Proceedings of the 2015 Winter Simulation Conference
L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, eds.

ADAPTIVE ROUTING AND GUIDANCE APPROACH FOR TRANSPORTATION EVACUATION

Bo Zhang
Wai Kin Victor Chan

Department of Industrial and Systems Engineering
Rensselaer Polytechnic Institute
110 Eighth Street
Troy, NY 12180, USA

Satish V. Ukkusuri

Purdue University
School of Civil Engineering
550 Stadium Mall Drive
West Lafayette, IN 47906, USA

ABSTRACT

We propose an adaptive routing and guidance approach called Adjacent Node Score (ANS). This approach is integrated with an agent-based simulation model and avoids several common assumptions made in conventional evacuation models. ANS does not assume altruistic travelers and considers traffic interaction, variable link travel times, and their dependencies. This makes it more realistic than network flow models and stochastic routing algorithms. ANS can generate effective and good solutions at a low computational cost. It only requires local network information for routing and guidance. ANS can be easily implemented in practice. We test the ANS method on two networks and compare it with other four network routing strategies including the user-equilibrium condition, myopic, aggressive, and a naïve strategy that is based on static network information. Experimental results show that ANS can disperse highly concentrated traffic flows and reduce network clearance time compared with other methods.

1 INTRODUCTION

Transportation evacuation is an important multi-disciplinary research topic that has received a great deal of attention from the research community and general public (Chiu et al. 2008; Dow and Cutter 2002; Hackney and Marchal 2009; Lindell et al. 2005; Zhang et al. 2014). To achieve efficient evacuation, it is desirable to have a well-coordinated evacuation plan to prevent unnecessary traffic jams and save lives and properties during an emergency evacuation.

The purpose of evacuation is to move residents from dangerous areas to safe places as soon as possible. A common metric used to measure the performance of an evacuation plan is the network clearance time, which is defined as the time elapsed from the first traveler leaving its origin to the last traveler arriving at its destination. The objective of an evacuation plan is therefore to minimize or reduce the network clearance time. Mathematical programming models and heuristic algorithms at macro or meso level have been developed to generate optimal or heuristic operating plans and routing schedules (Cova and Johnson 2003; Kim et al. 2007; Lu et al. 2005). However, mathematical-based optimization models usually require a number of assumptions to simplify the underlying problems into manageable and tractable mathematical forms.

There are methods for dealing with congestion in practice. In particular, traffic control strategies have been applied to guide travelers from congested paths to ones with excessive capacity. Contraflow operation reverses the direction of traffic flow in one or more of the inbound lanes or shoulders to greatly increase outbound capacity (Urbina and Wolshon 2003). Contraflow can also be used for non-emergency conditions such as daily rush hours. In the staged evacuation strategy, emergency management authorities

978-1-4673-9743-8/15/$31.00 ©2015 IEEE

separate the affected area into several zones with different evacuation times. The travelers in different zones are organized to evacuate in sequence. This strategy can help mitigate road congestion. When traffic is congested, the staged evacuation strategy may take less time than the simultaneous evacuation strategy (Chen and Zhan 2004).

Many prior studies made the following two common assumptions. First, evacuees are assumed altruistic and willing to take longer routes so that emergency management authorities can assign them to longer routes to improve the total evacuation time (Madireddy et al. 2011). However, in the real world, this assumption is not valid in general. In fact, route choice during an evacuation is a complex process involving random factors. Depending on the traffic conditions, evacuees may switch to a different route to obtain better travel time from the one initially attempted. Second assumption is that daily traffic data can be used to forecast traffic during an evacuation. This assumption was made mainly because the lack of disaster traffic data, which is quite rare. This assumption is problematic because the traffic pattern during a disaster could be quite different from daily traffic patterns.

To address these limitations, we model the evacuation problem by relaxing these assumptions and build an evacuation planning model from the perspectives of both individual evacuees and emergency management authorities. In this model, evacuees are presumed to have a high likelihood of self-preserving, self-interested behavior. They will prioritize their own evacuation time and will make decisions that best serve their interests. Meanwhile, authorities of emergency management do not have full control on the behaviors of individual evacuees. However, based on the information collected by traffic monitoring devices, authorities can set up rules and policies to influence and potentially alter the routing behaviors of evacuees (or travelers) to improve overall evacuation time.

In this paper, we propose a routing and guidance strategy called ANS (Adjacent Node Score) method and integrate it into an agent-based simulation model. ANS can disperse highly concentrated traffic flows during an evacuation and reduce network clearance time. This simulation-based method also considers traffic interaction and variable link travel times and their dependencies. This model is more realistic than static network flow models and stochastic routing algorithms. In terms of computational cost, ANS can generate high quality solutions at a low computational cost as opposed to conventional time-consuming simulation-based optimization methods which require iterating between a simulation model and an optimization algorithm many times and costing a large amount of computation.

