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REGULAR PAPER

An agent-based social forces model for driver evacuation behaviours

David Handford · Alex Rogers

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Abstract Realistic modelling of driver behaviour during evacuation scenarios is vitally important for creating effective training environments for disaster management. However, few current models have satisfactorily incorporated the level of complexity required to model the unusual driver behaviours which occur in evacuations. In particular, few state-of-the-art traffic simulators consider desires of a driver other than to travel the quickest route between two points. Whereas in real disaster settings, empirical evidence suggests other key desires such as that of being near to other vehicles. To address this shortcoming, we present an agent-based behaviour model based on the social forces model of crowds, which explicitly includes these additional factors. We demonstrate, by using a metric of route similarity, that our model is able to reproduce the real-life evacuation behaviour whereby drivers follow the routes taken by others. The model is compared to the two most commonly used route choice algorithms, that of quickest route and real-time re-routing, on three road networks: an artificial "ladder" network, and those of Louisiana, USA and Southampton, UK. When our route choice forces model is used our measure of route similarity increases by 21–169 %. Furthermore, a qualitative comparison demonstrates that the model can reproduce patterns of behaviour observed in the 2005 evacuation of the New Orleans area during Hurricane Katrina.

Keywords Agent-based simulation · Cognitive modelling · Evacuation simulation · Traffic simulation

D. Handford (✉) · A. Rogers
School of Electronics and Computer Science,
University of Southampton, Southampton, UK
e-mail: D.J.Handford@soton.ac.uk

A. Rogers
e-mail: acr@ecs.soton.ac.uk

1 Introduction

Evacuation of large areas due to disasters requires effective real-time management, and to this end realistic training environments are increasingly being used in order to teach operators how to manage traffic in the safety of a simulated environment. However for training to be effective, the simulated environment must have the flexibility to respond to the variety of actions operators can make, such as setting up road blocks or diversions, in addition to simulating situations with limited real-life data and producing an environment prescribed by the scenario manager. Multi-agent simulation systems are able to provide a more open and interactive system than traditional macroscopic implementations of driver behaviour and are therefore suitable for producing an immersive and interactive environment for training traffic controllers [3]. The simulation must be able to reproduce the driver behaviours observed in real-life evacuations but with the constraint of there being limited opportunity to gain real-world data. Studies of real-life evacuations have revealed patterns of traffic behaviour in which a perceived degree of physical danger causes drivers to ignore road maps and choose routes similar to those of others, so as to avoid being isolated [6,15]. This leads to a disproportionate increase in use of major routes and a spread of routes across the road network with suboptimum flow rates for evacuation. For example, in the evacuation of the New Orleans area during Hurricane Katrina in 2005, this interdependence in driver behaviour led to situations in which, despite there being two possible escape routes, a disproportionate number of drivers used just one leading to congestion.

However, route choice behaviour in current state-of-the-art evacuation simulations incorporate limited driver behaviours and thus it is difficult to reproduce there real-life patterns of traffic behaviour with such simulators. Evacuation modelling has most recently been carried out using existing well-established traffic simulators, including MATSIM [10] and PARAMICS [4]. Within these simulators, a driver's route choice behaviour is determined using a user-equilibrium assignment model. Drivers either use a static route choice algorithm, in which they remain on the same route to reach an exit, or a dynamic route choice algorithm, where they factor in real-time knowledge to re-plan their route. Both MATSIM and PARAMICS use variants of these algorithms [14]. However, the assumption that a driver's behaviour will be constrained by usual conditions of rationality and user equilibrium are unlikely to hold true in the evacuation scenarios where drivers are presented with an unfamiliar situation [13]. Instead an evacuating driver's route choice is influence by multiple factors, including their aversion to being isolated, which current route choice models ignore. Therefore these algorithms are unable to replicate the observed patterns of behaviour in evacuations and thus their use for disaster management simulation is significantly impaired [1,5].

To address this shortcoming, in this paper we present a novel agent-based route choice forces model which offers the flexible framework capable of simulating these driver behaviours. Our approach is inspired by the social forces model of pedestrian behaviour [7], which, in turn, is derived from a model of behavioural changes caused by social fields [11]. Within social field theory, it is proposed that a variety of factors act on and influence an individual's decision making behaviour in any given scenario. Expanding on these models, our route choice forces model represents the desires of a driver explicitly as a set of "forces" which act on an influence an agent's decisions. Within our model these forces act along the direction of roads, representing the strength of an individual's desires to drive down any road. For evacuation simulation two forces are defined: the desire to take the quickest route to safety and a varying desire to be with others depending on the driver's particular level of panic. The force representing the desire to follow the quickest route is determined using a driver's current knowledge about the road network including knowledge of congestion. The force that represents a driver's desire to be with others is calculated using a driver's prior knowledge of a road network and where others are likely to be located. In order to reproduce this "mental map" of the road network, prior to running the evacuation simulation, drivers are simulated using their non-evacuation routes out of town, along which they leave a virtual trail which identifies the commonly used roads, similar to the floor field model in crowd modelling [9]. An algorithm is then used to determine routes which pass through commonly used roads.

