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Experiences with evacuation route planning algorithms

Shashi Shekhar[a]*, KwangSoo Yang[a], Venkata M.V. Gunturi[a], Lydia Manikonda[a], Dev Oliver[a], Xun Zhou[a], Betsy George[b], Sangho Kim[c], Jeffrey M.R. Wolff[a] and Qingsong Lu[a]

[a]*Department of Computer Science and Engineering University of Minnesota, Minneapolis, MN, USA;* [b]*Oracle, Nashua, NH, USA;* [c]*Geodatabase Team, Environment System Research Institute (ESRI), Redlands, CA, USA*

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Efficient tools are needed to identify routes and schedules to evacuate affected populations to safety in the event of natural disasters. Hurricane Rita and the recent tsunami revealed limitations of traditional approaches to provide emergency preparedness for evacuees and to predict the effects of evacuation route planning (ERP). Challenges arise during evacuations due to the spread of people over space and time and the multiple paths that can be taken to reach them; key assumptions such as stationary ranking of alternative routes and optimal substructure are violated in such situations. Algorithms for ERP were first developed by researchers in operations research and transportation science. However, these proved to have high computational complexity and did not scale well to large problems. Over the last decade, we developed a different approach, namely the Capacity Constrained Route Planner (CCRP), which generalizes shortest path algorithms by honoring capacity constraints and the spread of people over space and time. The CCRP uses time-aggregated graphs to reduce storage overhead and increase computational efficiency. Experimental evaluation and field use in Twin Cities Homeland Security scenarios demonstrated that CCRP is faster, more scalable, and easier to use than previous techniques. We also propose a novel scalable algorithm that exploits the spatial structure of transportation networks to accelerate routing algorithms for large network datasets. We evaluated our new approach for large-scale networks around downtown Minneapolis and riverside areas. This article summarizes experiences and lessons learned during the last decade in ERP and relates these to Professor Goodchild's contributions.

Keywords: evacuation route planning; emergency response

1. Introduction

Evacuation route planning (ERP) is an important component of emergency management that seeks to minimize the loss of life or harm to the public during natural disasters or terrorist attacks. Events such as Hurricanes Rita and Andrew in the United States and the 2011 earthquake/tsunami in Japan testify to the importance of emergency preparedness in densely populated regions. While civic authorities had indeed planned for such events, in each case, chaos and confusion marked much of the evacuation process. Few would disagree that much remains to be done to improve emergency planning.

*Corresponding author. Email: shekhar@cs.umn.edu

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Emergency preparedness involves many complex layers. Long before a disaster occurs, policy makers and civic authorities must determine what modes of transportation to use during an evacuation (e.g., walking, private vehicles, and public transportation), which locations take unacceptably long to evacuate, and which strategies should be used (e.g., traffic contraflow or phased evacuation). During an actual disaster, first responders need to know not only which routes minimize the time to evacuate the vulnerable population but also how to respond to secondary events not anticipated in the initial planning, such as bridge failures and traffic accidents.

In this article, we describe an algorithmic approach developed for ERP. Given a transportation network (e.g., a road map), a number of evacuees, their initial locations, and evacuation destinations, our goal is to find an evacuation plan consisting of a set of origin–destination routes and a scheduling of evacuees on each route. The aim is to minimize evacuation egress time (i.e., the time from the start of the evacuation to the time that the last evacuee reaches a destination) under the following constraints: (1) route scheduling should observe capacity constraints of the transportation network and (2) computation time is reasonable despite limited computer memory. Minimizing evacuation time is important because it minimizes exposure to potential hazards. Minimizing computation time is critical both for planning and during evacuation. During the planning phase, approaches with minimized computation time afford exploration of a large number of scenarios based on transportation mode, event location, and time. During evacuation, unexpected events could occur (e.g., the bridge failure as a result of Hurricane Katrina or the 100-mile traffic jams due to Hurricane Rita). Additionally, new evacuation routes may need to be planned to respond to events, such as the contraflow-based plan for Hurricane Rita.