The rest of this paper is organized as follows. Section 2 reviews related literatures. Section 3 details the ANS method. Section 4 compares the ANS method with four other methods. Section 5 concludes the paper.

2 LITERATURE REVIEW

Transportation networks are built to support normal daily demand. It is not designed specifically for rare events such as disaster evacuation. As a result, one major challenge in regional evacuations is to manage people and direct/transport them to safe locations within a short period of time through a large area. An efficient routing plan is very important because the network flow from origins to destinations will probably exceed the link capacity. Thus, using network flow models could be a general approach to model evacuation processes (Hamacher and Tjandra 2002). Because most traffic delays in regional evacuations occur at intersections, lane-based routing is one strategy for reducing these delays.

(Cova and Johnson 2003) introduce an integer programming-based minimum cost flow model for lane-based evacuation routing. Using this model, they can find the optimal routing plans for the whole traffic network. Although mathematical programming methods can provide optimal evacuation plans, their computational requirement can be demanded for large complex traffic networks, where the number of variables and constraints increases dramatically. (Lu et al. 2005) applies a shortest path algorithm along with capacity constraints to study time-dependent networks. They also model network capacity as a time series and use the algorithm to find sub-optimal solution for evacuation planning. This algorithm is effective for medium-sized networks. Later, (Kim et al. 2007) extend the scalability of the algorithm by adding heuristic structures to accelerate the routing computation. However, these algorithms require several assumptions, including an FIFO (First-In First-Out) property and constant travel time on links. When travel time is variable, these algorithms cannot be used. Time-varying travel time has been considered for congested networks (Miller-Hooks 2001). In addition, algorithms have also been proposed to address the problem of route choice in stochastic, time-varying networks (Gao 2005; Miller-Hooks and Mahmassani 1998, 2000). Most existing studies, however, assume that link travel times are known as a priori and stationary in time. Also, waiting is not permitted at intermediate nodes. Travelers must leave an intermediate node once they arrive. It is common in real-world transportation networks that travel times on connected links are dependent, especially when the network is congested. Congestion on one link is likely to affect the travel time of other links, and consequently cause a chain reactions. Furthermore, existing algorithms usually do not fully capture individual (traffic) interactions.

Computer simulation has been an effective experimental means for evacuation planning and management. A fast-time simulation model can help predict traffic conditions during evacuation, evaluate different alternative scenarios, and identify bottlenecks of transportation networks. Therefore, a good simulation model can assist the development of a well-coordinated evacuation plan. Indeed, traffic simulation models have been widely used to investigate emergency evacuation scenarios. With the help of traffic simulation methods, (Theodoulou and Wolshon 2004) model freeway evacuation around New Orleans and study the effectiveness of the New Orleans contraflow configuration for both emergency and non-emergency conditions. (Zou et al. 2005) develop a simulation-based emergency evacuation system, which can revise optimized plans for both evacuation planning and real-time operations. An iterative bi-level framework is provided by (Sbayti and Mahmassani 2006) to solve schedule evacuation trips between a set of origins and destinations and minimize network clearance time. In that bi-level model, the upper level solves dynamic network assignments to determine time-dependent routes, while the lower level employs a simulation-based dynamic traffic model to determine the corresponding route travel times. (Murray-Tuite and Mahmassani 2003) present a framework for modeling household trip chain planning in emergency evacuation. This framework first employs a simulation to obtain expected travel times of road links. Then, a series of linear integer programming models expressing household decision making and travel behaviors in evacuation conditions are solved based on these travel times. The optimized trip chains of each household can be incorporated into the simulation. Because for each household, a series of integer programming problems must be solved, the computational cost can be huge for large-scale networks.

During the actual course of an evacuation, vehicular scheduling can be difficult to implement because emergency management authorities may need to deliver to all evacuees the information of closest destinations and routes of a complex road network. Even though it is possible to communicate this information using existing devices, voluntary participation is required to guarantee the successful execution of the evacuation plan.

3 EVACUATION PLANNING

In this section, we present the Adjacent Node Score (ANS) method. The ANS method is composed of two sub-algorithms: route selection and score update. We first discuss the limitations of the user-equilibrium (UE) condition and then present the two sub-algorithms.

