Stochasticity

The model is stochastic in several aspects. The allocation of the starting time can, depending on the scenario, depend on a random draw. The scheduling of the agents also has a random part: the closer a road is to an evacuation point, the more the *Moving agents* on it will be activated in priority. When two roads have the same distance from evacuation points, the choice from the agents will be made randomly between the two roads. Finally, when the *Moving agents* perceive a traffic jam, the fact of recalculating the current route will depend on a random draw.

4.3.5. Observation

Important observations can be done on the time needed for the complete evacuation of the area and the one spent on the road. Indeed, as many tragic events have shown, spending too much time on the road can be dangerous. As mentioned in the introduction, the 55 deaths during Hurricane Rita in Texas were associated with the evacuation process. Being able to limit as much as possible this time spent on the road is thus critical.

4.4. Details

4.4.1. Initialization

The initialization of simulation is based on several pre-computation steps that are done once. The model takes as input 3 types of geographical data:

- roads - linear geometries
- buildings - linear geometries
- evacuation points - point geometries

Roads must be oriented and have 3 attributes: the number of lanes, the speed limit and whether it is a one-way road or not. In the case where the road is not one-way, the model considers two roads in opposite directions (reverse roads) with the same characteristics (number of lanes and speed limit). For the creation of the population, the process is as follows: while there are still inhabitants to place, choose a random building according to the area of the building, then create a car, a motorcycle, a bicycle or a pedestrian on this building according to the mobility mode probabilities. Depending on the type of agent created (*car*, *motorbike*, *bicycle* or *pedestrian*), a specific number of agents will be removed from the population. Indeed, we consider that there can be several people in a car or on a motorcycle. This number of people is defined uniformly according to the type of transport and the acceptable maximum values (e.g. no more than 3 people on a 2 wheels vehicle). This initialization process therefore requires, in addition to the geographic data, to define the following parameters:

- total population
- probability of use of each mode of transport
- maximum number of people per mode of transport

4.4.2. Input data

The model does not use any input data to represent time-varying processes.

4.4.3. Sub-models

4.4.3.1. Intelligent Driver Model (IDM). We use the classic Intelligent Driver Model to compute *Moving agent's* speed. In this model, the acceleration of a vehicle is determined by its leading vehicle, i.e. the closest vehicle ahead in the same lane. Let a be an agent characterized by f its leading agent (front agent), max_acc_a its maximum acceleration, v_a its current speed, $v_a^0(r)$ its desired speed on road r , i.e. the speed the vehicle would drive in free traffic, s_a^0 , its minimum desired spacing, i.e. minimum desired distance from its leading vehicle, s_a , the actual distance between agent a and its leading vehicle, T_a its desired time headway, i.e. minimum possible time to reach its leading agent, and b_a its comfortable braking deceleration. The actual acceleration of *Moving agent* a , denoted acc_a , is computed following equation $acc(a)$ below:

$$acc(a) = \frac{d_{acc_a}}{dt} = max_acc_a \times \left[1 - \left(\frac{v_a}{v_a^0} \right)^4 - \left(\frac{s^*(v_a, v_f)}{s_a} \right)^2 \right], \quad (3)$$

With:

$$s^*(v_a, v_f) = s_a^0 + \max \left[0, \left(v_a \times T_a + \frac{v_a \times (v_a - v_f)}{2\sqrt{max_acc_a \times b_a}} \right) \right]. \quad (4)$$

The desired speed of an agent a on a road r is defined by:

$$v_a^0(r) = \min(max_v_a, cv_a * v_r) \quad (5)$$

with max_v_a the agent's maximum speed, v_r the road speed limit, and cv_a the agent's speed coefficient, i.e., its propensity to travel below and above the road speed limit.

4.4.3.2. Minimizing Overall Braking deceleration Induced by Lane changes (MOBIL). The MOBIL model is used to define whether or not the agent will change its lane. It is based on the IDM model to evaluate the relevance of the different possible lanes. Concerning the tested lanes, we consider in this model that the agent can use all the possible lanes of the road. In addition to that, it will have a certain probability (p_r_a for agent a) to also test the lanes on the reverse road side. The number of lanes the agent can use on this side is defined by an attribute (rl_l_a for agent a).

The MOBIL model provides two criteria to define whether the agent should change lanes for another given lane: the safety criterion (is it safe for the agent following on the targeted lane?) and the incentive criterion (is the new lane more interesting?).

Let a be an agent who wants to change from lane l to a new lane l' . We note b the back agent of agent a on lane l , and b' the agent who would be behind a if the agent changes its lane to the targeted one l' . We also note acc_a the current acceleration of the agent a , acc_b the current acceleration of the agent b , and acc'_b the current acceleration of the agent b' . $a\tilde{c}_a$ denotes the acceleration of a if the agent has really changed lane for lane l' (calculated with equation 3). Similarly, $a\tilde{c}_b$ is the acceleration of agent b if agent

a changed lane to lane l' , and $a\tilde{c}c_{b'}$ is the acceleration of agent b' if agent a' changes lane to lane l' .

The safety criterion, which ensures the lane change does not cause the new follower to brake too hard, is stated as:

$$a\tilde{c}c_{b'} > -b_{b'}^{\text{save}}, \quad (6)$$

with $b_{b'}^{\text{save}}$ the maximum safe deceleration of agent b' . The incentive criterion is stated as follows:

$$a\tilde{c}c_{a'} - acc_a > p_a \times (acc_b + acc_{b'} - a\tilde{c}c_b - a\tilde{c}c_{b'}) + thr_a \quad (7)$$

with p_a the politeness factor of agent a . A politeness factor higher than 1.0 means a very altruistic behavior and a value of 0.0 is a purely selfish behavior. thr_a is a threshold for agent a which has for goal to avoid frenetic lane change by limiting the fact of changing lane for a marginal advantage. Note that the decision to change lane is only considered when the first component of the equation 7 is positive, meaning that current acceleration is lower than expected acceleration in the target lane. In other words, *Moving agents* consider moving to another lane only when they face an obstacle that force them to decelerate on their current lane. Finally, if the agent has multiple lanes to choose from, the one with the highest raw incentive (equation 8) will be chosen.

$$a\tilde{c}c_{a'} - acc_a + p_a \times (acc_{b'} - a\tilde{c}c_{b'}) \quad (8)$$

5. Experiments

The model was applied to the Phúc Xá case study using the geographical data described in Section 2. All the parameter and attributes values are described and justified in Appendix B (Tables B1, B2, B3, and B4). The choice of parameters resulted in the generation of 123 car agents, 7427 motorbike agents, 1997 bicycle agents and 609 pedestrian agents.