Thus in more detail, this paper extends the current state-of-the-art in driver route choice models in the following ways:

- We develop a probabilistic agent route choice mechanism known here as the route choice forces model, in which decisions are influenced by a set of forces representing the factors which influence a driver's behaviour. We incorporate real-life observed evacuation behaviours as two forces, one representing a driver's desire to travel the quickest route and another representing a driver's desire to be with others.
- We evaluate our model against two existing route choice algorithms (shortest time and real-time re-routing) using three road networks: a simple "ladder" network and the cities of Louisiana, USA and Southampton, UK. For a quantitative evaluation we define a metric which determines how effectively an algorithm can replicate a driver's desire to use the route of others during evacuations. We show that our model increases the metric by 21–169 % over using other algorithms, in addition to conforming to qualitative observations from evacuation during Hurricane Katrina in 2005.

The rest of the paper is arranged as follows: Sect. 2 describes the context within which the model is developed. Sections 3 presents the model itself. Section 4 describes the metric and empirically evaluates the model. Finally, Sect. 5 discusses the model's further development.

2 The evacuation setting

Our route choice force model forms a behavioural component within a disaster management and traffic operator training simulator in development at BAE SYSTEMS. This simulator is being developed to train operators to manage traffic flows in the event of emergencies. Our model is being developed as part of a simulation framework which is made up of three components: the traffic control centre environment which provides the traffic controllers with an environment comparable to that of a real-life traffic control centre; the 3D visualiser engine, which allows controllers to view the state of the roads through virtual CCTV cameras (as demonstrated in Fig. 1); and the underlying agent-based traffic behaviour model which provides both strategic level behaviours such as route choice and tactical level behaviours such as car following and lane changing. An agent-based event-driven mesoscopic traffic simulation model, based on the agent-based MATSIM traffic simulator [2] and implemented in C++, is used to model the individual movement of the cars as they evacuate from a start zone to a predetermined safe zone. A region is represented by a road network defined by a set of roads with lengths and speed limit connecting a set of junctions. Within the queue model each road section has a corresponding queue, implemented as a FIFO queue with restrictions on entering and exiting. Drivers are represented

Fig. 1 BAE SYSTEMS traffic simulator 3D visualiser demonstrating the simulated feed from a CCTV camera

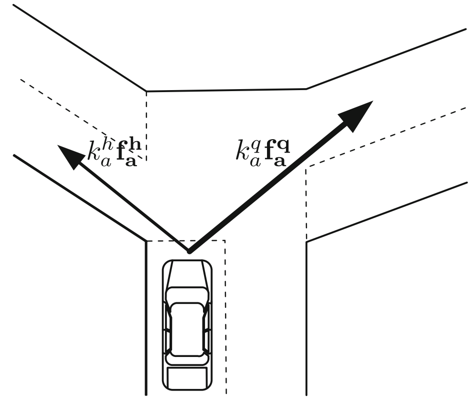


Fig. 2 Schema of behavioral process of an agent arriving at a junction

by agents with the goal of reaching a safe destination by planning a route and then travelling through the road network. The only choice an agent must decide upon is which way to go once it reaches a junction, which is achieved using our route choice forces model.

Table 1 Forces acting upon the decisions of agent *a*

Force	Coefficient	Description
$\mathbf{f_a^q}$	$k_a^\mathbf{q}$	Desire to travel the quickest route
$\mathbf{f_a^h}$	$k_a^\mathbf{h}$	Desire to be with others

3 The route choice forces model

As discussed earlier, our route choice forces model builds on the concept of social fields used in the social forces model of crowd behaviour [7,12] in order to capture the interactions between a driver's different desires and their ultimate choice of route. This framework allows us to incorporate driver behaviours required to adequately train traffic controllers but missing from current simulators. The social fields concept provides a model of the human cognitive process which is transferable between different situations. We apply this model of decision making to driver route choice by representing the desires of a driver as forces which act along the direction of the roads. Extending upon ideas from other models each force explicitly represents a specific desire of the driver. The direction of the force represents the route a driver would take if they were to follow that desire, and the magnitude represents the strength of the desire. These forces are resolved once an agent reaches a junction and must make a decision about their route choice. As with the floor field model in crowd behaviour, we use a probabilistic mechanism to choose between these available routes, which dynamically diffuses the routes around the road network, representing the choices of different drivers [9]. The probabilities are given by the strength of the forces, with agents being more likely to choose routes in the direction of stronger forces. For our evacuation simulation the forces are defined to represent the two desires of an agent: to evacuate along the quickest route and to be with others.

