Evacuation Planning: A Spatial Network Database Approach

Xun Zhou[1], Betsy George[2], Sangho Kim[3], Jeffrey M. R. Wolff[1], Qingsong Lu[1], Shashi Shekhar[1]
[1]Department of Computer Science and Engineering, University of Minnesota, Minneapolis, USA
{xun, jwolff, lqingson, shekhar}@cs.umn.edu
[2]Oracle, Nashua, NH, USA
betsy.george@oracle.com
[3]Geodatabase Team, ESRI, Redlans, CA, USA
skim@esri.com

Abstract

Efficient tools are needed to identify routes and schedules to evacuate affected populations to safety in face of natural disasters or terrorist attacks. Challenges arise due to violation of key assumptions (e.g. stationary ranking of alternative routes, Wardrop equilibrium) behind popular shortest path algorithms (e.g. Dijkstra's, A) and microscopic traffic simulators (e.g. DYNASMART). Time-expanded graphs (TEG) based mathematical programming paradigm does not scale up to large urban scenarios due to excessive duplication of transportation network across time-points. We present a new approach, namely Capacity Constrained Route Planner (CCRP), advancing the idea of Time-Aggregated Graph (TAG) to provide Earliest-Arrival-Time given any Start-Time. Laboratory experiments and field use in Twin-cities for Homeland Security scenarios show that CCRP is more efficient than previous methods.*

1 Introduction

Evacuation planning is a crucial task for managing public safety. Whether natural (flood, hurricanes, etc) or man-made (release of chemical or toxic substances, etc) disasters require that emergency personnel be able to move affected populations to safety in as short a time as possible. Despite the increased threat of disasters posed by global climate change and the rise of terrorism, however, current evacuation planning tools have serious limitations. Evacuation conducted during Hurricane Katrina and Rita in 2005 were a stark reminder of how much it can go wrong despite intensive emergency population. For example, Figure 1 shows the miles of backed-up traffic that occurred as Houston residents followed orders to flee the path of Hurricane Rita. Therefore, efficient tools are needed to produce plans that identify optimal evacuation routes and

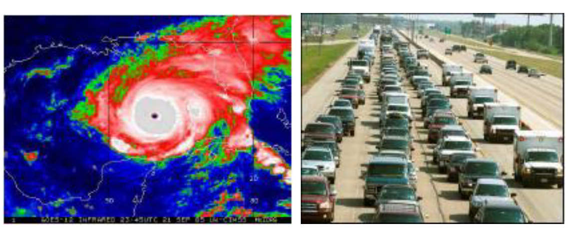

Figure 1: Hurricane Rita and Evacuation Traffic. Source: National Weather Services and FEMA

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schedules, given a transportation network, node/edge capacity constraints, source/destination nodes and evacuee population. Current methods of evacuation planning can be divided into two categories, namely traffic assignment-simulation and route-schedule planning. Micro-scopic traffic assignment-simulation [2] often requires a long time to complete for a large transportation network, and mostly employ the Wardrop equilibrium model [3] which will be violated in emergencies. The route-schedule planning approaches use network flow and routing algorithms to produce routes and schedules, and obtain the optimal solution by using linear programming (LP) based methods. An extensive literature review of these methods was proposed by Hamacher and Tjandra [5]. However, this kind of approach significantly increases the problem size and does not scale well to large transportation networks. It also requires the user to provide an upper bound T of the evacuation time which is almost impossible to precisely estimate.

We propose the Capacity Constrained Route Planner (CCRP) to efficiently solve the evacuation planning problem in large scale of transportation networks, with the capacity of the network taken into consideration. This paper gives an overview of the evacuation planning problem as well as the CCRP system, and shows the utility of CCRP in real scenarios.

2 Problem Statement

Transportation networks are usually modeled as graphs. Nodes represent the intersections of roads, and edges represent the road segments between them. Cost of edges represent their travel time. The capacity attribute associated with each edge represents the maximum flow rate (flow per unit of time), and the capacity of each node indicates the maximum number of evacuees that can be held at this node. Source nodes are the initial starting points of evacuees, and destination nodes are the safe places that they are supposed to arrive finally. The evacuation planning problem is formulated as follows:

Given: A transportation network with non-negative integer capacity constraints on nodes and edges, non-negative integer travel time on edges, the total number of evacuees and their initial locations, and locations of evacuation destinations.

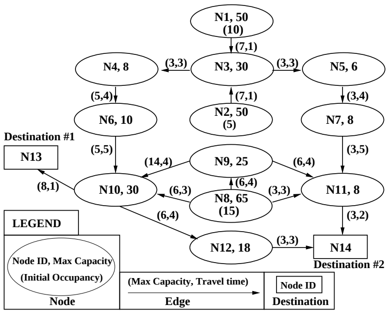
Output: An evacuation plan consisting of a set of origin-destination routes and a scheduling of evacuees on each route. The scheduling of evacuees on each route should observe the capacity constraints of the nodes and edges on this route.

