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Traffic evacuation simulation based on multi-level driving decision model

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ABSTRACT

Traffic evacuation is a critical task in disaster management. Planning its evacuation in advance requires taking many factors into consideration such as the destination shelter locations and numbers, the number of vehicles to clear, the traffic congestions as well as traffic road configurations. A traffic evacuation simulation tool can provide the emergency managers with the flexibility of exploring various scenarios for identifying more accurate model to plan their evacuation. This paper presents a traffic evacuation simulation system based on integrated multi-level driving-decision models which generate agents' behavior in a unified framework. In this framework, each agent undergoes a Strategic, Cognitive, Tactical and Operational (SCTO) decision process, in order to make a driving decision. An agent's actions are determined by a combination, on each process level, of various existing behavior models widely used in different driving simulation models. A wide spectrum of variability in each agent's decision and driving behaviors, such as in pre-evacuation activities, in choice of route, and in the following or overtaking the car ahead, are represented in the SCTO decision process models to simulate various scenarios. We present the formal model for the agent and the multi-level decision models. A prototype simulation system that reflects the multi-level driving-decision process modeling is developed and implemented. Our SCTO framework is validated by comparing with MATSim tool, and the experimental results of evacuation simulation models are compared with the existing evacuation plan for densely populated Beijing, China in terms of various performance metrics. Our simulation system shows promising results to support emergency managers in designing and evaluating more realistic traffic evacuation plans with multi-level agent's decision models that reflect different levels of individual variability of handling stress situations. The flexible combination of existing behavior and decision models can help generating the best evacuation plan to manage each crisis with unique characteristics, rather than resorting to a fixed evacuation plan.

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1. Introduction

Life-disrupting disasters are an inevitable threat and challenge to human society. Geophysical, biological, chemical or nuclear threats result in great loss of life and economic damages every year. While such eventualities may not be preventable, their reliable prediction could lead to mitigation of casualties. In case of impending disaster events, efficient mass evacuation is necessary. Unfortunately, studies such as Pel et al. (2012) have pointed out the increasing difficulty and time consumption inherent in mass evacuation, due to rising urban populations and density of development, as well as growing road infrastructure. Recent large-scale disasters required mass evacuation responses. For example, the number of people evacuated in the Sichuan earthquake was over 200,000 (Cui et al., 2012) and that in the Fukushima Daiichi nuclear reactor failure reached 300,000 (Thielen, 2012). These emphasize the important tasks in emergency management of moving people in highly populated areas away from disasters rapidly and safely from the scene of such disasters.

Large-scale evacuation, involving hundreds of thousands of motorists on the road, poses a tremendous challenge to emergency response planners. Federal, state, and local departments responsible for developing evacuation plans must enable as many people as possible to flee to safety under pressure, considering both the time it takes for evacuation and the psychological states of people such as anxiety or nervousness. This challenging and complex task is dependent upon elements which include timing between warning and response, procedure for dissemination of information and instructions, availability of planned evacuation routes, traffic flow conditions, dynamic traffic control measures, evacuation time estimates, etc. It also relies on uncontrollable factors, determined in natural and social environments, such as economic conditions and mass psychology (Dash and Gladwin, 2007). During a disaster, individuals seek to save their own lives and social cohesion is tested. Decisions are made without regard to any previous plan for response. During a disaster, although every detail of an evacuation plan affects the evacuees, it is unrealistic to expect such a plan to be fully and perfectly executed.

Agent-based simulation, that represents evacuees as agents and models their behaviors and decisions in a global traffic environment, is an effective tool to help in the exploration of reasonable scenarios. Many simulation models have been applied in Intelligent Transportation System software (Fellendorf, 1994; Fellendorf and Vortisch, 2010; Smith et al., 1995; Halati et al., 1997; Balmer et al., 2009; Cameron and Duncan, 1996). However, the emergency management decision-making mechanism differs from that of normal situations (Murray-Tuite and Wolshon, 2013) where traffic activities are repetitive (e.g., morning and afternoon rush hours, etc.). Decisions under these circumstances usually aim at an efficient utilization of the traffic system. While a wrong decision may lead to a traffic jam, it is less likely to result in tragedy. Emergency evacuation, as an extraordinary measure under dire conditions, can cause more chaos. Studies have pointed out the significant impact of heterogeneity of evacuees' behaviors on the evacuation effectiveness such as delayed clearance time (e.g., Murray-Tuite and Mahmassani, 2003; Yin et al., 2014). Thus, in order to be an effective decision-making tool for both emergency managers and transportation planners, an agent-based simulation tool should provide the capability to model evacuees' driving behaviors and diverse psychological states that may affect the driving behavior decisions during evacuation. The simulation tool can provide response planners with knowledge and capabilities to identify the most plausible scenarios relevant to the disaster characteristics for both planning and execution.

The evacuation behavior of evacuees consists of multiple types and levels of planning and decision making, before or during an evacuation. Before evacuation, they must decide on their necessity to evacuate, on their instructed destination, and on their time of departure. During evacuation, they must choose a route to their destination and they must consider events, such as a traffic jam. While driving their vehicles, they must decide whether to follow a car ahead of them or to change lanes. A driver's response depends on multitude of decisions that select one from these various behaviors, observed external factors, and the evacuation contexts. Car following and lane changing behaviors for example, while affecting evacuation clearance time (Tu et al., 2010), are not as critical as decisions of destination and route choice in a large-scale evacuation. Some psychological conditions, such as panic, may be highly critical during no-noticed evacuations. In multi-agent evacuation simulation system, ESCAPES (Tsai et al., 2011), fear felt by an individual agent due to the uncertainty of emergency situation and concerns of one's safety is modeled. They propose an emotional model to simulate agent's decision making and behaviors in airport evacuation scenarios that are influenced by the inherited fear from other agents. In pedestrian evacuation, panic causes people to exhibit more irrational behaviors driven by short-term personal interests, due to the reduced attention and fear in emergency situations, and to exhibit nervousness, resorting to other people's behaviors, i.e., herding phenomenon (Helbing et al., 2002).

In this paper we propose a *multi-level agent driving decision framework* for traffic simulation to support emergency evacuation planning. We further show how this framework enables the simulation of complex and realistic agents' driving behaviors during emergency situations. We have designed and implemented a traffic simulation system based on this framework and have tested it under various emergency scenarios in order to identify traffic jam locations and to help develop strategies for selecting shelters. Our system employs microscopic traffic models where a single vehicle-driver is represented by an agent. Multi-level decision models, including strategic, cognitive, tactical and operational levels are proposed for each agent to simulate the evacuation. Each agent's decisions, ranging from those of pre-evacuation activities and choice of evacuation route, to decisions as to following or overtaking, can thus be captured and dealt with, out of a wide spectrum of behaviors.

The paper is organized as follows. Related work is discussed in Section 2. The proposed framework and the system architecture for evacuation decision support are discussed in Section 3. Section 4 includes definitions of agent and driving behavior models. This is followed by a discussion of multi-level driving decisions in Section 5. The validation of the framework is included in Section 6. The details of our experiments are discussed in Section 7, and our conclusions are presented in Section 8.

2. Related work

We organize our review of the related literature into 6 categories: evacuee's decisions, route choices, driving behaviors, mental factors and variability, traffic simulation software, and model integration. Before evacuation, an evacuee usually has to decide on whether or not to evacuate (trip generation decision), where to evacuate (destination choice), how to evacuate (evacuation mode choice), and when to evacuate (departure time choice) (Murray-Tuite and Wolshon, 2013). These decisions are often made at the household level, especially in large-scale evacuations (e.g., hurricane evacuations). Hasan et al. (2010) applied a mixed (random-parameters) logit model to the choice of trip generation due to a hurricane threat, and found several important factors influencing evacuee's trip generation. The random parameters in the model are used to represent the heterogeneity of households' responses. Using a similar method, they introduced random parameters in hazard-based duration models and discussed some influential factors as to choice of departure time (Hasan et al., 2013). Mesa-Arango et al. (2012) used a nested logit model to determine the number of households heading to different destination types (e.g., friend's houses, hotels, public shelters, churches, etc.). Using actual data from Hurricane Ivan, they identified the relationship between the household's characteristics and their destination type choice. Similarly, Sadri et al. (2014) applied a nested logit model to evacuee's mode choice. They considered non-household transportation modes such as special evacuation buses, taxis, and regular buses. Applying a small sample survey, they found that there exist several strong relationships between the evacuee's characteristics and their mode choice.

Yin et al. (2014) proposed an agent-based decision framework to describe all of these pre-evacuation decisions. Their framework is capable of estimating the movements of evacuees who are not part of the required evacuation, known as shadow evacuations (Zeigler et al., 1981). Murray-Tuite and Mahmassani (2003) pointed out that families tend to assemble prior to an evacuation, and that a household's decision as to meeting place plays a crucial role in the assignment of persons to vehicles in which they would be picked up. Such behaviors are referred to as being of a trip chain, or an intermediate trip. The authors presented an evacuation simulation model which incorporated household trip-chaining behavior in an emergency situation (Murray-Tuite and Mahmassani, 2004). Lindell and Prater (2007) summarized some principal behavioral variables affecting hurricane evacuation time estimate in the decisions of trip generation, departure time, and destination choice. They pointed out that the research on household evacuation has focused on a very few behavioral variables. In these studies, the heterogeneity of evacuees and their behaviors was a subject of much attention and variability among evacuees is considered in many different ways.

With respect to route choice, researchers considered two different perspectives: global view and evacuee's view. At the global level, researchers seek an optimal solution minimizing clearance time. Balakrishna et al. (2008) applied a dynamic traffic assignment model to the improvement of transportation network performance. Their model is capable of addressing the need for one that is robust and can be used under a wide range of mitigation measures (e.g., contraflow, and signal priority). Hsu and Peeta (2015) used dynamic network flow problems (DNFPs) to map out routing strategies. Their model focuses on finding the quickest flow by inferring the risk of different evacuation areas and estimating the clearance time. Macroscopic methods are often used in global route strategies to simplify the problem, usually arriving at a certain solution. In an evacuee's view, however, route choice is considered complex, or random. Sadri et al. (2013) pointed out that evacuees may not follow a recommended route but may take a usual or familiar one instead, or they may change their mind and switch to another when they observe longer than expected traffic delays on their intended. The proportion of evacuees who are willing to follow a recommended route can have a world of difference in different areas (Sadri et al., 2014; Carnegie and Deka, 2010). These studies show the difference between a global optimal solution of route strategy and the heterogeneity of evacuees' actual route choices.

