

NEAR REAL-TIME BULK TRAFFIC REROUTING UNDER DISTRESS CONDITION

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ABSTRACT

Controlling traffic flow in response to a disturbance in a major arterial road is an important issue in almost every highly populated transportation network in the world. The fundamental mathematical issues have been resolved in graph and network theory. However, there have not been many practicable strategies developed to generate real-time optimal evacuation routes. Recent development in vehicle sensor technology and enormous growth in computing and telecommunications enables real time monitoring of the traffic situation. As a result there is a large effort among traffic planners and researchers to develop solution strategies that fully take advantage of these developments. This paper presents an algorithm to generate more accurate alternate routes in the presence of a disturbance by utilizing real-time dynamic traffic data, whether the disturbance is a traffic incident, a chemical spill, a natural or manmade disaster.

Keywords: Dynamic traffic rerouting, shortest path problem, real-time vehicle routing.

1. INTRODUCTION

Any part of a Transportation network, by nature, possesses a certain level of uncertainty in assuring continuous flow. The capacity reduction in any of the major highways because of a perturbation in the system requires redistribution of traffic around the location of perturbation. This research presents an algorithm for near real-time redistribution of traffic in the auxiliary link roads and bringing the flow back to the major highway passing the point of perturbation.

The algorithm finds pragmatic solution by searching a significantly reduced network rather than guaranteeing a global optimal. Moreover, the algorithm considers the arc costs as function of time and space, hence capturing the inherent dynamic nature of the traffic re-routing problem.

The next section presents the mathematical treatment and state of the art in the general area of traffic management. The subsequent sections describe the problem statement, model development, an implementation of the model, results and conclusion.

2. MODELS AND STATE OF THE ART

A static transportation network can be described by a capacitated directed graph $G = (M, A, c, u, s)$ where $M = \{set\ of\ all\ nodes\}$, $A = \{set\ of\ all\ arcs\}$, c is the set of arc costs such that $c = \{c_{ij}; \exists ij\ and\ i, j \in M\}$, u is the set of arc capacities, $u = \{u_{ij}; \exists ij\ and\ i, j \in M\}$, s is the set of arc speed limits, $s = \{s_{ij}; \exists ij\ and\ i, j \in M\}$.

The general topology of a transportation network is depicted in figure 1. In this network flow model, arcs

represent the road segments and nodes represent the juncture of two or more roads.

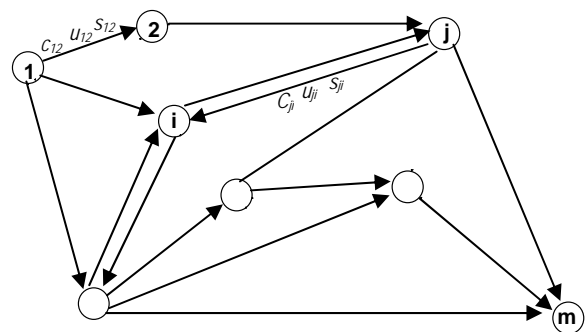


Fig 1: Transportation Network Modeled as Digraph

In the static domain, the travel time minimization from any node to any other node of this graph is essentially finding the 'shortest path' for any individual traffic. This problem is efficiently solved by Dijkstra^[1] and many other algorithms like A*^[2] in polynomial time. A comparative study of the shortest path algorithms is presented by Dreyfus^[3]. Fu et al.^[4], studied the heuristic algorithms in relation to the route guiding system (RGS) implementation. Laporte^[5] evaluated computational efficiency of exact and heuristic algorithms in vehicle routing problem.