The first series of experiments carried out is dedicated to the stochasticity analysis of the model to define a relevant number of replications for the following experiments. The second set of experiments evaluates drivers' capacity to question their evacuation point and path. What is the impact of drivers' behavior facing traffic jam on the evacuation?

We then focus on the impact of the implementation of a spatio-temporal evacuation policy through two series of experiments: what is the efficiency of an evacuation policy per proximity to the exits compare to a zonal evacuation. Finally, we study the impact on the evacuation process of small enhancements applied to the road network: is it possible to improve the evacuation's efficiency by a minimal modification of the road network?

For all these experiments, we will analyze 2 main outputs: the evacuation time, which stands for the time between the first evacuation order and the last agent to leave the area, and the average time spent on the roads, which is the average time between order to evacuate and actual exit of the agents.

5.1. Stochasticity study of the model

In the first experiment, we analyze the impact of simulations' randomness on the results and in particular on evacuation time and on the average time spent on roads. The main objective is to find a threshold value of replications beyond which an increased number of replication would not imply a significant change in-between results. To do so, we compare the evacuation time and the average time spent on roads between repetitions of the simulation. We run 100 repetitions of such a simulation and compare the variability of the results for the first 10, 25, 50 and 100 repetitions. The departure time of each agent is randomly set (uniform distribution) between 0 and 1h. The goal is to choose parameter values that favor as much as possible the impact of stochasticity on simulation's results (in most of the other experiments conducted, agents' departure time is fixed and not random) to be sure of the robustness of the results for the other experiments. A simulation (complete evacuation) takes about 10 minutes using a single core on a laptop with an Intel Core i7-7700HQ CPU (2.80GHz).

First, Figure 5 shows the evolution of the number of agents left to evacuate along the time over all the repetitions. The red line is the median value. The curves follow a constant decrease throughout the time highlighting the capacity limitation of the evacuation points. After a certain time (around 60 minutes), only some exits are still in use, the remaining agents being stuck in traffic jams and waiting for their turn to evacuate, which explains the bending of the evacuation curves. We also can see that cars have more difficulty to evacuate being more easily blocked in traffic jams.

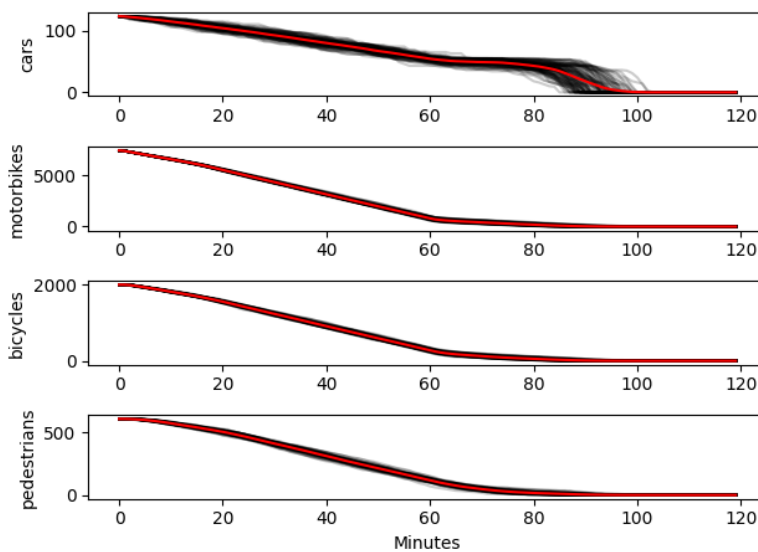


Figure 5. Number of agents not yet evacuated along the time. In red, the median values.

Concerning stochasticity impact, Figure 6 shows the standard error obtained with different number of replicates on the evacuation time and on the average time spent on roads. Figure 7 shows the impact of the number of replication on the evacuation time and on the average time spent on roads: black lines are the median, boxes show the second and third quartiles (IQR), whiskers show the minimum and maximum excluding outliers (simulation results which differ from the median by more than 1.5 times the IQR). We can observe that with 10 repetitions the standard error is very high. With

10 replicates, significant differences can be observed from the 100 replicates. With 25 replicates, the difference is small enough to ensure sufficient robustness of the results. Thus, the experiment suggests that increasing the number of replicates beyond 25 does not have an important impact on the aggregate trend of the simulated evacuation.

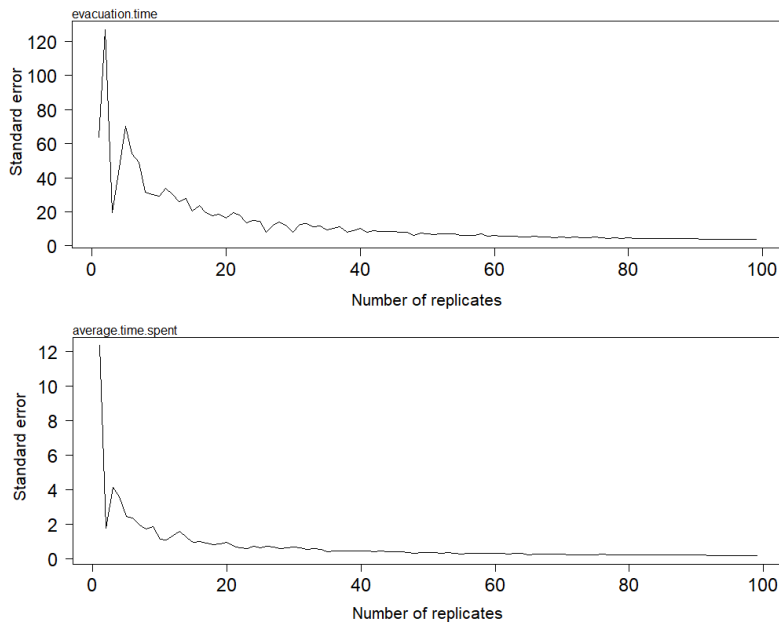


Figure 6. Comparison of the standard error on the evacuation time and of the average time spent on roads for the different number of replicates.

