A DECISION SUPPORT SYSTEM FOR TRAFFIC DIVERSION AROUND CONSTRUCTION CLOSURES

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Abstract

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As highway infrastructure ages and road congestion increases, roads need to be expanded and reconstructed. It results in creating many construction sites and work zones on highways, which leads to an unavoidable interruption in normal traffic flows and have resulted in traffic congestion, more vehicle emissions, and traffic safety problems. During roadway 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 would 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. The objective of this study is to develop a decision support system to identify the optimum alternate routes around highway construction sites. The developed system, which is named TDS (Traffic Diversion System), helps traffic network managers divert traffic from the disrupted area and reduce the traffic demand through the congested region. TDS's modules, models, and algorithms allow assessment of alternate routes that optimize network performance.

An optimization model (a traffic diversion model) is developed and implemented in TDS to determine the optimum alternate routes around construction activities. To simplify computations, a subnetwork is extracted from the complete network to use in the diversion

model instead of the entire network. The size of the subnetwork is estimated based on the modeling framework proposed in this research. Linear regression models, which are functions of the closed link demand and network topology, are developed to estimate the size of the subnetwork around the disruption. The closed link's area type, traffic volume on the closed link, and travel time on the first and second alternative paths with lowest travel times are significant variables that influence the size of the subnetwork. The proposed traffic diversion model is developed to find the optimum alternate routes around the construction activities, while minimizing the total travel time of the system. Travelers are assumed to follow their historical user equilibrium routes before and after the closure while a certain percentage of them is assumed to divert to the proposed alternate routes. The developed system has an easy to use graphical user interface that allows users to work easily with the system. This system is of interest to construction agencies and traffic network managers to help them divert traffic from the congested area and reduce traffic demand through the construction sites.

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Chapter 1. Introduction

1.1. Background

Traffic congestion poses serious problems in most urban areas and especially on urban highways. In the last three decades, vehicle miles traveled (VMT) have doubled on U.S. highways. However, the total number of highway lane miles has increased by only 5% during the same period (1). 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 (2). Traffic congestion is categorized as either recurrent or non-recurrent. Recurrent congestion is caused by routine traffic volumes such as morning and evening peak periods and are mostly predictable and expected. Non-recurrent congestion is triggered by non-recurrent causes such as traffic incidents, work zones, weather conditions, and special events and are unexpected and unusual congestion. About 50% of all highway congestion is caused by non-recurrent conditions (3).

Moreover, as highway infrastructure ages and road congestion increases, roads still need to be expanded and reconstructed. Therefore, the federal and state government agencies have considered the maintenance, rehabilitation, expansion, and upgrading of the existing highway networks, which results in creating many construction sites and work zones on highways. Furthermore, 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 (4). About 24% of non-recurrent congestion and 10% of overall congestion resulted from work zones on freeways, which led to an annual fuel loss of over $700 million (5). Moreover, in 2010, there were 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 (6). In addition to delay and safety problems, work zone activities have an adverse impact on the environment. Work zones cause additional vehicle emissions which results from reduced speed and queueing.

During roadway construction, when lanes or entire highway sections must be temporarily closed, it would be desirable to inform motorists of alternative routes around the construction site well in advance of the project location. This would 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 (7). The purpose of designing route guidance and information systems are improving the system efficiency and assisting drivers in making their route decisions. There are different approaches to propose routes to road users. Examples include shortest path which assigns users to the shortest path or the path with smallest travel time, user equilibrium (UE) that assigns users to the paths of smallest individual travel time, and system optimal (SO) which is minimizing total travel time of the system (8). Moreover, the routing of traffic, which is a core component in traffic management to mitigate traffic congestion, faces a well-known dilemma. Traffic managers want the network to reach to reach system optimal, which may discriminate against some users in favor of others. Also, the users want to use their shortest path to minimize their cost, which may result in lower system performance (9). 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 (10). To solve this dilemma, some researchers implemented both UE and SO in their proposed road guidance system by adding an additional constraint to the system optimal model to guarantee that drivers are assigned to acceptable paths (8, 11).

In addition, the routes proposed by route guidance systems should be disseminated to travelers to enable them to make more informed route switching decisions (12). Advanced Traveler Information Systems (ATIS) have been widely used in recent years to influence driver decisions and enable them to use the existing transportation system more efficiently and improve overall traffic flow. Understanding these influences and driver behaviors are important to improve 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 (13). When a non-recurrent incident such as construction activities causes unexpected congestion, drivers may have to revise their travel choices. They should explore the new traffic condition and adjust their travel pattern accordingly (14). While some drivers may not change their travel choices, others may be more willing to adapt to the new traffic condition by following the information provided by ATIS on alternative travel choices. Therefore, considering driver behavior can improve the effectiveness of traffic assignment models for realistically representing traffic operations.

1.2. Study Objective

The advent of personal computers with high computing power as well as readily available maps and network algorithms allow for a more systematic and optimal approach to developing diversion routes around major construction sites. The objective of this study is to develop a decision support tool with a user-friendly graphical interface that investigates optimal alternative routes around highway construction sites. The resulting tool is named TDS (Traffic Diversion System). A traffic diversion methodology is applied in TDS to investigate the optimum alternative route, which minimizes the impact of the closed link in the whole system while considering drivers’ behavior in following the recommended alternate route. TDS is capable of recommending a diversion path and displaying the results in an easy-to-view graphical user interface.

This dissertation consists of five chapters. Chapter 2 presents a modeling framework to estimate the size of the affected area around the closed link due to non-recurrent incidents. A subnetwork extracted from the original network that includes all affected links can help reduce the complexity of the prediction models and obtain the results in a timely manner. For this purpose, linear regression models are presented to predict the maximum distance from the closed link to the link with an expected increase in travel time based on network topology and the closed links traffic volume. In doing so, travelers are assumed to follow user equilibrium routes before and after the closure. Therefore, the proposed models in this chapter are used to estimate the size of the subnetwork.

Chapter 3 describes the traffic diversion methodology. The algorithm of the traffic diversion model is presented in this chapter to propose optimum alternative routes to divert drivers and mitigate traffic congestion around work zones. To identify the alternative routes, the traffic diversion model aims to minimize the total impact of the closure on the network. Models and algorithms developed in this chapter allow investigation of diversion routes that optimize network performance while considering drivers' behavior in finding their alternate route during a closure. In addition, TDS and its features are presented in Chapter 4. TDS is a decision support system with a user friendly graphical interface to identify optimum alternative routes around highway construction sites. TDS is capable of identifying alternative routes upstream of single or multiple lane closures. TDS modules, models, and algorithms as well as a user's manual for the system are also discussed in this chapter. Finally, the conclusion and discussion of the results are presented in Chapter 5.

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Chapter 2. A Modeling Framework to Identify an Affected Area for Developing Traffic Management Strategies

2.1 Introduction

The road network system is one of the important elements of the modern society. In the last three decades, vehicle miles traveled (VMT) have doubled on U.S. highways, while the total number of highway lane miles have increased by only 5% during the same period (1). In 2014, road congestion caused a total delay of 6.9 billion hours for urban Americans, and use of an extra 3.1 billion gallons of fuel, which resulted in a total congestion cost of $160 billion (2). Traffic congestion is generally divided into recurrent and non-recurrent congestion. Recurrent congestion is caused by routine traffic volumes such as morning and evening peak periods and are mostly predictable and expected. Non-recurrent congestion is triggered by non-recurrent causes such as traffic incidents, work zones, weather conditions, and special events and are unexpected and unusual congestion. A significant part of the delay time and cost related to urban congestion is caused by non-recurrent incidents (3). According to the Federal Highway Administration (FHWA) (4) about 50% of all highway congestion is caused by non-recurrent conditions.

With the limited ability to expand the physical capacity of the roadway system to meet the growing travel demand, traffic network managers seek to develop efficient traffic management schemes to mitigate the congestion in the traffic network (5). Nonetheless, developing efficient traffic management schemes requires modeling the traffic network with high reliability which is capable to estimate and predict the traffic congestion. With a traffic network performance model, the traffic network managers are able to develop and evaluate different traffic management schemes, and eventually propose an efficient one for deployment in the network. In the past two decades, many researchers have developed traffic network congestion models (6-13). However, providing accurate traffic network prediction remains a challenge. It requires an accurate prediction of the travel demand, network supply and their interactions. The traffic demand could be affected by factors such as adverse weather conditions, information received on non-recurrent congestion, and traffic and demand management strategies implemented in the network. Similarly, traffic networks are continuously subject to disruptions such as severe traffic incidents, work zones, and road closures due to flooding/snow that affect their capacities. In addition, the traffic network prediction is computationally cumbersome, which limits the opportunity to develop and evaluate a wide range of traffic management strategies in a limited time (8). Thus, the evaluation of management strategies requires developing accurate and reliable traffic network models with prediction results that are obtained in a timely manner.