The main goal of evacuation planning is to disperse traffic flow to make the best use of limited network capacity, and maintain the efficiency of the evacuation over time. One quick method is to use the user-equilibrium (UE) condition to determine a stable distribution of travelers on the network and then follow this traffic distribution to evacuate. The main problem of this simple approach is that it is almost impossible for a real evacuation network to reach the UE condition. One reason is that the UE condition assumes that travelers have perfect network information. They know the travel time on every possible route and consistently make the best decisions for themselves regarding route choice. In reality, it is almost impossible for every evacuee to have perfect and up-to-date network information. Hence, achieving the UE condition is almost infeasible in practice. Nevertheless, this UE-based method can serve as a benchmark criterion for evaluating evacuation strategies.

In the ANS method, the underlying transportation network is denoted by a directed graph $G(V, E)$, where E is the set of links representing roads and V is the set of nodes representing intersections, sources, and destinations. For each Node $i \in V$, its adjacent nodes are denoted by the set A_i. Let $C(i, j)$ be the real-time travel time from Node *i* to Node *j*, where *j* is in the set A_i. $C(i, j)$ can be viewed as the real traffic conditions in ANS.

Each node $i \in V$ maintains a score S_i. The score value of a node is the negative value of the expected total travel time to the destination. It represents the node's *promising level* to reaching the destination from the current node: The higher the score (i.e., smaller absolute value), the smaller the expected travel time is from the node to the destination. S_i. is always negative in ANS. Initially, S_i is set to the negative value of the travel time from Node i to the destination. It will then be updated during the evacuation process to reflect the real-time travel time (as shown in the Score Update algorithm in Table 2).

A simple example is shown in Figure 1. There, if an evacuee is at Node *i* and he/she takes the middle route from Node *j* to destination (red square), the expected travel time of this route (denoted by $-R_j$) is $-R_j = -S_j + C(i, j)$. The minimum $-R_j$ (or maximum R_j) among all directly connected nodes gives the score of Node *i*. In case of multiple destinations, one score for each destination is stored. Each score then represents the promising level to the corresponding destination.

Specifically, at the beginning of the evacuation, all road segments have free flow travel time. As the evacuation progresses, the network could get congested and the travel times on roads vary over time. This also affects the node scores, which are updated at a constant time interval to reflect the nodes' current promising levels. In the ANS method, we assume that travelers have the ability to obtain the score information of direct coming road segments. This is a reasonable assumption because drivers can observe the traffic conditions of nearby roads. Also, most vehicles are equipped with radio and/or GPS to collect traffic conditions to identify better alternative routes. In addition, variable message signs (VMS) can also be used on the roads to provide evacuees with the traffic information of nearby routes, such as the score information obtained by ANS. This real-time local and adjacent road information will then allow the travelers to adaptively choose a route to the destination. This is described in the Route Selection algorithm given in Table 1.

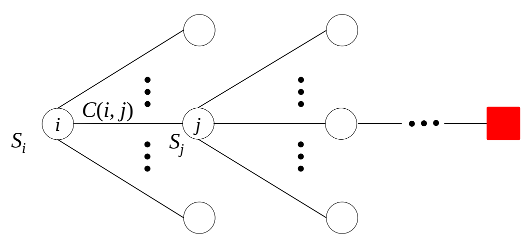


Figure 1: Example of ANS score

Table 1: Route selection.

Step 0:	Select initial route with the least cost based on free flow travel time before departure
Step 1:	While traveling en route
	If approach Node i
	For each Node j in A_i
	Obtain the real-time travel time from Node *i* to Node *j*, $C(i, j)$
	Calculate the score of route from Node *j* to destination: $R_j = S_j - C(i, j)$
	Select the route with $\max\{R_j \mid \forall j \in A_i\}$
Step 2:	If reach the destination, STOP

Otherwise, go to Step 1

Since the traffic condition may vary as the evacuation progresses, the score of each node in the network needs to be updated by emergency management authorities to provide evacuees with up-to-date traffic information. The update frequency can be set based on the capability of network communication devices, communication expenses, and real-time traffic situation. The score update procedure is shown in Table 2.

Table 2: Score update.

Step 0: For each Node i in the network
    Set the initial scores for the corresponding destinations
Step 1: At each update cycle
    For each Node i in the network
        For each Node j in A_i
            Estimate the current travel time from Node *i* to Node *j*, $C(i,j)$
            Update the score of route from Node *j* to destination: $R_j = S_j - C(i,j)$
    Update the score of Node *i* to be: $S_i = \max\{R_j | \forall j \in A_i\}$
Step 2: if evacuation completes, STOP
    Otherwise, go to Step 1

We implement the ANS method in the agent-based simulation model developed in (Zhang et al. 2014). In this model, each traveler is an agent in the simulation. We consider dynamic vehicular traffic interaction, variable link travel time, and link dependencies. Therefore, ANS can work on stochastic time-varying networks and capture the behavior of adaptive route choice, which cannot be adequately modeled in conventional traffic assignment models. In our model, evacuees are presumed to have self-interested behaviors. ANS provides traffic guidance information to let evacuees make their decision that best serve their own evacuation times.

