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Optimizing the Use of Transit System with Information Updates during No-Notice Evacuations

FINAL REPORT

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1.0 Abstract

Evacuation of the affected population is a very common response to disasters such as hurricanes, chemical spills, and terrorist attacks. This paper proposes a rolling horizon framework for a previously proposed mixed integer linear program to find the optimal routes during no-notice evacuation. Rolling horizon framework provides the opportunity of using information updates along the time horizon.

2.0 Introduction

Evacuation of people from affected areas is a very common response to disasters in order to minimize casualties and losses. As Chiu et.al. [1] stated, the efficient coordination and utilization of roadway capacity, traffic management equipment, and available emergency response resources is crucial to build an effective evacuation plan. Nevertheless, there is a dichotomy between evacuation strategies with respect to type of disasters: short-notice and no-notice disasters. In short-notice disasters, such as hurricanes, there exists prior information about the timing, location, and severity of the disaster. Obviously, existence of aforementioned information facilitates the construction of evacuation plans. On the contrary, no prior information exists in the case of no-notice disasters such as terrorist attacks and chemical spills. Thus, in no-notice disasters, evacuation is performed immediately after the occurrence of the disaster [1].

"Among different modes of transportation, transit system plays crucial role in all four phases of the process of emergency management including mitigation, preparedness, response, and recovery" [2]. Evidently, the impact of employing the transit system depends on the extent of transit dependency of the population. For example, during hurricanes Katrina and Rita, a number of casualties occurred due to the fact that a large part of the population in New Orleans did not own nor had access to a car. Hence, the transit system could have been employed to evacuate approximately 100,000 to 200,000 people in New Orleans in advance of hurricane Katrina [3]. Therefore, one would claim that impact of transit system over evacuation planning is largely underrated.

In no-notice evacuations, since there exists no prior information about the disaster, an evacuation plan should be immediately developed with current information on-hand. Unfortunately, uncertainty on road network, traffic condition, and human behavior arise the need for rapidly and frequently updating traffic control and routing strategies according to unfolding conditions [1]. Rolling horizon is commonly used in inventory control and production planning literature in order to deal with stochasticity as well as forecasting limitations. It mainly refers to revising plans in response to realized information. Therefore, one would claim that rolling horizon is a conventional frame for capturing the dynamics of the evacuation problem.

A methodology is proposed to develop an evacuation plan for transit dependent people using transit system by Sayyady and Eksioglu [2]. Inside that methodology a mathematical model is proposed for determining the optimal routes for busses. The objective is to minimize the number of losses and total evacuation time. It is assumed that there is a central decision maker that can gather the speed and location information of vehicles. Furthermore, the decision maker can communicate with transit vehicles for dictating the routes. As a result of the model, it is aimed to determine the expected number of vehicles required, the expected number of citizens evacuated within a given time period, and the evacuation routes for transit vehicles. As a second component of the methodology, a preprocessing procedure is also proposed for decreasing the size of the problem. These approaches are discussed in more detail in next sections.

In this paper, the methodology proposed by Sayyady and Eksioglu [2] is employed in order to develop an evacuation plan. Although it is an elegant model to develop the optimal routes, it does not take into account high uncertainty of a disaster environment. Henceforth, we applied a rolling horizon frame in order to capture the highly dynamic nature of a disaster environment. In order to investigate the effectiveness of the proposed solution, Dynasmart-P, a traffic simulation software, is used to simulate real life traffic evolution. Perkins et.al. [4] analyzed the use of transit systems in case of a short-notice disaster. Furthermore, Mastrogiannidou et.al. [5] proposed an approach to deal with the issue of transit assisted evacuation procedures by using dynamic network model. Ran et.al. [6] and Peeta and Mahmassani [7] discussed traffic assignment problems with rolling horizon application.

To the best of authors' knowledge, no other work has been done that can be used as a guideline to optimize the use of transit vehicles in the case of no-notice evacuations by using rolling horizon.

In Section 2, we give the definition of the problem considered. In Section 3 we present a time-space network, a mixed integer programming model, a preprocessing procedure proposed by Sayyady and Eksioglu [2], and a rolling horizon application. Section 4 is devoted to the experimental design and computational results. Finally, in section 5, we draw some conclusions.