When an incident causes a non-recurrent traffic congestion, the traffic congestion starts to disseminate around the incident location. The travelers who use a part of the network close to the congestion source are more vulnerable to the congestion and their behaviors are more likely to change in response to the incident. In this case, developing traffic management schemes may assist in mitigating the traffic congestion for these travelers, which will result in an overall performance improvement for the network. However, the travelers who are at a further distance from the incident location may not be affected by the congestion. While traffic management strategies are developed for the entire traffic network, these travelers have a very minor contribution in the congestion. Consequently, the traffic network performance impact is negligible for them. Therefore, considering a suitable area to assess the impact of incidents and develop traffic network prediction models for evaluating traffic management schemes remains a challenging question. Only a limited number of studies in the literature have addressed this topic. This study aims at developing a modeling framework to investigate the expansion of the congestion in the network around the source of the non-recurrent congestion, and examines the effect of major variables in defining a suitable area around the source of the congestion for developing efficient traffic network management schemes. This paper is organized as follows. The next section presents the overall modeling framework of the problem. Computational experiments are then described including experimental design and data statistic. Next, the resulted models are presented and analyzed. Finally, conclusions and research extensions are discussed.

2.1.1 Literature Review

An extensive effort to study the effects of the link disruption in the traffic network currently exists. For example, modeling disaster spreading, identifying critical links and analyzing subnetwork performance during link closures are related studies that investigate the consequence of a link disruption in the network. Some events such as accidents and work zones typically cause a single link closure in the network (14). However, other events such as floods, wildfires, and earthquakes may affect a larger area and disrupt several links in the network. Buzna, et al. modeled the congestion in the network due to a link closure in directed networks (15). They simulated various network topologies to examine the robustness of the model. Their results show that network topology plays an important role in defining the threshold for disaster spreading, damage radius and network robustness. They observed a threshold for node recovery below which the traffic congestion disseminates only through a small fraction of the network. A nonlinear and monotonically increasing function of node inputs is modeled for this threshold. Then, a dynamic model of the nodes is suggested to investigate the topology dependence, robustness, and reliability of the network structures and to demonstrate the time dependent spreading of the disaster. This model includes three parts; the ability of system recovery, disturbance threshold, and internal noise or failure. Ouyang et al. used this model to evaluate the effect of redundant systems on controlling the disaster spreading in different types of the networks (16). In another study, Poorzahedi and Bushehri proposed a heuristic method to measure the importance of the links in the network (17). This measure is then used to define and solve a network improvement problem to reduce the vulnerability of links in the network under events with long-term effects. A selection of alternative actions is proposed in a resource constrained optimization for this purpose.

Several methodologies have been used to identify critical links in the network. Jenelius and Mattsson (18) proposed a grid-based analysis methodology to assess the vulnerability of the road networks under a large area disturbance. The results showed the significant factors to be considered for a network disruption covering extensive areas is different from a single link disruption. The flow on the link and the availability of alternate routes determined the impacts of the single link closure in the network. However, for a large area disruption, the level of outbound and inbound travel demand of the affected area impacts the area covering disruption. In another study, Murray and Mahmassani (19) developed a bi-level formulation to identify vulnerable transportation network links. In their model, at the lower level, the traffic management agency routes vehicles based on the system optimal traffic assignment. At the upper level, the evil entity maximizes network disruption. To identify important links, a vulnerability index is defined to measure the importance of the links in a network. Alternate paths, extra capacity, and travel time are the factors that are considered in defining the vulnerability index. In addition, Knoop et al. (20) proposed a macroscopic model to evaluate the road network robustness and identify vulnerable links while considering both spillback and non-spillback cases. The influence of dynamic road information to evaluate critical links was also investigated in their study. While most studies have investigated the link's role in the network when they themselves are disrupted, Jenelius (21) studied the importance of road links as backup alternatives when other links in the network are disrupted. Traffic flow and disruption impacts are considered to identify the importance of alternate links. However, the size of the affected area around the disruption has not been discussed in their studies.

Moreover, Scott et al. (22) presented a new approach to identify critical links and evaluate network performance. They compared Network Robustness Index (NRI) methodology and traditional volume-to-capacity (V/C) ratio and showed the NRI solution results in greater benefits for the system in terms of the total travel time savings. Furthermore, Sullivan et al. (23) applied a modified NRI and Network Trip Robustness (NTR) to evaluate the impact of the network disruption and to identify the most critical links in the network. Three test networks with different connectivity levels measured by the gamma index were used to investigate the effect of the capacity disruption level on the NRI. In addition, the effect of the coverage area around the disrupted link on the proposed real time traffic management system performance is studied by Hashemi and Abdelghany (8). They examined the effect of subnetwork extension on developing proactive traffic management schemes. The results demonstrate that considering a larger area leads to more effective traffic management schemes, and consequently reduces the total travel time in the traffic network system. Also, Erath et al. (24) proposed a methodology to assess link failure consequences across the Swiss national network. To reduce computational intensity and time, subnetworks are used to calculate failure consequences instead of the whole network and subnetworks are generated based on constant grid layers. Although their results show that subnetwork methodology is an accurate and reliable assessment approach for most of the links, some links required the use of the full network since the limited network does not cover all relevant detours. Therefore, a methodology is needed to define a subnetwork which considers an accurate affected area around the disrupted link.

The previous research indicates that link volume, alternate routes, network topology and total network travel time represent important factors in studying the effect of the link disruption and identifying the critical links in the network. In addition, most research efforts consider a constant subnetwork around the disruption to assess the link closure effects on the network performance; efforts to identify an accurate affected area around the disruption are limited. Therefore, the main purpose of this study is to investigate the effects of network topology and link demand on the size of the affected area around the disruption based on the expected increase in travel time and traffic flow.

2.1.2 Contributions

The objective of this study is to illustrate the potential network impacts resulting from a link disruption. This impact is investigated based on the expected increase in travel time and traffic flow for links located at a distance from the disruption. The disruption could cause a full or partial reduction of the link capacity. Travelers on those links will be diverted to alternate links. Disruptions may have been caused by any non-recurrent event such as accidents, work zone activities, or special events. Although several studies investigate the effect of the disrupted links, limited discussions about the effect of the network topology and demand on the size of the affected area around the disruption currently exist. For this purpose, linear regression models are presented to predict the maximum distance from the closed link to a link with a specified expected increase in travel time and traffic flow. Travelers are assumed to follow user equilibrium routes before and after the disruption. This study is of interest to traffic network managers to help them reduce the complexity of their traffic prediction models. They can improve model performance by using a subnetwork instead of the entire network for their congestion mitigation schemes. They may also define different sizes for the subnetwork based on models requirements. Different levels of increase in travel time are considered to identify the affected links to define subnetworks with different levels of sensitivity. Also, the outcomes of this study are valuable for developing incident response plans and managing work zones.

2.2 Methodology

2.2.1 Prediction Problem

Linear regression models are developed to assess the effects of the link disruption in the network. Linear regression is a commonly used predictive analysis model. Regression models describe the relationship between a response variable and one or more predictor variables (25). In this study, the response variable is the straight-line distance from the closed link and the farthest link with a significant increase in travel time and traffic flow.

2.2.2 Variables

The response variables focus on describing potential network impacts on system operations and the predictor variables cover two dimensions, which include network topology and demand. The demand variable is volume on the closed link and network topology variables measure connectivity and density of links in the network. Also, alternative routes and available exit and entry ramps around the closed link are considered to be network topology variables. Response and predictor variables are defined as follows:

2.2.2.1 Response variable

The response variable is the straight-line distance between the closed link and the farthest significant affected link in the network. Nine response variables are defined in this study. Nine levels of “significantly” affected links are considered to define affected areas with different levels of sensitivity. To estimate these variables, a traffic assignment model must be applied to the normal and affected network independently. The normal network is a network with no disruptions and the affected network is one with a link or links fully or partially closed. All links that experience an increase in travel time due to the closure are then identified by comparing the normal and affected networks after traffic assignment. However, some of the small increases in traffic flow can be due to the convergence level used in the traffic assignment and could result in high increases in travel time. To solve this problem, links with less than a 5% increase in traffic flow over capacity (ΔTraffic Flow/Capacity) are removed from the set of impacted links. Therefore, for each of these nine response variables, links with at least a 5%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, and 45% increase, respectively, in travel time are considered as the affected links in the network. Next, the straight-line distance between the closed link and the farthest affected link is investigated. For example, for the 5% increase in travel time, response variable is the distance between the middle of the closed links to the farthest link with a 5% increase in travel time.