For the study of the scenario presented in the following section, we decided to set the number of replicates at 25 to minimize the computation time required while trying to maintain realistic statistical properties, in particular the occurrence of extreme outcomes.

5.2. Impact of agent's behavior

The purpose of this experiment is to evaluate the impact of agents' capacity to question their evacuation point and path in case of congestion. More precisely, we tested the impact of the variation of the attributes "Traffic jam density threshold" over the variation of "Tendency to recalculate the evacuation point / path" on the evacuation times and on the average time spent on roads. The departure time of each agent has been set to 0, i.e. we consider that all agents left at the same time - at the beginning of the simulation.

We tested 4 values for each attribute:

- Traffic jam density threshold (tj_a): 0.25, 0.5, 0.75 and 1.0
- Tendency to recalculate the evacuation point / path (k_a): 0.1, 0.01, 0.001 and 0.0001

Table 1 shows the results obtained in terms of evacuation time, and Table 2 shows the results obtained in terms of time spent on the roads. A first observation is that the introduction of a path recalculation behavior has a strong impact on the result. In the case where there is almost no path recalculation ($tj_a = 1.0$ or $k_a > 0.001$), the average evacuation time (and the time spent on road) is much longer (more than twice higher). For the other cases, we can observe a better evacuation time when the tj_a is at 0.25 and

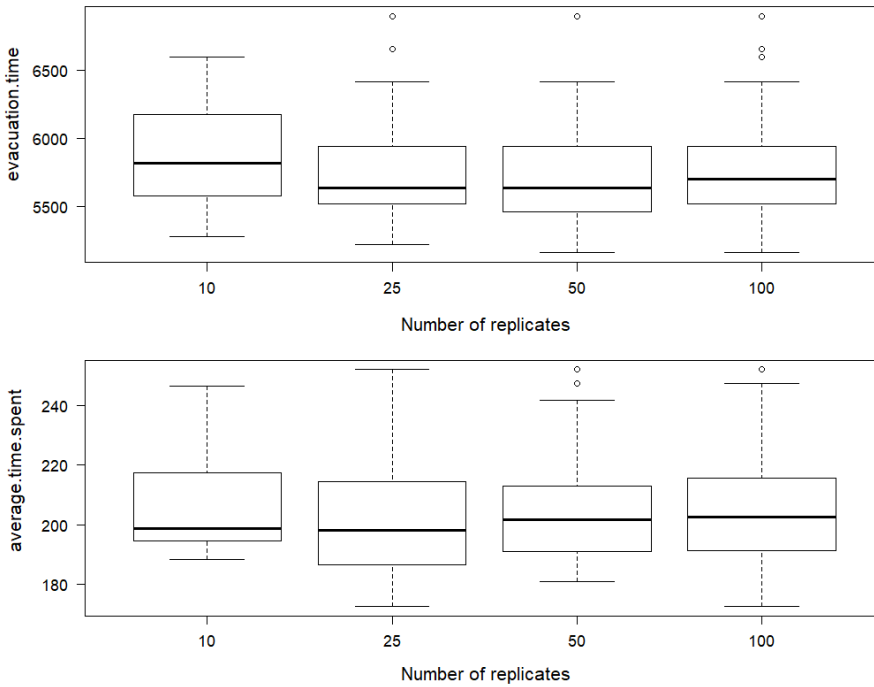


Figure 7. Whiskers plot of the evacuation time (in seconds) and average time spent on roads (in seconds) for the different number of replications. Black lines represent the median values; boxes represent the interquartile range (IQR), whiskers represent the minimum/maximum excluding 1.5 IQR outliers. Points are outliers beyond that distance.

k_a at 0.01 which seems to be a good compromise between persisting in the path and changing it when there are too many people.

Note that in reality, people rarely follow an optimal behavior. Thus, for the other experiments, we chose to take a value of tj_a of 0.75 and k_a of 0.01, which seemed coherent through our empirical observations on the driving behavior in Vietnam, who generally tend to really change their route only if the density on the road is really important and if there are not already close to their target.

$tj_a \backslash k_a$	0.1	0.01	0.001	0.0001
0.25	4539 (± 408.33)	4068 (± 318.85)	8983 (± 411.0)	9510 (± 157.8)
0.5	4260 (± 568.38)	4127 (± 448.29)	8724 (± 336.0)	9710 (± 574.37)
0.75	4534 (± 720.82)	4464 (± 527.73)	8555 (± 209.94)	9526 (± 245.5)
1.0	9368 (± 153.54)	9468 (± 105.33)	9480 (± 129.24)	9442 (± 44.51)

Table 1. Mean evacuation time (in s) and standard deviation for different values of tj_a and k_a

$tj_a \backslash k_a$	0.1	0.01	0.001	0.0001
0.25	1254 (± 27.57)	1172 (± 25.39)	2498 (± 23.95)	2733 (± 14.85)
0.5	1218 (± 28.99)	1232 (± 24.57)	2493 (± 66.09)	2739 (± 14.25)
0.75	1363 (± 28.0)	1363 (± 31.12)	2484 (± 50.65)	2737 (± 16.67)
1.0	2714 (± 48.58)	2743 (± 30.86)	2743 (± 9.74)	2740 (± 10.26)

Table 2. Mean time spent on the roads (in s) and standard deviation for different values of tj_a and k_a

5.3. Impact of Proximity/Time

The goal of this experiment is to test the effectiveness of an evacuation strategy based on proximity to the exit and to compare such approach to a random strategy (no spatial rules on evacuation priority). We defined two parameters to define the departure time of agents:

- α : this is a parameter between 0.0 and 1.0 which allows to weight the strategy consisting in preferentially warning peoples closest to an exit to evacuate them first. If α is 0.0, the evacuation order is given randomly following a uniform law over the whole area. If α is 1.0, it will warn -gradually- people closest to one of the exits who are ordered to evacuate. In this case, peoples closest to the exits will be warned first.
- β : this is a parameter which allows to control the speed (in people notified per second) at which evacuation orders are given. If β is 0.0, the speed is infinite in the sense that the order is given to all individuals at the beginning of the evacuation. If β is at 1.0, the speed will be of $N/MaxDuration$ which makes it possible to send the order of evacuation to N individuals in the $MaxDuration$.