Dynamic rerouting is required when a transportation network becomes distressed as one of the arcs in a main artery is incapacitate. The in situ remedy is to divert the traffic to an auxiliary roadway, which eventually will

lead back to the main artery. The approach is easily understood, but difficult to implement effectively, especially if the scope of transportation network being analyzed is large and complex. The difficulties arise as:

$$\left. \begin{array}{l} s_{ij} \xrightarrow{t \gg} \phi(t) \\ c_{ij} \xrightarrow{t \gg} \psi(s_{ij}) \end{array} \right\} \forall i, j \in \{\text{nodes in the de tour}\} \quad (1)$$

Where, ϕ and ψ are some nonlinear functions. These changes in the auxiliary arcs make the graph non-static and demand for continuous evaluation. Mapping this problem in the exact algorithm for shortest path solution or even shortest path heuristic approach is not computationally viable. However, many researchers are addressing the issues of dynamic rerouting and peripheral challenges in the context of modern day intelligent transportation systems (ITS).

Fu^[6] presents an adaptive routing algorithm for in-vehicle RGS with real time traffic information. The research examines adaptive routing problems in traffic networks in which link travel times are modeled as random variables with known mean and standard deviation. An approximate probabilistic adaptive labeling model, based on the Label Correcting (LC) algorithm is used to select route for individual vehicle. In order to effectively understand traffic levels, Chan and Lam^[7] present a bi-level programming model to determine the optimal speed detector density for a network with travel time information via RGS. Furthermore, Kim et al.^[8] describe the implementation of transportation systems integrated with real time Traffic Information (IT) and develop decision-making procedures for determining the optimal driver attendance time, optimal departure times, and optimal routing policies under time-varying traffic flows. However, bulk traffic evacuation and impacts on the auxiliary arcs, with much lesser capacities are not considered. Ozdamar et al.^[9] develop a logistics planning model for relief operations in times of a natural disaster or evacuation. The model utilizes a Lagrangian relaxation and heuristic approach to treat multiple commodities with time-dependent supply, demand and fleet size variables, in addition to real-time schedule updates. Cova^[10] proposed large scale lane based evacuation strategy. The model reported to reduce 40% crossing congestion. Sawaya et al.^[11] introduce a predictive feedback control approach that produces dynamic control strategies in the form of alternate routes around freeway incidents and in response to the prevailing traffic conditions. The solver generates predictive travel times for the output from a dynamic traffic assignment model and the times are continuously updated via feedback from the online traffic sensors such that accurate travel time information is disseminated via variable message signs (VMS) to the affected commuters. Potvin et al.^[12] considered dynamic travel time in vehicle routing and scheduling problem.

Unfortunately, while there are many algorithms to suite the abundance of transportation planning type problems, none of them presents a practical strategy for bulk traffic rerouting under the distress condition that encompasses the non-static, non-linear features in the networks. The key issues are to consider:

- (1) Dynamic changes in a transportation networks flow optimality.
- (2) Intelligent heuristic search strategies for improving overall computation time and tractability.
- (3) Adjusting solution and search strategies in response to the real-time feedback from technological advancements in ITS.

3. PROBLEM STATEMENT

The mathematical model described here, borrows features from its predecessors, namely those of shortest path and vehicle routing formulations, but in addition adds several unique facets that describe the dynamic considerations of the bulk traffic rerouting.

This algorithm models the transportation network by a capacitated directed graph with time dependent arc attributes. Referring to figure 1 and incorporating equation 1, the modified dynamic model of the network is,

$$G = (M, A, c(s), u, s(t)) \quad (2)$$

3.1. Cost Computation

The model considers weighted sum of three factors contributing to the arc cost: the arc length (d_{ij}), the flow rate (traffic volume) to capacity ratio (v_{ij}/u_{ij}), and the vehicle speed (s_{ij}). The instantaneous flow rate and speed in any given arc can be obtained from the ITS infrastructure. For simplicity of developing the full-scale model and test implementation, the variable vehicle speed was simulated as nonlinear function of the volume/capacity ratio and the instantaneous flow rate was computed from historical flow data. Hence, the cost of traveling through any particular arc is:

$$c_{ij} = \alpha \left[\frac{v_{ij}}{c_{ij}} \right] + \beta [d_{ij}] + \gamma [s_{ij}] \quad (3)$$

The weight coefficient assigned to each of the three objective variables can be scalar or multivariate functions to fit the need of a specific topology, nature of distress and local ITS strategy.

