An Optimization-Based Traffic Diversion Model during Construction Closures

Arezoo Memarian, Ph.D., Department of Civil Engineering, The University of Texas at Arlington. arezoo.memaian@mavs.uta.edu **(Corresponding Author)**

Jay M. Rosenberger, Ph.D., Department of Industrial and Manufacturing Engineering, The University of Texas at Arlington. jrosenbe@uta.edu

Stephen P. Mattingly, Ph.D., Department of Civil Engineering, The University of Texas at Arlington. mattingly@uta.edu

Siamak A. Ardekani, Ph.D., Department of Civil Engineering, The University of Texas at Arlington. ardekani@uta.edu

James C. Williams, Ph.D., Department of Civil Engineering, The University of Texas at Arlington. jimwilliams@uta.edu

Hossein Hashemi, Ph.D., Singapore-MIT Alliance for Research and Technology (SMART). hossein@smart.mit.edu

Abstract

During major highway construction, when lanes or entire highway sections must be temporarily closed, traffic managers would like to inform motorists of alternative routes around the construction site well in advance of the project location. This study develops a traffic diversion model to propose an optimum alternate route to drivers during a construction activity. The models and algorithms developed in this study assess a potential diversion route in order to optimize network performance while considering the drivers' behaviors in following the proposed alternate route during a closure. A bi-level optimization model is proposed to minimize the total travel time in the entire network considering the link closure and a proposed alternate route for the travelers. A travelers' route choice decision is modeled based on the user equilibrium traffic assignment, while a certain percentage of drivers are assumed to divert to the recommended alternate route. A set of simulation experiments is conducted using the Tarrant County network in north Texas. The results show the ability of the model to improve the overall network performance during hypothetical closure scenarios.

Keywords: Traffic Diversion Model, Bi-Level Optimization, Alternate Route, Network Performance

1. Introduction

Traffic congestion has reached an alarming level in most urban areas. In 2014, road congestion caused a total delay of 6.9 billion hours for urban Americans, and the use of an extra 3.1 billion gallons of fuel, which resulted in a total congestion cost of $160 billion (1). According to the Federal Highway Administration (FHWA) (2) about 50% of all highway congestion is caused by non-recurrent conditions. In addition, about 24% of non-recurrent congestion and 12% of overall congestion resulted from work zones on freeways, which led to an annual fuel loss of over $700 million (3). Moreover, in 2010, 87,606 crashes and 576 auto-related fatalities occurred in work zones in the United States. These crashes included 26,282 injury crashes and 60,448 property damage only crashes (4). Therefore, work zones have led to an unavoidable interruption in normal traffic flows and have resulted in traffic congestion, more vehicle emissions, and traffic safety problems (5). During a roadway construction project, when lanes or entire highway sections must be temporarily closed, traffic managers would prefer to inform motorists of alternative routes around the construction site well in advance of the project location. This will help reduce traffic demand through the construction site, enhance the safety of the workers and motorists, reduce traffic delays, and minimize fuel wastage and emissions. However, inappropriate traffic diversion plans will degrade the alternative routes and increase the travel time of the entire network (6).

The purpose of designing route guidance and information systems is to improve system efficiency and assist drivers in making route decisions. Multiple approaches exist to propose alternate routes to road users; these examples include shortest path, which assigns users to the shortest path or path with the lowest travel time, User Equilibrium (UE), which assigns users to their individual shortest paths, and System Optimal (SO), which finds paths to minimize the total travel time of the system (7). The routing of traffic, which is a core component in traffic management, entails a well-known dilemma. Traffic managers seek to reach system optimal, which may discriminate against some users in favor of others, while the users want to use their shortest paths to minimize their costs, which may result in a lower system performance (8). Thus, inefficient or unfair traffic assignments cause users to travel on long paths or discourage them from accepting the route guidance, which could reduce the potential impact of the route guidance system (9). To solve this dilemma, some researchers implemented both user equilibrium and system optimal models in their proposed road guidance systems (7, 10).

In addition, the routes proposed by route guidance systems should be disseminated to travelers to enable them to make more informed route switching decisions (11). Advanced Traveler Information Systems (ATIS) have been widely used in recent years to assist drivers' decisions and enable them to use the existing traffic road capacities more efficiently and improve the overall traffic flow in the congested network. Understanding these influences and driver behaviors remains important for improving route guidance systems. However, most traffic assignment models assume a rigid behavioral tendency for drivers and categorize them into classes such as UE, SO, or a combination of both (12). When a closure causes unexpected congestion, drivers may revise their travel choices. The drivers explore the new traffic conditions and adjust their travel patterns accordingly (13). They may either divert to the new routes based on their congestion perception, or use the information provided by ATIS. Therefore, considering driver behavior can improve the effectiveness of traffic assignment models on realistically representing traffic operations. This study develops a traffic diversion model that proposes an optimum alternate route to drivers during roadway construction. The developed model minimizes the total travel time in the entire network considering the link closure and the proposed alternate route for the travelers. While some travelers use the new alternate route to reach their destination, other travelers follow the UE traffic assignment in the network.

1.1. Literature Review

Although significant research efforts have been devoted to improving traffic conditions in work zone corridors, the literature remains unclear about the methods to find and evaluate the alternate routes or diversion plans. However, several studies have been conducted to improve network congestion caused by non-recurrent incidents. These studies examine the impacts of alternate routes on network performance, evaluate driver behavior, and investigate route guidance systems and traffic assignment methodologies used in traffic diversion schemes.

Some studies evaluated drivers' behaviors during unexpected congestion. For example, Khattak et al. examined short-term commuter response to unexpected congestion (14). Discrete choice models were used to model drivers' diversion and return behavior to study factors that influence their decisions. The results showed the delay information received from radio traffic reports, longer delays and longer travel times, and the number of alternate routes used in the past increase the probability of diversion. Moreover, Horowitz et al. determined the degree of alternative route selection from a rural freeway due to implementation of a traffic-responsive variable message signage system in a work zone (15). The message signs gave real-time estimated travel time to the end of the work zone without any information related to the alternative routes. The field study results indicated that a large percentage of drivers did not divert; a behavior that might be related to the lack of travel time information for alternative routes. Therefore, a traffic variable message sign system, which provides the travel times through the work zone and alternative routes, could encourage more drivers to divert. In addition, Khattak et al. assessed the effects of ATIS on travel behavior based on the alternatives and information provided to travelers (16). Their results indicated that travelers seem most likely to respond and overcome their behavioral inertia when faced with unexpected congestion with specific quantitative delay information. In another study, Kattan et al. investigated drivers' behavioral response to real-time information that provided traffic updates and advisory detours (13). The results showed the drivers' response to Variable Message Signs (VMS) can be useful for ATIS in response to network disruptions.