2.2.2.2 Predictor variables

Two sets of predictor variables are considered in this study to build the model. Network topology and demand are considered to evaluate the disrupted network performance. The network variables include area type, network density, network connectivity, Network Robustness Index (NRI), existence of alternative routes, travel time on alternative routes, and exit and entry ramps around the closed link. The link's traffic volume is defined as the demand variable. The set of predictor variables consists of continuous and categorical variables of two or more levels (for those variables of more than two levels, dummy variables are used).

2.2.2.2.1 Network topology variables

1- **Area Type** is defined by the Activity Density (AD) at the Regional Area Analysis (RAA) level (26). Based on the report of North Central Texas Council of Governments (NCTCOG), the activity density is defined as follows:

$$AD_i = (POP_i + B * EMP_i)/AREA_i \quad (2.1)$$

where AD_i is the activity density; POP_i is the population; EMP_i is the total employment; $AREA_i$ is the total area, all for RAA i; and B is the regional population to employment

(P/E) ratio. In this study “area type” is categorized into five groups; 1- central business district (AD >125), 2- outer business district (30<AD <125), 3- urban residential (7.5<AD <30), 4- suburban residential (1.8<AD <7.5), and 5- rural area (AD <1.8) (26). As shown in Table 2-2, four binary variables are defined to consider area type effects. Area type 1 is selected as the base case for all groups.

2- Network Density is defined as the total length of the network links per area. A subnetwork within a one-mile radius around the closed link is considered for this purpose. A one-mile radius is defined to show the network characteristics close to the selected link. Thus, the total length of links in the subnetwork divided by the area of the subnetwork is defined as network density and it is a continuous variable.

3- Network Connectivity is identified with the gamma index. The gamma index is defined as the ratio of the actual number of links and the maximum number of possible links in the network (22). The value of the index is between 0 and 1. A value of 1 represents a completely connected network, which is not likely in a real network. The gamma index (γ) is computed with the following formula:

$$\gamma = l/l_{max} = l/3(n-2) \qquad (2.2)$$

where l is the number of observed links and l_{max} is the maximum number of links in the network and is computed as $l_{max} = 3(n-2)$ where n is the number of nodes in the network (22). In this study only one network with different characteristics spreading all around the network is used. Therefore, to estimate the connectivity around the disruption, a subnetwork (same as network density assumption) within a one mile radius from the closed link is considered. The gamma index as a measure of network connectivity is used as a continuous variable.

4- Network Robustness Index (NRI) identifies the critical links in a traffic network (22). It measures the importance of a link in a road network by estimating the effect of closing that link on the network's performance (27). The NRI represents the differences in time between the total travel time of the normal and affected network as shown in equation 2.3.

$$NRI_k = \sum_i (t_i^a * v_i^a) - \sum_i (t_i^n * v_i^n) \qquad (2.3)$$

where NRI_k is the network robustness index for link k, t_i^a and v_i^a are the travel time and traffic volume, respectively, of link i in the affected network with closed link k, and t_i^n and v_i^n are the travel time and traffic volume, respectively, of link i in the normal network without no closed links (22).

5- **Nearest Alternative Routes around the Closure** are captured by four variables as follows:

  1. Frontage Road: This is a binary variable (0 or 1), which shows the existence of an alternative route near the closed link. In this study, authors assume that only links located on freeways will be closed due to a disruption. Thus, this variable is one when there is a continuous frontage road for the closed link and zero otherwise.
  2. Travel Time of First Alternate Path: The total travel time of the mutually exclusive alternate path with smallest travel time around the closed link.
  3. Travel Time of Second Alternate Path: The total travel time of the mutually exclusive alternate path with the second smallest travel time around the closed link
  4. Travel Time of Third Alternate Path: The total travel time of the mutually exclusive alternate path with the third smallest travel time around the closed link.

6- **Exit Ramp at the Start Node** is a binary variable (0, 1) with the value being 1 when there is an exit ramp at the beginning of the closed link and zero otherwise.

7- **Entry Ramp at the End Node** is a binary variable (0, 1) with the value being 1 when there is an entry ramp at the end of the closed link and zero otherwise.

2.2.2.2.2 Demand variables

Traffic Volume of the Closed Link: Any disruptions on freeways cause heavier congestion compared to disruptions on arterial roads due to the higher traffic volume that exists on freeways. Since freeways are more sensitive to disruptions (i.e. arterials are regularly disrupted by traffic signals), only freeway links are considered for closure in this study. Link volume is considered as a continuous variable in the model. For the experimental design study, 10 volume groups are defined based on both the volume distribution in the network and the importance of the links with higher volumes. The traffic volume for the PM peak period for one typical day in the Dallas/Fort-Worth area is used for this study. Table 2-1 shows the 10 volume categories.

Table 2-2 summarizes all predictor variables descriptions, names, and associated codes as applied in the model.

Table 2-1. Volume Categories

Volume group	Volume Range (veh/hr)
1	<1000
2	1000-2000
3	2000-3000
4	3000-4000
5	4000-5000
6	5000-6000
7	6000-7000
8	7000-8000
9	8000-9000
10	>9000

Table 2-2. Predictor Variables Descriptions, Names, and Codes

Description	Variable Name	Code
Area Type	AT_2 AT_3 AT_4 AT_5	Yes=1 No=0 Yes=1 No=0 Yes=1 No=0 Yes=1 No=0
Network Density	Density	Continuous
Network Connectivity	Gamma	Continuous
Network Robustness Index	NRI	Continuous
Nearest Alternative Routes around the Closure	FrontageRoad	Yes=1 No=0
Travel Time of First Alternate Path	SPT_1	Continuous
Travel Time of Second Alternate Path	SPT_2	Continuous
Travel Time of Third Alternate Path	SPT_3	Continues
Exit Ramp at the start node	Start_Ramp_Exit	Yes=1 No=0
Entry Ramp at the end node	End_Ramp_Entry	Yes=1 No=0
Closed Link Volume	Volume	Continuous

2.2.3 Simulation-Based User Equilibrium Traffic Assignment

TransCAD is used for simulating the network response in this study, and the User Equilibrium (UE) model first proposed by Wardrop (28) is considered for the traffic assignment. The volume delay function (VDF) that estimates travel time is an important component in a UE traffic assignment model and must be continuous, monotone, increasing, and differentiable, and must be defined for oversaturated conditions (29). One of the well-known travel time equations was proposed by the Bureau of Public Roads (BPR) in 1964 (30). In this equation, the travel time on any link is estimated as a function of the link free-flow travel time and the volume to capacity ratio. According to Skabardonis and

Dowling (14), the BPR function is based on data that does not reflect today's operating conditions and does not consider signalization conditions on arterials. Therefore, a customized VDF that also considers traffic control delay is used (26). This VDF followed a conical form and consists of two main components: congestion delay and traffic control delay. The congested travel time is a function of the free-flow travel time and delays due to traffic volume on the link and delays due to traffic control devices (signals, stop signs, etc.) (26).

The study first simulates a baseline performance for the network with no disruptions. Next, for each of the experimental scenarios, the scenario performance when a link is closed is simulated. Therefore, the link volumes and travel times are estimated from the UE traffic assignment for the normal network and then for the other experimental scenarios. The simulation assumes that no change in the overall demand occurs and all trips from the base case must still occur. This assumption simplifies the analysis and represents a worst-case assumption of the potential operational impact.

2.3 Computational Experiments

2.3.1 *Study Area*

The North Central Texas Council of Governments (NCTCOG) maintains a TransCAD network database of the North Central Texas region. This network is utilized as a test network. The network area includes the entire counties of Collin, Dallas, Denton, Ellis, Hill, Hood, Hunt, Johnson, Kaufman, Parker, Rockwall, Tarrant, and Wise. This area consists of 5,386 travel survey zones (TSZ). The TSZs are aggregated into 720 regional area analysis (RAA) zones based on the distribution of the households among income groups and sizes. Figure 2-1 shows the study area within the North Central Texas region with defined TSZs and RAAs. This region consists of various area types ranging from central business districts to rural areas. Therefore, it should be a suitable region with various network topologies and demand levels for studying the effect of these factors on the network performance during a disruption.