Many simulation models have focused on traffic flow models, i.e., how vehicles move on the road network. Car-following models (e.g., Gipps, 1981; Addison and Low, 1998; Treiber et al., 2000; Bando et al., 1995) are a kind of continuous function describing the process of how vehicles follow one another in a single lane. They have been developed based on different assumptions so that they perform slightly differently from each other. For example, Addison and Low's model assumed a car-following regime only, i.e., that a follower maintains a desired distance while synchronizing his/her speed with that of the leader. On the other hand, Gipps' model is based on both a car-following regime and a free-driving regime, i.e., a driver accelerates to or drives at the desired speed if the leader is far from him/her (Ossen and Hoogendoorn, 2011). Lane-changing models such as MOBIL (Kesting et al., 2007), describe when and how drivers change their lanes, and are usually used in combination with car-following models.

Some other models such as Doniec's model (Doniec et al., 2008) expanded the scope of car-following models from roads to crowded intersections. Cellular Automata models (CA model) describe the position of vehicles within the change of cellular status, and are suitable for situations such as traffic intersections (Ruskin and Wang, 2002) and mixed traffic flow (Vasic and Ruskin, 2012). Tu et al. (2010) discussed the impact of traffic flow model parameters on evacuation clearance time, finding that reduction of mean headway and minimum gap can significantly reduce clearance time. They showed that driving behavior should be considered as a condition in an evacuation plan. These models, varying in scope of use, provide a broad background on driver performance during an evacuation.

Emergency officials must realize how differently evacuees behave. Driving variability increases the possibility that evacuees will not follow an ideal evacuation plan, that they may vary their actions and make independent decisions which may deviate from an ideal evacuation plan. A driver's mental state is considered an important determinant for the variability of his driving during an evacuation. Dynamic or random parameters are often used to describe variability among drivers. Ossen and Hoogendoorn (2011) discussed drivers' heterogeneity in car-following behaviors, proposing some hypotheses related to the group of passenger cars, different vehicle types, and leader-follower pair composition. Treiber and Helbing (2003) took into account memory effects in the change of driving behaviors over time. Danaf et al. (2015) applied the state-trait anger theory (Spielberger et al., 1983) to develop a choice-latent variable model, to analyze the causes of aggressive driving and to forecast its manifestations. The anger was presented as a dynamic continuous latent variable, changing over time, dependent on a driver's experience on the road, and affecting his/her behavior and decisions. Li et al. (2014) associated drivers' characteristics (e.g., age, gender, driving age, and mood) and situational factors (e.g., weather, congestion, and respect for law) with a set of changeable parameters in car-following and lane-changing models, and applied it to changing drivers' behaviors in a multi-agent simulation. Tawfik et al. (2010) showed that route choice is not a rational behavior. They carried out an experiment on the relationship between drivers' perceptions of different parameters and the variety of routing decisions, demonstrating that route choice is not identical to drivers' perceptions. Dia (2002) proposed a belief-desire-intention architecture, in a cognitive (mental model-based) agent-based approach, to describe a model of drivers' choice as to alternative routes based on real-time information. Each driver's route choice decision-making capabilities, based on his/her perceptions of his/her environment, were similar to the described intentions of the driver it represented, demonstrating the feasibility of using autonomous agents to model dynamic route choices. By modeling the variety of drivers and evacuees, emergency officials may gain a better understanding of their plan and improve its robustness.

Traffic simulation software tools, of proven capability in complex systems across a range of urban environments, include, for microscopic study: PARAMICS (Cameron and Duncan, 1996), CORSIM (Halati et al., 1997), VISSIM (Fellendorf, 1994; Fellendorf and Vortisch, 2010), MITSIMLab (Jha et al., 2004), TRANSIMS (Smith et al., 1995), and MATSim (Balmer et al., 2009; Lämmel et al., 2010), and for meso-scopic or macroscopic study: DynusT and DYNASMART (Hsu and Peeta, 2015), DynaMIT (Balakrishna et al., 2008), and TransCAD (Andrews et al., 2010). While those who focus on emergency evacuation are using such tools as their implementation platform, they often rely on pre-specified rules of behavior (Murray-Tuite and Wolshon, 2013) and they are limited in representing the heterogeneity of evacuees (Zhang et al., 2009).

Some simulation studies use a multi-model integration approach in order to capture complex driving behaviors which consider various scenarios, re-using existing behavior models as atomic components. This integration model can use different combinations of existing driving, route choice, and psychological models that are suitable for more realistic simulation scenarios involving differences in vehicles, time, or environments. For example, Traffic Simulation Framework (Gora, 2012) supports the selection of cellular automata models in a traffic simulation, while Open Traffic (Tamminga et al., 2012) is an open-source framework for a modular approach of combining travel choice behavior models and car-following models. Pan et al. (2007) proposed a simulation framework for pedestrian evacuation, which classified the behavior of the evacuees into locomotion, steering, and social. Although it is a challenging task to combine various models with different perspectives and different levels of granularity, these integration models discussed in the literature show the interests in, and feasibility of, applying model integration to evacuation simulation.

In earlier years, Wahle et al. (1999) proposed a two-layer agent architecture for integrating individual driver behaviors and decisions. The first layer (tactical) can be modeled by any microscopic traffic flow models, describing the perception and reaction of the drivers. The second layer (strategic) is responsible for information assimilation and the decision-making process. Yuan et al. (2014) designed a meta-model framework for traffic simulation in emergency evacuations, utilizing multi-level agent decisions to select individual driving behaviors. Based on the concept of multi-layer decision and model integration in these two works, we present a formal model of agent-based driving behavior using multi-level decision process that reuses and flexibly combines existing behavior models, including evacuee's decisions, route choices, and traffic flow models. Driving variability of each agent is modeled through different decisions making perspectives from each layer.

3. Traffic simulation architecture for evacuation decision support

As mentioned above, agent-based simulation systems for traffic evacuation can support an emergency management team in exploring and visualizing realistic scenarios, as well as in analyzing different evacuation plans according to a set of evaluation criteria. Our proposed integrated simulation system includes four key components: geospatial manager, agent manager, behavior manager, and mission manager (shown in Fig. 1). Together they provide the capability to simulate complex scenarios.

- **Geospatial Manager.** This component is designed to generate and utilize an evacuation roadmap and initial traffic scenarios. The roadmap describes traffic as a directed graphic structure in which arcs refer to roads and nodes refer to intersections. The system supports Shapefile, one of the standard geospatial vector data formats, so that open traffic roadmaps can be imported from Geographic Information Systems (GIS). The scenario database (DB) provides the initial distribution

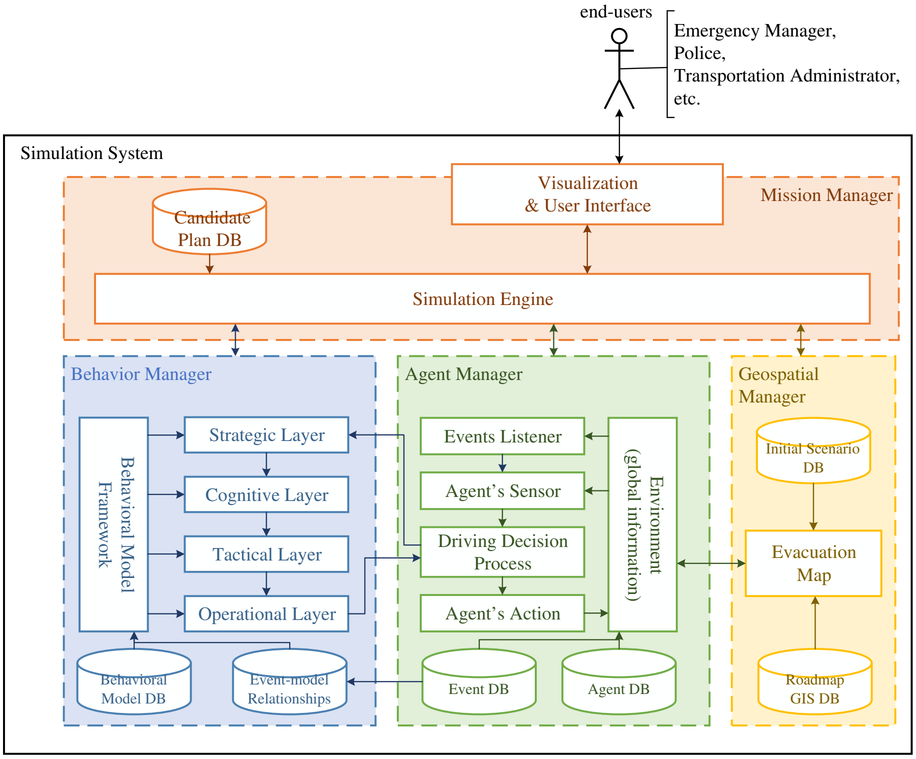


Fig. 1. Components and architecture of the simulation system.

of agents (i.e., evacuees, cars). Users are able to apply various initial scenarios on a roadmap, for example, three typical traffic distributions on rush hours, daytime, and nighttime. The system thus generates flexible scenarios for different city roadmaps.