Traffic diversion schemes represent one of the traffic network management strategies for recurrent and non-recurrent traffic congestion. Relevant studies investigated the effectiveness of traffic diversions on the performance of transportation networks. Bhavsar et al. developed a generic decision support system using support vector regression that predicts the traffic diversion impacts on a transportation network with a reasonable degree of accuracy (17). In another study, Hu et al. proposed a systematic framework to investigate the potential diversion points and evaluate the value of traffic information provided to drivers by VMSs (18). They applied Dynasmart-P to conduct relevant simulation experiments. Their framework was based on traffic assignment under the UE principle. Moreover, Aved et al. presented the Real-Time Route Diversion System (RTRDS) (19). RTRDS used the Dynasmart-P traffic simulator to generate optimal route diversions based on available real-time and historical traffic information with the goal of optimizing the overall system performance. In these two studies, the framework was based on traffic assignment under UE or SO and did not consider both at the same time.

In addition, some researchers implemented both UE and SO in their proposed road guidance systems. Jahn et al. proposed a Constrained System Optimum (CSO) approach that guarantees fairness comparable to that of the ordinary SO traffic assignment (7). They proposed a model, which implements a SO approach, but also considers the individual needs by adding constraints to ensure that users are assigned to acceptable routes. They used a column generation method to solve the CSO problem. In another study, Schulz and Moses (20) presented a theoretical analysis of the route guidance system proposed by Jahn et al. They analyzed the efficiency and fairness of the normal unfairness factor to ensure that routes suggested to users are not much longer than the shortest paths for the prevailing network condition. In another study, game theory was used to solve the conflict between UE and SO (21). They defined a concept of satisfactory degree to achieve an optimum traffic routing and proposed an integrated-equilibrium model based on double–objective optimization. However, the application of their models in a network with a disruption has not been discussed. A network with a closed link due to construction activities has an altered traffic pattern. Therefore, minimizing the total effects of the closure on the network performance is the purpose of this study.

1.2. Contribution

Unlike the aforementioned literature, the purpose of this study is to develop a traffic diversion model, which proposes an optimum alternate route to travelers during a roadway construction project that closes a sequence of links. The objective of the developed model is to minimize the total travel time in the entire network considering the link closure and the proposed alternate route for the travelers. Based on previous research (13), the authors assume that some travelers utilize the proposed alternate route to reach their respective destinations, while others follow UE traffic assignment in the network. The models and algorithms developed in this study assess the potential diversion route. The recommended route is the first to optimize network performance while considering drivers' behaviors in selecting alternate routes during a closure. This system is of interest to traffic network managers and construction companies to help them divert traffic from the disrupted area and improve throughput through the congested region.

2. Methodology

2.1. Definition of Variables and Notation

Data sets, parameters, and variables used for this model are given as follows.

$\mathcal{G}$ is a full traffic network

$\mathcal{A}$ is a set of links in the network $\mathcal{G}$

$\mathcal{N}$ is a set of nodes in the network $\mathcal{G}$

$\mathcal{Z}$ is a set of zones in the network $\mathcal{G}$

$\mathcal{I}$ is a set of origin nodes where $\mathcal{I} \subset \mathcal{Z}$

$\mathcal{J}$ is a set of destination nodes where $\mathcal{J} \subset \mathcal{Z}$

a is a link in the network, $a \in \mathcal{A}$

n is a node in the network, $n \in \mathcal{N}$

$\imath$ is an origin node, $\imath \in \mathcal{I}$

$\jmath$ is a destination node, $\jmath \in \mathcal{J}$

$K_{\imath\jmath}$ is a set of routes between origin-destination pair $(\imath, \jmath)$

k is a route in the network, $k \in K_{\imath\jmath}$

l_a is the length of link a

c is a closure identification index

A_c is a sequence of closed links

a_c is a closed link, $a_c \in A_c$

G is a subnetwork around the closed links A_c with disrupted links

A is a set of links in the subnetwork G, $A \subset \mathcal{A}$

N is a set of nodes in the subnetwork G, $N \subset \mathcal{N}$

Z is a set of zones in the subnetwork G

I is a set of origin nodes in the subnetwork G and i is an origin node where $I \subset Z$

J is a set of destination nodes in the subnetwork G and j is a destination node where $J \subset Z$

x_a is the number of travelers on the link a in the full network $\mathcal{G}$

x_a^G is the number of travelers on the link a in the subnetwork G

t_a is travel time on the link a in the full network $\mathcal{G}$

t_a^G is travel time on the link a in the subnetwork G

$f_{\mathscr{i}\mathscr{j}}$ is the number of travelers between OD pair $(\mathscr{i},\mathscr{j})$

$f_{\mathscr{i}\mathscr{j}k}$ is the number of travelers on route k connecting OD pair $(\mathscr{i},\mathscr{j})$

$\hat{f}_{\mathscr{i}\mathscr{j}k}$ is the number of travelers on route k connecting OD pair $(\mathscr{i},\mathscr{j})$ in a UE solution with no closed link

$t_{\mathscr{i}\mathscr{j}k}(f_{\mathscr{i}\mathscr{j}k})$ is the travel time on route k between OD pair $(\mathscr{i},\mathscr{j})$

$\hat{f}_{ij}$ is the number of travelers between OD pair (i,j) in the subnetwork G in a UE solution with no closed link

f_{ijk} is the number of travelers on route k connecting OD pair (i,j) in the subnetwork G

$\hat{f}_{ijk}$ is the number of travelers on route k connecting OD pair (i,j) in the subnetwork G in a UE solution with no closed link

$t_{ijk}(f_{ijk})$ is the travel time on route k between OD pair ij in the subnetwork G

I_c is a set of origin nodes for the closed links A_c in the subnetwork G where $I_c \in I$

J_c is a set of destination nodes for the closed links A_c in the subnetwork G where $J_c \in J$

N_s is a set of nodes upstream of the closed links (start nodes)