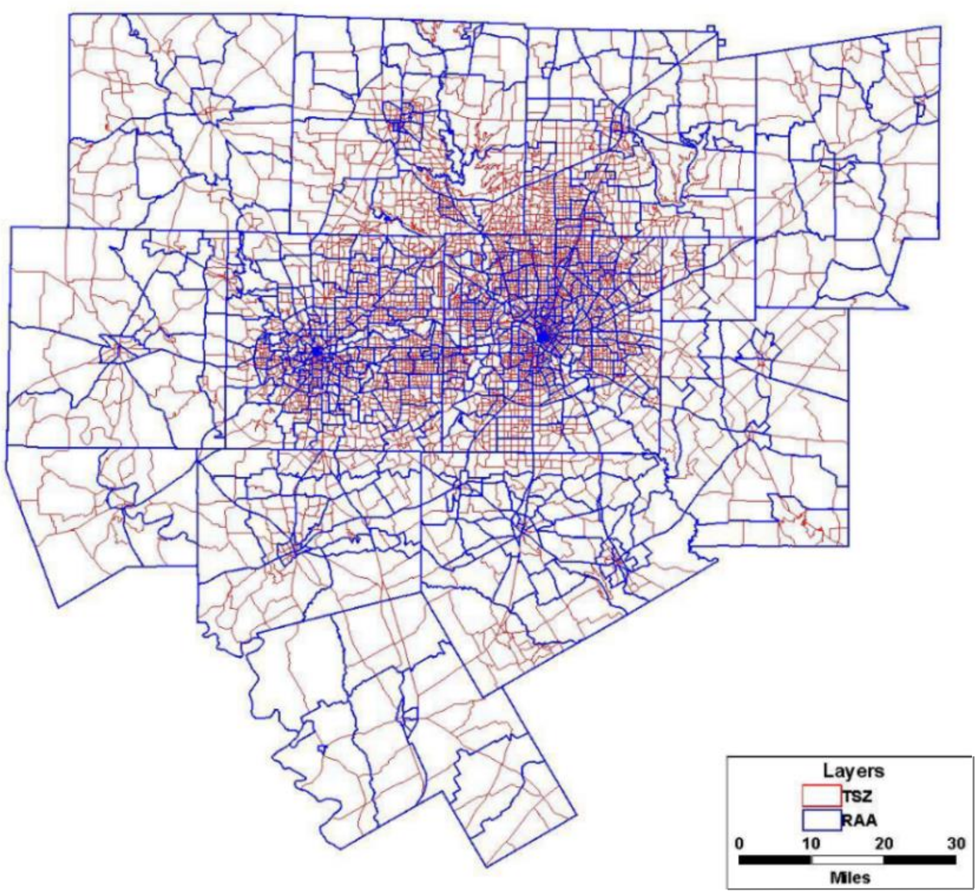

Figure 2-1. The Study Area within the North Central Texas Region (26)

2.3.2 *Experimental Design*

A factorial experiment is designed across the selected dimensions. Similar variables are not included in the experimental design even though they are included in the analyses. The experiment is designed based on two predictor variables from two different dimensions; network and demand. Area types (network dimension) and link volumes (demand dimension) are used for the factorial design. These predictors are selected because of the simplicity of identification and correlation that exists between similar variables. As mentioned in section 2.2.2.2, there are five groups for area type and ten groups for link volume. Therefore, based on the experimental design, 50 sites should be selected (5*10). However, only 42 links can be matched to the sample sites in the test network. Some combinations do not exist, e.g., no links in the network with area type equal to 5 and link volume group equal to 6, 7, 8, 9 or10 exist. This means in a rural area (area type 5) no links with volumes more than 5000 vehicles per hour occur. Therefore, 42 links are selected within the test network for the simulation as shown in Figure 2-2. In Figure 2-2, each sample site is identified by a number. The first number indicates the area type and the second number represents the volume category. For example, site 43 shows a link in area type 4 with a volume in the third category (between 2000 and 3000 vehicles per hour).

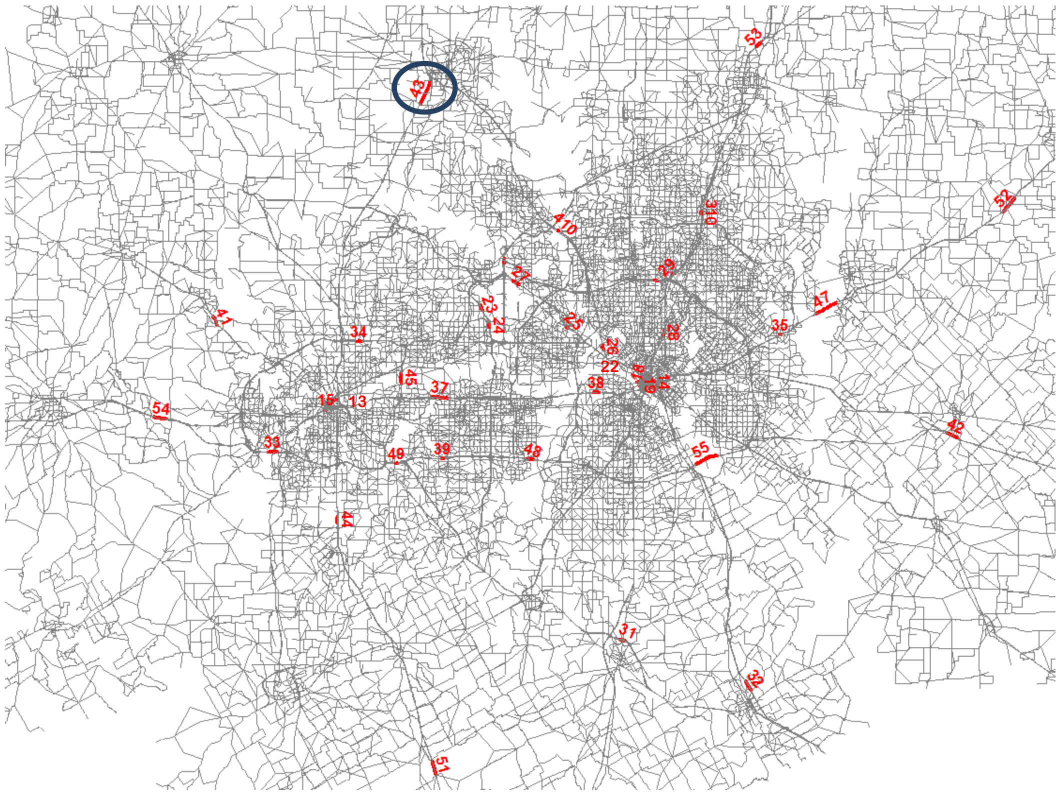

Figure 2-2. Sample Sites

2.3.3 *Data Statistics*

As mentioned in section 2.3.2, 42 sample sites are selected and response and predictor variables are estimated for each of these samples. Table 2-3 shows the data statistics for the predictor variables.

Table 2-3. Data statistics

Simple Statistics						
Variable	N	Mean	Std. Dev	Median	Minimum	Maximum
AT2	42	0.21	0.41	0.00	0.00	1.00
AT3	42	0.23	0.43	0.00	0.00	1.00
AT4	42	0.23	0.43	0.00	0.00	1.00
AT5	42	0.11	0.32	0.00	0.00	1.00
Volume	42	4827	2681	4441	747	9781
Density	42	11.08	8.70	6.81	0.99	32.23
FrontageRd	42	0.57	0.50	1.00	0.00	1.00
Start_Ramp_Exit	42	0.33	0.47	0.00	0.00	1.00
End_Ramp_Entr	42	0.21	0.41	0.00	0.00	1.00
Gamma	42	0.46	0.06	0.44	0.37	0.57
T_SPT1	42	6.92	3.94	6.12	1.75	24.04
T_SPT2	42	12.74	7.59	11.75	4.31	46.30
T_SPT3	42	17.79	9.63	16.31	5.60	56.61

From the data set, the frequencies between the different area types are 19%, 21%, 24%, 24%, and 12% for area types 1 to 5, respectively. The closed link volume, density, and gamma index are continuous variables that range from 747 to 9781 vehicles per hour, 0.99 to 32.23 miles per area, and 0.38 to 0.58 in index values, respectively. Also, the total travel time on alternate paths 1, 2 and 3 range from 1.75 to 24.04, 3.31 to 46.30, and 5.60 to 56.62, respectively. In addition, 57%, 33%, and 21% of the sample sites have frontage roads, exit ramps at the start nodes of the closed links, and entry ramps at the end of the exit ramps. These statistics show that the incident links used in this study contain a wide range of data and can yield a suitable data set for use in calibrating the prediction model.