Objective: (1) Minimize the evacuation egress time, which is the time elapsed from the start of the evacuation until the last evacuee reaches the evacuation destination. (2) Minimize the computational cost of producing the evacuation plan.

Constraint: (1) Edge travel time preserves FIFO (First-In First-Out) property. (2) Edge travel time reflects delays at intersections. (3) Limited amount of computer memory.

The following example illustrates the input and output of the problem. In the evacuation network shown in Figure 2 (a), each node is shown by an ellipsis. Each node has two attributes: a maximum node capacity and an initial node occupancy (in the number of evacuees). In Figure 3, each edge, shown as an arrow, represents a link between two nodes. Each edge also has two attributes: a maximum edge capacity and a travel time. For example, at edge N4-N6, the maximum edge capacity is 5, which means at each time point, at most 5 evacuees can start to travel from node N4 to N6 through this link. The travel time of this edge is 4, which means it takes 4 time units to travel from node N4 to N6. This approach of modeling an evacuation scenario to a capacitated node-edge graph is similar to methods presented in related work listed in [1].

As shown in Figure 3, suppose we initially have 10 evacuees at node N1, 5 at node N2, and 15 at node N8. The task is to compute an evacuation plan that evacuates the 30 evacuees to the two destinations (node N13 and N14) using the least amount of time. Figure 2 (b)shows an example evacuation plan for the evacuation network in Figure 2(a). In the result, each row shows one group of evacuees moving together during the evacuation with a group ID, source node, number of evacuees in the group, the evacuation route with time schedule, and the



(a) Node-edge graph model of example evacuation network

Group of Evacuees			Route with Schedule	Dest. Time
ID	Source	Group Size		
A	N8	6	R8(T0)−N10(T3)−N13	4
B	N8	6	N8(T1)−N10(T4)−N13	5
C	N8	3	N8(T0)−N11(T3)−N14	5
D	N1	3	N1(T0)−N3(T1)−N4(T4)−N6(T8)−N10(T13)−N13	14
E	N1	3	N1(T0)−N3(T2)−N4(T5)−N6(T9)−N10(T14)−N13	15
F	N1	1	N1(T0)−N3(T1)−N5(T4)−N7(T8)−N11(T13)−N14	15
G	N2	2	N2(T0)−N3(T1)−N5(T4)−N7(T8)−N11(T13)−N14	15
H	N2	3	N2(T0)−N3(T3)−N4(T6)−N6(T10)−N10(T15)−N13	16
I	N1	3	N1(T1)−N3(T2)−N5(T5)−N7(N9)−N11(T14)−N14	16

(b) An example of evacuation plan

Figure 2: An example illustrating the input and output of the evacuation planning problem

destination time. The route is shown by a series of node numbers and the time schedule is shown by a start time associated with each node on the route. Take source node N8 for example: initially there are 15 evacuees at N8. They are divided into 3 groups: Group A with 6 people, Group B with 6 people and Group C with 3 people. Group A starts from node N8 at time 0 and travels to node N10, then it travels from node N10 at time 3 to node N13, reaching destination N13 at time 4. Group B follows the same route but has a different schedule due to capacity constraints of this route. This group starts from N8 at time 1 and travels to N10, then travels from N10 at time 4 to N13, and reaches destination N13 at time 5. Group C takes a different route. It moves from N8 at time 0 to N11, then moves from N11 at time 3 to N14, and reaches destination N14 at time 5. The procedure is similar for other groups of evacuees from source node N1 and N2. The whole evacuation egress time is 16 time units since the last groups of people (Groups H and I) reach their destination at time 16. This evacuation plan is an optimal plan for the evacuation scenario shown in Figure 2 (a). According to Hoppe and Tardos [10], this problem can be solved using the ellipsoid method, and the total time complexity will reach $O((T \cdot n)^6)$, where n is the number of nodes in the network and T is the user-provided evacuation time upper bound. This problem is hard also due to the violation of assumptions like the stationary ranking of alternative routes, etc. For example, in Figure 2(b), the best route starting at N8 changed from N8-N10-N13 to N8-N11-N14.

3 The Capacity Constrained Route Planner (CCRP)

In our problem formulation, we allow time dependent node capacity and edge capacity, but we assume that edge capacity does not depend on the actual flow amount in the edge. We also allow time dependent edge travel time, but we require that the network preserve the FIFO (First-In First-Out) property. In this section, we briefly describe the main idea of the CCRP algorithm and its experimental evaluation results.