N_e is a set of nodes downstream of the closed links (end nodes)

n_s is a start node upstream of the closed link where $n_s \in N_s$

n_e is an end node downstream of the closed link where $n_e \in N_e$

P_{se} is the set of available paths between a start node n_s and an end node n_e

p is an available path between a start node n_s and an end node n_e where $p \in P_{se}$

A_p is a set of links on the path p

${K_{ij}}^p$ is a set of paths between origin i and destination j, which contains alternate path p

P_{se}^{ℓ} is a set of available alternate paths in iteration ℓ of the proposed algrothm, $P_{se}^{\ell} \subseteq P_{se}$

p_{ℓ} is the alternate path in iteration ℓ of the algorithm

α is a percentage of drivers that follow the recommended alternate path

y_p is a binary variable (0,1) for whether path p is selected as a detour path

$\sigma_{\mathscr{i}\mathscr{j}k}^{ij}$ is the path flow indicator for path flow $f_{\mathscr{i}\mathscr{j}k}$ passing, or traveling into or from the subnetwork (defined in section 2.3.1)

$\delta_{ijk}^{a_c}$ is the path flow indicator which is one if the closed link a_c is on the path k between i and j and zero otherwise

2.2. Problem Definition

Given $\mathcal{G}(\mathcal{N}, \mathcal{A})$ is a traffic network where $\mathcal{A}$ is a set of links and $\mathcal{N}$ is a set of nodes. A node can represent an origin node ($\imath$), a destination node ($\jmath$), and/or a junction of links (n). A network with multiple origins $\imath \in \mathcal{I}$ and destinations $\jmath \in \mathcal{J}$ is considered. A set of OD vehicle trips, expressed as the number of travelers $f_{\imath\jmath}$ going from origin $\imath$, to destination $\jmath$ is given. Thus, $f_{\imath\jmath k}$ is the number of travelers on route k between origin $\imath$ and destination $\jmath$, and $t_{\imath\jmath k}$ is the travel time for traveling between $(\imath, \jmath)$ along route k, which is a function of $f_{\imath\jmath k}$.

2.3. Subnetwork

When a closure c occurs on a link a_c or a set of links A_c due to construction activities, it results in either a capacity reduction or a full closure along that link. The closure or reduction in the link capacity could cause significant congestion upstream of the closure, and the traffic congestion could extend over a large area. To reduce the complexity of the model and to ensure that the results are obtained in a timely manner, a subnetwork needs to be defined around the closure, which covers the significantly affected areas (22). Therefore, a linear regression model, which is a function of the closed link's demand and network topology can be used to estimate the radius of the affected area and define the subnetwork (23).

2.3.1. Subnetwork OD Demand Estimation

As a subset of the full network, the subnetwork zonal structure is defined as a set of origin zones with origin nodes I and a set of destination zones with destination nodes J. Therefore, the OD trips in the subnetwork are the number of vehicle trips traveling from origin node i to destination node j, $\forall i \in I,\ \forall j \in J$. Inspired by the work of Zhou et al. (24), to estimate the origin-destination matrix for the subnetwork, the first step is generating path flow patterns in the full network ($\hat{f}_{\imath\jmath k}$). In this study, the user equilibrium model is used to generate these patterns. Once the subnetwork is defined, and its boundary is specified, all origin and destination nodes that have traffic passing through this region are named as external nodes, while those lying within this region are labeled internal nodes. All of the OD pairs in the network are categorized into four groups: Internal-Internal (I-I), External-External (E-E), Internal-External (I-E), and External-Internal (E-I), as shown in Figure 1.

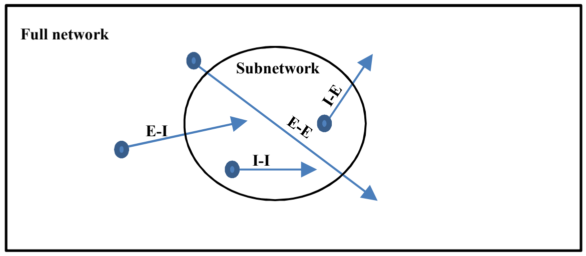

Figure 1: Four Types of OD Pairs with Respect to Subnetwork (24)

For I-I OD pairs, the vehicle trips from i to j (f_{ij}) are assumed to be the same as the full network OD matrix (set $\hat{f}_{ij} = \hat{f}_{\imath\jmath}$ for I-I OD pairs). For E-E, E-I and I-E pairs, the following equation is used to estimate the number of vehicle trips between each OD pair:

$$\hat{f}_{ij} = \sum_{k \in K_{ij}} \hat{f}_{ijk} = \sum_{\imath \in \mathcal{I}, \jmath \in \mathcal{J}, k \in K_{ij}} \hat{f}_{\imath\jmath k} \sigma_{\imath\jmath k}^{ij} \text{ }, \forall i \in I, \forall j \in J \qquad (1)$$

where $\sigma_{\imath\jmath k}^{ij}$ is the path flow indicator for path flow $\hat{f}_{\imath\jmath k}$ passing, or traveling into or from the subnetwork. Specifically, $\sigma_{\imath\jmath k}^{ij}$ is 1 if node i is in the first entering zone into the subnetwork and node j is in the last exit zone from the subnetwork, or node i is in the first entering zone into the subnetwork and node j is in the subnetwork, or node i is in the subnetwork and node j is in the last exit zone form the subnetwork; otherwise $\sigma_{\imath\jmath k}^{ij} = 0$. It should be noted that the paths between the E-E pairs can enter and exit the subnetwork multiple times. In this study, when more than half of a path is in the subnetwork, it is considered as a path passing through the subnetwork. The algorithmic steps to solve Equation (1) are described as follows;

- Initialize $\hat{f}_{ij} = \hat{f}_{\imath\jmath}$ for $\forall i \in I, \ \forall j \in J$,
- For each origin $\imath \in \mathcal{I}$, each destination $\jmath \in \mathcal{J}$, and each path $k \in K_{\imath\jmath}$, scan the path node sequence from $\imath$ to $\jmath$ on the full network,
- Identify the first entering zone and the last exit zone in the subnetwork to identify origin node i and destination node j for all E-E OD pairs, identify the first entering zone in the

subnetwork and origin node i for all E-I OD pairs, and identify the last exit zone in the subnetwork and destination node j for all I-E OD pairs,

- If path $k \in K_{ij}$ is traveling in the subnetwork and origin i and destination j can be found for the path, then $\hat{f}_{ij} \leftarrow \hat{f}_{ij} + \hat{f}_{ijk}$.