- **Agent Manager.** This component manages all agents and the dynamic environment affected by them, performing the following five functions:
  1. Generate/destroy agents. An agent database provides all of the potential vehicle types in the simulation, e.g., cars, SUVs, vans, buses. At the start of the simulation, the manager generates agents according to the initial scenarios. When the agents complete their trips, e.g., getting to evacuation shelters or other safe places, they are destroyed by the manager to release the computation resources.
  2. Update agents' parameters. The agent manager also updates agents' physical and psychological parameters such as location, speed and nervousness. Each agent has a simulated sensor which observes local information about nearby agents at the beginning of every time interval. In each time step agents make their driving decisions according to a process which applies and changes parameters of the behavioral models. Section 4 discusses the details of agent's parameters and the updating process.
  3. Manage events. The agent manager also maintains and controls an event database which defines a set of events which may affect an agent's behavior, for example, a heavy traffic jam, or a full-capacity alert from a crowded shelter. An event listener is set up for tracking all environmental events.
  4. Communicate with agents. The system provides a broadcast messaging function for the agent manager. Agents are able to receive messages from the agent manager anytime during the simulation.
  5. Collect statistical information. The agent manager monitors and collects statistical data on the environment, e.g., the flow speed of every road segment and the number of evacuees left in dangerous areas. The data is made available to end users via the graphical user interfaces in mission manager.
- **Behavior Manager.** This component manages a model base with all behavioral models that can be applied in a simulation task. Three of these model types are: traffic flow (e.g., car-following models), cognitive (e.g., nervousness models) and decision (e.g., route choice models and destination choice models). It manages the event-model relationship database which links the events from the agent manager to all of the potential behavioral models that can respond to them. For example, a heavy traffic jam may lead an agent to change their route (route choice models), or keep waiting in road (car-following models). Since there are a large number of models representing various perspectives, a behavioral model framework is designed to organize all of the models in a unified architecture. The event to model relationship mapping

can be configured to achieve the intended driving behaviors during the simulation. The behavior manager interprets the agent's parameters and triggering events, invoking the corresponding models. Section 5 presents the architecture and workflow of the behavior manager.

- **Mission Manager.** It manages a plan database, allowing users to define the configuration, and interacting with the system. The plan database stores all of the global configurations for simulation scenarios which end users (e.g., emergency manager) intend to apply or to compare. A visualization component enables users to track scenarios graphically, controlling the initial conditions. It sets up candidate plans, the loop of the simulation tasks, ending conditions, animation of the traffic, and diagrams of numerical results.

The seven databases in our architecture, in Fig. 1, provide all of the system's requirements to begin a simulation task. Specifically, the roadmap DB contains the roadmap of the evacuation area; the scenario DB contains a set of possible distributions of vehicles, their initial locations and parameters; the agent DB stores different types of agents; the plan DB contains a set of parameters on mass evacuation decisions: locations of shelters, types of evacuation (e.g., mandatory or not), routes to them, etc.; the behavioral model DB comprises a set of widely used behavioral models; the event DB includes a set of events which may affect driver's decisions; and the event-model relationship DB contains the relationship between every event and each potential behavior responsible to it.

During the initial phase of the simulation, the system chooses one evacuation plan and one scenario from the plan DB and the scenario DB respectively. The simulation repeats the agent's decision process at regular time intervals until a set of ending conditions is reached, for example, all of the agents arriving at shelters. At each time interval, all of the agents choose a driving behavior and arrive a new status and parameters according to the behavioral models updating the critical data. The same process is executed for each combination of candidate plan and initial scenario, ensuring that every initial scenario, under the guide of every candidate plan, will be simulated separately. Finally, a simulation's animation and visualization statistics are delivered to emergency managers for further analysis and comparison.

4. Agent and driving behavior models

We model a vehicle as an *agent* represented by a set of attributes: static, dynamic and environmental.

Definition 1 (*Agent*). An agent a is represented by tuple, $\boldsymbol{a} = \langle \boldsymbol{p_s}, \boldsymbol{p_d}, \boldsymbol{p_e} \rangle$, where p_s, or static parameters, represents the agent's attributes whose values remain unchanged during the entire simulation process, p_d, or dynamic parameters, represents the agent's attributes whose values may change during the simulation, p_e, or environmental parameters, represents the agent's attributes whose values come from the environment.

Table 1 lists the agent parameters used in our simulation model. Examples of $\boldsymbol{p_s}$ include physical attributes of a vehicle and its driving limitations. Examples of $\boldsymbol{p_d}$ include a driver's mental and physical status. For instance, nervousness value is a fuzzy value from 0 to 1 to measure an agent's state of nervousness, according to the Helbing's Model (Helbing et al., 2002). A larger number stands for a more nervous state. Examples of $\boldsymbol{p_e}$ include traffic conditions, driving constraints and evacuation information.

The system simulates a traffic scenario, updating agents' parameters at each time step, according to a *behavioral model*, consisting of both driving models and psychological models.

Definition 2 (*Behavioral Model*). A behavioral model, $m: \ \boldsymbol{a}^{(t)} = \langle \boldsymbol{p_s}, \boldsymbol{p_d}^{(t)}, \boldsymbol{p_e} \rangle \mapsto \boldsymbol{p_d}^{(t+1)}$, is a function that changes p_d in agent a from time t to time t+1. A model base $\mathbb{M} = \{\mathbb{m}_1, \mathbb{m}_2, \ldots\}$ is defined as a set of driver's behavioral models.

The current implementation of the system includes a base of the six widely used behavioral models listed in Table 2. The shortest path is implemented using the A$*$ Pathfinding Model (Hart et al., 1968). The potential network model (Dommety and Jain, 1998) uses a road's mean transit time as a weight to build a potential network and to let agents traverse a path in the theoretical minimum time, like a GPS device that provides an agent with global traffic information. Gipps' Model (Gipps, 1981) of car-following helps an agent to keep a safe driving distance behind the car ahead of it. Doniec's Intersection Model (Doniec et al., 2008) is a rule-based simulator of drivers' behavior in turning at an intersection. Lv's Model (Lv et al., 2013) describes a microscopic lane-changing process of an agent changing its lane for overtaking or preparing for turning. Helbing's Model (Helbing et al., 2002) uses the nervousness value to change agent's other parameters. It is worth noting that these models are selected as illustrative of our framework's capability to integrate different behavioral models. Our framework is flexible and general enough to accommodate other models pursuant to specific evacuation contexts.

An external function is required in m_6 to change the nervousness value. This paper assumes that it follows the logistic differential function and changes based on agent's driving speed, increasing if the agent moves slowly, decreasing if quickly.

$$\frac{d\mu_i(t)}{dt} = (2\eta_i(t) - 1)\frac{1}{t_r}\mu_i(t)(1 - \mu_i(t)), \qquad \mu_i(0) = \mu_i^{(0)} \tag{1}$$

Table 1
Agent parameters in the current implementation of the system.

Parameter	Range	Notation
Static attributes		
Low speed threshold (m/s)	(0, 50)	V_{low}
Safety reaction time (s)	[0, 4]	h
Reaction time (s)	[0.5, 3]	t_R
Maximum lane changing angle (degree)	[5, 20]	θ_M
Dynamic attributes		
Maximum desired acceleration of the following car (m/s^2)	[0.5, 4]	acc
Maximum desired deceleration of the following car (m/s^2)	[−6, 0]	b
Maximum desired deceleration of the leading car (m/s^2)	[−6, 0]	$b^{(n-1)}$
Distance at standstill (m)	[4, 15]	g
Nervousness value	(0, 1)	μ
Position (latitude and longitude)	–	Pos
Speed (m/s)	(0, 50)	v
Lane changing angle (degree)	[0, 20]	θ
Destination	–	sd
Environmental attributes		
Evacuation time (s)	(0, ∞)	t
Distance from the front car (m)	(0, ∞)	gap
Average speed in the current road (m/s)	(0, 50)	v

Table 2
Behavioral model base in the current implementation of the system.

Notation	Model name	Description
m_1	Shortest Path	Give the shortest path to get to the destination (Hart et al., 1968)
m_2	Potential Network	Give a suggest route like a GPS device (Dommety and Jain, 1998)
m_3	Gipps' Model	A car-following model by Gipps (1981)
m_4	Doniec's Intersection Model	A model for intersections by Doniec et al. (2008)
m_5	Lv's Lane-changing Model	A lane-changing model by Lv et al. (2013)
m_6	Nervousness Model	A psychological model by Helbing et al. (2002)

$$\eta_i(t) = \begin{cases} 0, & v_i(t) \geqslant V_{low}, \\ 1, & otherwise. \end{cases} \tag{2}$$

where t is the simulation time, μ is the nervousness value of agent i, $\mu_i^{(0)}$ is the initial value of μ_i, t_r is the nervousness reaction time which refers to the time of an agent's gaining its nervousness from 0.5 to $1/(1+e^{-1}) \approx 0.731$, V_{low} is the threshold of speed at which an agent thinks that it is driving slowly, and $\mu_i(t)$ is the event that agent i drives at low speed.

The maximum nervousness value of each agent is recorded during simulation. An agent whose maximum nervousness value is greater than 0.8 is regarded as a "*panic*" agent.

$$\mu^{(M)}(i) = \max_t \mu_i(t) \tag{3}$$

$$\text{Panic}(i) = \begin{cases} 1, & \mu^{(M)}(i) \geqslant 0.8 \\ 0, & otherwise. \end{cases} \tag{4}$$

where i is the agent's id number, $\mu_i(t)$ is the nervousness value of agent i at time t, $\mu^{(M)}(i)$ is the maximum nervousness value of agent i, and $Panic(i)$ is a panic flag indicating that agent i is in a panic state.

Each agent decides on a *behavior pattern*, as a driving strategy, that can be achieved by a combination of driving actions (models) and an *event* to trigger agents' patterns among differing alternatives.

Definition 3 (*Behavior Pattern*). A behavior pattern λ is defined as a course of behavioral models: $\lambda \in 2^{\mathbb{M}}$, where $\mathbb{M}$ is a set of behavior models and $2\mathbb{M}$ is the power set of $\mathbb{M}$. An alternative base $\Lambda = \{\lambda_1, \lambda_2, \ldots\}$ is defined as a set of driving behavior patterns.

Table 3 lists the relationship between the alternative patterns and the behavioral models in our system.