The departure time of an agent a is defined as follows:

$$leavingTime(a) = TIME_MAX \times \beta \times ((\alpha \times rnd(1.0)) + (1 - \alpha) \times \frac{distance_a}{distance_{max}}) \quad (9)$$

with $TIME_MAX$, the maximum time to start evacuating; $rnd(1.0)$, a function that returns a random number between 0.0 and 1.0 following a uniform distribution; $distance_a$ the distance between a and its nearest evacuation point (using the road network) and $distance_{max}$ the maximum distance between the agents and their nearest evacuation point (using the road network). In our case, $TIME_MAX$ was set to a constant value of 1h – which is enough time for every agent to evacuate according to our exploratory analysis – and we tested 6 values for α and β (0.0, 0.2, 0.4, 0.6, 0.8, 1.0).

Table 3 shows the mean evacuation time and Table 4 the mean time on roads. The results may seem counterintuitive in several regards. First, on the evacuation time: the simulation shows that it is more efficient to evacuate everyone at the same time ($\beta = 0$) than to try to integrate a delay for the departure of some agents ($\beta > 0$). The longer the delay is, the worse is the result in terms of evacuation time. In fact, we are typically in a case with a bottleneck which is the access to the evacuation points, in particular those of the west center and the South which constitutes two strongly engorged points. We can note that the complete evacuation time is more than 2h30 in all cases, underlying that some traffic jams will last long after the maximal delay (1h). The fact that everyone is leaving at the same time will just create traffic jams more quickly, so more people will decide to change their route and thus participate less in the traffic jam.

However, we observe an expected result: when we increase the delay time (β), the time spent on the roads decreases. Indeed, the traffic jams have already started to disappear when the last agents arrive, so their time spent on the roads is lower. Nevertheless, and this is an interesting result, making the closest agents to the evacuation points leave first have a negative effect ($\alpha = 0.0$). On the contrary, it is in the case of a purely random departure ($\alpha = 1.0$) that we obtain the best results in terms of time spent on the roads: it allows fewer agents coming from the same area to leave at the same time and therefore to get stuck in a congestion. Even if the agent is farther away from its exit point, it will go faster than another agent supposedly closer because it has a lower chance to cross by any traffic jams.

$\alpha \backslash \beta$	0.0	0.2	0.4	0.6	0.8	1.0
0.0	4491 (± 567)	4541 (± 508)	5035 (± 448)	5250 (± 538)	5443 (± 492)	5798 (± 334)
0.2	4503 (± 562)	4603 (± 433)	4774 (± 284)	5256 (± 754)	5398 (± 374)	5785 (± 495)
0.4	4210 (± 344)	4670 (± 501)	4837 (± 506)	4998 (± 536)	5520 (± 674)	5833 (± 593)
0.6	4242 (± 350)	4721 (± 602)	4808 (± 517)	5094 (± 416)	5433 (± 492)	5676 (± 397)
0.8	4342 (± 371)	4724 (± 377)	4642 (± 374)	4912 (± 420)	5209 (± 358)	5763 (± 350)
1.0	4373 (± 494)	4452 (± 472)	4612 (± 433)	4766 (± 425)	5302 (± 453)	5815 (± 431)

Table 3. Mean evacuation time (in seconds) and standard deviation for different values of α and β

$\alpha \backslash \beta$	0.0	0.2	0.4	0.6	0.8	1.0
0.0	1365 (± 43)	1141 (± 43)	958 (± 33)	778 (± 33)	611 (± 37)	522 (± 23)
0.2	1368 (± 40)	1132 (± 32)	948 (± 34)	779 (± 33)	632 (± 26)	538 (± 38)
0.4	1365 (± 36)	1143 (± 27)	943 (± 31)	785 (± 29)	661 (± 24)	569 (± 30)
0.6	1365 (± 35)	1117 (± 41)	918 (± 31)	758 (± 35)	630 (± 36)	527 (± 33)
0.8	1376 (± 33)	1120 (± 43)	853 (± 28)	696 (± 49)	539 (± 32)	436 (± 36)
1.0	1365 (± 33)	1066 (± 34)	810 (± 34)	590 (± 46)	446 (± 35)	410 (± 31)

Table 4. Mean time spent on the roads (in seconds) and standard deviation for different values of α and β

5.4. Optimal scheduling of zones

We saw in the last experiment how evacuation time is impacted by a scheduling tailored on proximity to the evacuation points. However, in addition to not being efficient, such a strategy is difficult to implement as it requires giving to all people a precise time of departure. A simpler strategy is to make evacuations by zone. We propose in this experimentation to divide the Phúc Xá district in several areas and to evacuate the population zone by zone. The challenge is then to determine when and to which evacuation points evacuating the agents from each zone to minimize the evacuation time and the average time spent on the roads.

Concerning the zones' construction, we made the choice to define them according to building's nearest road. We have thus defined a group of buildings (and thus of *Moving agents*) by road. We then fusion the closest contiguous groups until we obtained groups gathering at least 1000 agents.

The 10 zones obtained are presented in Figure 8. We defined thus 10 parameters T_z ranging from 0.0 to 1.0 corresponding to these 10 zones. The departure time of each agent a leaving in the zone $z(a)$ was defined as follows:

$$leavingTime(a) = TIME_MAX \times T_{z(a)} \quad (10)$$

with $TIME_MAX$, the maximum time to start evacuating. Like in the previous experiment, it was set to $1h$.