2.4 Results and Analysis

Linear regression models are developed to predict the effects of the link disruption on the network performance based on the network topology and link demand. The response variable for each model is the distance between the closed link and the farthest link with a significant increase in travel time and traffic flow. The significant level of travel time increase can be defined based on the expected sensitivity for the affected area in the study. All of the predictor variables, which are defined above, are used to generate the model except NRI. The NRI is removed from the set of predictor variables for two reasons. First, the traffic pattern is needed for both networks before and after closure to calculate the NRI. Therefore, to simplify the use of the models that are being proposed in this section, only predictor variables that can be estimated from the normal network (before closure) are considered. Second, when NRI is considered in the set of predictor variables, it appeared to be a significant predictor in the final model. However, the model, which contains NRI, has a high Mallow's C_p value, which indicates important predictors are missing in the model. Mallow's C_p estimates the size of the bias in estimating the true regression coefficients and predicting responses and should be small and close to the number of predictors in the model. Therefore, when NRI is in the set of predictor variables, other variables cannot be significant in the final model, thus, the value of C_p is high in the model.

Therefore, the statistical software SAS is used to generate linear regression model with the PROC REG function using a stepwise selection. In the stepwise selection procedure, a significance level of 0.05 is required to allow a variable into the model and a significance level of 0.05 is required for a variable to stay in the model. Table 2-4 shows nine linear regression models that are estimated based on nine different levels of increase in travel time (5% to 45%).

Table 2-4. Regression Models for 5% to 45% Increase in Travel Time

Variables	Percent Increase in Travel Time								
	5%	10%	15%	20%	25%	30%	35%	40%	45%
Intercept	-5.177	-3.664	-5.007	-6.009	-6.255	-6.138	-5.594	-5.004	-4.821
AT_4	3.911	4.683	3.461	3.324	3.593	2.565	-	-	-
Volume	0.0011	0.0008	0.0009	0.0009	0.0008	0.0008	0.0006	0.0006	0.0005
T_SPT_1	-	-	-	0.918	0.889	0.883	-	-	-
T_SPT_2	0.510	0.464	0.477	-	-	-	0.510	0.453	0.456
Adj R^2	0.804	0.717	0.746	0.774	0.787	0.744	0.754	0.743	0.741

The results show that the area types, volumes, and travel times on the first and second alternate paths with the lowest travel time are the significant predictors in the models to estimate the radius of the affected area. The adjusted R^2 is relatively high for all the models, indicating that the models fit the data well. Moreover, in general, the results show that the affected area has a larger radius around the closed link when a lower level of increase in travel time is considered to define the farthest affected link in the network. In models for which the affected links experienced 20%, 25%, and 30% increases in travel times, the alternate path with the smallest travel time is a significant variable instead of the alternate path with the second smallest travel time. In addition, in the last three models (35%, 40%, and 45%), area type is not a significant variable. This indicates that the area type may not have a significant impact on the affected area around the closure when a high level of increase in travel time is considered to define the farthest affected link in the network. The first model is explained in more detail below.

The regression model generated by the use of stepwise regression based on a 5% increase in travel time is as follows:

$$Distance = -5.18 + 3.91 * AT_4 + 0.001 * Volume + 0.51 * T\_SPT_2 \qquad (2.4)$$

The above model indicates that a greater traffic volume on the closed link, an incident location in area type 4, and a larger travel time on the shortest path with the second lowest travel time all increase the distance of the closed link's impact on the network. A large volume on the closed link causes more changes in the network because more vehicles need to divert. In addition, area type 4 is suburban residential area with links that contain all volume categories compared to area type 5 that only contains links in five volume categories (less than 5000 vehicles per hour). Also, area type 4 is less dense compared to area types 1, 2, and 3 and vehicles on the closed links should use farther links as alternates since link spacings are generally larger for this area type. However, this variable is not significant when only links with a high increase in travel time are considered as affected links. This shows network topology may not have a significant effect on the subnetwork size in those cases. Moreover, data shows that the first shortest alternate path is usually close to the normal path and the third one is usually far from that, but the second shortest alternate path has a different pattern. This in turn indicates that a higher travel time on the alternate path results in a larger radius for the affected area. However, to define the affected area with medium sensitivity (20%, 25%, and 30% increases in travel time) the shortest path with the smallest travel time can be a better fit in related models.

Table 2-5 is the summary of the stepwise selection from SAS, which shows more details about the first model. All of the parameters that stay in the model have small p-values (less than 5%), which indicate they are all significant parameters. The coefficient of determination (R^2) of this model is 0.82 and the adjusted R^2 is 0.80, which shows the model fits the data fairly well. Also, the Mallow's C_p value is 0.23 for this model, which is small and indicates that the model is relatively precise and unbiased in estimating the true regression coefficients and predicting future responses.

Table 2-5. Summary of Stepwise Selection

Summary of Stepwise Selection								
Step	**Variable Entered**	**Variable Removed**	**Number Variable in**	**Partial R^2**	**Model R^2**	**C(p)**	**F Value**	**Pr > F**
1	T_SPT2	-	1	0.50	0.50	55.51	40.71	<.0001
2	Volume	-	2	0.24	0.75	10.56	39.31	<.0001
3	AT4	-	3	0.06	0.81	0.22	13.70	0.0007

2.5 Conclusions

This paper presents nine different models to investigate the effects of network topology and demand on the size of the affected area around the disruption based on the expected increase in travel time and traffic flow. A set of simulation experiments is designed based on area type and link demand to define the response and predictor variables using the North Central Texas network. TransCAD is used to simulate the network and the User Equilibrium (UE) model is applied for traffic assignment. The models demonstrate that traffic volume on the closed link, a link's area type, and the travel time on the first and second alternative paths with lowest travel times significantly impact the radius of the affected area around the disruption. This study can be used by traffic network managers to reduce the complexity of their models and improve model performance by using a subnetwork instead of the entire network for their congestion mitigation plans. They may also define different sizes for the subnetwork based on the study's sensitivity. To extend this study, more experiments can be used to develop these models more generally. For example, volumes in other peak periods (AM peak and off peak) can also be considered to select the sample sites. Future research enhancements may also explore the use of a dynamic traffic assignment models. Additional exploration into the potential for an overall decrease in localized demand in response to an incident may yield further improvements in the models presented in this study.

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Chapter 3. An Optimization-Based Traffic Diversion Model during the Network Disruption

3.1 Introduction

In the last three decades, vehicle miles traveled (VMT) have doubled on U.S. highways. However, the total number of highway lane-miles has increased by only 5% during the same period (1). 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 (2). Traffic congestion is generally categorized into recurrent and non-recurrent conditions. Recurrent congestion is caused by routine traffic volumes such as morning and evening peak periods and is mostly predictable and expected. Non-recurrent congestion is triggered by non-recurrent causes such as traffic incidents, work zones, weather conditions, and special events. They are unexpected, and they remain very difficult to predict. According to the Federal Highway Administration (FHWA) (3) about 50% of all highway congestion is caused by non-recurrent conditions. During a non-recurrent incident, when lanes or entire highway sections must be temporarily closed, traffic managers would prefer to inform motorists of alternative routes around the congestion well in advance of the incident location. However, inappropriate traffic diversion plans will degrade the alternative routes and increase the travel time of the entire network (4).

The purpose of designing route guidance and information systems is to improve system efficiency and assist drivers in making their route decisions. Multiple approaches exist to propose alternate routes to road users. 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 the paths of lowest individual travel time, and System Optimal (SO), which finds paths to minimize the total travel time of the system (5). 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 path to minimize their cost, which may result in a lower system performance (6). 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 (7). To solve this dilemma, some researchers implemented both user equilibrium and system optimal in their proposed road guidance systems (5, 8).

In addition, the routes proposed by route guidance systems should be disseminated to travelers to enable them to make more informed route switching decisions (9). 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 overall traffic flow in the congested network. Understanding these influences and driver behaviors are important to improve 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 (10). When a non-recurrent incident causes an unexpected congestion, drivers might revise their travel choices. The drivers explore the new traffic conditions and adjust their travel patterns accordingly (11). 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 the traffic assignment models in the operational context. In this study, a traffic diversion model is developed to propose the optimum alternate routes to drivers during non-recurrent traffic congestion events such as accidents or work zones. The developed model minimizes the total travel time in the entire network considering the link closure and the proposed alternate routes for the travelers. While some travelers utilize the new alternate routes to reach their destination, other travelers follow the UE traffic assignment in the network. This paper is organized as follows. The next section presents the methodology of the problem including a description of the problem, model, and solution algorithms. The efficiency of the proposed approach is then evaluated, and the computational results are analyzed. Finally, conclusions and research extensions are discussed.