Definition 4 (*Event*). An event is a characteristic function $\xi: \ \boldsymbol{a} = \langle \boldsymbol{p_s}, \boldsymbol{p_d}, \boldsymbol{p_e} \rangle \mapsto e \in \{0, 1\}$, which determines whether the event is present or absent depending on the parameters of agent a. An event base $\Xi = \{\xi_1, \xi_2, \ldots\}$ is defined as a set of events.

The current system defines five events in the event database, which describe a basic interactive environment for all the agents. Table 4 lists a description of each event.

5. Multi-level driving decisions

During simulation each agent follows an agent-based driving decision process to generate its own alternative behavior patterns within a given time interval and to update each agent's parameters. Below we define Strategic, Cognitive, Tactical, and Operational (SCTO) Process.

Definition 5 (*SCTO Process*). An agent-based driving decision process, denoted as $\mathcal{P}$, is defined as an ordered tuple $\mathcal{S}, \mathcal{C}, \mathcal{T}, \mathcal{O}$, where

$\mathcal{S} : \boldsymbol{a} \mapsto (sd_i, t_d)$, represent an evacuee's strategic decision that selects an evacuation destination sd_i and the departure time t_d.
$\mathcal{C} : \boldsymbol{a}, \xi(\boldsymbol{a}) \mapsto \lambda \in \Lambda$ represents an evacuation cognitive process to consider and select a driving behavior pattern λ among alternative base Λ according to the triggered events $\xi(.)$.
$\mathcal{T} : \boldsymbol{a}^{(t)}, \lambda \mapsto \bigvee_{m \in \lambda} m(\boldsymbol{a}^{(t)}) = \boldsymbol{p}_d^{(t+1)}$ represents an agent's tactical decision to apply a driving behavioral model m, and
$\mathcal{O} : \boldsymbol{a}^{(t)}, \boldsymbol{p}_d^{(t+1)} \mapsto \boldsymbol{a}^{(t+1)}$ represents an operational process to update every agent's status.

The architecture of the multi-level driving decision process is shown in Fig. 2. Behavior Manager is the component responsible for carrying out all of these critical functions. It consists of four layers, each of which respectively contains a sub-process of $\mathcal{S}$, $\mathcal{C}$, $\mathcal{T}$ and $\mathcal{O}$. It is able to answer the following four general questions that may be encountered in any traffic model.

1. *Strategic* layer: Where should an agent drive to, given the current status?
2. *Cognitive* layer: Which driving behavior pattern does the agent desire to select among alternative choices to achieve its goal?
3. *Tactical* layer: Which behavior model should the agent execute for a selected behavior pattern?
4. *Operational* layer: What are the agent's new parameters after executing a behavior model?

These four questions are a top-down guideline directing an agent's driving behaviors. According to the driving decision model, which is discussed above, the constraints of the first question, i.e., the current status, are given by the current agent's parameters $\boldsymbol{p_s}$ and $\boldsymbol{p_d^{(t)}}$ as well as the extracted information $\boldsymbol{p_e}$ from the sensor. The answer to the last question, i.e., the updated parameters, is the agent's new parameters $\boldsymbol{p_d^{(t+1)}}$. Therefore, an agent's behavior decision is equivalent to a process of answering these four questions. Examples of behavior models in each layer of the SCTO process include evacuation planning models, evacuee's destination choice models, route choice models, and traffic flow models. The model chosen from a higher layer is interconnected with the models in the following layer as shown in Table 3 (see also Fig. 10).

The models in different layers require different time scales. For example, destination choices are always made before evacuation and do not change during evacuation. Behavior patterns only change when some specific events occur. Driving actions, however, happen in almost every time interval. In the framework, each layer has a trigger condition and a layer is activated only if the condition is met.

Fig. 3 shows how the agents in the Agent Manager operate during each time interval. A sensor observes and reports environmental information (i.e., $\boldsymbol{p_e}$) about nearby agents at the beginning of every time interval. The function *Decide & Update* interfaces with the behavior manager to select and execute a behavior model, and updates dynamic parameters from $\boldsymbol{p_d^{(t)}}$ to $\boldsymbol{p_d^{(t+1)}}$. At the end of every time interval, the sensor collects an agent's new parameters $\boldsymbol{p_d^{(t+1)}}$ and sends them to the environment function subsystem for the calculations of the next time interval. The agent manager sends notification messages to all agents. For example, if a shelter is full, the agent manager sends a broadcast message.

Below we describe the four layers for the agent's driving decision process in more details.

Table 3
Alternative behavior patterns and corresponding driving behavior models.

Notation	Behavior patterns	m_1	m_2	m_3	m_4	m_5	m_6
λ_1	Follow the shortest path	+					
λ_2	Follow an emulated GPS device		+				
λ_3	Follow a leading car			+			+
λ_4	Overtake			+		+	+
λ_5	Turn in line			+	+		+
λ_6	Turn ignoring line				+	+	+

Table 4
Events in the current implementation of the system.

Notation	Name	Description
ξ_1	Default driving	Agent encounters no environmental change
ξ_2	Navigation request	Agent is required to determine his route to his target
ξ_3	Low speed in lane	Agent's speed is less than V_{low}
ξ_4	Turning at intersection	Agent is preparing to turn at an intersection
ξ_5	Full capacity of shelter	Agent's target shelter is full and cannot accommodate him/her

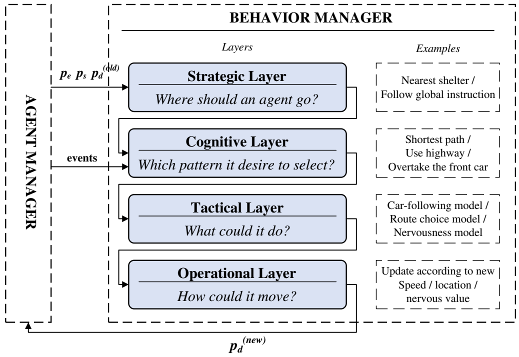


Fig. 2. Architecture of the agent-based driving decision process.

5.1. Strategic layer

The Strategic layer focuses on the overall decision behavior of how an agent determines its destination (e.g., shelter to evacuate) and departure time. A global mandatory decision plan specifies a shelter location for each agent, while a voluntary evacuation plan allows an agent to choose a destination shelter. The Strategic layer is invoked if an agent chooses to decide where to evacuate by applying the process $\mathcal{S}$ according to Definition 5. In large scale evacuations, decisions in the strategic layer are often made at the household level. In these cases, all agents with the same household attributes get the same output of function $\mathcal{S}$. This layer can apply different decision functions to enable the representation of various scenarios. For example, if all of the agents select the target shelters on their own, it will be an unplanned voluntary evacuation. In this case, an agent's decision uses a default function to identify the nearest shelter's location.

$$\mathcal{S}(a_i) = \text{argmax}_{sd_j}\left(\frac{\text{distance}(a_i, sd_j)}{1\text{ km}} + 1\right)^{-1}, \tag{5}$$

where distance is the shortest length from shelter sd_j to agent a_i. If a plan is mandatory, a global function $\mathcal{S}$ assigns a shelter location to each agent; if merely suggested, an agent uses a combination of these two different functions.

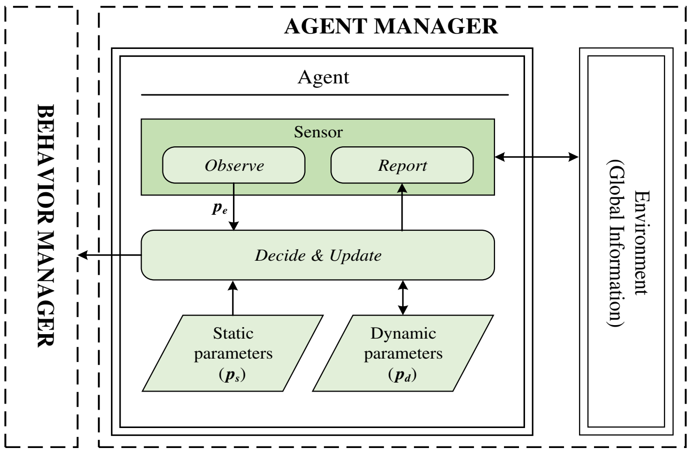


Fig. 3. Architecture of the agent manager.

The departure time for each evacuee is, by default, set to 0 for immediate evacuation. It is possible to apply a distributed departure model, such as an "S"-curve (Sorensen, 2000), to assign a departure time for each agent.

The strategic layer is also able to model trip generations and intermediate trips. For example, agents deciding to not evacuate can be described by simply setting their destinations to their current locations. Intermediate trips can be modeled as a chain of destinations and corresponding departure time.

The basic process of the decision layer is shown in Fig. 4.

5.2. Cognitive layer

The Cognitive Layer focuses on behavior patterns which agents desire to select on their way to their destinations. In this layer, agents strategize as to how to achieve their goal of reaching their final destinations, e.g., route selection. Agents do not change their patterns at every time interval, rather, some decisions are triggered from the *event*, pursuant to Definition 4, e.g., a route choice decision is necessary only if an agent is at an intersection. All events are defined in the event DB.

If an event ξ_i is triggered (i.e., $\xi_i(a) = 1$), there are several alternative driving behavior patterns $\Lambda = \{\lambda_1, \lambda_2, \ldots\}$ to respond to it. An agent needs to choose one alternative λ_j as the answer. To make a decision on which alternative behavior pattern to use for an event, the agent uses a desire function. The desire function is defined as:

$$\text{desire}: \ (\boldsymbol{a}; \xi_i) \mapsto \lambda_j \in \Lambda_i \tag{6}$$

where *desire* is the function of alternative λ_j in event ξ_i, and Λ_i is the alternative behavior patterns in event *i*. Suppose the amount of the potential behavior patterns is *n*, then the agent chooses an alternative among all the n alternatives in the triggered event ξ_i.

$$\mathcal{C}(\boldsymbol{a}) = \text{desire}(\boldsymbol{a}; \xi_i), \text{s.t.} \xi_i(\boldsymbol{a}) = 1. \tag{7}$$

The Cognitive layer is crucial in modeling the variability of different agents' behaviors. An agent's driving behavior model depends on its rational decisions, as to how to respond to various types of events resulting from interactions between agents and their environments, as well as on its irrational decisions motivated by nervousness and panic. Some group psychological phenomenon such as herding can be captured in this layer. The behavior of ignoring traffic lights, for instance, results in an event at that intersection. Drivers arriving at that intersection, at that moment, must respond to that event by either herding or not herding.