3.0 Problem Definition

We used the same assumptions which are employed by Sayyady and Eksioglu [2]. Thus it is assumed that there is a no-notice disaster scenario in which evacuation time should be less than a few hours. Before the disaster, transit vehicles are either performing their daily operations or waiting at the main depot. There are some certain pick-up locations for evacuees such as bus stops or train stations. Evacuees will be picked up from those locations. For a single vehicle, evacuation will be finalized at a predetermined shelter. In other words, transit vehicles can perform only one route during the disaster. Since evacuation time window is limited, sometimes with less than one hour, single route assumption may not violate real-life practice. Once an evacuation order is released, a particular transit vehicle starts its evacuation route with being discharged from its daily scheduled path.

The importance of the proposed model is two-fold, such that, it can be used for both planning and operation purposes. In the planning case, it can be used to estimate the capabilities of the current transit system, such as, determining how many transit-dependent people can be saved by the on-hand transit system and/or determining the expected number of transit vehicles in order to evacuate all transit-dependent people. In the case of operations, it can be used to find out the evacuation routes for the transit vehicles. The main drawback for the proposed model is that the highly dynamic structure of the evacuation environment has not been explicitly taken into account in the model. Henceforth, we employed a rolling horizon frame to be able to revise the evacuation plan according to unfolding events.

4.0 Time-Space Network

In the literature, time-space network is widely used in order to represent the time dimension on the physical network. Time-space networks allow modeling the problem as a minimum cost flow model. Time-space network is denoted by G = (N,A), where N denotes the set of nodes and A denotes arc set. In the next subsection, components of the time-space network shall briefly be discussed.

4.1 Nodes and Arcs in the Time-Space Network

Let T be the length of the planning horizon. The network contains three types of nodes ($N = P \cup P' \cup D$). Set P represents the set of pick-up nodes, whereas set P' is the set of shelter nodes and set D represents the sink node. Set P in the time-space network is the duplication form of physical pick-up locations over T. Thus, nodes in set P have two indices. The first index indicates the physical location attribute of the node whereas the second index indicates its time dimension attribute. For instance, node S(2, 3) in a time-space network indicates that the node belongs to node 2 in time period 3. Note that pick-up nodes are the supply nodes, whereas sink node is the demand node.

There are three types of arcs in our time-space network ($A = W \cup M \cup S$). W denotes the set of waiting arcs. W has two subsets such that W_e represents evacuees waiting for a transit vehicle, and W_b represents evacuees loaded on a transit vehicle, and waiting at a station. $W = W_e \cup W_b$. Obviously, W_e connects two pick-up nodes which represent the same physical node, and time attributes are consecutive. Note that the capacity of W_b is equal to the capacity of a transit vehicle, whereas W_e are uncapacitated. Furthermore, number of W_b arcs between two nodes is equal to the total number of transit vehicles.

M denotes the set of moving arcs which represents a physical movement on the original network. There are two classes of moving arcs, $M = M_{pp} \cup M_{ps}$. M_{pp} denotes the set of arcs that connect pick-up nodes and M_{ps} denotes the arcs between a pick-up node and a shelter node. The capacities of the movement arcs are equal to the capacity of a transit vehicle. It is not needed to add backup paths into our time-space network because of rolling horizon application. Hence, unlike [2], number of movement arcs between two nodes is equal to the number of transit vehicles. Additionally, travel times between pick-up nodes are equal to the difference between time attributes of the nodes regardless of the type of arc.

S denotes the set of sink arcs which connects shelters and the pick-up nodes, which belongs to last time period, to the sink node. Travel time on sink arcs in which starting node is a pick-up node is infinity, whereas it is zero for connecting shelters with the sink node. The flow on sink arcs connecting sink node with a pick-up node represents the losses, whereas it represents saved people for arcs connecting the sink and a shelter. The sink arcs are uncapacitated.