1.1. Professor Goodchild's influence

Our approach to evacuation routing algorithms was significantly influenced by Professor Goodchild and his arguments a decade ago on the importance of geographic information system (GIS) for emergency management. Goodchild believed that geospatial tools were essential for evacuation planning to help save lives, limit damage, and reduce the costs of dealing with emergencies (Goodchild *et al.* 2007). His focus was on GIS system technologies and methods to facilitate emergency response to hurricanes, tsunamis, and other disasters (Goodchild (2003a, 2003b), and he called for research to ensure GIS capabilities such as quick access to geographic data, accuracy, and interoperability to support decisions for emergency situations (Goodchild 2003a). These capabilities involved large volumes of data about facilities, local streets, residential population, events, and so on and would require new computational methods to achieve. Most important for our work, he made it clear that GIS-related capabilities had to be fast or else they would be useless in emergency situations. This notion became a guiding principle for our research on evacuation route planning, and it is what has set our approach apart over the last decade.

Professor Michael Goodchild suggested two key research needs in this area. First, it is necessary to provide GIS capabilities for an emergency response situation as quickly as possible (Goodchild 2003a, Goodchild *et al.* 2007). These abilities include quick access for geographic data, accuracy, and interoperability to support decisions for emergency situations (Goodchild 2003a). Our research extends his work to develop evacuation planning tools for quick response and high scalability that have become an integral part of day-to-day operations of emergency managers and responders at all levels of government. This need is certainly justified, given the series of recent large-scale disasters, such as hurricanes and tsunamis, causing the greatest volumes of evacuation traffic. Our approach uses time-aggregated graphs (George and Shekhar 2007) to reduce the size of datasets and novel capacity constrained route planning algorithms (Lu *et al.* 2003, 2005, Kim *et al.* 2007, Lu *et al.* 2007) to minimize the response time without sacrificing the quality of results.

Second, Goodchild and Glennon (2010) explored the potential of geographic information created by amateur citizens (i.e., Volunteered Geographic Information (VGI)) during emergencies. Despite data quality concerns, Professor Goodchild argued that the benefits of VGI far outweigh the risks during emergencies. This was due to the limited resources of agencies versus the speed, with which the average citizen can produce maps and status reports (ESRI 2011). The fundamental question of how society can employ the eyes and ears of the general public, their eagerness to help, and their recent digital empowerment to provide effective assistance to responders and emergency managers was raised. We have identified this as a future trend in the field and we elaborate on it further in Section 6.

1.2. Related work

There has been a considerable amount of research on route planning for evacuation scenarios. Recent work falls into three categories: (1) network flow methods (Francis and Chalmet 1984, Kisko and Francis 1985, Ahuja *et al.* 1993, Kisko *et al.* 1998, Hamacher and Tjandra 2001), (2) simulation methods (Ben-Akiva 2002, Mahmassani *et al.* 2004), and (3) heuristic methods (Hoppe and Tardos 1994, Lu *et al.* 2003, 2005, 2007). Network flow methods can again be divided into two approaches: linear programming and dynamic minimum cost flow problem. Linear programming uses a cost function with constraints to minimize the total evacuation time (Chalmet *et al.* 1982, Hamacher and Tufekci 1987, Cova and Johnson 2003). The transportation network is transformed into a time-expanded graph (TEG) by copying the original evacuation network for each time step (Ford Jr and Fulkerson 1958, Ford and Fulkerson 1962). Then, iterative algorithms (e.g., simplex or ellipsoid method) are applied to optimize the cost function (Schrijver 2003). Although this approach generates optimal solutions, the problem size increases significantly due to the large-size of a TEG. It also may not be able to scale up to large-size transportation networks due to high computational cost. Dynamic minimum cost flow problem uses a successive shortest path algorithm based on residual network and path decomposition (e.g., lexicographic maximum flow and universally quickest flow) (Wilkinson 1971, Minieka 1973, Hoppe and Tardos 1994). Unfortunately, the number of routes cannot be bounded by the number of edges; this method needs pseudo-polynomial iterations, making it hard to handle large networks (Zadeh 1973). Simulation methods focus on individual evacuees' movements and interaction between evacuees (Church and Sexton 1998, Ben-Akiva 2002, Mahmassani *et al.* 2004). These approaches regulate individual behaviors or assign traffic flow using Wardrop's equilibrium model in greater detail (Wardrop 1952). However, the process is quite complicated and labor intensive, making it inappropriate for large evacuation scenarios. While these approaches offer some useful insights, the lack of any means to improve scalability makes them inherently impractical for real-world emergency planning.