In the current implementation, alternative behavior patterns chosen by an agent, i.e., the desire function, are determined by the state of whether or not the agent is in panic, derived from the formula (1)–(4). The relationships between events and alternative behavior patterns are stored in the relationship database, as shown in Table 5. In the current implementation, the alternative behavior pattern chosen by the agents who are not in panic is considered a rational choice, and the alternative behavior pattern chosen by agents who are in panic are considered an irrational choice. For instance, among alternative behavior patterns for event ξ_3, such as "λ_3: Follow a leading car" vs. "λ_4: Overtake", the agent chooses "Overtake" behavior pattern when it is in panic. This basic desire function to describe rational and irrational choices can be extended to support more complex decision-making model (e.g., rational, bounded rational, or fully irrational), considering other parameters such as herding.

The Cognitive Layer effectively generates behavior variability. Minute differences in an agent's attributes may lead to significant changes in an evacuee's behaviors. During a simulation, a few of the agents may trigger an event which influences a larger group. Each affected agent can then choose a different alternative behavior pattern. In this way, the Cognitive Layer creates complicated and dynamic traffic scenarios, greatly enhancing the variability of agent's behaviors. For example, when a target shelter is determined, a decision on a route choice is made by selecting from the available alternative models (e.g., the shortest path model, or potential network model). When a slow car is in front of an agent, that agent may adopt, for

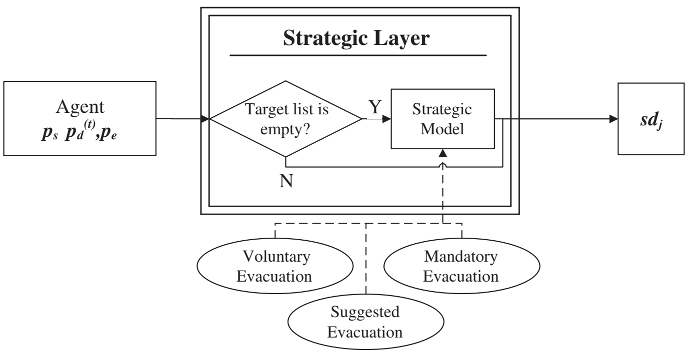


Fig. 4. Flowchart of the Strategic Layer.

Table 5
Relationship between events and alternative behavior pattern.

Event	Alternative 1 (not panic)	Alternative 2 (panic)
ξ_1	λ_3	λ_3
ξ_2	λ_2	λ_1
ξ_3	λ_3	λ_4
ξ_4	λ_5	λ_6
ξ_5	λ_2	λ_1

example, either one of the two behavior pattern: a "Follow leading car" strategy, or "Overtake" strategy (see Table 3 for different alternative behavior patterns). Fig. 5 shows the flowchart of the Cognitive layer.

5.3. Tactical layer

The Tactical Layer focuses on an agent's decision as to which driving behavior model will be used to achieve the driving pattern from the Cognitive Layer. The model base $\mathbb{M}$ is used which stores existing driving behavior models such as Gipps' Model (following the front agent), Lv's Lane-Changing Model (overtaking), Doniec's Intersection Model (waiting at an intersection), and Shortest Path model (selecting a route). Depending on the behavior pattern triggered in the Cognitive Layer, an agent selects and instantiates a driving behavioral model from the model base. For example, the behavior strategy "*following the leading car*" can be implemented with a car-following model such as Gipps' Model; "*overtaking*" with Lv's Lane-Changing Model. Fig. 6 summarizes the process flow. In every time interval, an agent in this Tactical layer executes the behavioral model m which belongs to the chosen alternative behavior pattern λ.

5.4. Operational layer

This layer focuses on the impact of the behavioral models on the traffic environment in every time interval (which is 0.1 s in the current implementation). It is responsible for how the models change the value of an agent in the next time interval, i.e., $\boldsymbol{a}^{(t+1)}$, by applying the process $\mathcal{O}$. For example, some car-following models change an agent's speed so that Operational Layer needs to calculate a new position according to the model's results. Some other models may change agent's position directly and, in these cases, the Operational Layer is required to recalculate the speed and other parameters. Several behavioral models may share one operational method and it should be executed if at least one of the models is activated. For example, car-following models and lane-changing models trigger speed operational models to recalculate agents' positions, speed, and other parameters.

In the current implementation, two models are designed to finalize the behavior manager. One is the physical speed operational model whose responsibility is to calculate an agent's position using its speed.

$$\Delta s = v\Delta t, \tag{8}$$

where Δs is the distance of an agent driving in a time step Δt. The other is a mental operational model represented as a linear function to change an agent's behavioral parameters according to a nervousness value μ.

$$p = (1-\alpha)p_0 + \alpha p_1, \tag{9}$$

where p is any of an agent's physical behavioral parameters in Table 6, p_0 means the value in normal state and p_1 means the value in panic state. An agent's parameters in the behavioral models, and the setting of their initial values, are also listed in Table 6. Fig. 7 shows the basic flow chart of the Operational Layer.

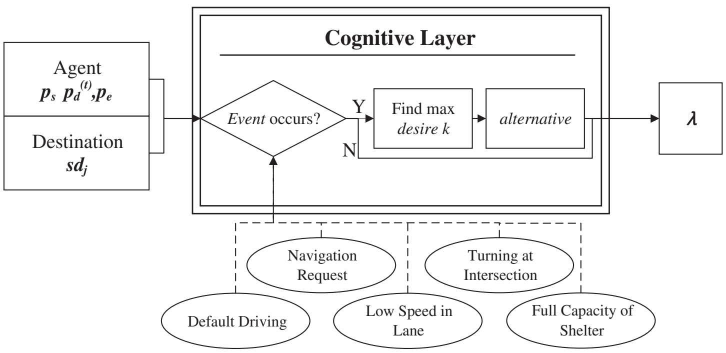


Fig. 5. Flowchart of the Cognitive Layer.

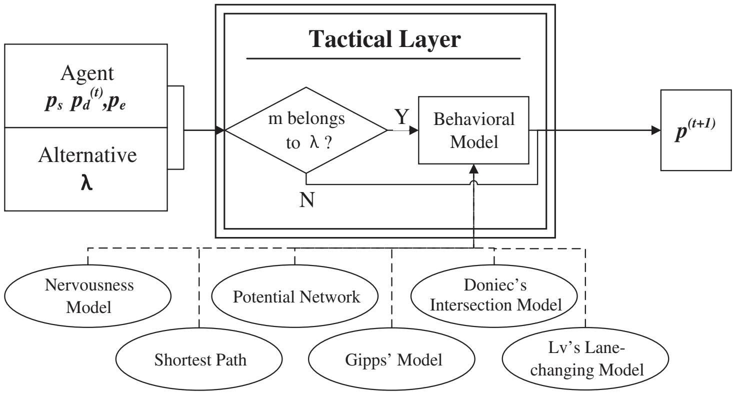


Fig. 6. Flowchart of the Tactical Layer.

6. Framework validation

In order to validate our proposed framework, we compare performance results of our system with a popular traffic simulation tool MATSim that has been effectively applied for evacuation modeling (Balmer et al., 2009; Lämmel et al., 2010). We chose the city of Newark, New Jersey, USA, as the evacuation area, shown in Fig. 8. The evacuation map was imported from Open Street Map. We developed three evacuation cases to validate our framework and showed the similarity and difference between our simulation system and MATSim. Three cases with 10,000, 20,000 and 30,000 agents were generated in evenly distributed locations and evacuated from the area. We assumed that all of the agents began evacuation at time 0. Each simulation run was replicated five times with different initial distributions of agents. The results of the average and standard deviation of clearance time are shown in Table 7. To validate the proposed framework, we used three different validation methods: First, we compare the SCTO, without multiple model choices, with MATSim, to show that the performance of SCTO is comparable with the MATSim; secondly, we compare the SCTO, with fully-enabled multiple models and behavior patterns, without the SCTO, to show that the fully enabled version actually performs better, justifying the use of multiple models and behavior patterns; and thirdly, we varied agents' nervousness levels to show the differences in driving behavior and the overall impact on the evacuation time.

Validation 1. We disabled all of the models, behavior patterns, and events (see Tables 2–4) except the Gipps' car-following model and the shortest-path model (see Table 7a), and we compared the clearance time to MATSim. There was no significant difference with respect to clearance time in any of the three cases between our SCTO system and MATSim (49.4 min versus 46.2 min, 86.4 min versus 84.8 min, and 141.6 min versus 149.6 min). This indicates that our simulation system, when multiple models and behavior patterns are turned off, shows results comparable to those of the MATSim.

Validation 2. We enabled all of the models, behavior patterns, and events (Table 7b) then compared the clearance time to that of the disabled SCTO (Table 7a). The results were similar (49.4 min versus 50.2 min, and 86.4 min versus 85.6 min) between disabled and enabled SCTO in cases 1 and 2, indicating that the changes of agent behaviors do not impact the clearance time if the number of agents (i.e. drivers/vehicles) is not large. In case 3, the enabled SCTO showed less clearance time than disabled SCTO, indicating that agents in the enabled SCTO process are smarter than the ones in the disabled SCTO process. The result shows that using the additional route choice model, i.e., potential network model, reduces the agent's travel time from that of the shortest path model.

Validation 3. We tested the enabled SCTO with all driving models, behavior patterns, and events, and with varying degrees of the nervousness model. We tested the performances of the SCTO model fixing the nervousness value to 0 (agents are not at all nervous), to 0.5 (agents are slightly nervous) and to 1 (agents are extremely panicked) respectively, as shown in Table 7c, d and e. The results showed a significant impact of the nervousness value on the clearance time.

Table 6
Initial parameters of agent's behavioral models.