Different from the UE condition which assumes that all the travelers have perfect global online information, ANS only requires local link information and local offline node information. The update frequency can be set at different level. But even at high frequent update level, ANS can still be more efficient than UE because it selects the route with the maximal score, which can prune out most unpromising alternative routes. ANS is a feasible and easy-to-implement method in practice. Compared with conventional simulation-based optimization schemes, which find optimal solutions by iterating between a simulation model and an optimization algorithm, ANS can generate good solutions at a low computational cost.

4 PERFORMANCE EVALUATION

In this section, we compare the performance of ANS and four other methods based on two commonly used networks. Although the UE condition is unrealistic in practice, we will use it as a benchmark. In the first test network, we mainly compare ANS and UE when evacuees tend to compete for the same shortest path to the destination. In the second test network, we extend the comparison to include three other types of routing strategies, each of which requires different amount of online network information. Therefore, together, we test five routing strategies: a strategy based on static-network information with zero online network information, (2) myopic strategy with partial online network information, (3) aggressive strategy with partial online network information, (4) ANS method, and (5) UE with perfect online network information. The simulation model is developed using the agent-based toolkit, Repast Simphony (North et al. 2006).

4.1 Test Network 1

The first test network is shown in Figure 2. The three left-most triangles nodes in the network are the origins of evacuation and the single square node on the right side of the network is the destination. The remaining circles are intermediate nodes. All the links are bi-direction with a single lane in each direction. One major property of this network (and other networks with a similar structure) is that the shortest paths from the three origins to the single destination overlap; they all go through the second row of the network. As a result, selfish travelers will compete to use the middle path (the second row).

We examine how the number of evacuees influences the evacuation process by varying the number of evacuees from 400 to 1000. In each experiment, evacuees enter the network from the origins and go through the nodes one by one. The population are equally (i.e., uniformly) distributed among the origins. The simulation ends when all travelers have reached the destination. For each experiment, 10 independent replications are made and the results are averaged to obtain the final result.

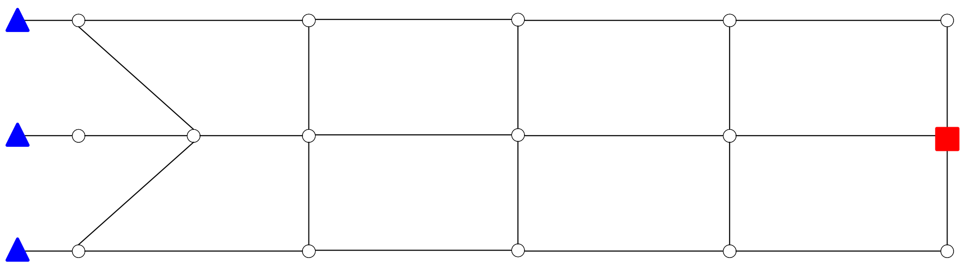


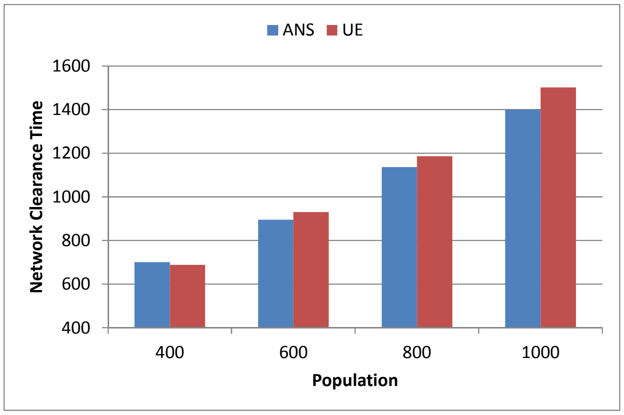
Figure 2: Test network 1.

Both network clearance time and average evacuation time are estimated and compared. The network clearance time is the time duration from the beginning of the simulation until all travelers have evacuated. The average evacuation time is the average value of all travelers' individual evacuation times. For all the experiments, the evacuation time is measured using virtual simulation time units. Therefore, the absolute value of this evacuation time is irrelevant. Instead, we are interested in the difference between the virtual evacuation times of different routing strategies.

The network clearance time and average evacuation time under different numbers of travelers are shown in Figure 3. It can be observed that ANS and UE perform similarly when the population is small at 400 (i.e., the network is not congested). However, when the population gets larger and larger (i.e., more congested, which is true in the real world), ANS can obtain better results than UE, especially when population gets larger.