Now, we define the mechanism used by agent *a* to choose which road to follow once they reach a junction *j*, as shown in Fig. 2 and Table 1. Each force $\mathbf{f}$ acting upon the agent's decision is multiplied by a coefficient k_a^f, which is personal to the individual agent, and which governs the degree to which it is affected by each of its desires. These coefficients are dynamic and can be used by the scenario manager to control the driver's individual level of panic by altering their ratio. If the coefficient for a desire is very large in comparison to others then it will be the governing desire. For each of the possible roads that an agent may choose to take, as defined by set N_j, a score $Score_i(j)$ is calculated by combining the magnitude of all the social forces which are in the direction of that road *i*. Thus if F_{ij} is the set of all forces acting along the direction of road *i* at junction *j* then the score for road *i* is calculated by:

$$Score_i(j) = \sum_{\mathbf{f} \in F_{ij}} k_a^f |\mathbf{f}| \tag{1}$$

Using the score, the probability of taking road *i* is calculated. Our model uses a linear choice model which maintains the linear connection between a road's score and the probability that it is selected. Thus, the probability of a particular route *i* being selected by a driver at junction *j* is given by:

$$p_{ij} = \frac{Score_i(j)}{\sum_{r \in N_j} Score_r(j)} \tag{2}$$

where N_j is the set of all the roads leading off junction *j* that it is possible for a driver to take.

In the follow sections we describe the methods used to create the two forces representing the two desires identified for evacuation scenarios.

3.1 Desire to travel the quickest route

At junction j, the force $\mathbf{f_a^q}$ representing the desire of agent a to travel the quickest route to an exit point, acts in the direction which the agent believes is the evacuation quickest route. Dijkstra's algorithm is used to identify the set of the roads R which represent the quickest route that can be taken from junction j to reach an exit point. The cost of each road is the time an agent believes it will take it to traverse the road, calculated by dividing the length of the road by the average speed the agent believes they will be able to travel at. The knowledge of this speed initially comes from the speed limit of the road, but will be updated if the agent gains extra knowledge, such as the location of congestion. The magnitude of this force is determined by the distance the agent must travel to reach the exit point, as determined by the sum of the lengths of all the roads in set R. This magnitude is normalised to a range zero to one, and for agent a at junction j is given by:

$$|\mathbf{f_a^q}| = \frac{1}{\sum_{l \in R} d_l} \tag{3}$$

where d_l is the length of road l and the magnitude of the force is equal to the inverse of the total cost of using the route R.

3.2 Desire to be with others

In order to create a force which represents a driver's desire to be with others during an evacuation, we must provide the agent with a "mental map" which represents their beliefs about the road network, from which they can determine where they believe others to be located and the route they wish to take. This map will have been built up from their prior experiences, which have occurred during normal conditions on the road network. Thus, the drivers will be forced to use their knowledge gained in normal conditions to make a route choice in the evacuation situation. Here we use a model inspired by the floor field model of pedestrian behaviour [8,9] to build up this map, since it is capable of generating cognitive maps of environments. In such models, agents lay down abstract trails as they move through the environment, to which others are attracted. This, in turn, is based on the phenomena of chemotaxis or stigmergy found in ant colonies. To generate an agent's prior knowledge within our simulation, we implement a learning phase in which we simulate drivers, over a number of simulation runs using their non-evacuation routes to travel to an exit point, along which they leave a trail. These trails build up along road sections used most often, providing the agent with a "mental map" of the road network. Within our model the non-evacuation route choice is made using the shortest time route choice algorithm. Other algorithms may be used here, which will result in different trails being left, however we choose shortest time since it provides a close representation of the usual route choice of drivers. The strength of the trail on road section l is given by u_l. If R is a set of all the routes taken by each individual agent to reach an exit point and each route V in that set of routes is defined as the set of road sections l which make up that route, then the strength of the trail on road section is given by:

$$u_l = \frac{|\{V : V \in R, l \in V\}|}{|R|} \tag{4}$$

In order to provide a meaningful example of calculating the desire to be with others a road network is defined with road lengths d_l as shown in Fig. 3a. Using this network three drivers are simulated travelling to the exit point F; the set of routes they use R is:

$$R = \begin{Bmatrix} \{\overrightarrow{AD}, \overrightarrow{DF}\} \\ \{\overrightarrow{BE}, \overrightarrow{EF}\} \\ \{\overrightarrow{CE}, \overrightarrow{EF}\} \end{Bmatrix}$$