We used a Genetic algorithm to search for the parameter set that minimizes the evacuation time (we used the one provided within the GAMA platform). The experiment was performed on a classical computer and not on a computing grid or a cluster, which necessarily limited the number of parameter sets tested. Nevertheless, we were able to test about 461 different parameter sets. Figure 9 shows the results obtained with the different parameter sets.

The best solution found resulted in an average evacuation time (over 25 replications) of $3887s$ (standard deviation: $323s$) and an average time spent on the roads of $690s$



Figure 8. 10 zones defined by grouping buildings per closest roads

(standard deviation: 16s). Figure 10 shows the best solutions over the whole explored space: the target defined for each zone and their departure time.

An interesting point with this solution is that it allowed to obtain both a good result on the evacuation time (better than all those obtained whatever the values of α and β) and the time spent on the roads (close to the best results obtained at this level with a very high level of beta and therefore a very long evacuation time). Another interesting element is that the west center evacuation point is not used even though it is the closest exit for many agents. Even though no zone has defined this evacuation point as a reference point, this does not mean that no agent will use it: the process of questioning the path may lead to changing the evacuation point and therefore choosing this particular evacuation point. The access road to this evacuation point is very narrow, which often leads to the generation of major congestion and can explain why this exit is not used. Thus, it is also interesting to look at the road network to see if some minor modifications can improve the evacuation efficiency.

5.5. *Impact of infrastructure modification*

We have already seen that implementing a spatio-temporal evacuation strategy can improve the efficiency of the evacuation process. A final question is whether a minor modification of the road network could lead to a major improvement in the efficiency of the evacuation process. Figure 11 shows the most used roads by the shortest paths from each building to its closest exit. It is possible to see that some roads are particularly critical,

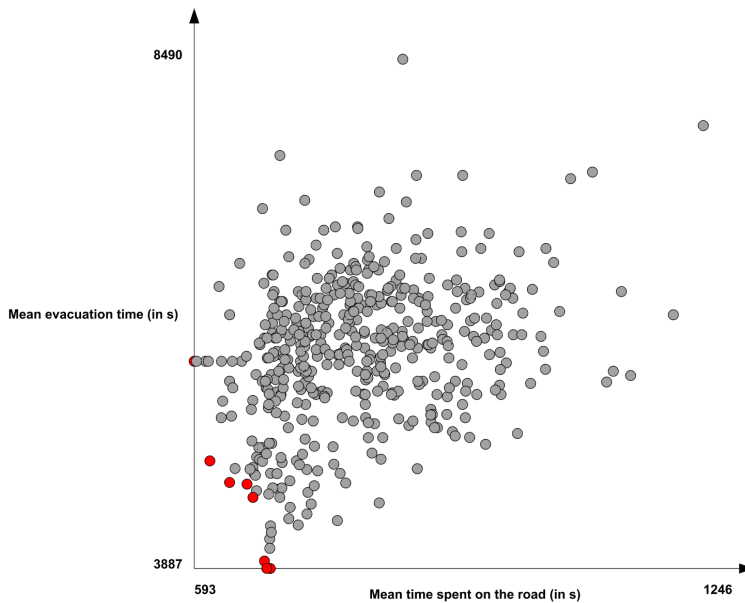


Figure 9. Distribution of the solutions explored according to the evacuation time and the mean time spent on the roads. The red circles are the solution on the Pareto front.

especially those that connect the district to the main road west.

We, therefore, tried to increase the number of lanes on the most used roads. More precisely, starting by the most used ones, we added a lane to roads until we reach a certain "road perimeter threshold" (sum of the perimeters of the roads for which a lane has been added). The district of Phúc Xá includes 50,849m of road. So, we elicit these value for the road perimeter threshold: 0m, 100m, 500m, 1km and 5km. Figure 12 shows in magenta roads for which we added a lane according to these different values of the road perimeter threshold.

Table 5 shows the simulation results obtained for each values of the perimeter threshold.

road perimeter threshold (in m)	evacuation time (in s)	Time spent on the roads (in s)
0	4686 (± 624)	1372 (± 31)
100	3736 (± 550)	1196 (± 22)
500	3643 (± 417)	1178 (± 22)
1000	3307 (± 292)	1132 (± 22)
5000	3383 (± 392)	1090 (± 14)

Table 5. Mean evacuation time (in second) and time spent on roads (in second) with standard deviation for different values of the road perimeter threshold

As shown by the results, adding a lane to the most heavily used roads resulted in substantial improvements in the evacuation time and in the average time spent on the roads. While adding lanes on more roads still improves the evacuation result, this improvement is more negligible as the number of roads increases. There is no significant difference between 1km of roads and 5km.

To conclude this part, it is indeed interesting to work on the improvement of the road network to ease evacuations, and, even, avoid traffic jams in general. Even minor modifications, if concentrated on the right road, can have a significant impact on evacuation, especially in a case like this one, with an enclave with limited exits. It should be noted



Figure 10. best Solution find: the arc represents the chosen evacuation point and the number in the circle the departure time (in minutes)

that Vietnamese major cities are now undergoing major changes on the road network with the widening of many roads, the construction of urban bridges, etc. If the district of Phúc Xá, built in a flood-prone area, was not yet concerned, it is likely that in the future this district will also undergo deep change.

6. Conclusion

We have presented in this paper a model dedicated to the evaluation of spatio-temporal mass-evacuation strategies. A specific focus has been put to consider mixed and non-normative traffic as it can be found in many developing countries. An application for the evacuation of the Phúc Xá district, in Hanoi, Vietnam, was presented. The experiments showed the impact of individual behaviors on questioning followed paths and the interest of setting up evacuation policies by zones. We also showed that even minor modifications of the road network could have a significant impact on the evacuation process.