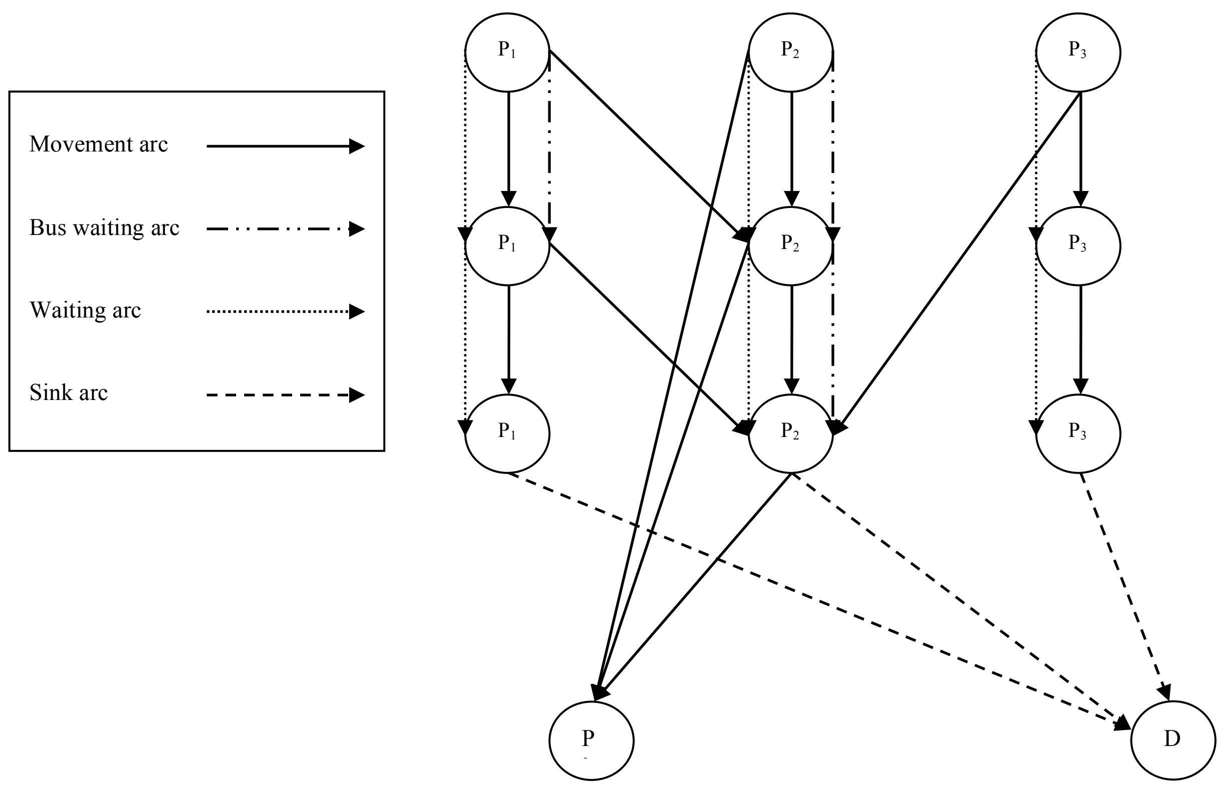

Figure 1: Time-Space Network

Figure 1 illustrates a simple time-space network example. There are 3 pick-up locations and 3 time periods. The only way to shelter passes through pick-up location 2. Travelling time from pick-up location 1 to pick-up location 2 is 1 period, whereas travelling time from pick-up 3 to pick-up 2 is 2 periods.

4.2 The Mixed-Integer Programming Formulation

In this section, the MIP model for the problem discussed above is presented. There are three sets of decision variables in the model. The notation used is as follows:

x_{ij} = variable that represents the flow of evacuees on the network for (i, j) ∈ A.

y_{ij} = binary variable that takes value 1 if there is a positive flow on arc (i,j), and 0 otherwise for (i, j) ∈ M

z_{ij} = binary variable that takes value 0 if there is a positive flow on (i, j), and 1 otherwise for (i, j) ∈ W_e.

Z = very large number

ω = total number of available transit vehicles

δ_i = the number of evacuees at pick-up node i

u = the capacity of a transit vehicle

b_i = the number of transit vehicles at pick-up node i.

$$Min \sum_{(i,j)\in A} t_{ij}x_{ij} \tag{1}$$

$$\sum_{\{j:(i,j)\in A\}} x_{ij} - \sum_{\{j:(j,i)\in A\}} x_{ji} = \begin{cases} \delta_i & i \in P \\ 0 & i \in P' \\ -\sum_{k\in P} \delta_k & i \in D \end{cases} \tag{2}$$

$$\sum_{\{j:(i,j)\in\{M\cup W_b\}\}} y_{ij} - \sum_{\{j:(j,i)\in\{M\cup W_b\}\}} y_{ji} = b_i \qquad i \in P \tag{3}$$