Parameter	Fixed initial value	Parameter	p_0	p_1
$\mu^{(0)}$	0.1	acc	2.0	4.0
t_r	300	b	−2.8	−6.0
V_{low}	5	$b^{(n-1)}$	−2.8	−6.0
h	0.33	d	7	4
t	0.67	θ	10	20

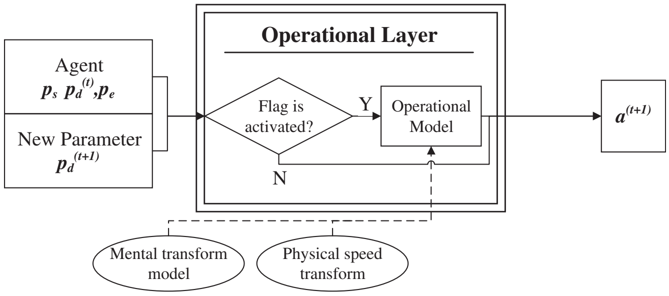


Fig. 7. Flowchart of the Operational Layer.

Fig. 8. Evacuation map for the comparison experiments.

When agents are not nervous (i.e., nervousness value is 0), they keep the minimum gap between vehicles at a reasonable distance (see Table 6), thus taking longer evacuation time. Whereas, when agents are slightly nervous (i.e., nervousness value is 0.5), the minimum gap between vehicles decreases, thus, resulting in the reduction of clearance time. Those results are similar to the ones shown in Tu et al. (2010). On the other hand, when evacuees are extremely panicked (i.e., nervousness value equals 1), the clearance time increases rapidly. These results were expected as one's state of panic may cause an agent to switch his route choice model from potential-network to shortest-path. Furthermore, lane-changing criteria became more difficult to satisfy due to the reduced gap between vehicles causing agents to spend more time passing a congested intersection. Clearance times resulting from these three nervousness levels are shown in Table 7c, d and e, respectively.

7. Experimental evaluation

In this section, we present simulation experiments and results showing potential improvements in the evacuation decision making process. Our framework is flexible to accommodate different models in different evacuation contexts. In order to address various scenarios, we assume a no-notice evacuation of Beijing, a typical international metropolis of ultra-high

Table 7
Clearance time (minutes) and standard deviation between the MATSim and the SCTO process.

Case number Number of vehicles	1 10,000	2 20,000	3 30,000
MATSim	46.2 (1.1)	84.8 (0.4)	149.6 (0.5)
SCTO			
a. Gipps' car-following and the shortest path model	49.4 (1.1)	86.4 (0.5)	141.6 (0.9)
b. All models, behavior patterns, and events enabled	50.2 (1.2)	85.6 (0.8)	108.0 (3.3)
c. Nervousness fixed to 0	60.6 (3.5)	107.2 (6.8)	160.0 (2.5)
d. Nervousness fixed to 0.5	48.6 (2.5)	84.0 (2.2)	123.2 (5.1)
e. Nervousness fixed to 1	89.0 (2.5)	159.6 (4.2)	234.2 (5.6)

population density. We focus on those evacuees who would drive their cars to public shelters set up by emergency officials. Traffic simulation experiments show how the efficiency of the evacuation (see metrics below) can vary with the number of shelters and with their distribution around Beijing. Experimental results from various scenarios are compared with those of existing plans for Beijing's shelters. We focus mainly on two important metrics of evacuation performance: clearance time, i.e., the time of all agents reaching their evacuation destinations, and evacuation rates, i.e., the number of agents evacuated per time period. We also take into account a psychological parameter representing nervousness which helps to forecast agents' panic during the evacuation.

7.1. Configuration

Simulation uses the following four initial conditions required by the mission manager:

7.1.1. Evacuation map

Fig. 9 depicts the experimental roadmap of Beijing's urban areas covering an area of 1415 km^2, containing 64,601 nodes; 87,995 roads with a total length of 9959 km. In 2014, the Beijing Emergency Committee (BEC) published the locations of 39 shelters in this area, accommodating 1.557 million evacuees. Considering that 26.5% of this area's residents own cars, the experiment assumes a maximum of $1{,}557{,}000 \times 26.5\% \approx 413{,}000$ evacuating vehicles in this area.

7.1.2. Candidate evacuation plans

An evacuation plan specifies various decisions ranging from whether and when to initiate it, to its extensiveness, and to whether it would be voluntary or mandatory. It depends on information such as probability of a disaster, rates and costs of false alarms, population, shelter distribution, and traffic conditions. (Regnier, 2008). In this experiment, we have focused on varying the number and locations of shelters. To evaluate the efficiency of an existing plan, a set of alternative plans, listed in Table 8, are used for comparison.

We have assumed that all plans are for the no-notice, mandatory, evacuation of everyone, all beginning at the same published time. The total capacity of each shelter is assumed to be constant, and the area's population is 1.557 million. Target destinations and routes have not been issued to evacuees, each deciding his own. The existing plan has 39 shelters distributed as shown in Fig. 8, while four alternative evacuation plans include a variation of the 39, specifically: 30, 50, 80 and 100 shelters whose locations are randomly generated, from all of the 64,601 intersections in the map, using a uniform distribution. Each plan assumes the same total shelter capacity. As this capacity is fixed, plans with more shelters have a smaller capacity for each shelter. Shelter locations are randomly distributed in the simulated plans.

7.1.3. Behavioral models

Behavioral models needed in the behavior manager in all four layers of Strategic, Cognitive, Tactical, and Operational are stored in a model base. The experiment applies the events, alternative patterns and behavioral models listed in Tables 2–5. Shortest-path model and potential-network model are used to simulate evacuees' route choices, which are considered highly critical in a large-scale evacuation. Gipps' Model and Lv's Model are validated to maintain the physics of traffic flow. Psychological pressure or panic is critical in no-notice evacuation situations, and we choose Helbing's model to simulate it simply and effectively. Fig. 10 summarizes the models in their relevant layers and in their event interrelationships.

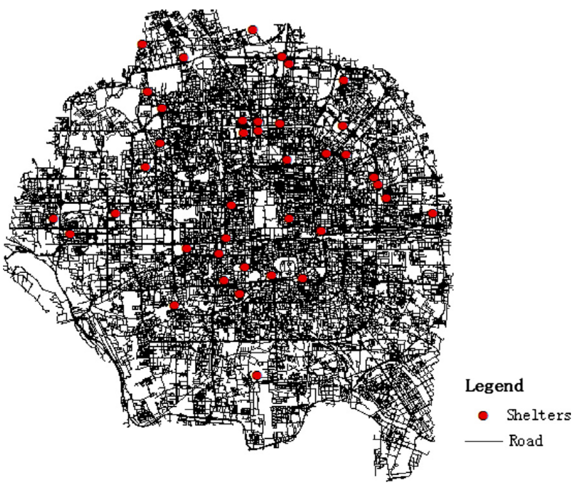


Fig. 9. Experimental roadmap.

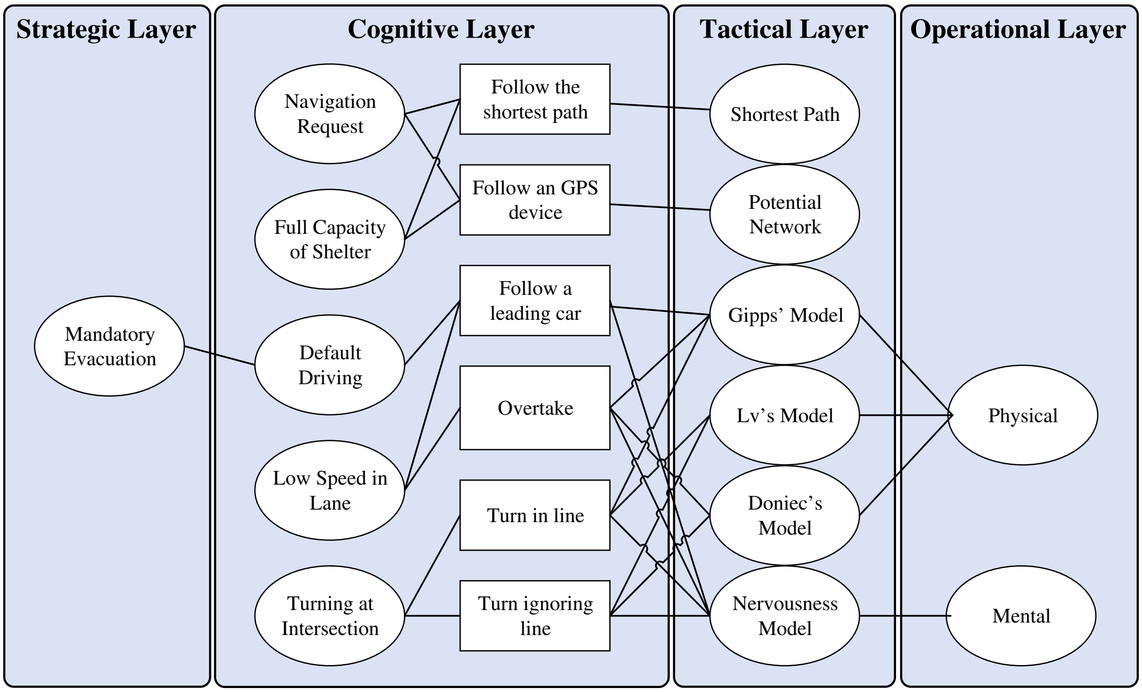


Fig. 10. Experimental model interrelationships

Table 8
Candidate plans in experiment.

	Existing plan	Plan 1	Plan 2	Plan 3	Plan 4
Time to start	Immediate				
Type	Mandatory				
Target & route designated	No				
Full capacity in total	1.557 million				
Number of shelters	39	30	50	80	100
Full capacity per shelter	39,923	51,900	31,140	19,463	15,570
Shelter's location	Fig. 8	5 random distributions			

7.1.4. Scenarios

To compare candidate plans efficiencies in different situations, the experiments use four scenarios of different numbers of agents: Scenario 1 (100,000), Scenario 2 (200,000), Scenario 3 (300,000) and Scenario 4 (413,000). Agents are generated and distributed uniformly in the roadmap. The simulation focuses on four metrics: (1) *Clearance time* (T_c); (2) *Total evacuation rates* and *mean evacuation rates per shelter*; (3) *Panic population* ($\boldsymbol{N_p}$), i.e., $N_p = \sum_i \text{Panic}(i)$, where Panic($i$) represent each agent's panic level, and (4) The number of *Jammed intersections*, i.e., intersections with high waiting time.