In contrast to previous approaches, heuristic approaches use approximate methods to find near-optimal solutions by minimizing the computational cost. A well-known approach that falls in this category is the Capacity Constrained Route Planner (CCRP) (Lu *et al.* 2003, 2005, 2007). These methods use time-aggregated graphs (George and Shekhar 2007) and evaluate a shortest route with capacity constraints to find the evacuation route at each time step. It is useful for medium-sized networks (e.g., 1-mile evacuation zone), but has a limitation for large-scale networks (e.g., 50-mile evacuation zone). Kim *et al.* (2007) present a new scalable heuristic by reusing shortest routes based on bottleneck saturation checking. It showed a 95% reduction in computational time with small degradation of solution quality.

1.3. Our contributions and outline

In keeping with Professor Goodchild's vision of fast, scalable solutions for emergency applications, our approach has been to focus on heuristic methods to find near-optimal solutions that minimize computational cost. We describe one new research result related to CCRP, offer reflections on what we have learned about evacuation planning working with first responders and policy makers in the last decade, and lay out some of the trends that we believe will affect research in this area. We limit the scope of this article to algorithmic approaches to ERP solutions, including areas such as civil engineering and operations research.

The rest of the article is organized as follows: Section 2 states the ERP problem in formal terms. Section 3 summarizes the CCRP, provides evidence of its scalability, and describes the impact it had on actual evacuation planning in the state of Minnesota. To illustrate our ongoing efforts to improve CCRP scalability, we also briefly describe a dartboard network structure. Section 5 outlines the lessons we have learned from research in this area. Finally, Section 6 summarizes some of the trends and challenges we face in the future, and Section 7 concludes the article.

2. ERP problem

In this section, we describe the ERP problem from a computational perspective. In a typical evacuation planning scenario, the spatial structure is represented and analyzed as a network model with non-negative integer capacity constraints on the nodes and edges. With additional information pertaining to initial locations of all evacuees and their final destinations, the ERP problem produces a set of origin and destination routes for evacuees. Consider a simple building ERP problem in Figure 1. Each room, corridor, staircase, and exit of the building is represented as a node, and each pathway from one node to another node is represented as an edge. Every node has two attributes: maximum node capacity and initial node occupancy. For example, the maximum capacity of node N1 is 50, indicating that the node can hold at most 50 evacuees at any time step. The initial occupancy is shown to be 10, which means that 10 evacuees prepare to move out of the node. Every edge has two attributes: maximum edge capacity and travel time. For example, the maximum edge capacity of N4–N6 is 5, indicating that at most five evacuees can traverse the edge. The travel time of this edge is 4, which means that it takes four time steps to traverse the edge. Suppose we initially have 10 evacuees at node N1, 5 at node N2, and 15 at node N8, the ERP produces evacuation routes as shown in Table 1. The objective of the ERP problem is to minimize the computational cost of producing the evacuation plan while minimizing evacuation time.

3. Evacuation route planning

A key aspect of designing an evacuation route solution is modeling the dynamics involved in the movement of evacuees. When combined with the capacity constraints of the underlying network, the problem becomes immensely challenging. Here, we need to model the dynamic nature of the capacity of an edge. Linear programming-based approaches for evacuation planning usually handle this situation using iterative algorithms (e.g., simplex or