$$\sum_{\{j:(i,j)\in M, j\in P`\}} y_{ij} = \omega \tag{4}$$

$$x_{ij} - uy_{ij} \le 0 \qquad (i,j) \in M \cup W_b \tag{5}$$

$$\sum_{(i,j)\in M} x_{ij} \le \rho_j \qquad j \in P' \tag{6}$$

$$-x_{ij} + uy_{ij} - Zz_{ik} \le 0 \qquad (i,j) \in M; (i,k) \in W_e \tag{7}$$

$$x_{ik} - Z(1 - z_{ik}) \leq 0 \qquad (i,k) \in W_e \tag{8}$$

$$y_{ij} \in \{0,1\} \qquad (i,j) \in M \tag{9}$$

$$x_{ij} \geq 0 \qquad (i,j) \in A \tag{10}$$

$$z_{ij} \in \{0,1\} \qquad (i,j) \in W_e \tag{11}$$

Equation (1) is the objective function which aims to minimize the total clearance time. Equation (2) is the flow conservation constraints for evacuees, whereas (3) is the flow conservation constraint for vehicles. Equation (4) represents the number of buses available. Equations (5) and (6) ensure that a transit vehicle cannot leave a pick-up location unless it has no available space or there is no other evacuee waiting. The remaining constraints are the binary and the non-negativity constraints.

Although it is not explicitly incorporated, the objective function aims to minimize the number of losses as well. Since the travel times on the arcs from a pick-up node to a sink node, which actually represents the casualties, is very large, the model is imposed to avoid using such arcs. Therefore, the model is forced to minimize the total number of casualties.

4.3 Preprocessing

One of the major problems for no-notice disasters is the lack of preparation time for making and implementing the evacuation plan. In this section we explain a method for decreasing the problem size in order to increase computation time. We mainly aim to determine promising candidate paths between pick-up locations prior to a disaster so that limited number of candidate paths will be evaluated in the case of a disaster. To do so, a two step procedure is proposed. In the first step, a certain number (m) of paths are chosen among the original network by using an iterative penalty method (IPM), i.e, a shortest path based algorithm. In this method the shortest path algorithm is executed repetitively. After each run of the shortest path algorithm, a penalty term is added to the selected shortest path in order to increase the chance of determining different shortest paths in the next runs. In the second step of the preprocessing procedure, by using a p-dispersion algorithm, the final candidate paths are selected out of the paths which are determined in the first step. The P-dispersion algorithm selects a number of paths out of a given path set in such a way that the minimum dissimilarity between the selected paths is maximized. To be able to measure the dissimilarity of roads an index proposed by [8] is employed. P_{ij} and R_{ij} are two arbitrary paths between i and j. $L(P_{ij})$ and $L(R_{ij})$ are the length of each corresponding path. Dissimilarity index, d_{ij}, is computed as follows:

$$d_{ij} = 1 - \frac{\frac{L(P_{ij} \cap R_{ij})}{L(P_{ij})} + \frac{L(P_{ij} + R_{ij})}{L(R_{ij})}}{2} \quad (12)$$

4.4 Rolling Horizon Application

In this section, the implementation of the rolling horizon framework is discussed. Traditionally, in a rolling horizon framework, decisions are made over either the entire or some part of the planning horizon. However, only the first period's decisions are implemented, and then the system is re-planned for the remaining periods of the planning horizon by using new information realized in the previous period. The rolling horizon framework is employed for dealing with uncertainty and/or limited forecast window. In our case, we aimed to re-optimize the system in response to unforeseen events unfolding along the planning horizon.

At the beginning of the planning horizon, the MIP model is used to develop an evacuation plan for the entire planning horizon. However, it is implemented only in the first roll period t, and then system is re-optimized by using the MIP model with updated location of transit vehicles, speed, and network information for the remaining planning horizon. This process continues up to the end of the planning horizon. Notice that the time-space network has to be re-constructed with updated information at each re-planning epoch. Unlike [2], there is no need to incorporate alternative routes between two particular pick-up nodes in the time-space network since the rolling horizon framework provides a re-planning ability. Re-construction of the time-space network is important for the rolling horizon implementation. Since the structure of the network is affected from the time dimension of the physical network, i.e. travel times, it is a necessity to reconstruct the network at each roll period. Hence, the time-space network is dynamic along the planning horizon unlike a traditional single static network. Number of arcs, start and end points of a particular arc, and even the number of nodes may change from one roll period to the next.