Therefore, $\hat{f}_{ij}$, which is the total number of vehicle trips traveling from origin node i to destination node j in the subnetwork G, is estimated.

2.3.2. Closed Link OD pairs

Origin and destination nodes for the traffic on the closed links are obtained as follows:

$$I_c \times J_c = \left\{ (i,j) \in I \times J \,\middle|\, \sum_{a_c \in A_c, k \in K_{ij}} \delta_{ijk}^{a_c} \geq 1 \right\} \qquad (2)$$

where $\delta_{ijk}^{a_c}$ is the path flow indicator which is one if link a_c is on the path k between i and j and zero otherwise.

2.4. Model Formulation

The goal of this model is to provide a single alternate route around the construction site to divert traffic and mitigate traffic congestion. The problem aims at determining the most efficient alternate route that minimizes the total impact of the closed links on network performance. The total travel time of the affected area (subnetwork G) is considered to measure the impact of the closed links on the system. Because construction usually occurs over a scheduled period of time, a travelers' route choice decision is modeled based on the UE traffic assignment. While user equilibrium satisfies the drivers' goals, it does not necessarily minimize the total travel time of the system (7). The study assumes that traffic information such as an alternate route and its travel time is provided for drivers upstream of the closure and disseminated via ATIS. In addition, a certain percentage of drivers (α) are assumed to divert to the recommended alternate route, while others are assumed to divert based on the UE assignment. With the use of the modern technologies such as GPS devices, it can be assumed that drivers have perfect information of the roads, which is one of the UE assumptions. Many studies that have been conducted on drivers' behavioral response to the traveler information systems are used to estimate the percentage of drivers (α) who are diverting (12-17). Moreover, the number of travelers $\hat{f}_{ij}$ going from origin i, to destination j in the subnetwork G is estimated in section 2.3.1. Finally, a bi-level model is proposed to identify the optimum alternate routes. The following mathematical model describes this problem.

$$Minimize \quad T_G = \sum_{a \in A} x_a^G \times t_a^G(x_a^G) \qquad (3a)$$

$$Subject\ to:$$

$$\sum_{p \in P_{se}} y_p = 1 \qquad (3b)$$

$$y_p \in \{0, 1\} \qquad \forall p \in P_{se}\ (3c)$$

$$Minimize \quad \sum_{a \in A} \int_0^{x_a^G} t_a(x_a) dx \qquad (3d)$$

$$Subject\ to:$$

$$\sum_{k \in K_{ij}} f_{ijk} = \hat{f}_{ij} \qquad \forall i \in I,\ \forall j \in J\ (3e)$$

$$x_a^G = \sum_{i \in I} \sum_{j \in J} \sum_{k \in K_{ij}} \delta_{ijk}^a f_{ijk} \qquad \forall a \in A\ (3f)$$

$$f_{ijk} \geq \alpha\, \hat{f}_{ijk}\, y_p \qquad \forall i \in I_c,\ \forall j \in J_c, \forall p \in P_{se}, \forall k \in {K_{ij}}^p\ (3g)$$

$$f_{ijk} \geq 0 \qquad \forall i \in I,\ \forall j \in J, \forall k \in K_{ij}\ (3h)$$

$$x_a^G \geq 0 \qquad \forall a \in A - A_c\ (3i)$$

$$x_a^G = 0 \qquad \forall a \in A_c\ (3j)$$

This model is formulated as a nonlinear mathematical program (NLP). The objective function minimizes the total travel time of the affected network (subnetwork with closed links), which is the upper-level problem of the bi-level optimization framework. Constraint (3b) ensures that a path $p \in P_{se}$ between a start node s and an end node e, upstream and downstream of the closed link, is served as the alternate path and only one path is served. Constraint (3c) shows the binary restrictions of the variable y_p. Constraint (3d) is the objective function of the lower level problem in the bi-level optimization framework. The lower level applies user equilibrium traffic assignment for travelers, who do not divert to the alternate path. Constraint (3e) represents the conservation of the OD demand over all the paths for each OD pair. They ensure that the sum of the travelers f_{ijk} over all paths connecting OD pair in the subnetwork is equal to total number of travelers between these OD pairs. Constraint (3f) estimates the traffic volume on each link in the network, and δ_{ijk}^{a} is either one or zero with the value being one when link a is on path k between OD pair (i, j), and zero otherwise. Constraint (3g) shows that total travelers between the closed links OD pair (i, j) should be at least as large as the number of travelers who divert to alternate routes. This constraint applies to the paths between closed link OD pair of which alternate route is part. Constraints (3h) and (3i) ensure that the variables are non-negative. Constraint (3j) ensures that the closed links' volumes are zero.

2.5. Solution Algorithms

This section discusses the algorithmic steps to solve the bi-level optimization model expressed in the previous section.

Step 1. Pre-algorithmic step

Apply the User Equilibrium (UE) model to load the OD demand onto the network in the normal condition (network without any closed link) to generate the traffic pattern ($\hat{f}_{ijk}$) in the network between each OD pair (i, j) and estimate links volume (x_a). Identify closed links A_c and define the subnetwork G around the closure based on the closed link demand and network topology (discussed in section 2.3) and determine OD demand for the subnetwork ($\hat{f}_{ij}$).

Close the specified link and apply the UE model to the subnetwork (affected subnetwork, which is a subnetwork with a closed link) to generate the traffic pattern (f_{ijk}) on the affected subnetwork and estimate the links volume (x_a^G). Define a set of start ($n_s \in N_s$) and end ($n_e \in N_e$) nodes upstream and downstream of the closed link in the subnetwork. Find all possible paths p between these nodes ($p \in P_{se}$) and identify all links on each path (A_p).

Set $\ell = 0$, the initial set of available paths $P_{se}^{0} = P_{se}$, and the best alternate path $p^* = \emptyset$.