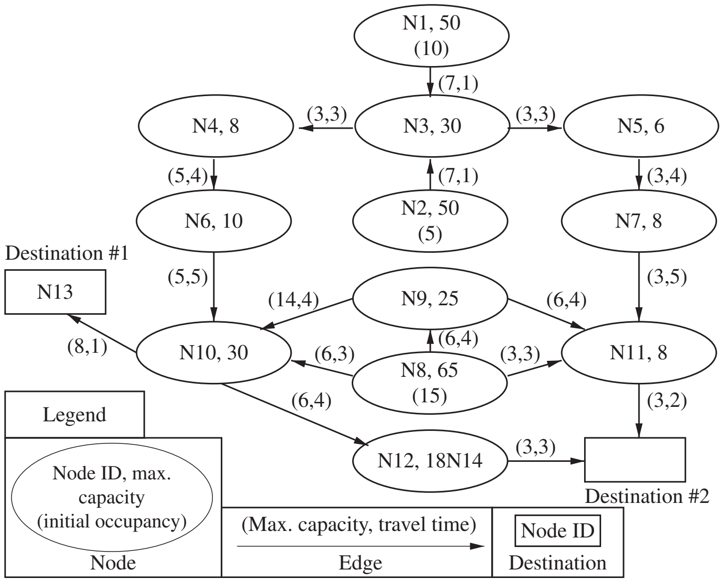

Figure 1. Building ERP problem: Network Model for simple building ERP scenario.

Table 1. Building ERP problem: Example of evacuation route scheduling.

Group of evacuees					
ID	Source	Group size	Route with schedule	Start time	Destination time
A	N8	6	N8(T0)–N10(T3)–N13	0	4
B	N8	6	N8(T1)–N10(T4)–N13	1	5
C	N8	3	N8(T0)–N11(T3)–N14	0	5
D	N1	3	N1(T0)–N3(T1)–N4(T4)–N6(T8)–N10(T13)–N13	0	14
E	N1	3	N1(T0)–N3(T2)–N4(T5)–N6(T9)–N10(T14)–N13	0	15
F	N1	1	N1(T0)–N3(T1)–N5(T4)–N7(T8)–N11(T13)–N14	0	15
G	N2	2	N2(T0)–N3(T1)–N5(T4)–N7(T8)–N11(T13)–N14	0	15
H	N2	3	N2(T0)–N3(T3)–N4(T6)–N6(T10)–N10(T15)–N13	0	16
I	N1	3	N1(T1)–N3(T2)–N5(T5)–N7(N9)–N11(T14)–N14	1	16

ellipsoid method) to minimize the cost function with given constraints. In this model, the network needs to be transformed into a TEG by constructing $T + 1$ copies of nodes and edges. Even though this approach gives an optimal solution, it suffers from a performance bottleneck when solving for large urban scenarios such as citywide evacuations (Lu *et al.* 2003, 2005, 2007, George *et al.* 2007), thus making it suitable for only small-scale scenarios such as building evacuations. In contrast, CCRP (Lu *et al.* 2005, 2007, Kim *et al.* 2007) is a near-optimal heuristic approach, which models the dynamic nature of the capacity constraints as a time-aggregated graph (George and Shekhar 2007, George *et al.* 2007) and exploits the shortest routes to reduce the computational complexity.

3.1. Capacity Constrained Route Planner

CCRP is based on an iterative approach for creating a complete evacuation plan. In each iteration, the algorithm searches for a route R with the earliest arrival time to any destination node from any source node, taking previous reservations and possible wait times into consideration. Then, CCRP computes the actual number of evacuees that will travel through R. This number is affected by the available capacity of R and the remaining number of evacuees. The maximum number of evacuees to be sent on R is then determined as the minimum of the available capacities on the component edges in R; CCRP reserves the node and edge capacity on R for these evacuees. The algorithm terminates when all the evacuees have been given an evacuation route to any of the destinations.

A key step in CCRP is to determine the route R with the earliest arrival time. A naive way to obtain the route R could involve executing Dijkstra's algorithm (Dijkstra 1959, Cormen *et al.* 2001) (generalized to work with edge capacities and travel times) for every source node and destination node, followed by selecting the minimum. However, this becomes a major performance bottleneck and adversely affects the scalability of the algorithm (Lu *et al.* 2005, 2007). This bottleneck is handled in CCRP by adding a pseudo-source node S_0 and edges with zero travel time and infinite capacity between S_0 and all other source nodes. The pseudo-code for CCRP is shown in Algorithm 1.