UE is based on an ideal condition that travelers have full real-time information to make correct decisions. On the contrary, ANS only requires local information for the route selection and score update. Nevertheless, global information if by chance available can still be disseminated through the update cycles to improve the score estimates. Although this dissemination is not done in real-time, it is still very helpful in the decision-making of evacuation planning. Furthermore, the computational cost of ANS is lower than that of UE. Since the number of adjacent nodes usually ranges from three to five in a typical transportation network, local information in ANS could be acquired and computed at an almost constant time, which does not increase significantly in network size. In contrast, the UE condition requires travelers to obtain the real-time congestion levels and compute the travel times of all road segments along every alternative path. The computational cost could be high for a large-scale network.

Figure 4 shows the completion percentage of travelers who have completed the evacuation when there are 1000 travelers in the network. At the early stage of the evacuation, ANS and UE achieve a similar completion percentage. But as the evacuation progresses, ANS starts and continues to have a higher and higher completion percentage . For example, at time 1350, 98% of the travelers under ANS reached the destination while only 92% under UE completed the evacuation.



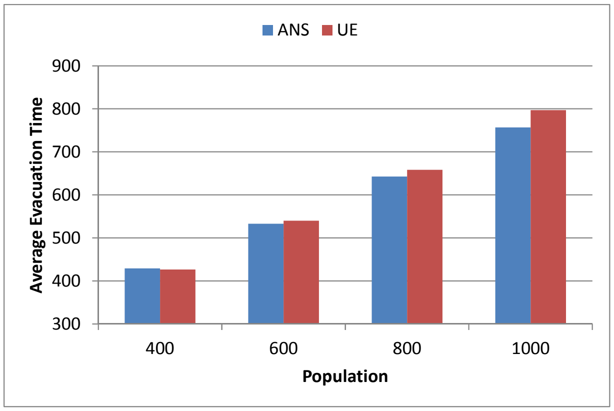


Figure 3: (a) Network clearance time: ANS vs. UE; (b) Average evacuation time: ANS vs. UE.

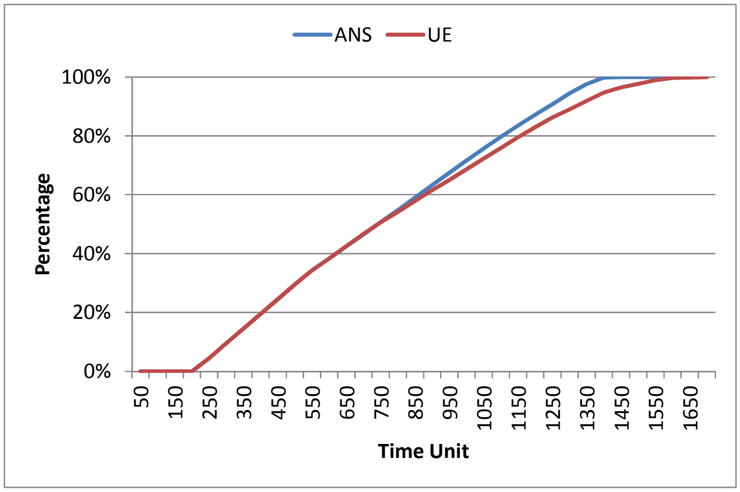


Figure 4: Completion percentage.

4.2 Test Network 2: Sioux Falls Network

Next, we test the performance of ANS in a larger and widely used network, the Sioux Falls network. The Sioux Falls network can be a good model for examining data and debugging models (Bar-Gera 2001). Figure 5 shows the structure of the Sioux Falls network. Again, triangles are origins; square is the destination, and circles are intermediate nodes. The traveler population here ranges from 3000 to 5000, which is equally (i.e., uniformly) distributed among the origins. Other experimental settings are the same as the previous experiment. We study the effectiveness of five routing strategies that use different amount of online network information: (1) Zero Online Information (ZOI) – a naïve method that is based on only static network information, (2 – 4) Imperfect Online Information (IOI) – a Myopic strategy, an aggressive strategy, and ANS, all three with partial online information, and (5) Perfect Online Information (POI) – UE condition with perfect online information.

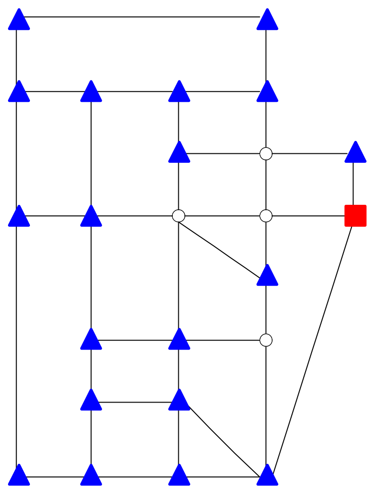


Figure 5: Test network 2: Sioux Falls Network.