Step 2. Path Selection

Compare the link volumes on the normal subnetwork (without any closed link) to the affected subnetwork and identify a path that contains links with most changes (volume changes per length) among all available paths (P_{se}^{i}) as the alternate path (p_i) based on the equation (4).

$$p_i \in \underset{p \in P_{se}^{\ell}}{\operatorname{argmax}} \left\{ \sum_{a \in A_p} (x_a^G - x_a) / (\sum_{a \in A_p} l_a) \right\} \tag{4}$$

Step 3. Alternate Route Evaluation

1. Identify p_ℓ as alternate route and set y_{p_ℓ} =1.
2. Solve the UE problem given by equation (3d) to (3j) in the model formulation, which results in $(x_a^{Gp_\ell})$ and $(t_a^{Gp_\ell})$.
3. Estimate the total travel time of the updated subnetwork considering the link closure and the proposed alternate route:

$$T_G(p_\ell) = \sum_{a \in A} x_a^{Gp_\ell} \times t_a^{Gp_\ell} \tag{5}$$

Step 4. Best Known Solution

1. If $p^* = \emptyset$ or $T_G(p_\ell) < T_G(p^*)$, set $p^* = p_\ell$ as the optimum alternate route between the evaluated routes.
2. Remove p_ℓ from the set of paths and set $P_{se}^{\ell+1} = P_{se}^{\ell} - \{p_\ell\}$.
3. Set $\ell = \ell + 1$.

Step 5. Stop Criteria

If P_{se}^{ℓ} is empty or CPU time is more than Δ, stop and return p^*as the optimum alternate route, otherwise go to step 2.

3. Experiments, Results, and Analysis

Experiments are conducted to examine the performance of the traffic diversion model described above. In these experiments, the traffic diversion model is applied to the Tarrant County network in north Texas. The network database for Tarrant County is maintained by the North Central Texas Council of Governments (NCTCOG). As illustrated in Figure 2, the network consists of about 7,500 nodes and 20,000 links, which contain several freeways and arterials that extend over multiple cities. A demand pattern that indicates a typical evening peak period is considered. The model is used to recommend an alternate route in closure scenarios due to construction activities on the freeway facilities. Under normal conditions (without any closure in the network), travelers are assumed to follow their historic user equilibrium routes. In the case of freeway construction, when a freeway section must be temporarily closed, variable message signs are assumed to show the selected alternate route along the freeway before the closure. The study assumes that a certain percentage of travelers follow the recommended route and others decide to divert based on their congestion perception. To estimate this percentage, many studies have been conducted on drivers' behavioral response to traveler information systems (12-17). The drivers' response is a function of various factors such as trip characteristics, the number of available alternate routes, delay information and duration (14). Based on the literature (13), this study assumes that 40% of drivers follow the suggested alternate route and the other 60% follow UE traffic assignment routes. To present a non-recurrent congestion scenario, a hypothetical incident is assumed to close the entire freeway section.

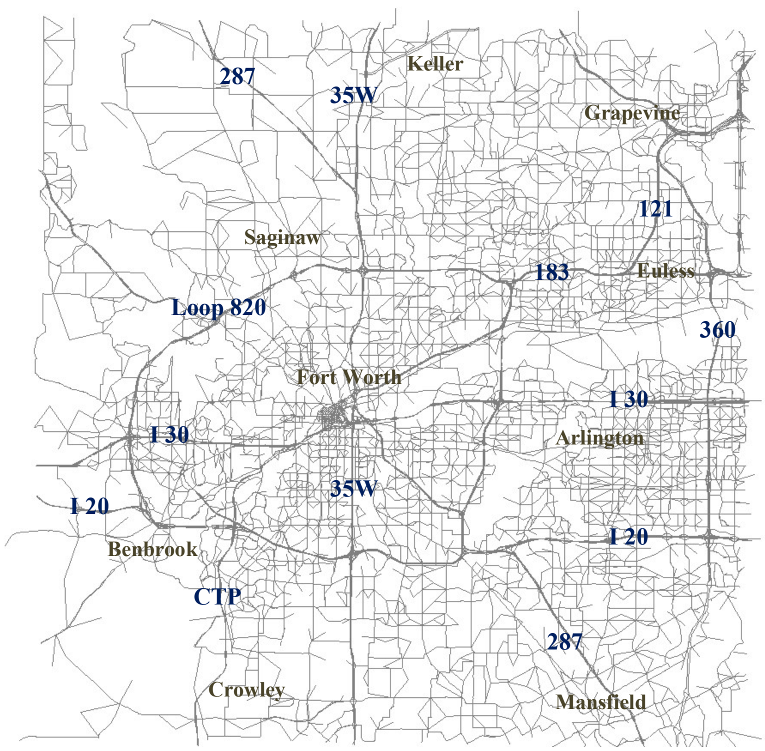

Figure 2: Tarrant County Network

The first set of experiments examines the effect of the subnetwork size on the traffic diversion model. A link with a volume of 4800 vehicles per hour on state highway 121 is closed and five subnetworks with different sizes are considered around the closure as illustrated in Figure 3. As shown in the figure, the subnetworks vary in radii, which are estimated as described in section 2.3. These models consider the distance between the closed link and the farthest link with 5%, 15%, 25%, 30%, and 40% increases in travel time, which result in radii of 5, 4, 3.5, 3, and 2.5 miles, respectively. For each experiment, the percentage savings in the total travel time is estimated by comparing the total network travel time before (the do-nothing scenario) and after deploying the traffic diversion model. To create a standard comparison between the results, a subnetwork with a radius of five miles is considered as a test network. The alternate routes, which are proposed from each experiment, are considered for traffic assignment in the test network. Finally, the total network travel time is estimated for each experiment and compared to the do-nothing scenario. Figure 3 illustrates the travel time savings and CPU execution times for the five subnetworks. The results show that bigger subnetworks result in more efficient alternate routes as indicated by an increase in the total travel time savings.