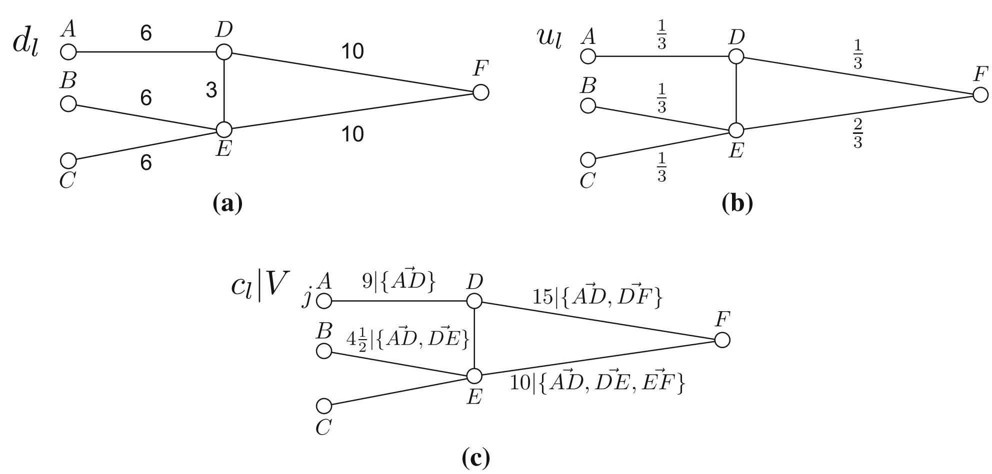
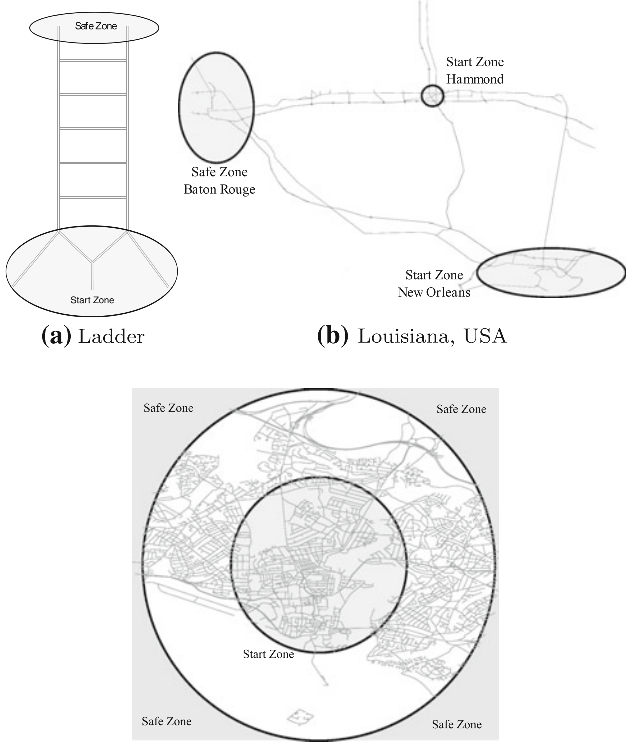


Fig. 3 Example road network for calculating the desire to be with others



(a) Ladder **(b)** Louisiana, USA

(c) Southampton, UK

Fig. 4 The three road networks on which the algorithms are evaluated

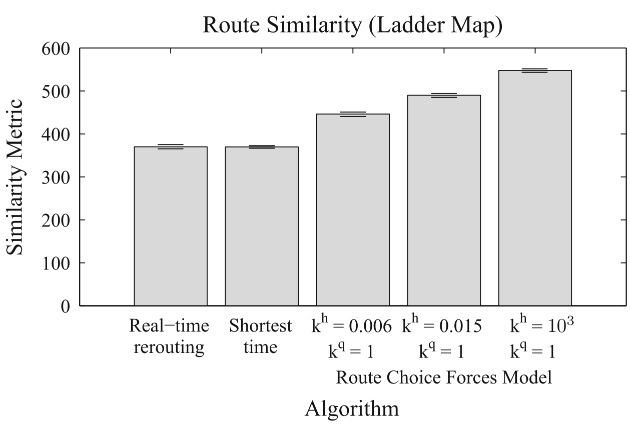


Fig. 5 Similarity in routes when using different route choice algorithms

Trails are laid along these routes and the u_l for each road l is calculated, as shown in Fig. 3b.