We plan several enhancements to this model in the future. Indeed, in this proposal we focused mainly on travel behavior without considering other types of behavior. However, many studies have highlighted the effects of panic, non-rational behavior or just poor knowledge of the instructions that could exist. Thus, it would be interesting to enrich the model with more complex behaviors. The fact that our model is based on the ESCAPE framework may allow, as it has been done in (Taillandier *et al.* 2021), to use the BEN (Behavior with Emotions and Norms) architecture which allows the integration of



Figure 11. Road network displaying the shortest path between a building, and its closest evacuation point. The width of the road is proportional to its number of lanes. The spheres represent the evacuation points. The color of roads depends on the number of times they have been part of a shortest path to an exit point: the more it is red, the more it is supposed to be used by the agents to clear out the area.

cognitive, emotional, social and normative dimensions in the behaviors Bourgeois *et al.* (2020).

Another point of improvement concerns the population of agents created: we limited ourselves here to create a realistic number of agents from the population data and the mobility data in Vietnam. It would have been interesting to go further, especially if we wanted to go towards a more realistic model by integrating a real population generation process taking advantage of every available data. In this regard, ESCAPE already integrates the Gen* framework which allows to generate a spatialized and socially structured population Chapuis *et al.* (2018, 2019b).

We also plan to work on the validation of the model. Actually, a recurrent problem with evacuation simulations concerns their validation: it is very rare to see models confronted with real data (only a few articles presented in the state-of-the-art section resort to this). At best, some patterns emerging from simulations are confronted with real observations. A problem for our case study is that although there are real risks for the Phúc Xá district, there has never been a massive evacuation of this district or even exercises performed.

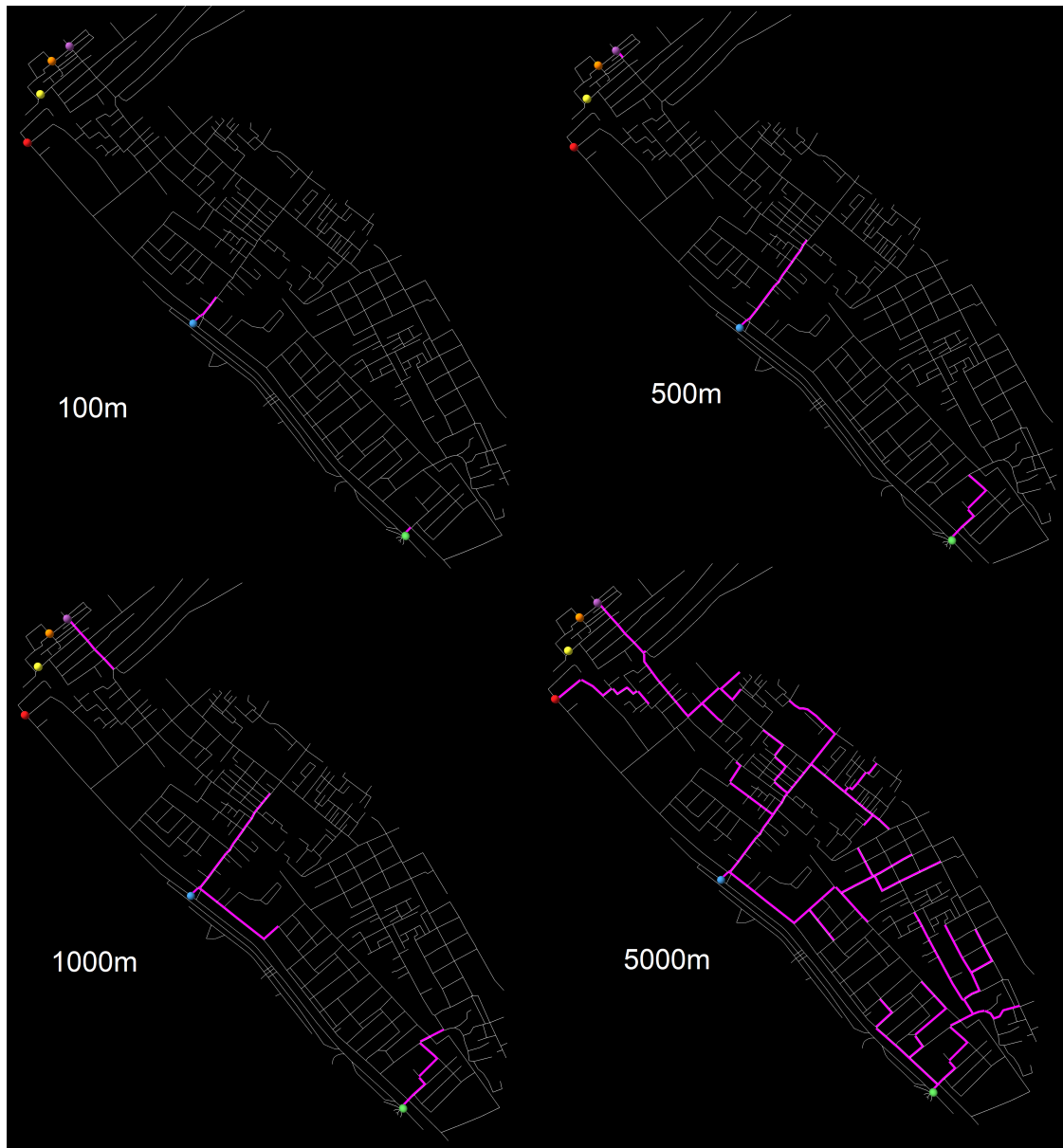


Figure 12. In magenta, roads for which a lane has been added according to the road perimeter threshold

Moreover, as previously said, our paper focuses only on the movements of people in an ideal world where everyone follows the evacuation instructions, which is unlikely to happen in reality. Nevertheless, we have undertaken a validation of the mobility model used. If this one is based on very classical sub-models and already validated on many case-studies (IDM and MOBIL), the general model proposed and the parameter values used, even if they are coming as much as possible from field data, would deserve to be validated. In this regard, we have started a data collection to compare traffic observations with simulations.