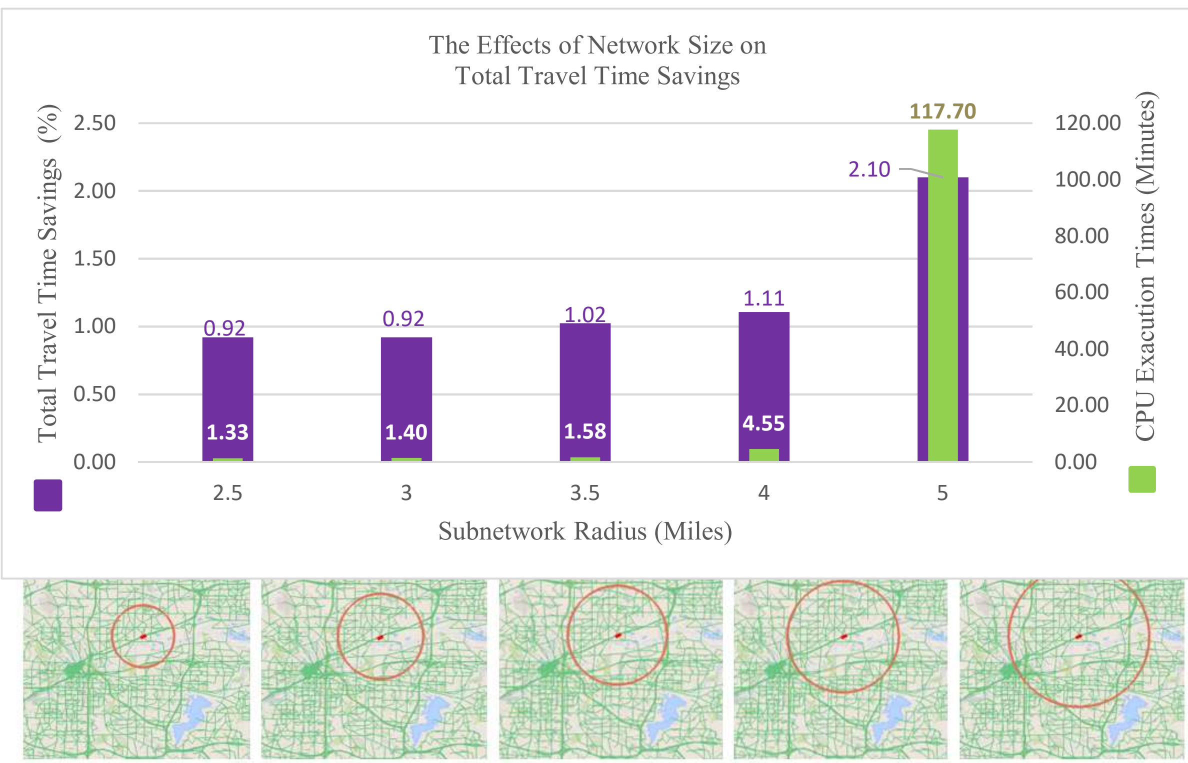

Figure 3: The Effect of Subnetwork Size

As shown in Figure 3, the CPU execution times (to evaluate all of the alternate paths) also increase with the increasing the size of the subnetworks. However, as illustrated in Figure 4, an alternate path with travel time savings close to the optimum alternate path can be obtained in less than fifteen minutes for the subnetwork with a five miles radius. Therefore, a proper sorting method along with a time limit can result in an alternate path with travel time savings close to the optimum alternate path in a short time (Section 3.1).

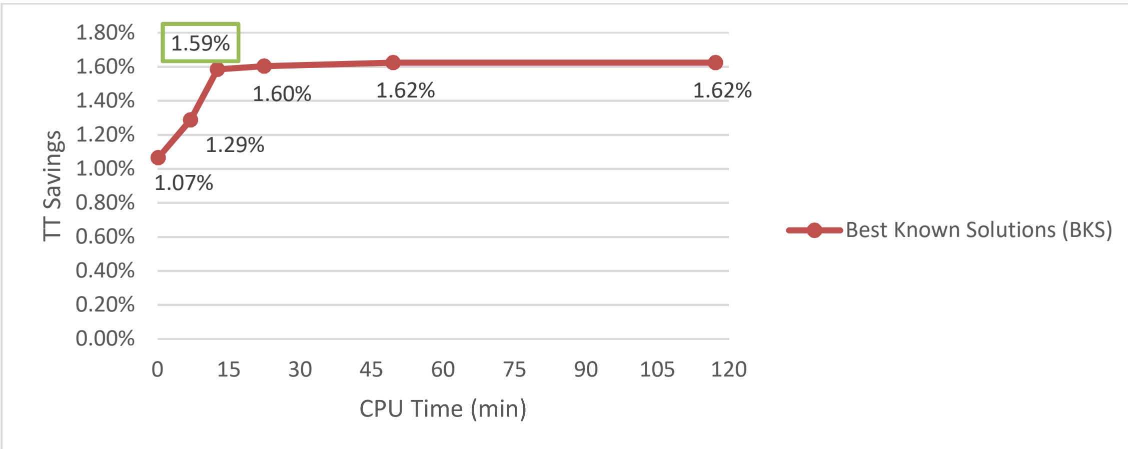

Figure 4: The Execution Time and Travel Time Savings of the Best Known Solutions for 5-Mile Radius Subnetwork

The second set of experiments examines the performance of the traffic diversion model considering the closure occurs on links with different levels of traffic volume. For this purpose, the authors conduct three experiments for the low, medium and high levels of traffic volume. In three different experiments, links with volumes of 2300, 5400, and 8500 vehicles per hour are considered to be closed for this purpose. Figure 5 presents the results of these experiments. As shown in Figure 5, when comparing to the do-nothing scenario in which the traffic diversion model is not applied, the best network performance is achieved in the case when a closure occurs on a link with a high level of traffic volume (6.3% travel time savings). The results show the importance of applying the traffic diversion model around a construction site to improve network performance, especially when closure occurs on links with high traffic volumes.