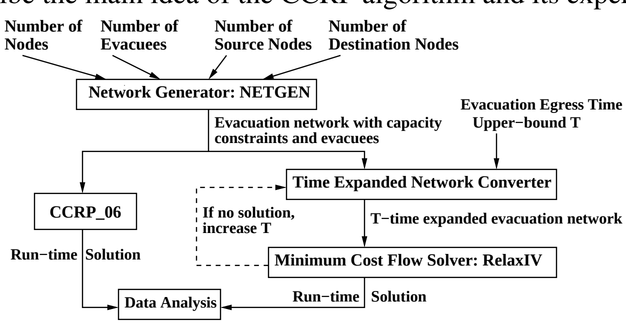


Figure 3: Experiment design

The CCRP Algorithm: The CCRP produces sub-optimal solutions for evacuation planning. We model edge capacity and node capacity as a time series instead of fixed numbers. A time series represents the available capacity at each time instant for a given edge or node, which advances the idea of Time-Aggregated Graph [6]. CCRP uses a heuristic approach based on an extension of shortest path algorithms to account for capacity constraints of the network [1]. The CCRP uses an iterative approach. In each iteration, the algorithm first searches for route R with the earliest destination arrival time from any source node to any destination node, taking previous reservations and possible waiting time into consideration. Next, it computes the actual number of evacuees that will travel through route R. This number is affected by the available capacity of route R and the remaining number of evacuees. Then, it reserves the node and edge capacity on route R for those evacuees. The algorithm continues to iterate until all evacuees reach the destination. The cost model of the above CCRP algorithm is $O(p \cdot nlogn)$, where n is the number of nodes and p is the number of evacuees. A formalized algorithm and detailed analysis can be found in the paper by Lu et al. [1]. In our later work, the CCRP was improved by adding a super node which connects all the source nodes by edges with infinite capacity and zero travel time [9]. This allows us to complete the search for route R by using only one single generalized shortest path search starting from the super node. The run time of the algorithm is reduced most when using Dijkstra's algorithm to search the shortest path.

Experimental Evaluation: We tested the CCRP (the improved algorithm) with different settings and compared its performance with the linear programming-based system Relax IV [7]. Figure 3 shows the experiment design (CCRP_06 refers to the improved CCRP algorithm). First, we studied how the number of nodes in the network affects the run-time cost and the result quality (total evacuation time). The network generated had 5000 evacuees, 20 source nodes and 10 destination nodes. The total number of nodes ranged from 50 to 50000. Results showed that the time cost of CCRP, compared to Relax IV, is not only faster but also grows more slowly as the network size increases (See Figure 4 (a)). Meanwhile, the result quality of CCRP is almost the same as Relax IV (See Figure 4(b)). Then we tested how the number of evacuees affects the run-time and the result quality. The network had 5000 nodes with 2000 sources. The number of evacuees ranged from 5000 to 50000. CCRP produced almost as good result as Relax IV, with much less time spent dealing with increasing numbers of evacuees (See Figure 4(c) and (d)). We also tested the impact of the number of sources and destinations on the time cost and the result quality (see [9]). 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 2.8GHz CPU, 2GB RAM and Linux operating system. Each experimental result shown is the average over 5 experiments runs with networks generated using the same parameters.

