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AGENT DRIVING BEHAVIOR MODELING FOR TRAFFIC SIMULATION AND EMERGENCY DECISION SUPPORT

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ABSTRACT

Traffic evacuation is one of the most important tasks in emergency management, and it is challenging for governments to plan an efficient and safe evacuation before a huge disaster strikes. This paper presents a traffic evacuation simulation system that generates agent's driving behavior based on multi-level driving decision models. The agent's driving behavior combines multiple widely used behavior models from each decision level. The agent-based traffic evacuation system is proposed and a prototype system implements each agent's multi-level modular driving decision models. The simulation experiment studies show varied clearance time, evacuation rates per shelter, and the variety and number of traffic jams to support traffic evacuation planning decisions in a crowded city liked Beijing, China. The simulation studies compare the existing evacuation plan with other simulated plans and evaluate it for designing a better and more realistic traffic evacuation plan.

1 INTRODUCTION

Disasters have been threatening human society for a very long time. Every year, huge loss of lives and massive economic damage are caused by various man-made or natural disasters such as hurricanes, floods, wildfires, tsunamis, or chemical spills. There are lots of risks of these disasters that result in human loss and property damage. Although these risks could be predicted, they cannot be completely eliminated. Mass evacuation, which is one of the necessary and efficient responses to such disasters, helps reduce the resulted damage. Unfortunately, studies such as Pel et al. (2012) pointed out that mass evacuation is becoming more difficult and time consuming due to the population and urban development growing faster than road infrastructure capacity. In recent years, some large-scale disasters, such as the Sichuan earthquake during which more than 200,000 people were evacuated (Cui et al. 2012) and the Fukushima Daiichi nuclear disaster during which 300,000 people were evacuated (Thielen 2012), showed that moving people in highly populated areas away from disasters rapidly and safely has been one of the most important tasks in emergency management.

In general, roadway transportation plays an important role in large-scale evacuations and affects hundreds of thousands people. Emergency departments at the federal, state, and local levels, are responsible for the effectiveness of making evacuation plans that enable as many people as possible evacuate to safe places within a limited period of time. This is a challenging and complex task since it is dependent on several factors, including warning time, response time, information and instructions dissemination procedure, evacuation routes, traffic flow conditions, dynamic traffic control measures, evacuation time estimates, etc. (Lindell and Prater 2007) and relies on so many factors such as the natural and social environment, economic conditions, mass psychology of the public, etc. (Dash 2007). During a disaster, individuals try their best to survive and make their own decisions, despite having a perfect response plan in place. In real situations, every details of an evacuation plan affects evacuees, but cannot be expected to be fully and perfectly executed.

Therefore, decision makers are willing to gain information of what scenarios may occur when a specific evacuation plan is given. Agent-based simulation, which is capable of representing a global traffic situation by simulating each evacuees individually as agents, is an effective tool to explore realistic scenarios through understanding the driving decisions and behaviors of every individual. Many simulation models have been applied in Intelligent Transportation System and software (Fellendorf and Vortisch 2010; Halati et al. 1997; Balmer et al. 2009). Some widely used toolboxes, such as MATSim (MATSim 2014), implement large-scale agent-based transport simulations, and have a proven capability of simulating complex traffic system in many cities. Some works which focus on emergency evacuations are using MATSim as their platform (Lämmel et al. 2009). However, as Zhang et al. (2009) has pointed out, it does not take into account the human and social behaviors during emergency evacuation even though it can provide relatively accurate complete information on traffic impacts. The decision-making mechanism in emergency management is different from that in normal situations (Murray-Tuite and Wolshon 2013). In general, during emergency, individuals are usually impulsive and emotionally stressed and this may lead to various uncertain behaviors that may affect the execution of an evacuation plan. Our work takes into account the functions of microscopic models such as braking and lane changing, because these behaviors reflect the difference among drivers. During emergencies, there are so many uncertainties that can change the entire evacuation plan. For example, there may be a competition between some agents because they all are trying to get to the same shelter which has a limited capacity. A higher frequency of braking or lane changing may reduce the speed of major roads, causing more traffic jams.