When agent a reaches junction j, they use this prior knowledge to find a route from the junction to an exit point which they believe others will use. This represents the route they would take were they to follow their desire to be with others. Dijkstra's algorithm is used to identify the set of the roads R_f which represent this route, ensuring that one distinct route is identified. The knowledge of the routes of others is taken into account by adjusting the cost of using a road section in a route. Thus, the cost of using road l, given that the route

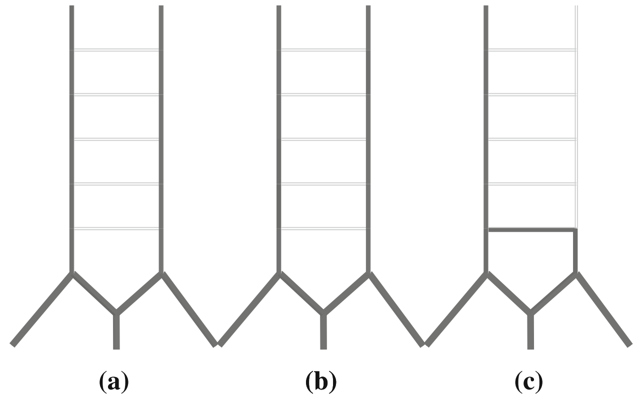


Fig. 6 Road network usage for the ladder road network after 1 hour when using **a** shortest time algorithm, **b** real-time rerouting algorithm and **c** route choice forces model with $k^h = 1$, $k^q = 0$. Road usage is represented by the *thickness of the line*

taken to get to the road from junction j is given by the set of roads, V and the length of the road l is given by d_l, is given by:

$$c_l(V) = \frac{d_l}{1 - \min_{k \in V} u_k} \tag{5}$$

Thus, the direction of the force at each junction is determined by this route and the magnitude is determined from the total cost of using the path. The magnitude is normalised to the range zero to one and is given by:

$$|\mathbf{f}_\mathbf{a}^\mathbf{h}| = \frac{1}{\sum_{l \in R_f} c_l} \tag{6}$$

where the magnitude of the force is equal to the inverse of the total cost of using the route R_f. For our example, the calculation of c_l given the set of roads V and that junction j is node A, is shown in Fig. 3c. The route R_f identified using Dijkstra's algorithm is $\overrightarrow{ADEF}$ and $|\mathbf{f}_\mathbf{a}^\mathbf{h}| = \frac{2}{47}$.

4 Empirical evaluation

Given the description of our route choice forces model, we evaluate its ability to produce the real-life behaviours observed in evacuation on three road networks against that of two other route choice algorithms. Evacuation scenarios are simulated in which the driver agents begin their evacuation journey in a "start" zone and drive to a "safe" zone. This section defines this evacuation setting, including the road networks used and the route choice algorithms, and then discusses the results.