Algorithm 1: CCRP Algorithm

Input:
(1) A spatial network $G = (N, E)$ where N is the set of nodes and E is the set of edges;
(2) S: set of source nodes, $S \subseteq N$;
(3) D: set of destination nodes, $D \subset N$;
Output: Evacuation plan: Routes with schedules of evacuees on each route
1: Add a pseudo-source node S_0
2: Add edges of 0 travel time and ∞ capacity between S_0 and all the source nodes
3: **while** any source has evacuees **do**
4: Find route R which has earliest destination arrival time using generalized version of Dijkstra's shortest path algorithm
5: Find maximum number of evacuees $f_{\max}$ that can be sent through R
6: Reserve the node and edge capacities $f_{\max}$
7: **end while**
8: Output evacuation plan

The algorithm starts by adding the pseudo-source node and edges of appropriate capacities and travel times (lines 1 and 2 of Algorithm 1). Then, the algorithm iterates (for loop lines 3–7) as long as there are still evacuees left at any source node. Each iteration starts with finding the route R with earliest arrival time to the destination while considering the available capacities. Then, it determines the maximum number of evacuees ($f_{\max}$) that can be sent through R. This is done by computing the minimum of available capacities on the component edges of the route R (line 5). Finally, the route R is reserved for $f_{\max}$ number of evacuees. The algorithm terminates when all the evacuees have been assigned a route.

3.2. *Evidence of scalability for CCRP*

We tested CCRP with different settings and compared its performance with the linear programming-based system Relax IV (Bertsekas *et al.* 1994). First, we studied how the number of nodes in the network affects the run-time cost and the result quality (total evacuation time). We fixed the number of evacuees (e.g., 5000 evacuees), and source and destination nodes (e.g., 20 source and 10 destination nodes). The total number of nodes in transportation networks ranged from 50 to 50,000. Results showed that the time cost of CCRP, compared to Relax IV, not only is faster but also grows more slowly as the network size increases. Meanwhile, the result quality of CCRP is almost the same as Relax IV. Then, we tested how the number of evacuees affects the run time cost and the result quality. We fixed the number of nodes in the network (e.g., 5000 nodes) and the number of source nodes (e.g., 2000 source nodes). The number of evacuees ranged from 5000 to 50000. CCRP produced results almost as good as Relax IV, with much less time spent dealing with increasing number of evacuees. We also tested the impact of the number of sources and destinations on the time cost and the result quality. Experimental results showed that CCRP can scale up to large networks and can always produce high-quality results with less time cost than Relax IV. The experiments were conducted on a workstation with Intel Pentium 4, 2.8-GHz CPU, 2-GB RAM, and Linux operating system. Additional details on our experiments may be found in Lu *et al.* (2007) and Zhou *et al.* (2010).

3.3. Case studies and societal impact

We applied CCRP in two real-world evacuation planning settings.

3.3.1. Monticello power plant case study

In the wake of the Fukushima nuclear disaster in Japan, the US Nuclear Regulatory Commission is considering annual revisions of evacuation plans for nuclear power plants (USA-Today 2011). The commission's interest in regularly updated plans due to changes in nearby populations or transportation networks is likely to accelerate adoption of CCRP-like computer-based selection of evacuation routes over manual methods (Vasconez and Kehrli 2010). As shown in Figure 2, the Monticello nuclear power plant is located about 40 miles northwest of the Twin Cities of Minneapolis and St. Paul. Evacuation plans need to be in place in case of accidents or terrorist attacks. The evacuation zone is a 10-mile radius around the nuclear power plant as defined by Minnesota Homeland Security and Emergency Management (Lu *et al.* 2007). An initial hand-crafted evacuation route plan called for the affected population to travel to a nearby high school. The plan did not consider the capacity of the road network in the area, nor the high traffic load that would be put on two nearby highways.