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Appendix A. Data on ABM for evacuation in urban area

Reference	Category	Hazard	Territory	Mobility model	Strategy or scenarios tested	number of agents
Al-Zinati and Zalila-Wenkstern (2018)	evacuation	any - not modeled	abstract	car: MATISSE (Al-Zinati and Zalila-Wenkstern 2015)	Road reversal and zoning	3,500
Nakasaka <i>et al.</i> (2020)	evacuation	Flood - not modeled (input)	Umeda area, Osaka, Japan	pedestrian: speed according to density	variation of the number of agents	20,000
Prédhumeau <i>et al.</i> (2021)	mobility model	-	abstract	pedestrian: Social Force Model	-	240
Hesham and Wainer (2021)	mobility model	-	abstract	pedestrian: Centroidal particle dynamics (variant of SFM)	-	900
Pan <i>et al.</i> (2021)	evacuation	any - not modeled	Maglev Transit Lines, China	pedestrian: Pathfinder (Thornton <i>et al.</i> 2011)	Variation of the proportion of small groups in passenger crowd, of the gathering status of small groups and on the the width evacuation walkway.	1,032
West and Sherry (2020)	evacuation	any - not modeled	abstract	Urban Air Mobility System: simple rules	Variation of the proportion of non-compliant agents	1,093
Wang <i>et al.</i> (2020)	evacuation	flood - not modeled	abstract	pedestrian: speed according to density	density of people; risk tolerance; vulnerable people	1,800
Haghpanah <i>et al.</i> (2021)	evacuation and mobility model	Tsunami - not modeled	city of Iquique, Chile	car: simplified car following algorithm; pedestrian: path planning and maximum density for collision avoidance	2 models tested for path planning and collision avoidance	34,000 people and 2,000 cars

Table A1. Synthesis on ABM for evacuation in urban area

Reference	Category	Hazard	Territory	Mobility model	Strategy or scenarios tested	number of agents
Taillandier <i>et al.</i> (2021)	behavior model	flood - modeled	La Ciotat, France	pedestrians and cars: simple move on a network (speed depending on density for car)	proportion of informed people and maintenance of the river and canal	6,145
Yang <i>et al.</i> (2018)	behavior model	flood - modeled	Ng Tung River basin, Hong Kong	household: no movement	different rainfall scenarios	3,294
Oh <i>et al.</i> (2021)	evacuation	flood - not modeled	abstract	car: simplified version of a cellular automaton traffic model (Nagel and Schreckenberg 1992)	comparison between simultaneous evacuation and staged evacuation plan (range of time delays between the evacuation processes of the different zones)	1,500
Makinoshima <i>et al.</i> (2018)	evacuation - Large scale model	tsunami - not modeled	Kesennuma City, Japan	pedestrian: Social force model	-	25,869
Daudé <i>et al.</i> (2019)	evacuation	any - possibility to model it	diverse case-studies	pedestrian: Social force model; car: model derived from the Intelligent Driver Model	-	several thousands
Li <i>et al.</i> (2019)	evacuation	flood - modeled	Niaodao Island	pedestrian: Cellular Automata model	different numbers of agents	up to 34,853
Bernardini <i>et al.</i> (2017)	behavior model	flood - not modeled	abstract	pedestrian: Social Force Model	-	-
Bianchin and Pasqualetti (2020)	evacuation	-	Manhattan, USA	car: SUMO (Behrisch <i>et al.</i> 2011)	Optimization of the duration of green lights at intersections	4,000

Table A2. Synthesis on ABM for evacuation in urban area

Reference	Category	Hazard	Territory	Mobility model	Strategy or scenarios tested	number of agents
Battegazzorre <i>et al.</i> (2021)	evacuation - behavior model - Large scale model	Earthquake - impact modeled	Turin, Italy	pedestrian: speed according to debris and health / characteristics of the agents	location and characteristics of the earthquake, number of ambulances	up to 900,000
Yin <i>et al.</i> (2020)	evacuation	any - not modeled	Huaqiangbei business district in Shenzhen, China	pedestrian: model based on the Reciprocal velocity obstacles (Van den Berg <i>et al.</i> 2008)	Optimization of the evacuation plan	50
Kim and Cho (2020)	evacuation	chemical accident - spatial extent computed by the model	Ulsan, Korea	vehicles: use of TRANSIMS (Smith <i>et al.</i> 1995)	Sensitivity of the proportion of private vehicles, of evacuation departure time period, of phasing policies, and of lane policies	223,083
Parikh <i>et al.</i> (2017)	evacuation - behavior model - Large scale model	Detonation of a nuclear device - not modeled	Washington DC, USA	agent: simple routing model	variation of information and communication	730,833
Chooramun <i>et al.</i> (2019)	evacuation	fire - not modeled	abstract	pedestrian (micro one): based on a steering model (Reynolds <i>et al.</i> 1999)	-	50,000
Aguilar <i>et al.</i> (2019)	evacuation	any, case study for Tsunami and earthquake - not modeled (only the damaged)	Japan	pedestrian and car: based on the computation of a collision-free velocity along a path	variation in the use of cars	57,000

Table A3. Synthesis on ABM for evacuation in urban area

Reference	Category	Hazard	Territory	Mobility model	Strategy or scenarios tested	number of agents
Wijerathne <i>et al.</i> (2018)	evacuation - Large scale model	any - not modeled	Kochi, Japan	pedestrian: based on Optimal Reciprocal Collision Avoidance Van den Berg <i>et al.</i> (2008)	-	10 millions
Sun <i>et al.</i> (2021)	evacuation	Earthquake - not modeled	Huaping community, Xiangzhou District, Zhuhai, China	pedestrian: movement based on a continuum model (with forces and different factors)	variation of the proportion of opportunity exit familiarity of pedestrians	19,948
Veeraswamy <i>et al.</i> (2018)	evacuation	forest fire - not modeled (input of the model)	Swinley forest (south-east England)	pedestrian (micro one): based on a steering model (Reynolds <i>et al.</i> 1999)	scenarios with different routes and critical locations	1220
Yamazaki <i>et al.</i> (2017)	evacuation - behavior model	any - not modeled	abstract	pedestrian: speed defined according to the agent characteristics	variation of different psychology parameters for the population	5,000
Len <i>et al.</i> (2020)	evacuation	Tsunami - not modeled	Via del Mar, Chile	pedestrian (micro) : based on Optimal Reciprocal Collision Avoidance Van den Berg <i>et al.</i> (2008)	-	22,846