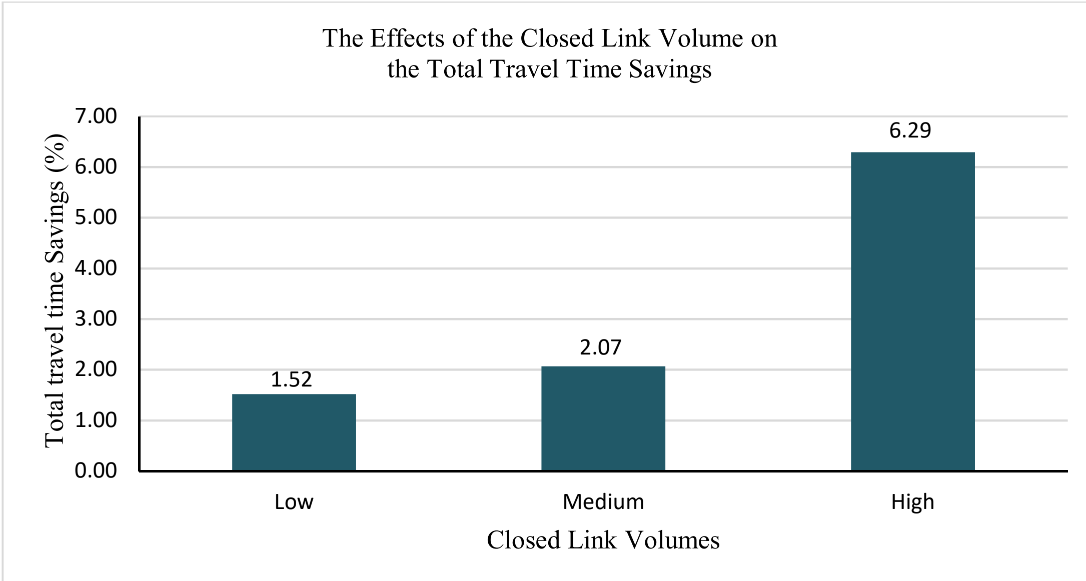

Figure 5: The Effect of Link Traffic Volume

The third set of experiments assesses the accuracy of the model by limiting the availability of links utilized in the alternate routes. For this purpose, only high-level links are assumed to be available for alternate paths in one of the experiments, and the two experiments are compared. In the first experiment, alternate paths can be selected from any available link in the network. For the second experiment, alternate paths can be only selected from freeways and major arterials. In each experiment, the thirteen best alternate paths are considered, and the total travel time of the network is estimated and compared to the do-nothing scenario. As shown in Figure 6, limiting the routes by using only freeways and arterials has a small effect on the total travel time of the network. Therefore, considering freeways and major arterials for alternate paths could be a suitable approach to reduce computation time as it does not have a substantial effect (an average of 1.92% differences between the results) on the network performance and also avoids diverting traffic to minor arterials.

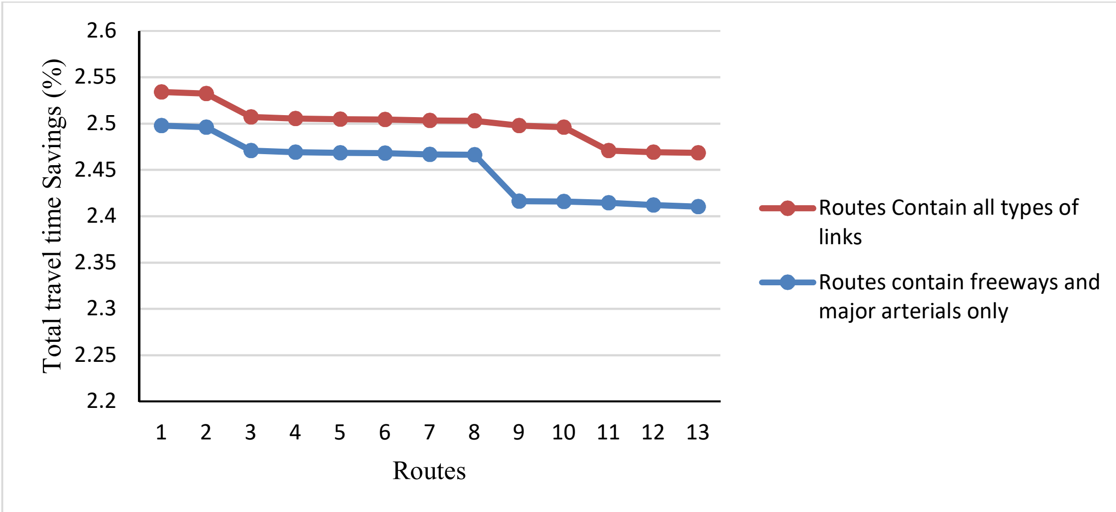

Figure 6: The Effect of the Links Availableility in Selecting Alternate Routes

3.1. Experiments related to the Path Selection Methods

Path selection (step 2) represents an important part of the algorithm explained in section 2.5. The method in step 2 highly affects the execution time spent to find a new best known solution in step 4. If alternate paths that result in a better performance for the entire subnetwork are located at the top of the alternate paths list in the sorting method, the best solution would most likely be reached in a short time. Therefore, after a specific time (Δ) the algorithms can be stopped without evaluating all of the paths and with confidence that the result is nearly optimal.

Three sorting methods are evaluated in this study (two other methods in addition to the proposed method in step 2). These methods are named as length, volume changes, and volume changes per length. In these methods, alternate paths are sorted based on the following criteria:

1- Length: Paths length from the shortest path to the longest one ($\sum_{a \in A_p} l_a$).
2- Volume changes: Total difference between the sum of the link volumes in the normal subnetwork and the affected subnetwork from the highest changes to the lowest changes ($\sum_{a \in A_p} (x_a^G - x_a)$).
3- Volume changes per Length: Total differences between the sum of the link volumes on the normal subnetwork and the affected subnetwork divided by the length of that path from the highest amount to the lowest amount ($\sum_{a \in A_p} (x_a^G - x_a) / (\sum_{a \in A_p} l_a)$).

A set of experiments compares these three sorting methods; the experiments consider twelve links with different characteristics as closed links. The algorithms mentioned in section 2.5 are applied three times for each of these links, and each time, one of the above three sorting methods are used (step 2) to find the best alternate path. The execution time to find a best known solution is estimated (when there is an improvement in the travel time savings or any updates in step 4) for each of these sorting methods. The results are shown on the figures (a sample figure is shown in Figure 7 for link 10), and the area under each curve related to each sorting method is estimated and compared.

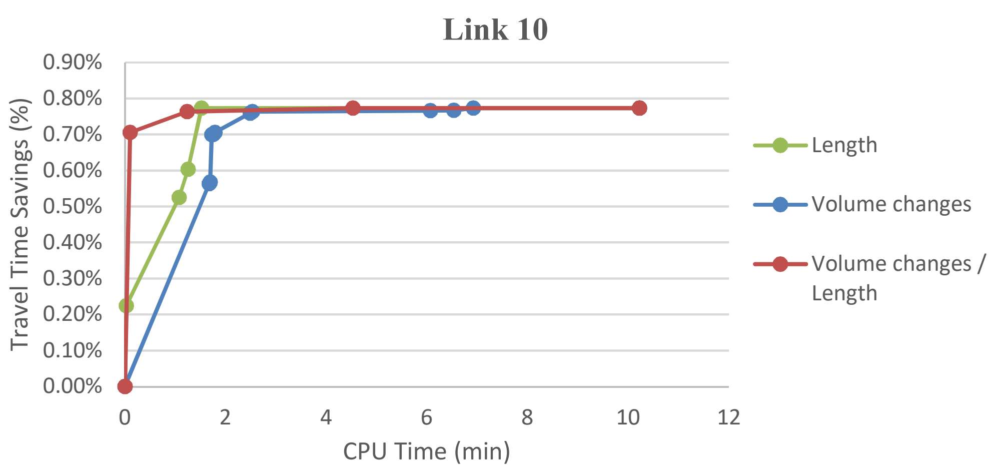

Figure 7: The Execution Time and Travel Time Savings of the Best Known Solutions for Three Sorting Methods