5.0 Numerical Study

We performed a small number of experiments on a relatively small but realistic network. Our purpose to show the effectiveness of our rolling horizon approach compared to the static solution. In the following paragraphs we describe our experiment design and present our numerical results.

5.1 Experiment Design

In our numerical study we assume that total available bus capacity is equal to the total number of evacuees in the system. We also assume that bus capacity (u) is 50. Arrival pattern of evacuees to pick up points is determined by so called mobilization curves introduced by [9] and using the following equation

$$\gamma_t = \frac{1}{1 + \exp[-LR(t-h)]} \tag{13}$$

where γ_t is the cumulative percentage of evacuees who show up in the network until time t, LR is response rate, and h is the half loading time. Basically, we generated two patterns by using mobilization curves. In the first pattern, we assume that citizens immediately respond to an evacuation order. In the second pattern, we demonstrate late response of citizens. For our case study we used the city of Forth Worth, TX which is provided by Dynasmart-P traffic simulation software. We selected 4 pick-up locations and one shelter location from the original network. Dynasmart-P also provides speed information on each road segment in the network. In our rolling horizon application we used Dynasmart-P in order to simulate real traffic network and get unfolding information. Hence, there is a closed loop feedback mechanism between the optimization model and Dynasmart-P.

The evacuation time limit is assumed to be 30 minutes. Therefore, number of pick-up points in the time-space network is 120 (4 pick-up locations across 30 time periods). In order to understand the effect of the length of rolling horizon, we employed three different roll length; $\tau=\{5,10,15\}$. Additionally, we also used two different number of transit vehicles; $\omega=\{5,10\}$. Overall, we generated 4 different problems (2 different arrival patterns and 2 different number of transit vehicles).

In this numerical study we used two different approaches to solve the same problem in order to measure the effectiveness of the rolling horizon approach. In the first approach, the initial plan that is generated in the beginning of the planning horizon is used for the entire planning horizon (static information). In the second approach, we present the best case scenario in which we have a perfect forecast about the network in the beginning of the planning horizon (perfect information). Note that perfect information is provided by Dynasmart-P. These two approaches represent two extremes in terms of knowledge update. Thus, rolling horizon approach stands between these two extremes. In order to analyze the solutions and measure the effectiveness of the results, we simulate these solutions using Dynasmart. Therefore, we are able to test our results in a realistic traffic network environment.

5.2 Results

As we stated earlier, the rolling horizon application lies between the static information and the perfect information approaches. Therefore, we expect that the rolling horizon approach will perform somewhere between perfect information case and static information case. Our results confirm that expectation. Table 1 presents the percentage of people saved for all problems. If we look at the results at the columns titled Roll-5 Roll-10 and Roll-15, we notice that these results lies between the results of the columns titled Perfect Info and Static Info. According to Table 1, it is also obvious that the length of rolling horizon is also important on the quality of the solutions. More specifically, solution quality improves as length of rolling horizon decreases. The length of the rolling horizon determines not only the frequency of re-planning but also frequency of information update. Therefore, higher re-planning activities with better information, naturally, provide better results. For instance, if we analyze row 4, we realize that the performance of Roll-5 is superior to both Roll-10 and Roll-15, whereas Roll-10 performs better than Roll-15. Furthermore, especially when the length of roll period is 5, the results are very close to the best case scenario represented by Perfect Info. Table 1 also reveals that late response of citizens decrease the chance of being saved. In the table, if we compare row 1 and row 2, it is obvious that results in the row 2 are slightly worse than row 1.

Table 1: Results

#	# of Bus	Arr. Pattern	Perfect Info	Static Info	Roll 5	Roll 10	Roll 15
1	5	1 (early arr.)	100%	96.8%	99.4%	97.2%	96.8%
2	5	2 (late arr.)	100%	95.2%	99.2%	96.8%	96%
3	10	1 (early arr.)	100%	97%	99.6%	98.6%	97%
4	10	2 (late arr.)	99.4%	94%	99.4%	97.6%	95%

6.0 Conclusion

In this paper we presented a mixed integer programming based procedure and its rolling horizon application for planning the evacuation of transit dependent citizens. Road and traffic condition in a disaster area is highly uncertain. Hence, it is crucial to revise the evacuation plans along the time horizon. Our study underlines the need for such revisions.

7.0 References

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