3.1.1 Literature Review

Several studies have been conducted to improve the network congestion caused by non-recurrent incidents. These studies examined the impacts of alternate routes on the network performance, evaluated driver behavior, and investigated route guidance systems and traffic assignment methodologies used in traffic diversion schemes.

Some studies evaluate drivers' behaviors during unexpected congestion. For example, Khattak et al. examined short-term commuter response to unexpected congestion (12). 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 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 (13). 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 the travel behavior based on the alternatives and information provided to travelers (14). Their results indicated that travelers are 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 the real-time information providing traffic updates and advisory detours (11). The results show the drivers' response to Variable Message Signs (VMS) can be useful for ATIS in response to network disruptions.

Traffic diversion schemes are one of the traffic network management strategies for recurrent and non-recurrent traffic congestion. Relevant studies have investigated the effectiveness of traffic diversion on the performance of the transportation network. Bhavsar et al. developed a generic decision support system that could predict the effects of a traffic diversion on a transportation network (15). A support vector regression (SVR), which is a set of regression algorithms based on the underlying theory of support vector machines (SVM), was used for this purpose. To train the SVR model, two highway networks in southern California were used, and then the model was tested on a third new network in Vermont. The results indicated that based on the size of the training data set and the number of transportation networks used in training, the SVR was capable of predicting the traffic diversion impacts with a reasonable degree of accuracy. 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 variable message signs (16). 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) (17). The Dynasmart-P traffic simulator was used by RTRDS 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 user and system in 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 (5). They proposed a model which implements a SO approach, but considers the individual needs by adding constraints to ensure that users are assigned to the acceptable routes. They considered an upper bound (φ) on the normal unfairness, which is a ratio of the length of the experienced path to the shortest path for the same OD pair. Therefore, only paths with normal unfairness less than φ are feasible in their constrained system optimal model. They used a column generation method to solve the CSO problem. In another study, Schulz and Moses (18) 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 shortest paths for the prevailing network condition. In another study, game theory was used to solve the conflict between UE and SO (19). They defined a concept of satisfactory degree for system and user to achieve a more optimum traffic routing and proposed an integrated-equilibrium model based on double–objective optimization. In their study, the objective functions are minimizing the total travel time in the network and the drivers' travel time, respectively. However, the application of their models in a network with a disruption has not been discussed. A network with a closed link due to an unexpected incident has a different traffic pattern. Therefore, minimizing the total effects of the disruption on the network performance is the purpose of this study.

3.1.2 Contribution

The purpose of this study is to develop a traffic diversion model, which proposes optimum alternate routes to the travelers during a network disruption. 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 routes for the travelers. Based on previous research, the authors assume that some travelers utilize the proposed alternate routes to reach their respective destinations, while others follow UE traffic assignment in the network (11). Models and algorithms developed in this study allow assessment of diversion routes that optimize network performance while considering drivers' behaviors in following the proposed alternate routes during a closure. This system is of interest to traffic network managers to help them divert traffic from the disrupted area and improve throughput through the congested region.

3.2 Methodology

3.2.1 Definition of Variables and Notation

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

A is a set of links in the network

N is a set of nodes in the network

Z is a set of zones in the network

R is a set of origin nodes where $R \subset Z$

S is a set of destination nodes where $S \subset Z$

K_{rs} is a set of routes between origin destination pair rs

a is a link in the network, $a \epsilon A$

n is a node in the network, $n \epsilon N$

r is a origin node, $r \epsilon R$

s is a destination node, $s \epsilon S$

k is a route in the network, $k \epsilon K_{rs}$

c is closure identification index;

N_c is a subnetwork around the closed links A_c with a disrupted link

A_c is a set of closed links

a_c is a closed link, $a_c \in A^c$

I is a set of origin nodes in the subnetwork N_c and i is a origin node where $I \subset Z^{N_c}$

J is a set of destination nodes in the subnetwork N_c and j is a destination node where $J \subset Z^{N_c}$

x_a is number of travelers on the link a

x_a^{Nc} is number of travelers on the link a in the subnetwork N_c

t_a is travel time on the link a

t_a^{Nc} is travel time on the link a in the subnetwork N_c

f_{rs} is number of travelers between OD pair rs

f_{rsk} is number of travelers on route k connecting OD pair rs

$t_{rsk}(f_{rsk})$ is travel time on route k between OD pair rs

f_{ij} is number of travelers between OD pair ij on the subnetwork N_c

f_{ijk}^{Nc} is number of travelers on route k connecting OD pair ij in the subnetwork N_c

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

I^{Ac} is a set of origin nodes for the closed links A^c in the subnetwork N_c where $I^c \in I$

J^{Ac} is a set of destination nodes for the closed link A^c in the subnetwork N_c where $J^c \in J$

d^{a_c} is the total volume using the closed links a^c

$d_{ij}^{a_c}$ is the proportion of d^{a_c} attributed to the trips between OD pair $ij \in I^c J^c$

$d_{ij}^{A_c}$ is an overall OD matrix for the traffic on closed links A^c

$f_{ijk}^{Nc\propto}$ is number of travelers on route k connecting OD pair ij with only $\propto$ percentage of the closed link OD demand

$f_{ijk}^{Nc\beta}$ is number of travelers on route k connecting OD pair ij with only β percentage of the closed link OD demand

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

N_e is a set of nodes downstream of the closed link (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

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

$A_{\rho_{se}}$ is a set of links on path ρ_{se}

3.2.2 Problem Definition

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

3.2.3 Subnetwork

When a closure c occurs on a link a_c or a set of links A_c due to an incident, it results in either capacity reduction or a full closure along that link. The closure or reduction in the link capacity could cause a 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 (20). 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 (chapter 2). Nine models have been presented in chapter 2 for nine different level increases in travel time to find the radius of the affected area around the closure. The general form of the model to define a subnetwork is as follows:

$$R = A + B * AT_4 + C * d^{Ac} + D * SPT_1 + E * SPT_2 \qquad (3.1)$$

where R is the radius of the subnetwork from the middle of the closed link, AT_4 is one when the closed link is in area type 4, which is suburban residential area and zero otherwise, d^{Ac} is the closed link volume, and SPT_1 and SPT_2 are the travel times on the mutually exclusive alternate routes with the first and second lowest travel time around the closure. Parameters

A, B, C, D, and E are the model's coefficients, which have different values based on the significant level increase in link travel time used to define the affected links in the network. To define a subnetwork with high sensitivity, when the subnetwork radius is a distance from the closed link to the farthest link with 5%, 10%, and 15% increase in travel time, AT_4, d^{Ac}, and SPT_2 are significant variables in the model. Moreover, to define a subnetwork with medium sensitivity AT_4, d^{Ac} and SPT_1 are significant variables in the model to extract a subnetwork with affected links that experience a 20%, 25%, and 30% increase in travel time. However, $d^{Ac}$and SPT_2 are the only significant variables for the model to define a low sensitivity subnetwork when a 35%, 40%, and 45% increase in travel time are considered for the affected links.

3.2.3.1 Subnetwork OD demand estimation

As a subset of the complete 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 where $\forall i \in I,\ \forall j \in J$. Inspired by the work of Zhou, Erdogan, and Mahmassani (21), to estimate the origin-destination matrix for the subnetwork, the first step is generating path flow patterns in the complete network (f_{rsk}). 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. Also, all the OD pairs in the network are categorized into four groups: 1- Internal-Internal (I-I), 2-External-External (E-E), 3-Internal-External (I-E) and 4- External-Internal (E-I), as shown in Figure 3-1.