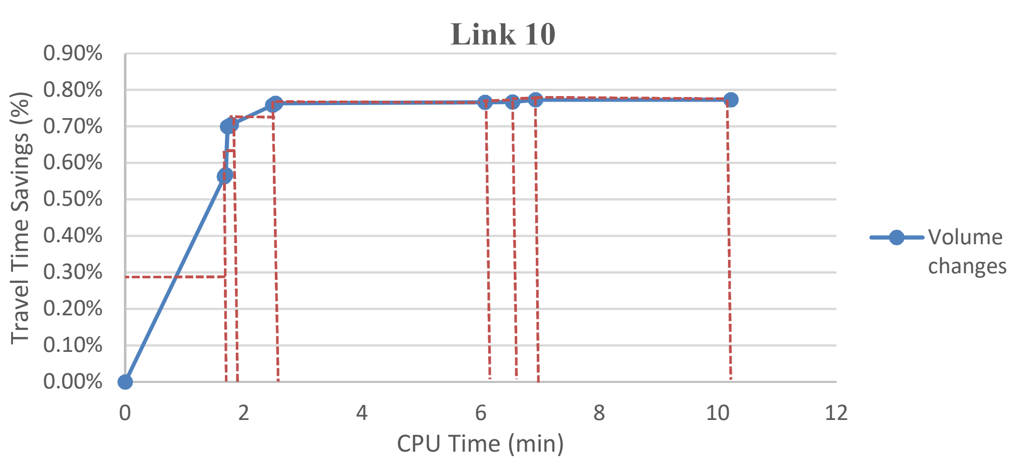

Figure 8: Illustration of Midpoint Rule Method for Calculating Area under the Curve

The midpoint rule method is used to calculate the Area Under the Curve (AUC) (25). To calculate the AUC, the curve is divided into a series of rectangles (Figure 8) and the area of each rectangle is summed to estimate the total area under the curve. AUC is calculated as:

$$AUC = \sum_{\ell=0}^{n-1} \left(\frac{TTS_{\ell} + TTS_{\ell+1}}{2} \right) (\, t_{\ell+1} - t_{\ell}) \tag{6}$$

where n is the total number of best known solutions, TTS_{ℓ} is the percentage of travel time savings at the ℓ^{th} best known solution, and t_{ℓ} is the CPU time at which the ℓ^{th} best known solution is found. Since the unit for TTS is percentage (%), and the unit for t is minutes, the unit of the AUC is percentage-minutes (%-min). The first term in the equation is the height of the rectangle (estimated as the midpoint between TTS_{ℓ} and $TTS_{\ell+1}$), and the second term is the width of the rectangle. Table 1 shows the calculated AUC for the sorting methods.

Table 1: AUC for Three Sorting Methods

Link	AUC (%-min)		
	Length	Volume Changes	Volume Changes/ Length
1	1.837	1.764	1.848
2	3.995	3.587	3.995
3	4.340	3.218	4.210
4	1.634	1.532	1.631
5	5.243	7.114	7.271
6	22.124	21.230	22.281
7	4.075	4.010	4.075
8	0.124	0.117	0.126
9	5.283	4.912	5.250
10	0.074	0.070	0.078
11	0.014	0.014	0.014
12	24.642	24.123	24.097
Average	**6.115**	**5.974**	**6.239**

The highlighted cells show the higher amount of AUC among the three methods and indicate the preferred method for each link. As shown in Table 1, the third method (Volume changes/Length) has the highest amount of AUC among the three methods for six links, which indicates that the third method is the preferred method for half of the links. In addition, the average AUC in the third method is slightly better than other methods on average. Therefore, this method is selected to use in step 2 of the algorithm.

4. Conclusions

This paper is the first to present a traffic diversion model to divert travelers to an optimum alternate route around a construction site. The model estimates the current network conditions with a closure in the network, compares the current conditions to the normal conditions, and proposes an optimum alternate route to improve the overall network performance. The travelers' route choice behavior is also considered in this model. A certain percentage of travelers are assumed to divert to the proposed alternate route, and others follow alternate routes based on UE traffic assignment. A set of experiments is conducted using the Tarrant County network in north Texas. The results show the ability of the model to improve the overall network performance during a hypothetical closure scenario.

Moreover, the results show that bigger subnetworks result in more efficient alternate routes, the highest network performance improvement could be achieved when a link with a high level of traffic volume is closed, and considering freeways and major arterials for alternate paths could be a suitable approach to reduce computation time in the algorithm. Furthermore, the use of the "Volume changes per Length" method to sort the alternate paths reduces the execution time to find a best known solution in the algorithms.

Moreover, construction is usually scheduled and publicized to drivers. Thus, UE traffic assignment model which is well establish in the literature (26-27) is developed for this research. Nonetheless, traffic networks are highly dynamic with numerous sources of uncertainties on the demand and supply sides. Determining traffic flow patterns and deploying efficient traffic management schemes could be challenging, especially if no adequate historical traffic data is available. A major extension of the current study is to model the traffic network at high reliability by capturing the temporal and spatial demand-supply interactions and associated congestion. This requires utilizing Dynamic Traffic Assignment (DTA), which models the interaction between travelers' behavior and congestion dynamics. The proposed traffic diversion methodology would adopt a DTA model, which is relatively consistent with travelers' behavior and incorporates the tempo-spatial changes in the demand and supply in the traffic network. Using DTA to evaluate alternate paths as described would likely be particularly appropriate for unscheduled and unpublicized closures, such as those from major accidents. Moreover, the traffic diversion model presented in this study is capable of identifying multiple alternate routes. The model evaluates and sorts all the available alternate paths, and can represent the paths in order from the best to the worst. However, in the experiments only a single alternate route is considered to divert drivers, which follow the signs to the detour path. In addition, partial closure instead of the whole closure is feasible in the presented model. Therefore, identifying multiple alternate routes and addressing partial closure represent another next step for this research.

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