Table A4. Synthesis on ABM for evacuation in urban area

Appendix B. Parameter and Attribute values

Attribute name	Value	Commentaries
<i>Total population</i>	21,559	data coming from the General Statistics Office of Vietnam
<i>Probability to use car</i>	0.01	taken by (Hee and Dunn 2017), see Section 2 for more details.
<i>Probability to use motorbike</i>	0.74	taken from (Hee and Dunn 2017), see Section 2 for more details.
<i>Probability to use bicycle</i>	0.19	taken from (Hee and Dunn 2017), see Section 2 for more details.
<i>Probability to walk</i>	0.06	taken from (Hee and Dunn 2017), see Section 2 for more details.
<i>Maximal people per car</i>	6	empirical data.
<i>Maximal people per motorbike</i>	4	empirical data. Corresponds to the classic use of a motorcycle in Vietnam with a family composed of 2 children.
<i>Maximal people per bicycle</i>	1	empirical data.

Table B1. Parameter of the simulations

Attribute name	Pedestrian	Bicycle	Motorbike	Car	Commentaries
<i>length</i> (l_a)	0.28m	1.71m	1.9m m	3.8 m	Sources for pedestrians (Buchmueller and Weidmann 2006), for bicycles (Jin <i>et al.</i> 2015) and for cars and motorbikes Dang-Huu <i>et al.</i> (2020)
<i>Max speed</i> ($max.v_a$)	Gaussian draw with mean of 1.34m/s and standard deviation of 0.26m/s	Gaussian draw with mean of 13.48km/h and standard deviation of 4km/h	70km/h	160km/h	Sources for pedestrians (Bosina and Weidmann 2017) and for bicycles (Jin <i>et al.</i> 2015); for cars and motorcycles, we have taken realistic values for the fleet installed in Vietnam.
<i>Speed coefficient</i> (cv_a)	1.0	1.0	Uniform draw between 0.375 and 0.725	Uniform draw between 0.9 and 1.0 s	pedestrians and bicycles are not influenced by the road speed limitation; for motorbikes data adapted from (Tong <i>et al.</i> 2011) and for car adapted from Dang-Huu <i>et al.</i> (2020)
<i>Number of lanes occupied</i> ($num.l_a$)	1	1	1	2	the typical width for pedestrian is 0.5m, for bicycle is 0.6m, for motorbike is 0.7m and for car is 1.7m (Buchmueller and Weidmann 2006, Dang-Huu <i>et al.</i> 2020, Jin <i>et al.</i> 2015). In order to simplify the model, and considering personal space, we consider that a pedestrian, a bicycle and a motorcycle take 1 lane and a car 2 lanes.
<i>Max acceleration</i> ($max.acc_a$)	Uniform draw from 1.1m/s ² to 1.6m/s ²	Uniform draw from 0.8m/s ² to 1.2m/s ²	Uniform draw from 2.8m/s ² to 5m/s ²	Uniform draw from 3m/s ² to 5m/s ²	Source for pedestrian (Zebala <i>et al.</i> 2012), for bicycle (Parkin and Rotheram 2010), for motorbike (Ngo <i>et al.</i> 2010)

Table B2. Attributes of agent a

Attribute name	Pedestrian	Bicycle	Motorbike	Car	Commentaries
<i>Min safety distance</i> (s_a^0)	0.2	0.2	0.2	0.5m	In the peak periods, Vietnamese are willing to accept to be close to the others. So we have defined low values. Cars are the only ones to keep a minimum distance more important in general.
<i>Time Headway</i> (T_a)	Gaussian draw with a mean of 0.5s and an standard deviation of 0.1s	Gaussian draw with a mean of 0.75s and an standard deviation of 0.4ss	Gaussian draw with a mean of 1.09s and an standard deviation of 0.5s	Gaussian draw with a mean of 1.25s and an standard deviation of 0.5s	Source for motorbikes (Minh <i>et al.</i> 2005). As we do not have data for the other types of agents, we have taken the values for my motorcycles considering that the more maneuverable the agent is, the lower this value is.
<i>Politeness factor</i> (p_a)	0.0	0.05	0.1	0.25 s	lane changes in Vietnam are often abrupt. few drivers look in their mirror before changing lanes. We have therefore set low politeness values - the smaller the agent the less likely he will pay attention to other agents (typical value: between 0.0 and 0.5)
<i>Acceleration gain threshold</i> (thr_a)	0.01	0.05	0.1	0.2	This attribute in the MOBIL model is used to avoid frantic lane change, but frantic lane change is part of the driving in Vietnam (except for cars), so we set low values for this attribute (typical value: 0.2)
<i>Maximum safe deceleration</i> (b_a^{save})	2	2	3	4	use of the typical value for cars of the MOBIL model. We adapted it for other types of agents

Table B3. Attributes of agent a

Attribute name	Pedestrian	Bicycle	Motorbike	Car	Commentaries
<i>Probability use reverse roads (p_{-r_a})</i>	1.0	1.0	1.0	0.0	We consider that cars to avoid maneuvering and getting stuck will not use the reverse road. The other agents can use it if necessary.
<i>Reverse road lane limit (rl_{l_a})</i>	1	1	1	0	We consider that the agents (except for the cars that will not use the reverse roads) will only use one lane of this reverse road once, to let the oncoming vehicles pass.
<i>Time before parking ($time_{-p_a}$)</i>	Uniform draw between 5s and 10s	Uniform draw between 10s and 20	Uniform draw between 10s and 30s	∞	The idea is that the bigger an agent is, the less easily it will let others through. Thus, cars will never try to make a maneuver to let others pass while pedestrians will be the first to do so.
<i>Traffic jam density threshold (tj_a)</i>	0.75	0.75	0.75	∞	As maneuvering in the narrow roads of Phúc Xá is difficult for cars, we consider that they will never recalculate their evacuations points and path.
<i>Tendency to recalculate the evacuation point/path (k_a)</i>	0.01	0.01	0.01	0.0	As maneuvering in the narrow roads of Phúc Xá is difficult for cars, we consider that they will never recalculate their evacuations points and path.

Table B4. Attributes of agent a