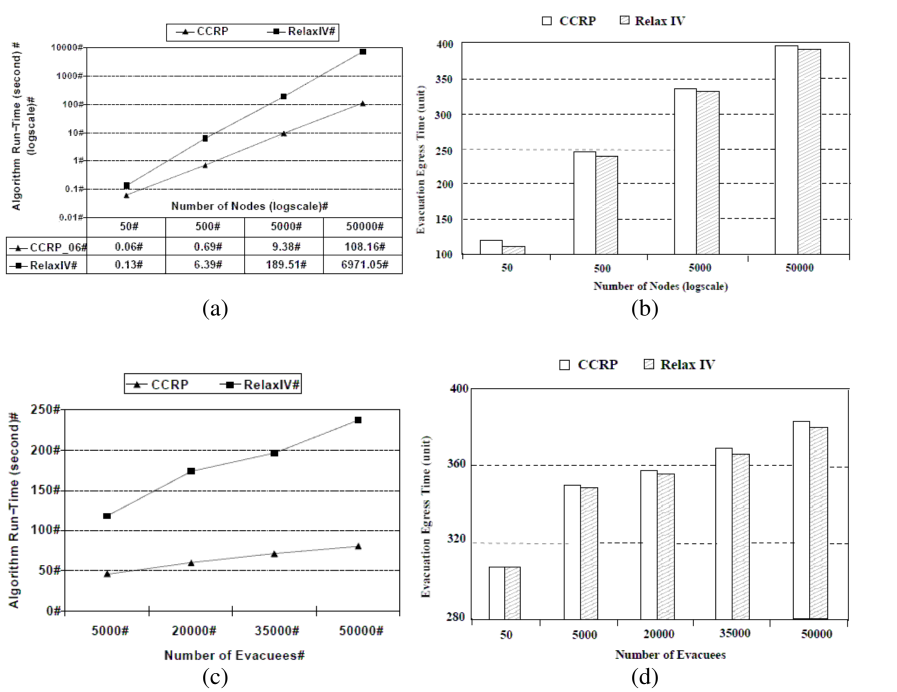


Figure 4: Evaluation results of CCRP: (a) Run-time (log-scale) with respect to network size; (b) Result quality(total evacuation time) with respect to the number of nodes in the network; (c) Run-time with respect to the number of evacuees; (d) Result quality with respect to the number of evacuees.

4 Case Study and Social Impact

In this section, we report the case study results of CCRP in a major metropolitan region evacuation planning.

Evacuation Planning: Monticello Power Plant: As shown in Figure 5, the Monticello nuclear power plant is located about 40 miles to the northwest of the Twin Cities of Minneapolis-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 [9]. An initial hand-drafted evacuation route plan called for the affected population to a nearby high school. However, this plan did not consider the capacity of the road network and put high loads on two highways.

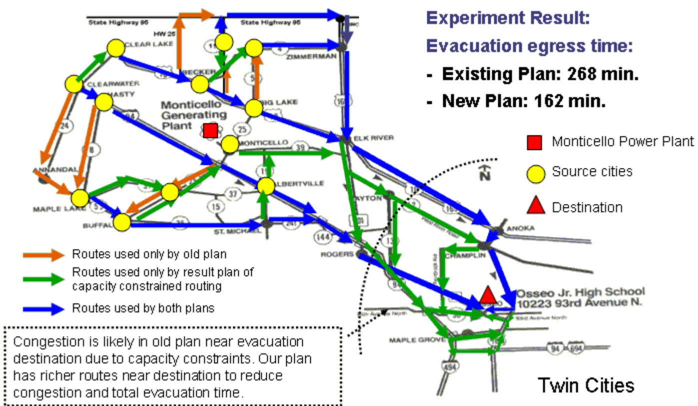


Figure 5: Overlay of result routes for Monticello power plant evacuation route planning. (Best in color)

We experimentally tested the CCRP algorithm using the road network around the evacuation zone provided by the Minnesota Department of Transportation [9] and the Census 2000 population data for each affected city (circle in Figure 5. The total number of evacuees was about 42,000. As can be seen in Figure 5, our algorithm produced a much better evacuation route plan a) by selecting shorter paths to reduce evacuation time, and b) by utilizing richer routes (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 improve existing plans.

Evacuation Planning System for Twin Cities Metro Area: Our method was also selected by the Minnesota Department of Transportation to be used in 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, the CCRP algorithm was incorporated into an evacuation planning system, and was tested on five pre-defined 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 (day-time and night-time) on population distribution. The settings we used in the five pre-defined scenarios are shown in Table 1. One especially interesting finding was that walking results in less congestion than driving, and thus can decrease total egress time. Transportation professionals evaluated the quality of the results and found them to be highly satisfactory.

Social Impact and Public 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 CTS award [11]. The research results are also reported by Fox TV [8], Pioneer Press, Star Tribune and other local and university media.

5 Extension and Future Work

We extended CCRP by adding contraflow reconfiguration in a later paper [12] which employs lane reversal as a method to reduce congestion by increasing capacity of roads. In the future, work is needed in a number of other areas. For spatial network databases, efficient data models and algorithms are needed for queries with time-variants in flow networks(see Table 2). Regarding emergency management, one of the limitations of current work is that it assumes constant travel time of edges in the traffic network model. In real emergencies, this assumption is sometimes violated due to dense traffic or road damage. We plan to work on improving our current methods to deal with dynamic network settings. Another challenge arises from the multi-criterion feature of evacuation

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

Table 1: Settings and results of the five scenarios in Twin Cities Metro Area evacuation planning

planning, which means that we may have multiple objects to optimize (e.g., food supply sufficiency, equatability, etc) rather than merely the egress time when designing evacuation plans. Since a global optimal plan is usually difficult to find, how to efficiently generate a complete and correct candidate set that does not include any plans worse than any existing plan on all objectives is a challenging problem that we will investigate in the future.

	Static	Time-Variant
Graph (No capacity constraints)	Which is the shortest travel time path from downtown Minneapolis to the airport?	Which is the shortest travel time path from downtown Minneapolis to airport at different times of a work day?
Flow Network	What is the capacity of Twin-Cities freeway network to evacuate downtown Minneapolis?	**What is the capacity of Twin-Cities freeway network to evacuate downtown Minneapolis at different times in a work day?**

Table 2: Example queries with time-variance and flow networks.

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