4.2.1 Zero Online Information – A Naïve Method

Travelers with Zero Online Information (ZOI) know their current location and destination and have determined the route to the destination before departure based on static network information. However, they do not have any real-time network information other than their current location and static network information. They do not even perceive nearby road conditions and just simply follow the shortest path calculated at the beginning of the simulation (i.e., before the trip starts).

The traffic pattern during an evacuation is probably very different from the traffic during a normal condition. Having some online traffic information would be helpful for the evacuation. Therefore, the next level of information is to allow travelers to use some but not full online information.

4.2.2 Imperfect Online Information – Myopic, Aggressive, and ANS

Travelers with imperfect online information know partial real-time link travel times. They have partial instead of full information due to probably temporal or spatial (or both) restrictions. For example, people living nearby and heading to the same destination may have information about the neighborhood; they may follow the same route and enter the transportation network within a short period of time during an evacuation.

When many travelers rush into the network at a short period of time, the traffic on the route will probably exceed the capacity, resulting in a severe congestion and a much longer travel time. With partial online information, travelers may be able to perceive the congestion level of the nearby roads. This is realistic because nowadays most vehicles are equipped with a radio and/or a GPS that can receive real-time traffic condition updates and help them to find better alternate routes on their behalf. Therefore, some people may prefer to adaptively change their evacuation route based on the real-time traffic conditions to avoid congestions.

We further separate travelers with imperfect online information into three categories. The first one is called *myopic* behavior, which has been studied in district evacuation (Rossetti and Ni 2010). Myopic travelers only have partial information of direct coming roads. When selecting a route, these travelers pick a road that has the maximal distance to the last car on that road. The second type is called *aggressive* behavior. When an aggressive traveler agent approaches an intersection, he/she gets the updated information of all direct connected roads. If the congestion level on the original route exceeds a predefined threshold, the traveler will choose the road with the least congestion level and obtain a new evacuation route starting from this newly selected road segment. Hence, this type of travelers have the capability to dynamically change their routes to avoid congestion. The third is those who follow the ANS method. This group of travelers receive the score value of nearby nodes, which represent the promising levels of the nearby nodes.

4.2.3 Perfect Online Information – UE Condition

The last category is UE, which assumes that travelers have perfect online information. As discussed earlier, this assumption does not hold in general.

We should point out that although the ANS method requires only local information (i.e., the score update process requires only local road information and adjacent node score), when this local information propagates throughout the network (via score update), local information becomes global information (with time lags due to the propagation).

4.2.4 Comparisons

Figure 6 shows the network clearance time and average evacuation time, respectively, under different traveler populations on the Sioux Falls network. Obviously, online traffic information is helpful for evacuation routing. ANS and UE perform far better than ZOI because travelers can access online network information and choose route adaptively. When the number of travelers is 3000, the network clearance time of UE is the smallest and the average evacuation time of UE is slightly more than that of ANS. As the traveler population increases (i.e., more congested), both the clearance time and evacuation time of ANS are smaller than those of UE and also the smallest among all strategies. Therefore, ANS is more suitable in heavy traffic situation.

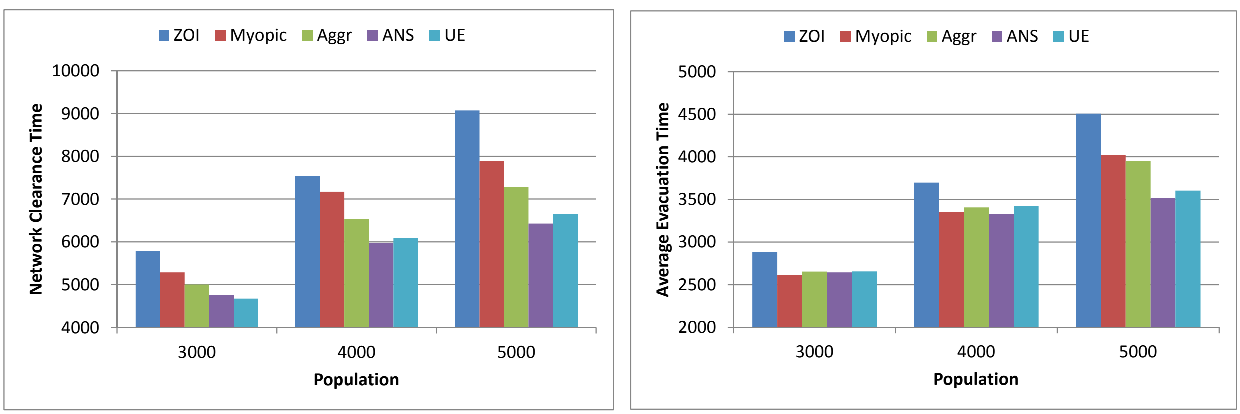


Figure 6: Sioux Falls Network: (a) network clearance time; (b) average evacuation time