In this paper, we propose a multi-level agent driving decision modeling framework for traffic simulation to support emergency evacuation planning (Section 2). This framework aims at simulating more complex and more realistic agent's driving behaviors in emergency situation (Section 3). Each agent's driving behavior is based on a multi-level decision model of an agent that combines multiple simple driving behavior models which have been widely used in the literature (Section 4). A traffic simulation system based on complex agent's decision model has been implemented. In our simulation studies (Section 5), we tested the evacuation simulations in diverse emergency scenarios to identify the traffic jam points and to support the best strategy for selecting a set of shelters. Our approach of multi-level decision based agent simulation considers each agent's ability to choose a different driving model from the existing simple agent models, which is more realistic than an agent behavior model based on one uniform model. It also takes into account that various scenarios can be simulated providing the capability to select more realistic emergency situation context for emergency planning decision support.

2 MULTI-AGENT SIMULATION MODELING FOR EVACUATION DECISION SUPPORT

Our proposed integrated simulation system includes four key components: geospatial manager, agent manager, behavior manager and mission manager (shown in Figure 1) which provides capability to simulate complex behaviors for different scenarios.

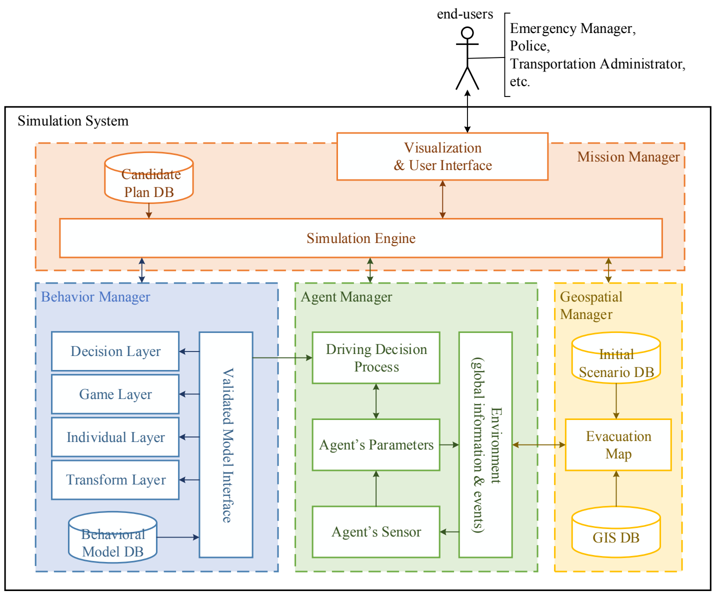

Figure 1: Components and architecture of the simulation system.

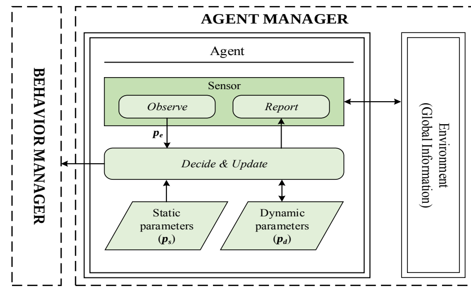

Figure 2: Process of the agent's driving decision model.

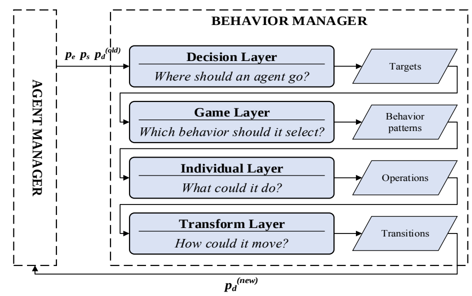

Figure 3: Architecture of the behavior manager.

The geospatial manager is designed to build a virtual traffic map, i.e., the simulation environment. It describes the structure of traffic roadmap as a directed graph structure in which arcs refer to roads and nodes refer to intersections. Shape file, one of the standard geospatial vector data formats, is supported in the system so that open traffic roadmaps can be imported from Geographic Information Systems (GIS). The agent manager, which manages all agents, performs three functions: 1) generate/destroy agents; 2) update agents' parameters; 3) communicate with agents; 4) collect statistical information. Section 4 discusses the details of the agent manager. The behavior manager aims at managing all the behavioral models that are to be applied in a simulation task. Since there are a large number of models representing various perspectives, a framework is designed to organize all the models in a unified architecture. Before a simulation task, a set of widely used agent-based models needs to be registered in the behavior manager. During the simulation, this component selects agents' driving behavior models, based on their parameters. Section 5 presents the architecture and workflow in the behavior manager. The mission manager defines the main process of the system including the initial conditions, the loop of the simulation tasks, the ending conditions, and a data-collecting function to generate numerical results to decision makers. The visualization component provides users to track the scenarios via screen.