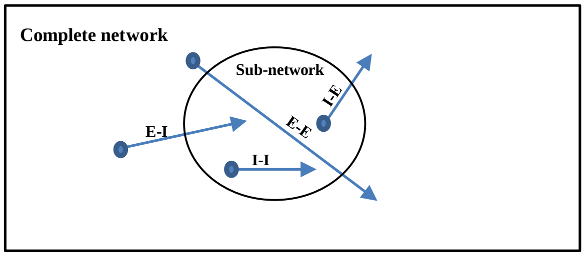

Figure 3-1. Four Types of OD Pairs with Respect to Sub Network (21)

For I-I OD pairs, the initial vehicle trips from i to j (f_{ij}^{I}) are assumed to be same as the complete network OD matrix (Initially, set $f_{ij} = f_{rs}$ 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:

$$f_{ij} = \sum_{R,S,K} f_{rsk}\sigma_{rsk}^{ij} \qquad (3.2)$$

where σ_{rsk}^{ij} is the path flow indicator for path flow f_{rsk} passing, or traveling into or from the subnetwork. σ_{rsk}^{ij} is 1 if zone i is the first entering zone into the subnetwork and zone j is the last exit zone form the subnetwork, or zone i is the first entering zone into the subnetwork and zone j is in the subnetwork, or zone i is in the subnetwork and zone j is the last exit zone form the subnetwork. The algorithmic steps to solve Equation (3.2) are described as follows;

- Initialize $f_{ij} = f_{ij}^{I}$ for $\forall i \in I,\ \forall j \in J$,
- For all paths (k) from origin r to destination s on the complete network, scan the path node sequence,
- Identify the first entering zone and the last exit zone in the subnetwork as origin node i and destination node j for all E-E OD pairs, identify the first entering zone

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

- If path $k^{th} \in k_{rs}$ is traveling in the subnetwork and origin i and destination j can be found for the path, then $f_{ij} = f_{ij} + f_{rsk}$.

Therefore, f_{ij}, which is the total number of vehicle trips traveling from origin node i to destination node j in the subnetwork N_c, is estimated.

3.2.3.2 Closed link OD demand estimation

In addition, the OD matrix for the traffic on the closed link must be estimated. To do so, $d_{ij}^{a_c}$ is defined as the proportion of d^{a_c} attributed to the trips between OD pair ij and estimated as follows:

$$d_{ij}^{a_c} = \sum_{k \in K_{ij}} \delta_{ijk}^{a_c} \times f_{ijk} \qquad i \in I\ , j \in J \qquad (3.3)$$

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.

Note that,

$$d^{a_c} = \sum_{i \in I^{a_c}} \sum_{j \in J^{a_c}} d_{ij}^{a_c} \qquad (3.4)$$

If more than one link is closed, an overall OD matrix for the traffic on the closed links is estimated by the following equation,

$$d_{ij}^{A_c} = \sum_{k \in K_{ij}} \gamma_{ijk}^{A_c} \times f_{ijk} \qquad i \in I', j \in J' \qquad (3.5)$$

where $\gamma_{ijk}^{A_c}$ is one if $\sum_{a_c \in A_c} \delta_{ijk}^{a_c} \geq 1$, which means at least one of the closed links is on the path k between i and j and zero otherwise. Furthermore, origin and destination nodes for the traffic on the closed links are obtained as follows:

$$I^{A_c}, J^{A_c} = \left\{ i \in I, j \in J \,\middle|\, \sum_{a_c \in A_c} \delta_{ijk}^{a_c} \geq 1 \right\} \qquad (3.6)$$

3.2.4 Traffic Diversion Model and Algorithms

The goal of this model is to provide alternate routes around the network disruption to divert traffic and mitigate traffic congestion. The problem aims at determining the most efficient alternate routes that minimize the total impact of the closed link on network performance. The total travel time of the affected area (subnetwork) is considered to measure the impact of the closed link on the system. Moreover, 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 (5). In this study, the total travel time of the system is considered to show the impacts of the closure. 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. Also, a certain percentage of drivers are assumed to divert to the recommended alternate routes, while others are assumed to divert based on the UE assignment. To estimate this percentage, many studies have been conducted on drivers' behavioral response to the traveler information systems (9-14). The following shows the algorithmic steps to find the optimum alternate route:

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 (f_{rsk}) in the network between each OD pair rs and estimate travel time on the links (t_a). Identify closed links A_c and define the subnetwork N_c around the closure based on the closed link demand and network topology (discussed in section 3.2.3) and determine OD demand for the subnetwork (f_{ij}) and for the closed links volume (d_{ij}^{Ac}).

Close the specified links 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}^{Nc})

on the affected network and estimate the link volume (x_a^{Nc}). Define a set of start ($n_s \epsilon N_s$) and end ($n_e \epsilon N_e$) nodes upstream and downstream of the closed link in the subnetwork. Find all possible paths ρ_{se} between these nodes ($\rho_{se} \epsilon P_{se}$) and identify all links on each path ($A_{\rho_{se}}$).

Compare the links volume on the normal subnetwork (without any closed link) to the affected subnetwork and rank all available paths (P_{se}) based on the total changes in the links volume. Use Equation 3.7 to rank the paths from high value changes in the links volume to low values.

$$\sum_{a \in A_{\rho_{se}}} (x_a^{Nc} - x_a) \quad \forall \rho_{se} \epsilon P_{se} \qquad (3.7)$$

Step 2. Initial Path

Set $i = 0$ and identify a path ($\overline{\rho_{se}}$) which contains links with most changes among all the paths between each start and end nodes as an initial alternate route.

$$\rho_0 = \overline{\rho_{se}} = \max\left\{ \sum_{a \in A_{\rho_{se}}} (x_a^{Nc} - x_a) \right\} \quad \rho_{se} \epsilon P_{se} \qquad (3.8)$$

Step 3. Alternate Route Evaluation

1. Identify ρ_i as alternate route and set $x_a^{Nc} = 0$ for all links in the subnetwork.
2. Assign only $\propto$ percentage of the closed link demand d_{ij}^{Ac} to the alternate route, which results in $f_{ijk}^{Nc_\propto} = \propto * d_{ij}^{Ac} \;\; \forall i \in I^c, \forall j \in J^c, k = f\ (K_{ij}, \rho_i)$ and update these links' volume ($x_a^{Nc_\alpha}$) and travel time ($t_a^{Nc_\alpha}$) in the network.
3. Apply the UE traffic assignment to the updated network with the remaining of the closed link's OD demand $(\beta = 1 - \propto) * d_{ij}^{Ac}$ and with the all demand of the other ODs which resulted in ($f_{ijk}^{Nc_\beta}$) and ($x_a^{Nc_\beta}$).

4. Add volumes for each link from the UE assignment and alternate route assignment as follows: $x_a^{Nc} = x_a^{Nc_\alpha} + x_a^{Nc_\beta}$ and updated link's travel time (t_a^{Nc}).
5. Estimate the total travel time of the updated subnetwork considering the link closure and the proposed alternate route:

$$T_{Nci} = \sum_a x_a^{Nc} * t_a^{Nc} \qquad (3.9)$$

Step 4. Best Known Solution

1. Remove ρ_i from the set of paths (P_{se}), set $i = i + 1$, identify the next alternate path with the most changes in the links volume among all the paths, and repeat all sub-steps related to step 3.
2. If $T_{Nci}(\rho_i) < T_{Nci}(\bar{\rho})$, set $\rho_i = \bar{\rho}$ as the alternative route.

Step 5. Stop Criteria

Repeat steps 3 and 4 for all ranked paths identified in step 1. If CPU time is more than Δ, stop and set $\bar{\rho}$ as alternative route, otherwise go to step 4.1.

3.3 Experiments, Results, and Analysis

A set of simulation experiments are conducted to examine the performance of the traffic diversion model described above. In these experiments, the traffic diversion model is applied for the Tarrant County network in north Texas. As illustrated in Figure 3-2, the network consists of about 7500 nodes and 20000 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 alternate routes in non-recurrent congestion scenarios due to an incident on the freeway facilities. Under normal conditions (without any incident in the network), travelers are assumed to follow their historic user equilibrium routes. In the case of a freeway incident (accident, work zone, etc.), when a lane or entire 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 the traveler information systems (9-14). The drivers' response is a function of various factors such as trip characteristics, the number of available alternate routes, delay information and duration (12). Based on the literature (11), in this study, 40% of drivers are considered to follow the suggested alternate route and the other 60% are assumed to follow UE traffic assignment routes. To present a none-recurrent congestion scenario, a hypothetical incident is assumed to close just a number of lanes or the entire freeway section.