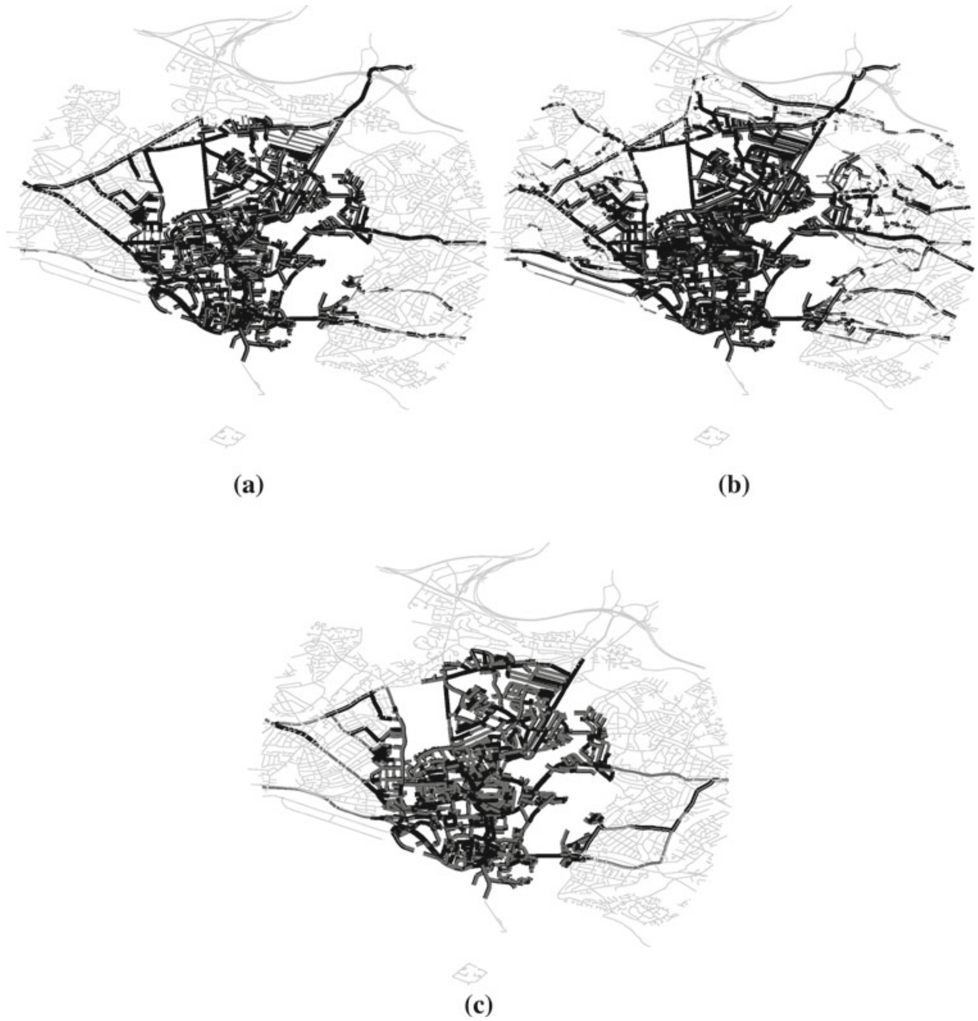


Fig. 7 Road network usage for the Southampton, UK network after 1 h when using **a** shortest time, **b** real-time rerouting and **c** route choice forces model. Road usage is represented by the *thickness of the line*

4.1 Evaluation setting

In order to evaluate our route choice forces model three road networks are now defined. These are used to simulate evacuation scenarios in which the driver agents begin their evacuation journey in a "start" zone and drive to a "safe" zone. Drivers flow into the network at a uniform rate and begin their journeys, producing a variety of start times. Three maps have been defined in order to evaluate the model:

- A theoretical construct of a "ladder", as shown in Fig. 4a. In this map, drivers start at the bottom and escape at the top through one of the two exit points. The drivers have the choice of using either of the exit routes to reach a safe point and the rungs provide points for the drivers to change which route they are using. The ladder is used to evaluate the situation where there the desire to be with others causes disproportionate usage of the two exit routes. Each leg of the ladder offers the driver an equal route to exit point, so in usual circumstances they equally distribute across the two legs. However when they have a desire to be with others they concentrate on one side more than the other, choosing a route they believe they will find others.
- A road network crafted from the roads in Louisiana, USA, shown in Fig. 4b. The map is generated from OpenStreetMap data for Louisiana, but only including the major evacuation routes. Drivers evacuate from New Orleans and Hammond, through the city of Baton Rouge, similar to the actual routes taken by residents during the 2005 Hurricane Katrina.
- A network that represents the full road network of the Southampton, UK area, shown in Fig. 4c, generated from OpenStreetMap data. Using this road network the performance of the algorithm over a large-scale area can be observed.

Using these road networks, the evaluation compares the three different algorithms,

- *Route choice forces model* A number of runs of our route choice forces model with different coefficient weightings for the forces. Two forces act upon the agent: shortest route time and desire to be with others.

- *Shortest time* A behaviour algorithm which has the simplistic behaviour of finding a quickest path tree to the exit points, with a preference of using major roads. This algorithm is the same as the one used in PARAMICS for "unfamiliar" drivers [14].
- *Real-time rerouting* A dynamically re-routing algorithm which at regular intervals re-calculates the quickest path trees to take into account the delays caused by congestion. This algorithm is the same as the one used in PARAMICS for "familiar" drivers [14].

Computationally, the simulation runs at 10–20 times quicker than real-time. Due to implementation, the shortest time and our route choice forces model complete in similar times, however the real-time rerouting algorithm takes longer since it must re-calculate routes at regular intervals.

In order to provide a quantitative comparison between the different route choice models, a metric is presented which determines the similarity of the evacuee's routes. The metric is used to show how our route choice forces model can be used to replicate the real-life evacuation behaviour of drivers desiring to be with others. Using each of the defined road networks, the traffic behaviour is simulated using each of the three route choice algorithms. After an hour of simulation time the simulation is stopped, and for each evacuated driver their route is analysed and a count is increased on each road which they have used, such that the count n_l represents the number of evacuation routes which have used road l and is given by:

$$n_l = \frac{|\{V : V \in R, l \in V\}|}{|R|} \tag{7}$$

and N is the set of all counts and is given by:

$$N = \{n_0 \ldots n_{m-1}\} \tag{8}$$

where R is all set of routes which have been taken to an evacuation safe point and m is the total number of roads in the road network. If the routes are equally distributed across the road network then each road will have an equivalent level of usage. However, if the routes are concentrated on a few particular roads, then the road usage count will be more varied. The metric is therefore defined as:

$$usage = stdev(N) \tag{9}$$

4.2 Simulation Results

Using this analytical comparison we run the simulation run five times using the different algorithms and different coefficients for the route choice forces. The simulation is run for one hour at which point the distribution of route choice