7.2. Simulation results

Simulation of all of the combinations of candidate plans and different scenarios has been conducted on a personal computer, implemented in C#, using Shapefile geographic data for the roadmap as well as for the three-dimensional dynamic display functions. Fig. 11 shows the visualization of the prototype simulations.

7.3. Number of agents and clearance time

Table 9 lists the mean *clearance time* (T_c) and standard deviation (in parenthesis) for each scenario/plan combination.
Fig. 12 shows the clearance time by different plans depending on different number of agents. The simulation is replicated 5 times for each case. Basically, it shows the more shelters the plan has, the shorter is the time to clear the vehicles (agents) for all scenarios, i.e., regardless of the number of agents.

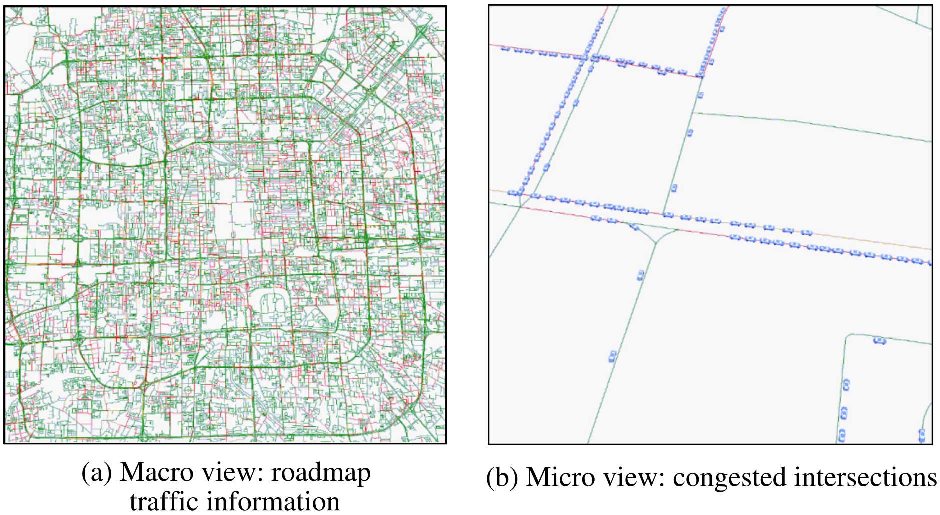


Fig. 11. Visualization of the experiment.

7.4. Number of shelters and evacuation rates

Fig. 12 shows that in mid-curve (i.e., between 20% and 80% of agents), the *evacuation rate* (i.e., the number of agents evacuated per minute) remains constant, close to linear. This is due to shelters receiving agents at their maximum capacity with the road to each shelter fully utilized, though possibly, slightly, affected by congestion close to shelters. In order to identify the evacuation rate for each plan, at the middle part of each evacuation curve, we applied the following linear regression model. Let $\widehat{N}(t)$ be the predicted number of agents to be evacuated in the roadmap at time period t, β be the slope and α be its intercept, the regression model is defined as following.

$$\widehat{N}(t) = \alpha + \beta t, \tag{10}$$

The slopes of the fitting results, shown in Table 10, reflect the maximum evacuation rate for each plan. The intercept and R^2 of the fitting results are also shown in Table 10 respectively. Fig. 13(a) shows the evacuation rate ($|\beta|$) for the entire evacuation environment, and Fig. 13(b) shows the *mean evacuation rate per shelter*, i.e., $|\beta|/N_s$, where N_s is the number of shelters, representing the average number of agents evacuated per minute per shelter.

For each scenario (with different numbers of agents), the total evacuation rate is higher for plans with larger numbers of shelters, as in Fig. 13(a), which means that the more shelters the faster the evacuation per minute. However, the mean evacuation rate per shelter generally decreases as shown in Fig. 13(b). Plans with more shelters have lower evacuation rates per shelter. This may be due to lower capacity shelters having reached their full capacity of evacuees, forcing many agents to re-route, in seeking another shelter. It may also be due to congestion around full shelters.

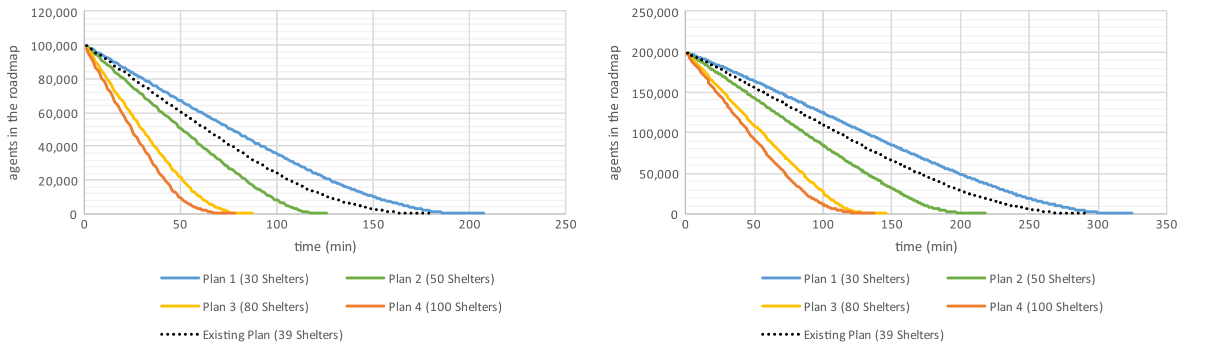
As shown in Fig. 12, the total time curve for evacuating the remaining 20% of agents does not appear linear, indicating that a few shelters are still receiving evacuees. This may be a result of a mismatch between the distributions of agents and shelters, causing many agents to crowd around shelters while they wait for those who arrived earlier to be settled into them. Evacuation decision makers may be interested in minimizing this settling period, especially at the end of the evacuation when shelters' capacity has been approached. Through linear regression, we can predict the earliest clearance time which we denote $T_c^{(P)}$, which can be found using the formula (11).

$$\widehat{N}(T_c^{(P)}) = 0 \tag{11}$$

$$T_c^{(P)} = -\frac{\alpha}{\beta} \tag{12}$$

Table 9
Average and standard deviation of clearance time in all the cases.

T_c (min)	Existing plan	Plan 1	Plan 2	Plan 3	Plan 4
Scenario 1	180.4 (1.4)	206.3 (8.0)	125.6 (5.5)	86.9 (2.7)	77.2 (2.2)
Scenario 2	290.0 (3.7)	323.3 (13.8)	217.3 (22.2)	146.0 (9.5)	136.9 (3.8)
Scenario 3	353.8 (4.8)	395.4 (33.8)	267.6 (12.7)	196.6 (12.6)	174.0 (20.8)
Scenario 4	421.6 (1.1)	475.1 (6.6)	351.8 (13.4)	241.0 (12.4)	187.7 (15.5)



(a) Scenario 1 (100,000 Agents)

(b) Scenario 2 (200,000 Agents)

(c) Scenario 3 (300,000 Agents)

(d) Scenario 4 (413,000 Agents)

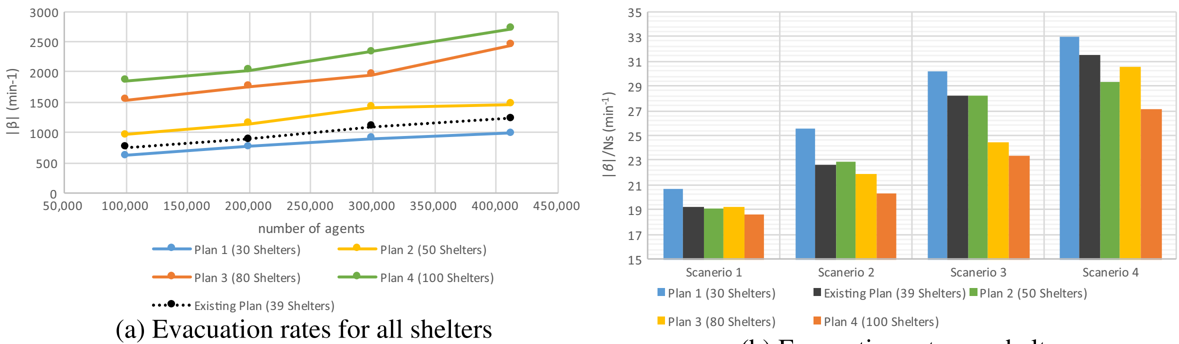
Fig. 12. Plots of agents evacuating to destinations versus time.

Table 10
Slope, intercept and R^2 of the linear fit for curves of evacuation traffic flow in all of the cases.

Scenario		Existing plan	Plan 1	Plan 2	Plan 3	Plan 4
1	$\|\beta\|$ (min^{-1})	750.5	620.8	956.6	1541.3	1860.3
	α	98,051	97,885	98,813	96,809	96,226
	R^2	0.9987	0.9993	0.9996	0.9991	0.9990
2	$\|\beta\|$ (min^{-1})	884.4	767.0	1142.8	1753.0	2029.0
	α	199,052	201,280	199,606	197,847	195,143
	R^2	0.9991	0.9994	0.9996	0.9996	0.9992
3	$\|\beta\|$ (min^{-1})	1098.7	903.6	1413.4	1959.5	2335.8
	α	307,721	307,597	308,443	301,992	299,043
	R^2	0.9995	0.9997	0.9997	0.9995	0.9994
4	$\|\beta\|$ (min^{-1})	1226.7	990.1	1466.5	2441.3	2709.2
	α	426,871	426,408	426,500	430,318	428,677
	R^2	0.9997	1	0.9998	0.9999	0.9999

Table 11 and Fig. 14 show $T_c^{(P)}$ and the ratio of actual clearance time T_c to predicted clearance time $T_c^{(P)}$ for all plans and scenarios. This ratio shows how much longer it takes to clear all vehicles, compared to the earliest predicted clearance time. These ratios may demonstrate to planners the efficiency of shelters.