To start a simulation task, the system requires four kinds of initial conditions in the mission manager: 1) evacuation map, i.e., the roadmap of the evacuation area, 2) candidate plan set, i.e., a set of decisions which contain the location of shelters, the route to reach them, etc., 3) behavioral model set, i.e., a set of widely used behavioral models which are going to be applied in this task, and 4) initial scenario set, i.e., a set of possible distribution of drivers which claims the location and the parameters of all the drivers.

Then the system chooses one plan from the candidate plan set and one scenario from the initial scenario set as initialization, and goes into the simulation loop. It keeps visiting all the agents in the agent manager, changing their status and parameters via the behavioral models in the behavior manager, and collecting critical data, until a set of ending conditions, for example, all the agents arrive at shelters, is reached. The same process is executed for all the combinations of the candidate plans and the initial scenarios, ensuring that every initial scenario under the guide of every candidate plan is going to be simulated separately. Finally, the collected data of every combinations, provided by animation and figures, is exported for further analysis and comparison.

3 AGENT-BASED DRIVING DECISION MODEL

In this paper, a vehicle is considered the smallest unit of the traffic simulation entity and is modeled as an agent. Each agent is modeled with a set of static attributes, dynamic attributes, local environmental parameters, and a driving decision process which generates the agent's dynamic behavior.

Definition 1 *An agent $\boldsymbol{a}$ is defined with tuple,* $\boldsymbol{a} = \langle \boldsymbol{p_s}, \boldsymbol{p_d}, \boldsymbol{p_e}, \mathcal{D} \rangle$*, where $\boldsymbol{p_s}$ represents the agent's basic attributes whose values remain unchanged during the entire simulation process, $\boldsymbol{p_d}$ represents the agent's attributes whose values change during the simulation, $\boldsymbol{p_e}$ for the local environment variables observed from the context, and $\mathcal{D}$ which is the agent's decision process to select one driving behavior model.*

Examples of $\boldsymbol{p_s}$ include physical attributes (e.g., length, width, and wheelbase), driving limitations (e.g., maximum speed, maximum acceleration, and braking ability) and driver characteristics, (e.g., gender, age, and driving experience). Examples of $\boldsymbol{p_d}$ include physical status (e.g., current position, speed, and acceleration) and mental status (e.g., driver's nervousness (Helbing et al. 2002)). $\boldsymbol{p_e}$ represents a set of local environment information that may affect the dynamic parameters and driving behavior. Examples of $\boldsymbol{p_e}$ include traffic conditions, (e.g., average transit time of roads), driving constraints (e.g., distance from the front agent), or evacuating information (e.g., shelter capacity). The process of selecting one driving model over another is denoted by $\mathcal{D}$ and includes the following steps:

1. Each agent $\boldsymbol{a_i}$ observes the local data around it.
2. The agent extracts the $\boldsymbol{p_e}$ from the observed data, e.g., getting close to another agent in the front.
3. Based on $\boldsymbol{p_e}$ as well as $\boldsymbol{p_s}$ and $\boldsymbol{p_d}$, $\boldsymbol{a_i}$ makes a driving decision which is controlled by the behavior manager, e.g., slowing down or overtaking.
4. Based on the driving decision $\boldsymbol{a_i}$ choses, the dynamic parameters $\boldsymbol{p_d}$, are updated accordingly, e.g., decreasing speed.
5. The new parameters are used to update the global environment for the next time interval.

Figure 2 shows the agent's driving decision model at each time interval. A sensor observes and reports local information about nearby agents at the beginning of every time interval. The function *Decide & Update* is responsible for generating the driving behavior and executing it by calling the corresponding widely used models in the behavior manager. Agent's dynamic parameters $\boldsymbol{p_d}$ will be updated from $\boldsymbol{p_d}^{(old)}$ to $\boldsymbol{p_d}^{(new)}$ so that they can move or change speed and direction at every time interval. At the end of every time interval, the sensor collects all the statistical information, e.g., the amount and average speed of agents in every road. All information is sent back to the global environment 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.