We experimentally tested the CCRP algorithm using the road network around the evacuation zone provided by the Minnesota Department of Transportation (Lu *et al.* 2007) and the Census 2000 population data for each affected city (circle in Figure 2). The total number of evacuees was about 42,000. As can be seen in Figure 2, our algorithm produced a much better evacuation route plan (1) by selecting shorter paths to reduce evacuation time and (2) by utilizing richer routes, that is, routes near the evacuation destination to reduce congestion. As a result, evacuation egress time was reduced from 268 minutes under the old plan to only 162 minutes with CCRP. This experiment demonstrated the effectiveness of our algorithm in real evacuation planning scenarios to reduce evacuation time and to improve existing plans.

3.3.2. Evacuation planning for the Twin Cities

Our method was also selected by the Minnesota Department of Transportation for an evacuation planning project for the entire Twin Cities Metro Area, a region with a road network of about 250,000 nodes and a population of over 2 million people. In this project,

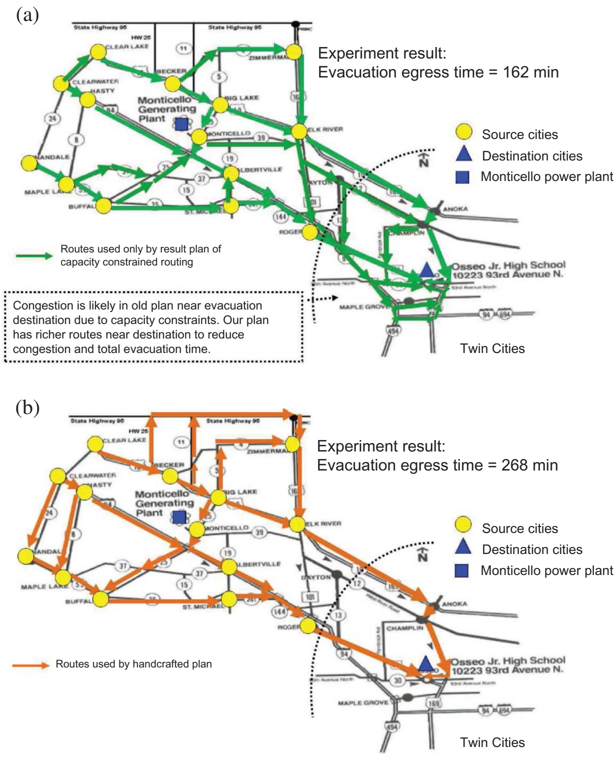

Figure 2. Overlay of CCRP (a) and hand-crafted result routes (b) for Monticello power plant ERP.

Table 2. Settings and results of the five scenarios in Twin Cities Metro Area evacuation planning.

	Radius			
Scenario	Source mile	Destination mile	Population	Evacuation time
A	1	1	148,077	4 hrs 46 min
B	1	1	84,678	2 hrs 44 min
C	1	1	27,406	4 hrs 27 min
D	1	1	49,800	3 hrs 39 min
E	1	1	2,586	1 hr 20 min

the CCRP algorithm was incorporated into an evacuation planning system and was tested on five predefined scenarios and some randomly selected locations. This system has several common settings and functions, such as identifying bottleneck areas and links and designing/refining transportation networks. Particularly useful are the compare options where users can compare the effect of transportation modes (walking and driving percentage) and time (daytime and nighttime) on population distribution. The settings used in the five predefined scenarios are shown in Table 2. One specially interesting finding was that walking results in less congestion than driving and, thus, can decrease the total egress time. Transportation professionals evaluated the quality of the results and found them to be highly satisfactory.

3.3.3. *Recognition*

Our approach was presented at the Congressional Breakfast Program on Homeland Security held by the University Consortium for Geographic Information Science (UCGIS), and also reported in the Minnesota Homeland Security and Emergency Management newsletter. In addition, this work received the 2006 Center for Transportation Studies (CTS) award (CTS.Report 2006). News of our research was also reported on local television (Fox TV News) and in the state's major newspapers.