Let $\tilde{G} \subseteq G$, is any valid detour which brings the flow back to the main arterial road passing the distress zone. The objective function of the model is:

$$\min \sum_{ij \in \tilde{G}} c_{ij} \quad (4)$$

3.2 Constraints

Let assume that arc(s) between nodes k and l in the main artery is incapacitated distressing the network. Let further assume that flow is from k to l and the nodes, k and l (junctures), are available for transition. Let $\tilde{A} \subseteq G$ = the arterial path in distress and $\tilde{A} = \overset{p}{A} \cup \overset{j}{A} \cup \overset{l}{A}$ where, $\overset{p}{A}$ is the segment of the arterial path upstream to the disturbance up to node k , $\overset{j}{A}$ is the segment enclosed between k and l and $\overset{l}{A}$ is the downstream segment passing the node l . Hence,

$$\left. \begin{aligned}
 u_{ij} &= 0 \quad \forall ij \in A \\
 \hat{G} \cap A &\neq \emptyset \\
 G \cap A &\neq \emptyset \\
 \frac{v_{ij}}{u_{ij}} &\leq T_{ij}
 \end{aligned} \right\} \quad (5)$$

The first set of constraints represents unavailability of the distressed zone, second set ensures the detour starts at some valid node in the downstream, third set represents the detour brings back the flow to the artery passing the distressed zone and the fourth set represents feasibility of any arc in the detour path. The threshold constants T_{ij} are preset constants based on the local requirements.

4. SOLUTION ALGORITHM

It is essential to introduce the base node set, B , prior to describing the procedure. The definition of the set is any \hat{G} (a detour path) must originate at a node $b \in B$. The solution algorithm derives its computational efficiency and practicality from the concept of base node set and base node extensions. The primary rule for locating the base node is to minimize the overall traffic disruption. Therefore, given the latitude-longitude of a distress location, the closest upstream node on the artery (k) will become the initial base node, i.e. $B = \{k\}$

The alternate routes commenced from the initial base node will increase in traffic volume over time, and depending on the capacity of the individual arcs on the alternate routes, all of them may become infeasible violating the fourth set of constraints in equation [5]. In that scenario, the base node set must be extended to incorporate further upstream nodes in the distressed artery. Figures 2 provide a pictorial example of how the base node principle is designed.

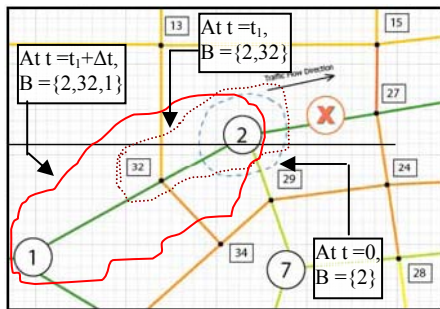


Fig 2: Base node set extension

This section describes the entire shortest path heuristic optimization scheme in simple block diagram. The basic implementation of the model is organized in procedural form. Figure 3 shows a detailed breakdown of all the relevant features of the procedure. The procedure retrieves relevant data for the disturbed section of the network from the master traffic database which contains static traffic information and graph topology. This step essentially reduces the size of the problem. It should be noted that for a given network, all detour routes originating from any node on the distress artery can be strategically arranged in lookup tables eliminating the

search through the adjacency matrix. The lookup tables can be prepared once and part of the master database. The lookup tables will be valid until graph topology in the neighborhood changes, i.e. new roads are built or old roads are destroyed.