4 MODELING FOR AGENT DRIVING BEHAVIORS

During a simulation task, every agent follows a set of unified instructions to generate its own behavior in every time interval. The behavior manager is the component whose responsibility is carrying out all of these critical functions, whose architecture is shown in Figure 3.

The behavior manager consists of four layers which are able to answer the following four general questions that may be encountered in any traffic models: 1) *Decision* layer: where should an agent go in the current status? 2) *Game* layer: which pattern of behaviors should the agent select to achieve its goal? 3) *Individual* layer: what action could the agent do in a pattern of behaviors? 4) *Transform* layer: how do the agent's parameters change during this action?

These four questions give a top-down guideline to the generation of 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 $\boldsymbol{p_d}^{(old)}$ 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 $\boldsymbol{p_d}^{(old)}$. Therefore, generating an agent's behavior is equivalent to answering these four questions by applying corresponding behavioral models.

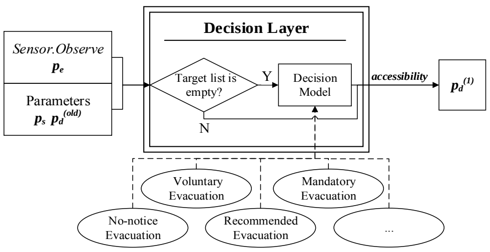

Figure 4: Flowchart of Decision layer.

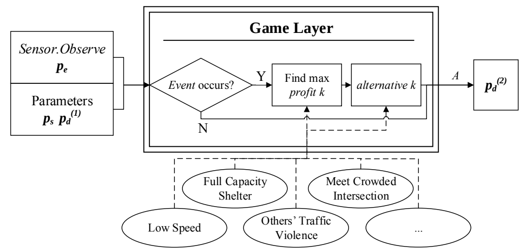

Figure 5: Flowchart of Game layer.

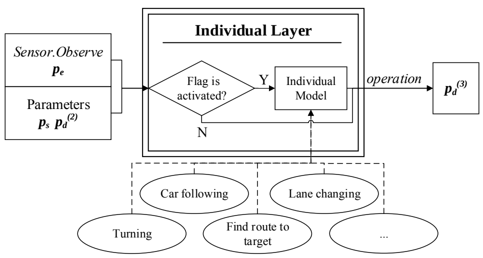

Figure 6: Flowchart of Individual layer.

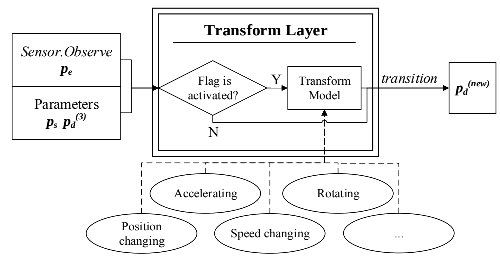

Figure 7: Flowchart of Transform layer.

4.1 Decision Layer

Decision layer focuses on the overall decision behavior of how an agent determines its destination. A global decision plan may give a suggestion of which shelter an agent should go to, but the agent also may chose not to follow this suggestion. The Decision layer is invoked if an agent chooses to decide where to evacuate. In this case, each agent calculates the accessibility level to evacuate to each potential target (e.g., all shelters). The *accessibility* of a target is defined as a dynamic weight between 0 and 1, where the higher value stands for a stronger desire to get to that place. Once these calculations are performed, every agent holds a list of their potential targets and visits them in descending order of their accessibility. The basic process of the decision layer is shown in Figure 4.

The definition of Decision layer is the set of functions which takes the extracted information and agent's parameters as input and measures the *accessibility* of every potential target as output. The output accessibility list is put in parts of the agent's dynamic parameters, which is defined as $\boldsymbol{p_d}^{(1)}$.

$$Decision: \left(\boldsymbol{p_e}, \boldsymbol{p_s}, \boldsymbol{p_d^{(old)}}\right) \mapsto \mathbf{accessibility} \in \boldsymbol{p_d^{(1)}}. \tag{1}$$

This layer can apply different decision functions to enable representing various scenarios. For example, if all the agents decide the target shelters on their own, it will be an unplanned voluntary evacuation. If the target list is defined globally, which is not controlled by the agents, it will become a mandatory evacuation. A suggested evacuation plan is a combination of these two scenarios.