4. Recent refinements to improve scalability

4.1. Dartboard network structure

CCRP finds a near-optimal evacuation plan with reduced computational cost. This is useful for medium-sized transportation networks (e.g., 1-mile evacuation zone), but new insights are needed to handle large-scale network datasets (e.g., 3 million residents in a 30-mile evacuation zone). It is well known that a transportation network structure has an extremely important effect on the way vehicles move and exit evacuation zones (EZs) for emergency situations. We are exploring a novel routing algorithm that exploits the underlying transportation network structure. In general, EZs are clearly defined in the evacuation plan documentation and often have a circular shape for nuclear evacuation plans and an elongated or irregular shape for hurricane evacuation plans. The network structure in EZs may be broken down into sections according to spatial movement patterns and analyzed independently for route evaluation. For example, circular EZs show 'outer first, inner last' flow patterns to evacuate the hazardous area, resulting in division of the transportation network in EZs into several rings. We define a dartboard network as a partitioned network according to the flow of vehicles such that all the vehicles in a single group reach to the exit zone at the same time. We propose using the notion of a dartboard network structure to model EZs (e.g., entire cities or coastal plains) in common evacuation scenarios. Instead of a single shortest route, we evaluate multiple node-independent shortest routes at the same time to reduce iterations. Our preliminary experimental results showed that the run time could be reduced by up to 80% compared to previous CCRP algorithms without sacrificing the solution quality (Yang *et al.* 2012).

4.2. Experimental evaluation

We tested our new approach using the most densely populated regions in Minnesota. In the first experiment, we evaluated the effect of large number of evacuees. We chose 774 source nodes, 98 destination nodes, and 2,035,276 evacuees. In the second experiment, we used large EZs (e.g., 30 miles) to check scalability. We chose 1 101 source nodes, 71 destination nodes, and 2,590,965 evacuees. Results for both experiments showed that the run time can be reduced up to by 90% compared to the CCRP algorithm.

5. Lessons learned

Our work has taught us five main lessons on the challenges of ERP. First, data may not be readily available (e.g., evacuee population, available transport capacity, pedestrian walkway maps, and link capacities based on width). Second, there are important transportation concerns such as modeling traffic control signals, ramp meters, and contraflow; these concerns are complex and should be accounted for. Third, evacuee behavior is hard to predict because of heterogeneity in terms of physical ability, age, vehicle ownership, language, and so on. It is also difficult to determine whether the unit of evacuation should be an individual or a family. Should the evacuation plan account for families first gathering before evacuating together? Fourth, important policy decision questions need to be answered (e.g., how to gain the public's trust in plans?, will they comply?, when to evacuate?, which routes?, etc.). Fifth, the question of how to evaluate an evacuation planning system needs to be answered. It is not clear the best way to scientifically determine *a priori* how good an evacuation planning system is compared to others. Thus far, we have focused on addressing the computational challenges of ERP. In future work, we plan to develop interdisciplinary collaboration in order to address some of the other challenges.

6. Future trends

We see three trends influencing the direction of evacuation planning research, such as contraflow, volunteered geographic information, and pedestrian modeling.

6.1. Computerized contraflow

Contraflow is an important technology in ERP that remedies the problem of severe traffic jams by increasing the evacuation route capacity. It achieves this by reversing lanes so that traffic flows one way. However, computerized contraflow is a combinatorial optimization problem because the number of possible contraflow network configurations exponentially increases with the number of road segments. The problem is NP-complete (Kim *et al.* 2008) and needs a significant amount of resources to take into account other factors such as travel time and capacity. In addition, research is needed to better exploit partial lane reversals and time-dependent capacity-varying edges.