The ratio of $T_c/T_c^{(P)}$ is usually greater than 1 because actual clearance time T_c generally takes longer than predicted one. Various contributing factors may include congestion around one shelter, at or approaching its capacity, causing late arriving evacuees to divert to an alternate shelter, thus extending T_c. For each plan (i.e., with a fixed number of shelters), actual clearance delays ($T_c/T_c^{(P)}$ ratio) seem to decrease with the number of remaining agents yet to clear, except Plan 3 as shown in Fig. 14(a). Under each scenario (i.e., to clear the same number of agents), more shelters seem to mean more delay in clearing the agents, as seen by the increasing ratio shown in Table 11. Fig. 14(b) likewise shows average actual clearance time, over those predicted, increasing with more shelters (except under the existing plan scenario). This indicates that building more shelters, of relatively smaller capacity, may not always be advantageous because late evacuating agents, upon their arrival at the more quickly-filling shelters, would more often have to divert to alternate shelters, thus requiring more clearance time than would be seen under a regime of fewer, larger, shelters. The existing plan in Fig. 14(b) shows a lower efficiency than Plan 2 in terms of the average $T_c/T_c^{(P)}$, which suggests room for improvement in the existing distribution of shelters.



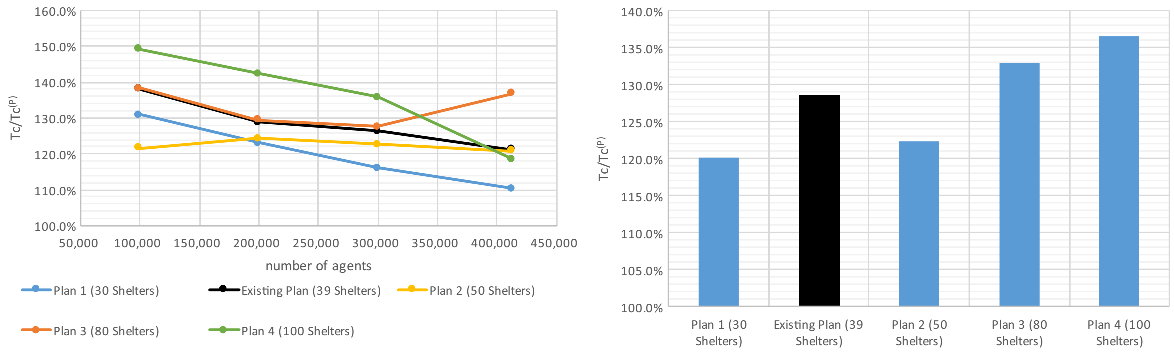
(a) Evacuation rates for all shelters

(b) Evacuation rate per shelter

Fig. 13. Maximum evacuation speed of candidate plans under different scenarios.

Table 11
Linear predicted clearance time in all the cases.

Scenario	Existing plan		Plan 1		Plan 2		Plan 3		Plan 4	
	$T_c^{(P)}$	$T_c/T_c^{(P)}$	$T_c^{(P)}$	$T_c/T_c^{(P)}$	$T_c^{(P)}$	$T_c/T_c^{(P)}$	$T_c^{(P)}$	$T_c/T_c^{(P)}$	$T_c^{(P)}$	$T_c/T_c^{(P)}$
1	130.6	138.12%	157.7	130.89%	103.3	121.65%	62.8	138.31%	51.7	149.25%
2	225.1	128.87%	262.4	123.15%	174.7	124.38%	112.9	129.37%	96.2	142.45%
3	280.1	126.26%	340.4	116.14%	218.2	122.70%	154.1	127.55%	128.0	135.87%
4	348.0	121.21%	430.7	110.38%	290.8	120.92%	176.3	136.80%	158.2	118.62%
Mean		128.62%		120.14%		122.41%		133.01%		136.55%



(a) Trends of $T_c/T_c^{(P)}$ under different scenarios

(b) Mean proportion of $T_c/T_c^{(P)}$

Fig. 14. Proportion of $T_c/T_c^{(P)}$ in all cases.

7.5. Panic population and clearance time

By investigating nervousness values we have counted agents exhibiting panic. Fig. 15 shows, for all cases, the panicked population as a proportion of the entire population (N_p/N). Consistent with common sense, the larger the evacuating population or the longer the clearance time given a constant number of shelters (i.e., a plan), the more people will exhibit panic. Also, under each population clearance scenario, the more shelters available the less people will exhibit panic. Results of the existing plan are consistent with expectations based on our nervousness model. Emergency managers may use it to estimate when public panic would become a major complication to the evacuation process, or when a plan might fail to support control of evacuating traffic. When the evacuating population reaches an estimated 300,000, for instance, a sharp increase in public panic is predicted.

7.6. Number of traffic jams at intersection

Demonstrating the decision-support advantages of a model with scenario variability, we conducted an experiment with the existing plan, under Scenario 4 (413,000 agents), in which we compared our integrated driving-decision agent model with two simple route-finding agent models: the shortest-path model and the potential-network model. Agents in this test

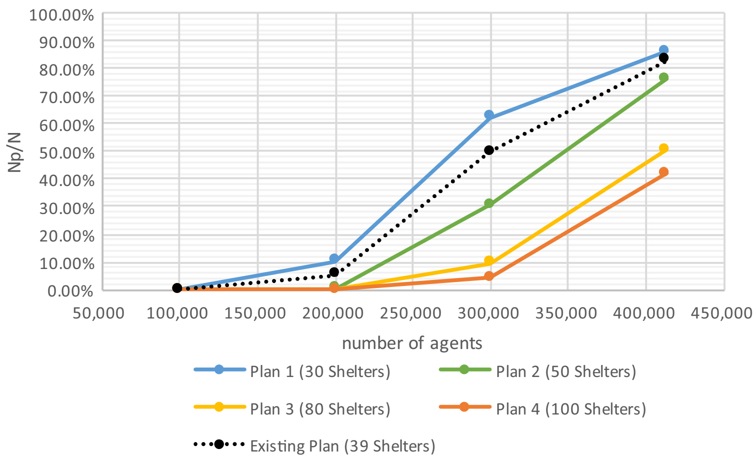


Fig. 15. Panic proportion of the entire population in all the cases.

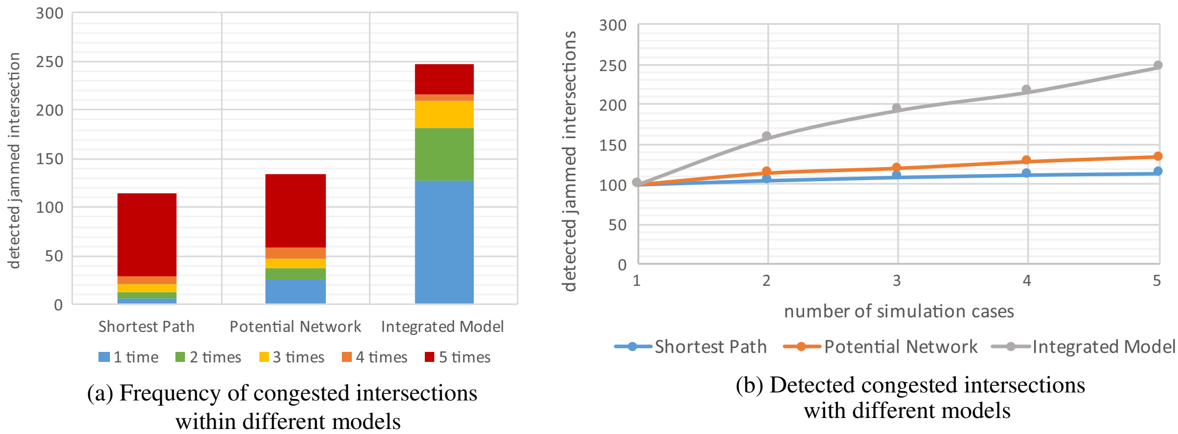


Fig. 16. Congested intersections in the top 100 of waiting time, in five simulation cases.

use only one fixed model and cannot change their targets during the simulation. Waiting time for each agent is recorded and the maximum waiting time at all intersections is captured. Simulation, by each of the three models, is replicated five times, intersections with the top 100 longest waiting time are recorded and results are graphed in Fig. 16.

Simulations by simpler models detect congestion less often, as shown in Fig. 16(a). Also, simpler models show little change in locations of congestion at intersections. Our integrated model shows congested intersections in more separate locations in each of five replications. This wider view of potentially congested intersections informs planners in their traffic engineering as well as emergency managers in deploying police to direct traffic.

8. Conclusions

In this paper, we presented the development and implementation of an agent-based simulation system which models each agent's driving behaviors by a multi-layer hierarchical decision-making process. Our approach uses a modular structure, reusing and combining existing driving behavior models. Our design of an agent's driving-decision process is based on a four-layer decision process (i.e., SCTO for Strategic, Cognitive, Tactical and Operational levels) in which each layer's driving-decision influences agent behavior in every other layer. Our framework is verified by comparing with the MATSim simulation tool. Our experimental results show that it is benefit for integrating into a model more variability of driving behaviors as are to be expected in an evacuation situation. Our results further show that while the building of more shelters may increase overall evacuation rates, it may diminish efficient utilization of shelters (i.e., the evacuation rate per shelter becomes low). Our new approach would provide emergency officials with a clearer view, enabling them to visualize outcomes of the possible alternative evacuation plans under various possible scenarios, and to more accurately predict and plan clearance time so that they can choose the optimal plan.

In future work we plan to integrate additional factors to better simulate the outcomes of evacuation-related decisions, such as varying types of evacuation agents, including vehicles, bicycles and pedestrians. We will also study how psychological characteristics affect drivers' behaviors, especially how such affects might be integrated into an agent's decision model in which evacuation rates can be estimated with varying proportions of agents failing to follow an evacuation plan.

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