4.2 Game Layer

Game layer focuses on the detailed decisions that agents are able to make on their way to the selected targets. This layer pays attention to the local parameters based on which it tries to achieve a goal to reach the final destinations, e.g., which route it selects to get to the targets. Agents do not make decisions at every time interval, rather some decisions are triggered from the *event* observed from a sensor, e.g., making a route choice decision is necessary only if the agent is at an intersection.

A set of potential alternative behaviors to an event is called an *alternative vector A,* which is defined as a list of Boolean vector. Each entry in the vector A identifies whether the agent would like to select a corresponding behavioral model in Individual agent behavior layer: $A = [m_1, m_2, \ldots m_k]$, where $m_i = 1$ if the corresponding behavioral model is activated, 0, otherwise. This flag vector is used in the Individual layer to activate the corresponding models (see Section 5.3).

When several alternatives exist to respond to a triggered event, the agent needs to choose one as the answer. For this, we use a profit function to represent the agent's desire of choosing this model over others. The profit function is defined as: $\text{profit}_{i,j}\colon \left(\boldsymbol{p_e}, \boldsymbol{p_s}, \boldsymbol{p_d^{(1)}}\right) \mapsto \mathbb{R}$, where $profit_{i,j}$ is the function of alternative j in event i. Among all the alternatives in the triggered event i, the agent chooses the alternative, j which has the highest profit, and update it in the agent's dynamic parameters, defined as $\boldsymbol{p_d^{(2)}}$.

$$\text{Game: } \left(\boldsymbol{p_e}, \boldsymbol{p_s}, \boldsymbol{p_d^{(1)}}\right) \mapsto \text{alternative}_j \in \boldsymbol{p_d^{(2)}},\ \text{s.t.} \begin{cases} \text{event}_i = 1, \\ j = \arg\max_k \text{profit}_{i,k} \left(\boldsymbol{p_e}, \boldsymbol{p_s}, \boldsymbol{p_d^{(1)}}\right). \end{cases} \tag{2}$$

The Game layer is crucial in modeling the variability of the agent's behaviors by rational use of the events which are able to cause interactions among each agent and the environment as well as designing psychological-attribute driven profit functions. A few of the agents may trigger an event which influences a larger group and lead the scenario out of decision maker's control. In this way, Game layer creates complicated and dynamic traffic scenarios and greatly enhances the variability of agent's behaviors. For example, when a car is in front of an agent, that agent may adopt, for example, either one of the two models: a car following model or overtaking model in this layer. Figure 5 shows the flowchart of the Game layer.

4.3 Individual Layer

Individual layer focuses on the driving operations which an agent is able to do, such as following the front agent, overtaking, waiting at an intersection, selecting a route based on the shortest path, etc. In order to deal with the alternatives given by Game layer, the Individual layer selects and instantiates a driving model from various models available for implementing an alternative behavior. It is defined as the binding of operations and flags, where the operation is a driving behavioral model which changes the speed, locations or other agent's dynamic parameters, and the flag is a Boolean value which indicates the activated status of the operation. In every time interval, Individual layer executes all the operations whose flags are set to 1 by the Game layer. Again, the output of the operations is entered in in the agent's dynamic parameters, defined as $\boldsymbol{p_d^{(3)}}$.

$$\text{Individual: } \left(\boldsymbol{p_e}, \boldsymbol{p_s}, \boldsymbol{p_d^{(2)}}\right) = \bigvee_{i\ s.t.\ \boldsymbol{p_d^{(2)}} \ni m_i = 1} \text{operation}_i\left(\boldsymbol{p_e}, \boldsymbol{p_s}, \boldsymbol{p_d^{(2)}}\right) \mapsto \boldsymbol{p_d^{(3)}}, \tag{3}$$

The existing models from the Model Base are selected and implement the operations in the Individual Activity module. For example, the operation "*following the front vehicle*" can be implemented with the *car-following model* and "*overtaking*" is implemented with the *lane-changing model*. Figure 6 summarizes the process flow.