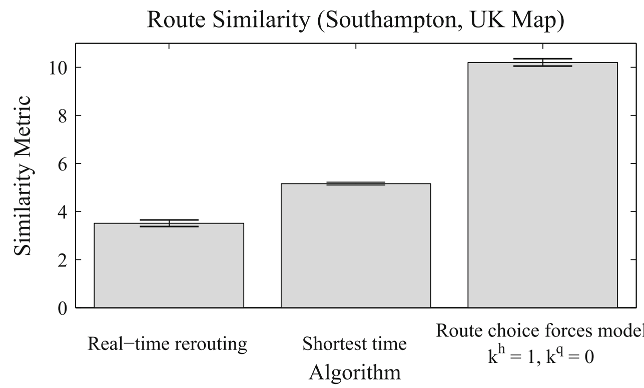


Fig. 8 Similarity in routes when using different route choice algorithms

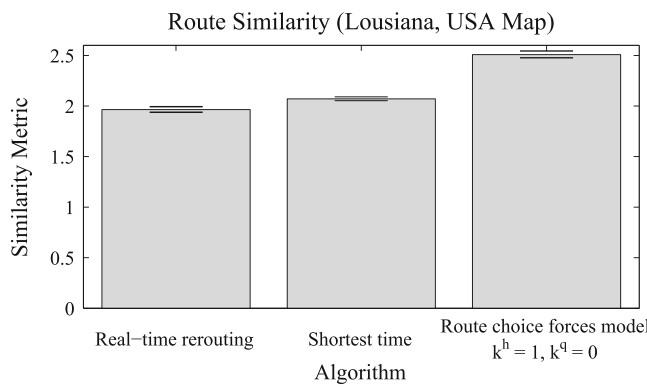


Fig. 9 Similarity in routes when using different route choice algorithms

across the map has become stable. First consider the results on the ladder road network, Fig. 6 presents the road usages for the ladder network after one hour of simulation time for the three different algorithms. As can be observed in Fig. 6a, when using the shortest time algorithm drivers use both legs of the ladder. A similar result can be seen in Fig. 6b when using the real-time re-routing algorithm, since traffic is free-flowing through the network and therefore there is no congestion to avoid. However, when our route choice force model is used, as shown in Fig. 6c, traffic uses only one of the legs of the road network to escape. The driver's desire to be with others when evacuating has led to only one of the two possible escape routes being used, similar to the pattern of behaviour described earlier which is observed in real-life evacuations [6]. Figure 5 plots the average value of the metric of similarity for evacuating routes over the five runs, as well as the standard error in the mean. Comparing the metric value for the shortest time algorithm, to the metric value for our route choice forces model with $k^h = 10^3$ and $k^q = 1$ shows a statistical significant increase by 49 % when using our model ($P < 0.001$ by unpaired t test). Setting the coefficient $k^q = 1$ for all agents and then varying the coefficient k^h gives a degree of control over the similarity of the driver's