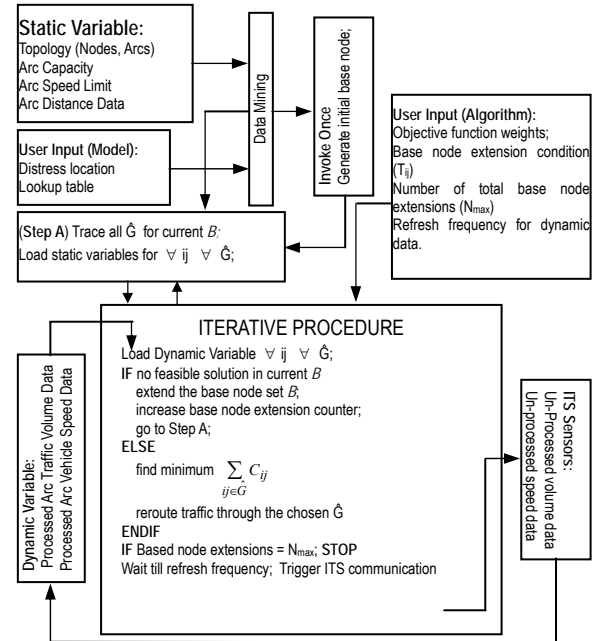


Fig 3: Procedural Block Diagram of Solver

The heuristic shortest path solver starts with processing two sets of user-defined parameters (Model and Algorithm). The first set defines the disturbance location on the traffic network and the label of lookup tables to be used in the synthesis. The other set provides guidance to the algorithm: weighing of the cost components, the base node extension logical condition, the total number of base node extensions and the refresh frequency for updating the dynamic variable data from the ITS infrastructure. The algorithm starts by first assigning the initial base node set, B from the static traffic information and the disturbance location. Once found, only the relevant parts of the lookup tables are extracted that includes the detours originating in the set B . Thereby the search space is tremendously reduced by considering only a small fraction of the overall graph. The solver calculates the cost information for each route in the lookup table and the lowest cost alternate route is chosen. According to user defined refreshing rate, the updated dynamic traffic information is loaded into the global matrices, and the path cost is again calculated for the current set of base node lookup tables. When no feasible solution exists, the base node set is extended further upstream until a new node enters. The lookup tables are then updated to reflect all of the updated nodes in the base node set, and the algorithm proceeds until a stopping criterion is met.

5. REAL-TIME TRAFFIC SIMULATION

The ITS infrastructure is still being evaluated with pilot runs in some controlled test beds. Therefore, in order to evaluate the solver a simulator mimicking dynamic traffic input was developed. The simulator is

invoked only once for the generation of random dynamic traffic volume in the neighborhood from historical data. After the initial dynamic cost matrices have been generated with the random volume and speed data from the simulator, the solver controls all subsequent dynamic transfer on rerouted arcs by incrementally increasing volume on paths that receive additional traffic volume from dispatch. For simplicity of building the full-scale model, the variable vehicle speed was assumed to be a nonlinear function of the volume/capacity ratio. The formulation still assumes that they are independent of one another, and both determine the final cost coefficient for a given possible route.

After the solver finds the initial alternate shortest path route, the inbound arterial traffic is loaded onto that route. The solver recalculates costs under new traffic scenario and finds the new alternate route.

6. APPLICATION AND RESULTS

The algorithm was evaluated by modeling the city traffic network at the center of the downtown Grand Rapids in western Michigan. Greater grand rapids has a population of 1.25 million^[13]. The modeled section incorporates the major north-south (US 131) and east-west (I-96) arterial roads of the city^[14]. Real traffic data was collected for the city of Grand Rapids, Michigan, USA from the Grand Valley Metropolitan Council's (GVMC) records for the two last years. Recorded traffic data was used as input to the dynamic traffic simulator. One scenario of distress location on US-131 southbound is shown in figure 4.