4.4 Transform Layer

This layer focuses on the impact of the driving operations on the traffic environment. It is responsible for how the driving operations change the value of agent's new dynamic parameters in the next time interval, i.e., $\boldsymbol{p_d^{(new)}}$. For example, some *car-following models* change agent's speed so that Transform layer needs to calculate the new position according to their results. Some other models may change agent's position directly, and in these cases, the Transform layer is required to recalculate the speed and other parameters. Several behavioral models may share one transform method and it should be executed if at least one of the models is activated. Therefore, the Transform layer is defined as the binding of transitions and a relationship matrix called **R** between transitions and operations, where a transition is a function that changes the value of $\boldsymbol{p_d}^{(new)}$ according to the results of $\boldsymbol{p_d}^{(3)}$, **R** indicates whether there is a request of transition after an operation, and each entry l_j in the vector $\mathbf{R}A^T$ identifies whether the agent needs to apply a corresponding model in the Transform layer.

$$\text{Transform: } \left(\boldsymbol{p_e}, \boldsymbol{p_s}, \boldsymbol{p}_{\boldsymbol{d}}^{(3)}\right) = \bigvee_{j\ s.t.\ l_j=1} \text{transition}_j\left(\boldsymbol{p_e}, \boldsymbol{p_s}, \boldsymbol{p}_{\boldsymbol{d}}^{(3)}\right) \mapsto \boldsymbol{p}_{\boldsymbol{d}}^{(\mathbf{new})}, \quad (4)$$

$$\mathbf{R}A^T = [l_1, l_2, \ldots, l_k]^T, \qquad \mathbf{R} = \left(r_{i,j}\right) \quad (5)$$

where $r_{i,j} = 1$ if operation i and transition j are binding, or 0 if not.

For example, car-following models and lane-changing models trigger speed transform model to recalculate agents' position, speed, and other parameters. Figure 7 shows the basic flow chart of the Transform layer.

5 EXPERIMENT

In this section, we present the simulation experiments and results to show the potential improvements in the evacuation decision making process. The traffic simulation experiments show how the efficiency of the evacuation (i.e., the total evacuation time) can vary with the number of shelters and the distribution of the shelters in Beijing, a typical international metropolis with ultra-high density of population. The experiment results from various scenarios are compared with that of the existing plan of Beijing's shelters.

5.1 Configuration

The simulation uses the following four initial conditions required by the mission manager.

Evacuation map: Figure 8 depicts the experimental roadmap of urban areas in Beijing. The map covers an area of 1,415 km^2, containing 64,601 nodes; 87,995 roads with a total length of 9,959 km. In 2014, the Beijing Emergency Committee (BEC) published 39 shelters in this area, accommodating 1.557 million people to be evacuated. Taking into account that 26.5% of the people in this area own cars, the experiment assumes that the maximum number of evacuating vehicles in this area is about 1,557,000 × 26.5% ≈ 413,000 cars.

Candidate evacuation plans*:* An evacuation plan specifies various decisions ranging from whether and when to initiate it, to the extent and the type of whether it will be voluntary or mandatory. In this experiment, we focuses on the different number and locations of shelters. To evaluate the efficiency of the existing plan, a set of alternative plans listed in Table 1 are used for comparison.

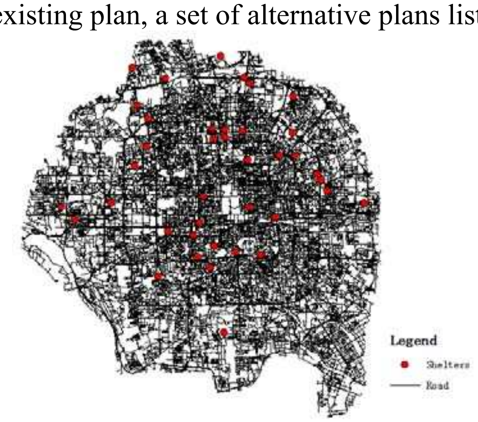

Figure 8: Experimental roadmap.

Table 1: 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	Figure 8	5 random distributions			

We assumed that all the plans are mandatory evacuations, i.e., all of the people are forced to evacuate, and they are required to start at the very beginning time after the plans are published. The total capacity of all the shelters are assumed to be constant, and the population in this area to be 1.557 million, across plans. The target and the route are not designated to evacuees so that people need to decide by themselves which shelter they intend to reach. The existing plan has the 39 shelters distributed as shown in Figure 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 the uniform distribution. All of the shelters are assumed to have the same total capacity. Since the total capacity is a fixed number, the plans with more shelters have smaller capacity for each shelter. Shelter locations are randomly distributed in the simulated plans.