6.2. Volunteered Geographic Information

Inputs available to evacuation planning systems from traditional sources such as sensors and transportation maps are often imprecise, which in turn affects the output quality. One way to improve input data is to follow Professor Goodchild's recommendation to exploit the potential of VGI, that is, the harnessing of tools to create, assemble, and disseminate geographic data provided voluntarily by individuals (Goodchild 2007). The volunteer frequently uses Global Positioning System (GPS) tracks to understand and share the potential threat as captured during geo-data collection. The main issue here is how we can improve VGI data quality in terms of volunteer participation and data accuracy. There are several challenges in gathering, modeling, and analyzing geo-data. First, encouraging volunteers to participate and produce reliable datasets is a non-trivial task (Tiwari 2011). Second, the dataset shows spatiotemporal properties such that dynamic GIS analysis techniques (e.g., complex geo-data type and spatiotemporal object interaction queries) are necessary. Third, geo-datasets should be combined with social network data to discover human behavior. Finally, since VGI can come in many different forms (e.g., text data, tagged photographs, and GPS points), multiple perspectives, and adversarial views, a generalized data format is needed to integrate these heterogeneous data. While these challenges are daunting, Professor Goodchild's vision of amateur citizens and VGI playing a role in emergency management will almost certainly be realized.

6.3. Pedestrian modeling

Evacuation plans need to consider both geo-environment and societal behaviors. This is especially true when thousands or even millions of people gather in one place, such as the annual Muslim pilgrimage to Mecca. Huge numbers of pilgrims gather at the Jamarat Bridge in Mecca during the Hajj and perform 'stoning of the devil' as part of the annual Islamic ritual. This ritual was one of the most dangerous parts of the pilgrimage and has caused extreme overcrowding and numerous occurrences of stampedes in the past (Wikipedia 2011). The gathering at Mecca is an annual reminder that highlights the need for evacuation planning that accommodates different environments (e.g., walking up a slope), interactive pedestrian movements (e.g., density of flow), and the spatiotemporal patterns in pedestrian crowds (e.g., walking speed and estimated travel time) (Ammar 2007, Helbing *et al.* 2007, Moussad *et al.* 2011).

The flow of large crowds of pedestrians varies not only with their physical characteristics (e.g., age and ability) but also with their psychological state. This crowd flow is especially challenging when trying to prevent panic and manage high-density pedestrian movement for emergency evacuations. Disastrous incidents such as landslide or flash flood make it even harder to handle large gatherings of people. Socio-psychological approaches for panic situations and special plans for infant, elderly, or disabled family members need to be considered. Also, worth exploring is the influence of group membership, such as community organizations, religious groups, and voluntary association, on emergency situations. Besides the physical and socio-psychological states of the pedestrians, the large mass gathering event requires public health planning and basic human needs, including fresh food, portable water, and accommodation. Insufficient storage, cooking, or food handling may lead to the pilgrim's injury and illness. Finally, flow segmenting models for open spaces should be developed to group moving crowds and schedule spatiotemporal crowd flows. The research effort for evacuation planning is necessary for catastrophic events involving large crowds, physical and mental attributes, food supplies, and open spaces.

In our study, Jamarat Bridge and Mina tent models for pilgrims are being constructed based on OpenStreetMap datasets. We are studying flash flood scenarios to design a possible evacuation plan where the residents of the tents would be evacuated to the Jamarat Bridge. Our further study will include crowd modeling (e.g., different speed and flow rate) and behavior (e.g., panic and heterogeneity of people) to provide the best ways of grouping pilgrims and scheduling the evacuation.

7. Conclusion

ERP is critical for homeland defense and protecting citizens during natural disasters. Existing methods cannot handle large urban scenarios, and in many cases, communities use hand-crafted evacuation plans. We presented the CCRP that can produce evacuation plans for large urban areas, reduce total evacuation time, and improve current hand-crafted evacuation plans. Then, we introduced a new approach to exploit spatial network structure to accelerate routing algorithms. We also summarized our experiences and lessons learned in ERP and related these to Professor Goodchild's contributions. By working with CCRP over the past decade, we gained an understanding of some of the main challenges in emergency planning and the future direction of the field. An interesting outcome of our work was the discovery that walking results in less congestion than driving and can thus decrease the total evacuation time. Going forward, we see ideas like VGI emerging as novel ways to improve emergency planning input data, thereby ameliorating output quality.

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