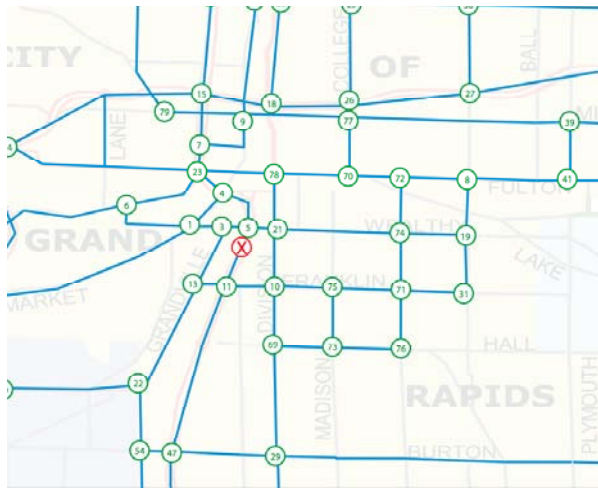


Fig 4: Disturbance Location in Downtown GR

The results of the five simulation runs are summarized in table 1. One of the iteration represents a successful finding of a detour route with a set of dynamic variable. After a given time interval, the dynamic data is reloaded and the next computation (iteration) is made. There is fluctuation in the total number of iterations before the solver terminates due to meeting the stopping criteria. This can be attributed to the dynamic considerations that the solver must accommodate in each calculation. The number of iterations before base node extension represents the time when there was no more feasible solution ensuing from *node 5*, in figure 4. From the

initial dynamic traffic data that the simulator generates, there will be a large effect on the number of iterations before the base node is extended. It is observed that shortest path cost data is similar in all of the simulations. This ensures that the geographic reality is captured and the little variation is due to the turbulence in the dynamic variables. Lastly, the computation times were taken for the total computation time for each simulation, and the results follow that the computation increases in proportion to the number of iterations for each simulation.

Table 1: Rerouting Result Summary

Simulation number	US-131 Scenario				
	1	2	3	4	5
Total number of iterations	31	22	22	23	23
Base node extension (# of iterations)	17	8	15	16	18
Shortest path cost (MAX)	27.74	31.28	31.02	30.82	30.10
Shortest path cost (MIN)	1.42	3.16	2.98	2.89	2.93
Shortest path cost (AVG)	16.79	16.25	14.52	17.39	17.02
CPU time (seconds)	9.2	4.8	5.1	5.6	5.8

7. CONCLUSIONS AND FUTURE RESEARCH

A dynamic heuristic methodology was introduced for computing near real-time optimal shortest paths around arc incidents. The methodology takes advantage of the closest neighboring arcs surrounding the disturbance location, and truncates the search model according to this characteristic. Moreover, prepared lookup tables were used in the search to further reduce the computational burden. While the model does not guarantee or search for global optima for the entire traffic network, the results indicate that this methodology is computationally feasible for solving the dynamic shortest path problem for a local optimum on the reduced search model. Although the proposed methodology is quite robust to system disturbances, it is a response to the measured traffic conditions which are always changing, and the collected information will always slightly differ than the instantaneous reality. This is due to inhomogeneous traffic flow and shortcomings of vehicle sensing technologies. As a result, further research is needed to understand the impact of these considerations. The performance of the proposed framework depends greatly on the accuracy of the ITS traffic sensors, however, its development is completely independent and not restricted to a specific type of sensor or simulator.

Regardless of the chosen approach for developing the solver strategy, further research on other realities of the actual network, such as traffic signal timing optimization and traffic sensor detector density optimization should also be incorporated into this model.

8. ACKNOWLEDGEMENT

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10. NOMENCLATURE

Symbol	Meaning
G	graph of the traffic network
\tilde{G}	a detour path
\tilde{A}	arterial path in distress
$\frac{p}{A}$	segment of the arterial path upstream to the disturbance
$\frac{j}{A}$	the distressed segment of the artery
$\frac{o}{A}$	downstream segment passing the disturbance
k	last exit from the artery prior to disturbance
l	first entry to the artery passing the disturbance
M	{set of all nodes}
A	{set of all arcs}
c_{ij}	Cost of arc ij
c	{set of all arc costs}
$c(s)$	speed dependent arc costs
u_{ij}	capacity of arc ij
u	{set of all arc capacities}
s_{ij}	speed limit on arc ij
$s -$	{set of all arc speed limits}
$s(t)$	dynamic speed
φ	nonlinear mapping of speed in relation to time
ψ	nonlinear mapping of arc cost in relation to speed
(d_{ij})	length of arc ij
v_{ij}	instantaneous traffic volume in arc ij
α, β, γ	weights for computing objective function value
T_{ij}	allowable volume/capacity ratio in arc ij
b	an exit node selected as base to start the detour prior to disturbance
B	{all base node, b }