***Behavioral models**:* Behavioral models needed in the behavior manager in all four layers of Decision, Game, Individual, and Transform are stored in a model base. To keep consistent with the scenario of mandatory evacuation, the Decision layer of driving behavior uses the accessibility value of 1 for all the shelters. In the remaining three layers, the experiment applies six agent-based behavioral models, listed in Table 2. All of the six behavior models used in the Individual layer are responses to five events whose names and brief descriptions are listed in Table 3. Figure 9 shows the relationship between the models in the Individual layer and the events in the Game layer.

Table 2: Behavioral models in the experiment.

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

Table 3: Events in the Game layer.

Name	Description
Default Driving	If nothing is happening, an agent moves using car-following model.
Navigation Request	If an agent is required to determine the route to the target.
Low Speed in Lane	If an agent has a low speed (less than 15 km/h) in lane.
Turning at Intersection	If an agent is going to turn at an intersection.
Full Capacity of Shelter	If the capacity of the target shelter is full.

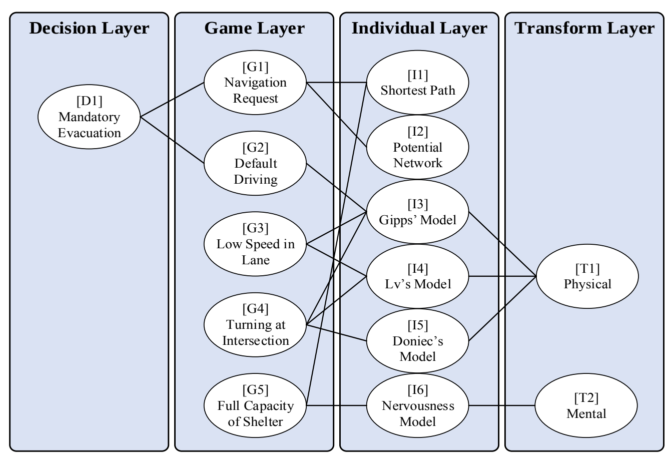

Figure 9: Relationship of the models in the experiment.

In the Transform layer, two models are designed to finalize the behavior manager. One is the physical speed transform model whose responsibility is to calculate agent's position using its speed. The other is a mental transform model represented as a linear function to change the agent's behavioral parameters according to the nervousness value α.

$$p = (1-\alpha)p_0 + \alpha p_1, \tag{6}$$

where p represents the agent's physical behavioral parameters in terms of the degree of nervousness and calmness. α equals 1 implies extreme nervousness level of the agent while α equals 0 represents the extreme calmness level of the agent. Table 4 shows various static and dynamic parameters of agent's behavioral models with respect to the extreme level of calmness (p_0) and the extreme level of nervousness (p_1). Main agent's parameters in the behavioral models and the setting of their initial values are also listed in Table 4.

Table 4: Static and dynamic parameters of agent's behavioral models.

Parameter	**Range**	**Description**	p_0	p_1
A	[0.5, 4]	Maximum desired acceleration of the following car (m/s^2)	2.0	4.0
B	[-6, 0]	Maximum desired deceleration of the following car (m/s^2)	-2.8	-6.0
$B^{(n-1)}$	[-6, 0]	Maximum desired deceleration of the leading car (m/s^2)	-2.8	-6.0
d	[4, 15]	Distance at standstill (m)	7	4
h	[0, 4]	Safety reaction time (s)	0.33	0.33
t	[0.5, 3]	Reaction time (s)	0.67	0.67
θ	[5, 20]	Lane changing angle (degree)	10	20

***Scenarios*:** To compare the efficiency of the candidate plans in different situations, the experiments use four scenarios with different number of agents: Scenario 1 (100,000), Scenario 2 (200,000), Scenario 3 (300,000) and Scenario 4 (413,000). The agents are generated and distributed in the roadmap with uniform distribution. The simulation focuses on three metrics: 1) *Clearance time* (T_c), i.e., the time of all the agents reaching safe places; 2) *Evacuation rates*, i.e., the number of agents evacuated per time period; and 3) *Jammed intersections*, i.e., intersections with high waiting time.