Among the five routing strategies, travelers under UE receive the most information. However, based on the experimental results, we found that UE is not always the best strategy for evacuation. In most cases, ANS produces smaller evacuation times than UE. Travelers receiving more current network information but not future information could behave myopically. Stability is another reason for the lower performance of UE. Because travelers act independently based on the current network information, they could all select the same route that is currently the most uncongested, thereby congesting this route when all travelers reach there. In addition, currently congested road segments far away from a traveler may clear up later when the traveler reaches there. These issues are mitigated to some extend in ANS because information is updated at discrete time intervals. Therefore, ANS could perform better than UE.

We conclude that online information can help travelers to avoid congestion and reduce evacuation time. However, more information is not always better. In other words, the value of information is not always positive. When travelers are selfish, they want to minimize their own evacuation times independently. In this case, more information provides travelers with more opportunities for competing network resources and therefore, it causes a worse overall result.

5 CONCLUSIONS

In this paper, we propose an adaptive routing and guidance approach called ANS for transportation evacuation and examine its effectiveness through an agent-based simulation. This ANS approach relaxes several assumptions made in conventional evacuation models. Through the simulation study, we find that real-time network information can certainly help travelers avoid congestion and reduce evacuation time. However, more information is not always better. UE condition assumes that travelers have perfect network information. On the other hand, ANS only uses local information. Experimental results show that ANS has a lower evacuation time than UE, in particularly, during heavy traffic. Because travelers are selfish and aim to minimize their own evacuation times independently, more information gives travelers more opportunities to compete for network resources and cause a worse overall result. Using only local network information, ANS can reduce unnecessary myopic detours. Future work of this research includes investigating the optimal information access level of travelers for evacuation routing and incorporating more traffic and social behaviors into our evacuation model, e.g., destination choice model and lane-changing behavior. Also, dynamic user equilibrium (DUE) could be another method for comparison.

REFERENCES

Bar-Gera, H. 2001. "Transportation Network Test Problems." Accessed June 18. http://www.bgu.ac.il/~bargera/tntp/.

Chen, X., and F. B. Zhan. 2004. Agent-Based Modeling and Simulation of Urban Evacuation: Relative Effectiveness of Simultaneous and Staged Evacuation Strategies. Proceedings of the 83th Annual Meeting of the Transportation Research Board, at Washington DC, U.S.

Chiu, Y.-C., H. Zheng, J. A. Villalobos, W. Peacock, and R. Henk. 2008. "Evaluating Regional Contra-Flow and Phased Evacuation Strategies for Texas Using a Large-Scale Dynamic Traffic Simulation and Assignment Approach." *Journal of Homeland Security and Emergency Management* 5 (34).

Cova, T. J., and J. P. Johnson. 2003. "A Network Flow Model for Lane-Based Evacuation Routing." *Transportation Research Part A* 37:579-604.

Dow, K., and S. L. Cutter. 2002. "Emerging Hurricane Evacuation Issues: Hurricane Floyd and South Carolina." *Natural Hazards Review* 3 (6):12-18.

Gao, S. 2005. "Optimal Adaptive Routing and Traffic Assignment in Stochasitc Time-Dependent Networks." Massachusetts Institute of Technology.

Hackney, J., and F. Marchal. 2009. A Model for Coupling Multi-Agent Social Interactions and Traffic Simulation. Proceedings of the 88th Annual Meeting of the Transportation Research Board, at Washington DC, U.S.

Hamacher, H. W., and S. A. Tjandra. 2002. *Mathematical Modelling of Evacuation Problems: A State of the Art*. edited by M. Schreckenberg, and S. D. Sharma, *Pedestrian and Evacuation Dynamics*. Berlin: Springer-Verlag Berlin. <Go to ISI>://WOS:000179254900016.

Kim, S., B. George, and S. Shekhar. 2007. Evacuation Route Planning: Scalable Heuristics. Proceedings of the 15th International Symposium on Advances in Geographic Information Systems.

Lindell, M. K., J.-C. Lu, and C. S. Prater. 2005. "Household Decision Making and Evacuation in Response to Hurricane Lili." *Natural Hazards Review* 6:171-179.

Lu, Q., B. George, and S. Shekhar. 2005. Capacity Constrained Routing Algorithms for Evacuation Planning: A Summary of Results. Proceedings of the 2005 International Symposium on Advances in Spatial and Temporal Databases.