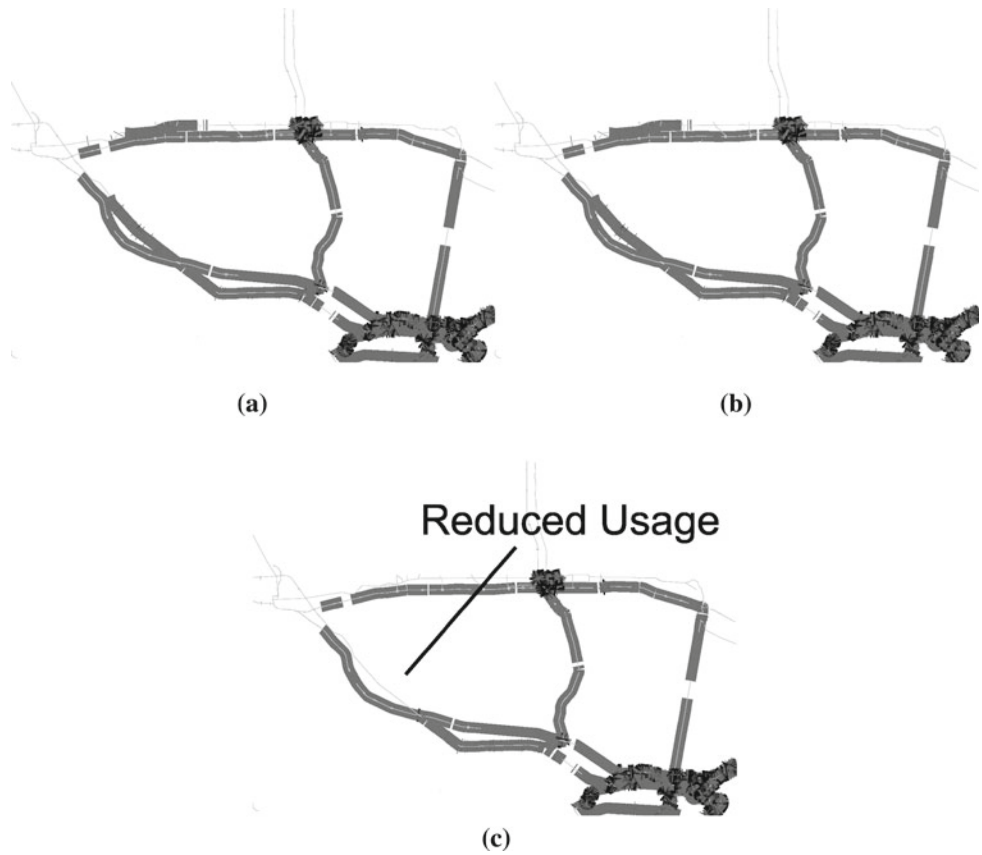


Fig. 10 Road network usage for the Louisiana, USA road network after 1 h when using **a** shortest time, **b** real-time rerouting and **c** route choice forces model. Road usage is represented by the *thickness of the line*

routes. A similar effect occurs in all the road networks presented here. Thus k^h can be used by the scenario manager to control the desirability drivers have for following the routes of others and thus their level of panic.

The road network usage maps for Southampton and Louisiana are shown in Figs. 7 and 10, respectively. Comparing these two networks it can be seen that Southampton represents a situation in which there are multiple routes across an urban environment which drivers can use to exit the city, whereas in Louisiana the environment is mostly rural with a limited number of highways. Figure 7 shows the routes being utilised in the Southampton road network when the driver's evacuation behaviour is being determined by each of the three different algorithms. Figure 7a shows that when agents are using the shortest time algorithm traffic takes six routes out of the town, utilising the closest major roads to their start position. When using a real-time re-routing algorithm the routes become more distributed around the network, with thirteen exit points being used as shown in Fig. 7b. Here, as a driver discovers congestion on roads they alter their route to less congested roads to complete their journeys in the quickest time. In contrast, when the route choice forces model is used the number of exit routes drops to three, with drivers purposely cutting across the road network to use an exit route used by others as can be observed in Fig. 7c. As Fig. 8 shows, the use of our model over the shortest time model gives an increase in the metric of 96 % and over the real-time re-routing model of 169 % (both with $P < 0.001$ by unpaired t test).

Considering the Louisiana road network, Fig. 10 shows that there is little difference between the use of the quickest route and real-time re-routing algorithm. Similar to the ladder network, this is due to there being very few alternative routes that drivers can choose to take if they discover congestion on their current route. Fig. 9 shows that, using our model, the metric of route similarity is increased by 21 % over the shortest time algorithm and 28 % over using real-time rerouting (both with $P < 0.001$ by unpaired t test). From Fig. 10c it can be observed that using the route choice forces model the use of the roads into Barton Rouge at the north-west corner have decreased from two to one, so that only the southern road in is used. These two roads have equivalent capacities however the southern road is signposted as the more major of the two roads, knowledge which has been captured during the learning stage of our model from agents' non-evacuation behaviours. This leads to a disproportionate number of vehicles using the southern route, a pattern of road usage which is the same as was observed during the evacuation of Louisiana, USA during Hurricane Katrina, in which it was recorded that a disproportionately large number of drivers used the southern road over the northern road from New Orleans to Barton Rouge [15]. Demonstrating that our model is able to reproduce real-life behaviours not currently captured in traffic simulators.

5 Conclusion

We have presented a route choice forces model which represents a driver's desires as a variety of forces or factors, which scenario managers can configure to represent different driver behaviours. Within the evacuation context, two factors have been defined: desire to take the quickest route and desire to be with others. By including these desires of a driver, we have shown that this model can be used to replicate driver behaviours in evacuation situations, including those seen in the 2005 evacuation of Louisiana, USA during Hurricane Katrina. Empirical evaluation using a metric of route similarity and the road networks of an abstract "ladder", Louisiana, USA and Southampton, UK, showed that our model gives a 21–96 % increase in the metric over the shortest path algorithm and 28–169 % increase over the real-time rerouting algorithm, and thus is able to simulate evacuation behaviours not captured by existing models. Within the context of the BAE SYSTEMS simulator, future work includes the expansion of the model to include driver desires relevant to other scenarios, including responses to directly observing the routes of others, route planning within unfamiliar environments, variable driver knowledge of routes and driver compliance behaviour to real-time information.

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