5.2 Simulation Results

The simulation has been carried out on a personal computer for all the combinations of candidate plans and different scenarios. The prototype simulation system to perform this simulation is implemented in C# for personal computers and uses shape file geographic data for roadmap.

5.2.1 Number of Agents and Clearance Time

Table 5 lists the mean *clearance time* (T_c) and standard deviation for all combinations of the four scenarios and the five candidate plans. The simulation is replicated 5 times for each case.

Table 5: 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)

5.2.2 Number of Shelters and Evacuation Rates

The *evacuation rate* (i.e., the number of agents evacuated per minute) remains stable, especially in the middle parts of the curves (i.e., between 20% and 80% of agents), which makes them close to linear. This is due to the fact that all shelters reached their maximum evacuation rate as shown in the middle parts of the evacuation curves, though it might be slightly affected by some traffic jams around the shelters. In order to identify the evacuation rate for each plan at the middle part of each evacuation curve, we applied the linear regression model. Figure 10(a) shows the evacuation rate for the entire evacuation environment, and Figure 10(b) shows the *mean evacuation rate per shelter*, representing the number of agents evacuated per minute per shelter.

The total evacuation rate increases as the number of shelters grow as in Figure 10(a), which means the more shelters the faster the evacuation. However, the mean evacuation rate per shelter generally decreases as shown in Figure 10(b), which means the more shelters the slower evacuation rate per each shelter. This may be due to the fact that each shelter has lower capacity thus reaching its full capacity with evacuees, leaving many other agents to seek another shelter. It also may be due to the traffic jams around full shelters.

(a) Evacuation rates for all shelters (b) Evacuation rate per shelter

Figure 10: Maximum evacuating speed of candidate plans in different scenarios.

5.2.3 Number of Traffic Jams at Intersection

To show the advantages in the scenario's variability and the ability of decision support benefitting from that, an experiment is carried out with the existing plan within Scenario 4 (413,000 agents) to compare our integrated agent driving decision model with two simple agent models: the shortest path model and the potential network model to find their route, where the agents use only one model and can not change their targets during the simulation. The waiting time for each agent is recorded and the maximum waiting time for all the intersections are captured. For each of the three models, the simulation are replicated 5 times and the intersections with top 100 of the waiting time are recorded and shown in Figure 11.

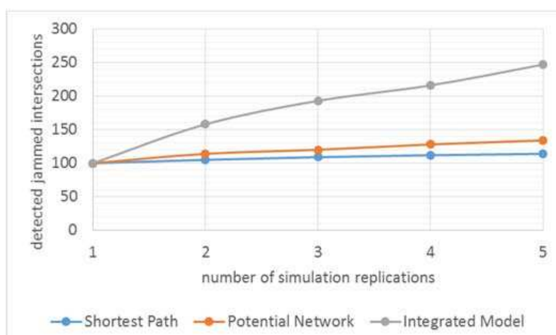

Figure 11: Jammed intersections with top 100 of the waiting time in five simulation replications.

The simulations using the simple models detect traffic jams, but the jam locations of the intersections do not change a lot. On the other hand, our integrated model shows the crowded intersections in more different locations in each five replications. This shows a wider possibility of jammed intersections which is significant information for decision makers, suggesting where traffic polices should be deployed.

6 CONCLUSION AND FUTURE WORK

This paper describes the development and implementation of an agent-based simulation system where each agent's driving behaviors are modeled with multi-layered hierarchical decision making process. Our approach uses a modular structure by reusing and combining existing driving behavior models. An agent's driving decision process is designed based on a four-layer decision structure where each layer's driving decision influences the behavior in other layers. Our experimental results support more variability of driving behaviors expected in an evacuation situation and wider distribution of traffic jams. In addition, building more shelters may increase the overall evacuation rate, but may decrease the efficient utilization of shelters (i.e., the evacuation rate per shelter).

In the future, we will consider additional factors (e.g., different types of vehicles, pedestrians, or bicycles) in the simulations for better understanding of evacuation-related decisions. We also plan to study how driver's psychological characteristics affect their behaviors, especially on the interaction between psychological factors and the consequence of plans, e.g., how different proportion of agents not following the evacuation plan might affect the evacuation rates. More comparative studies will be conducted to investigate computational requirements of our system in relation to others such as MATSim.

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