Madireddy, M., D. J. Medeiros, and S. Kumara. 2011. An Agent Based Model for Evacuation Traffic Management. the 2011 Winter Simulation Conference, at Phoenix, Arizona.

Miller-Hooks, E. 2001. "Adaptive Least-Expected Time Paths in Stochastic, Time-Varying Transportation and Data Networks." *Networks* 37 (1):35-52.

Miller-Hooks, E. D., and H. S. Mahmassani. 1998. "Least Possible Time Paths in Stochastic, Time-Varying Networks." *Computers & Operations Research* 25 (12):1107-1125.

Miller-Hooks, E. D., and H. S. Mahmassani. 2000. "Least Expected Time Paths in Stochastic, Time-Varying Transportation Networks." *Transportation Science* 34 (2):198-215.

Murray-Tuite, P. M., and H. S. Mahmassani. 2003. "Model of Household Trip-Chain Sequencing in Emergency Evacuation." *Transportation Research Record* (1831):21-29.

North, M. J., N. T. Collier, and J. R. Vos. 2006. "Experiences Creating Three Implementations of the Repast Agent Modeling Toolkit." *ACM Transactions on Modeling and Computer Simulation* 16 (1):1-25.

Rossetti, M. D., and Q. Ni. 2010. "Simulating Large-Scale Evacuation Scenarios in Commercial Shopping Districts - Methodologies and Case Study " In *Proceedings of the 2010 Winter Simulation Conference*, edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 3494-3505. Piscataway, New Jersy: Institute of Electrical and Electronics Engineers.

Sbayti, H., and H. S. Mahmassani. 2006. Optimal Scheduling of Evacuation Operations. Proceedings of the 85th Annual Meeting of the Transportation Research Board, at Washington DC, U.S.

Theodoulou, G., and B. Wolshon. 2004. Modeling and Analyses of Freeway Contraflow to Improve Future Evacuations. Proceedings of the 83th Annual Meeting of the Transportation Research Board at Washington DC, U.S.

Urbina, E., and B. Wolshon. 2003. "National Review of Hurricane Evacuation Plans and Policies: A Comparison and Contrast of State Practices." *Transportation Research Part A* 37:257-275.

Zhang, B., W. K. V. Chan, and S. V. Ukkusuri. 2014. "On the Modelling of Transportation Evacuation: An Agent-Based Discrete-Event Hybrid-Space Approach." *Journal of Simulation* 8 (4):259-270.

Zou, N., S.-T. Yeh, and G.-L. Chang. 2005. "A Simulation-Based Emergency Evacuation System for Ocean City, Maryland During Hurricanes." *Transportation Research Record* 1922:138-148.

AUTHOR BIOGRAPHIES

BO ZHANG is a Senior Analyst at American Airlines. He holds a Ph.D. in Decision Sciences and Engineering Systems from Rensselaer Polytechnic Institute. He is a technology contributor of next-gen airport operation decision support systems. His current areas of interest include simulation, optimization, machine learning, and their applications on airline operations and airport traffic management. His e-mail address is zhangbo.rpi@gmail.com.

WAI KIN (VICTOR) CHAN is an Associate Professor of the Department of Industrial and Systems Engineering at the Rensselaer Polytechnic Institute, Troy, NY. He holds a Ph.D. in Industrial Engineering and Operations Research from University of California, Berkeley. His research interests include discrete-event simulation, agent-based simulation, and their applications in social networks, service systems, transportation networks, energy markets, and manufacturing. He is a member of INFORMS, IIE, and IEEE. His e-mail address is wsc15chan@gmail.com.

SATISH UKKUSURI is a Professor in the Lyles School of Civil Engineering at Purdue University. Dr. Ukkusuri is recognized nationally and internationally in the area of transportation network modeling and disaster management. He leads the Interdisciplinary Transportation Modeling and Analytics Lab at Purdue. His current areas of interest include: complex network modeling, coupled systems modeling, network resilience, big data analytics for transportation systems, dynamic traffic modeling, innovative signal control algorithms, connected vehicle environment, behavioral issues in natural hazards such as hurricanes, evacuation modeling, modeling transportation sustainability policies such as cap and trade, emissions pricing etc, sustainable freight logistics and safety modeling. Dr. Ukkusuri is a member of the Transportation Network Modeling committee at Transportation Research Board (National Academies). He is a member of the Transportation Network Modeling Committee (ADB 30) and the Freight Transportation Planning and Logistics (ATO 15). He was the previous chair of the ITS Special Interest Group (SIG) at the Institute for Operations Research and Management Science (INFORMS). Dr. Ukkusuri is an Area Editor for the journal, Networks and Spatial Economics and an Associate Editor for Transportmetrica Part B. His e-mail address is sukkusur@purdue.edu.