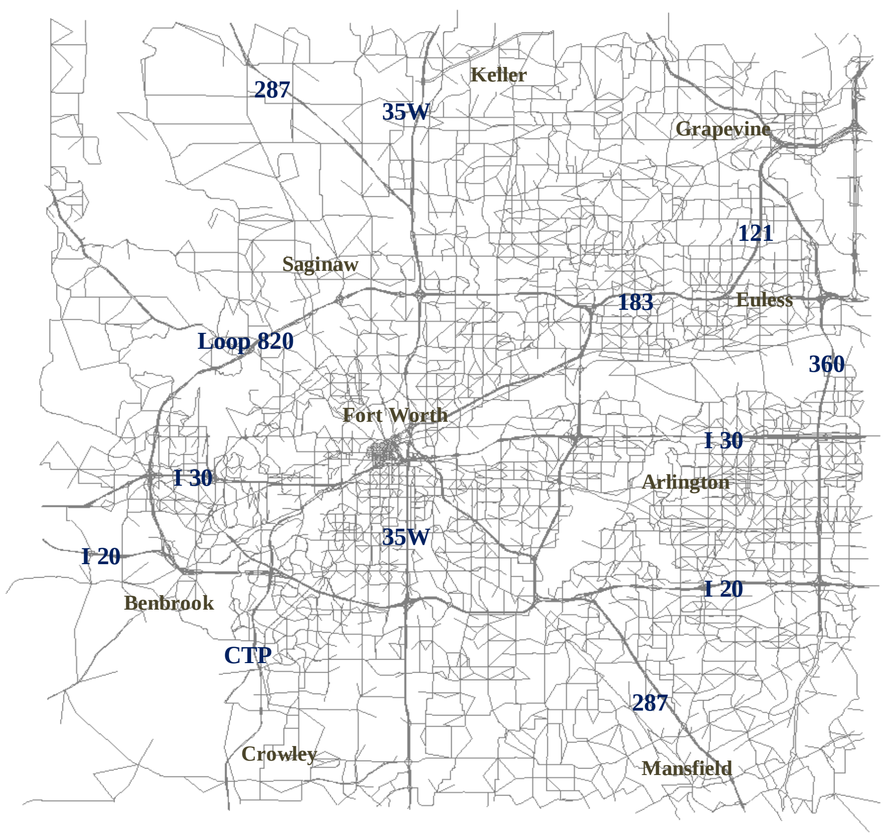

Figure 3-2. Tarrant County Network

The first set of experiments examines the effect of the subnetwork size on the traffic diversion model. A link with a 4800 vehicles per hour volume on state highway 121 is closed and five subnetworks with different sizes are considered around the closure as illustrated in Figure 3-3. As shown in the figure, the subnetworks vary in radius, which are estimated from five models that were explained in section 3.2.3. These models were developed based on the distance between the closed link and the farthest link with 5%, 15%, 25%, 30%, and 40% increases in travel time, which resulted in different 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 (do-nothing scenario) and after deploying the traffic diversion model. To have a fair comparison between the results, a subnetwork with a radius of five miles is considered as a test network. The alternate routes, which are proposed for each experiment, are considered for the traffic assignment in the test network. Finally, the total network travel times are estimated for each experiment and compared to the do-nothing scenario.

Figure 3-3 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. However, as shown in the figure, the CPU execution times are increased with the size of the subnetworks. A practical choice might be the subnetworks with medium size (e.g. 3.5 or 4 miles), which provide moderate travel time savings and have acceptable CPU execution times, to use in the traffic diversion model.

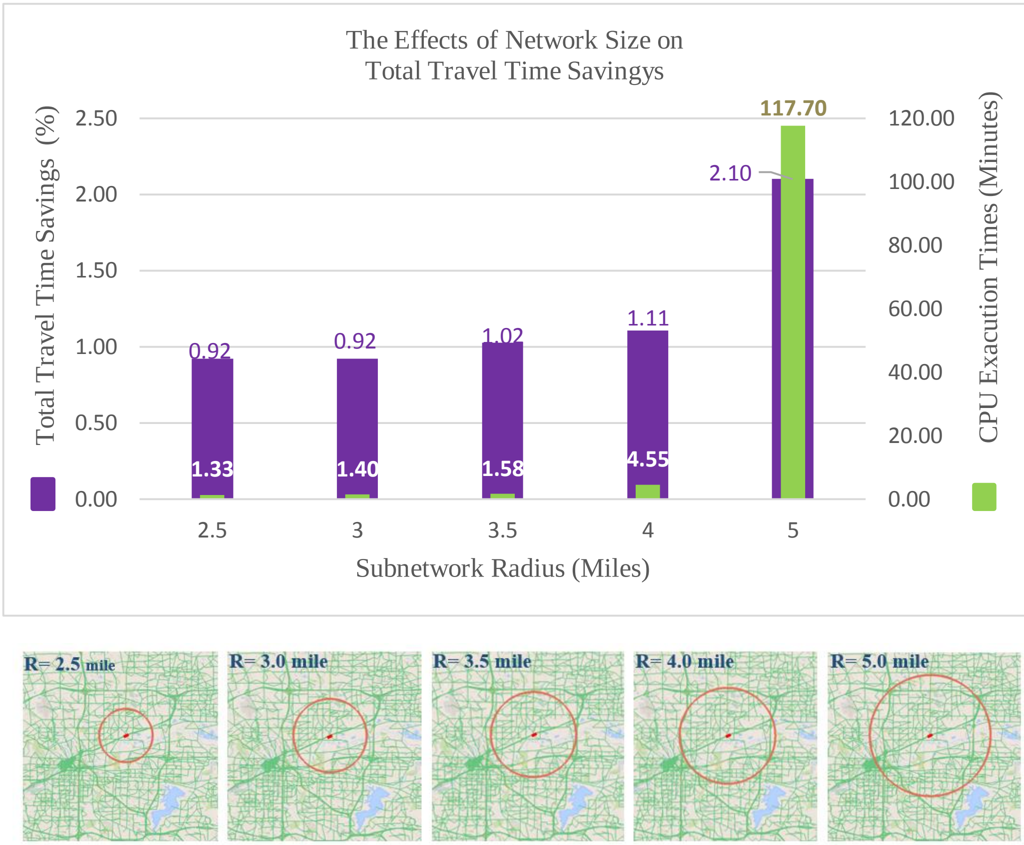

Figure 3-3. The Effect of Subnetwork Size

The second set of experiments examined the performance of the traffic diversion model considering the closure on the links with different levels of traffic volume. For this purpose, three experiments are conducted for the low, medium and high levels of traffic volume. In three different experiments, links with 2300, 5400, and 8500 vehicles per hour are considered to be closed for this purpose. Figure 3-4 presents the results of these experiments. As shown in Figure 3-4, 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 in a disrupted network to improve network performance especially when an incident occurs on links with a high traffic volume.

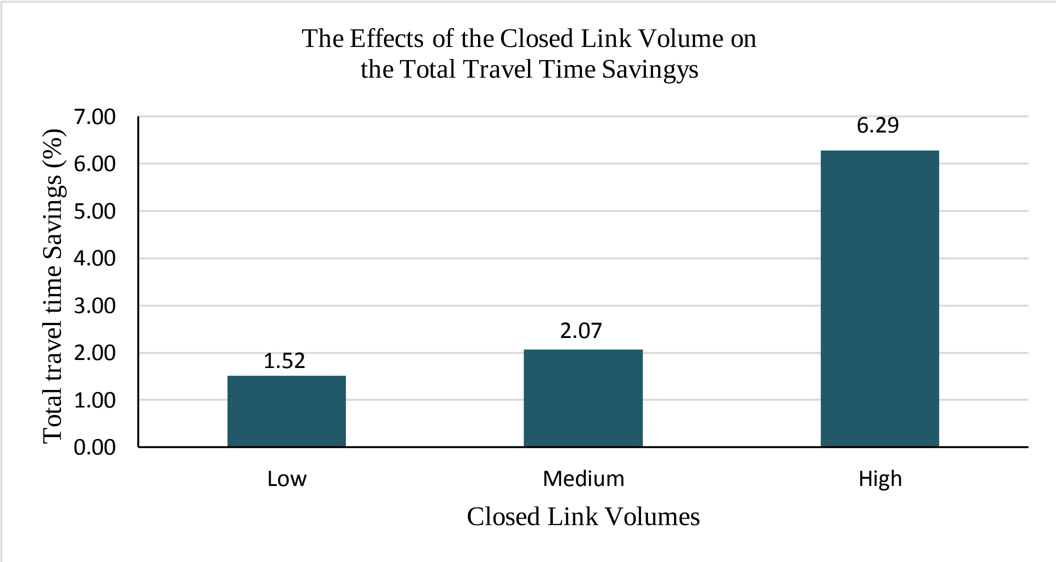

Figure 3-4. The Effect of Link Traffic Volume

The third set of experiments assesses the accuracy of the model by limiting the availability of links that are utilized in the alternate routes. For this purpose, only high-level links are assumed to be available for alternate paths and the two experiments are compared. In the first experiment, alternate paths can be selected from any available links 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 in each case, and the total travel time of the network is estimated and compared to the do nothing scenario. As shown in Figure 3-5, 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 as it does not have a big effect on the network performance and also avoids diverting traffic to minor arterials.

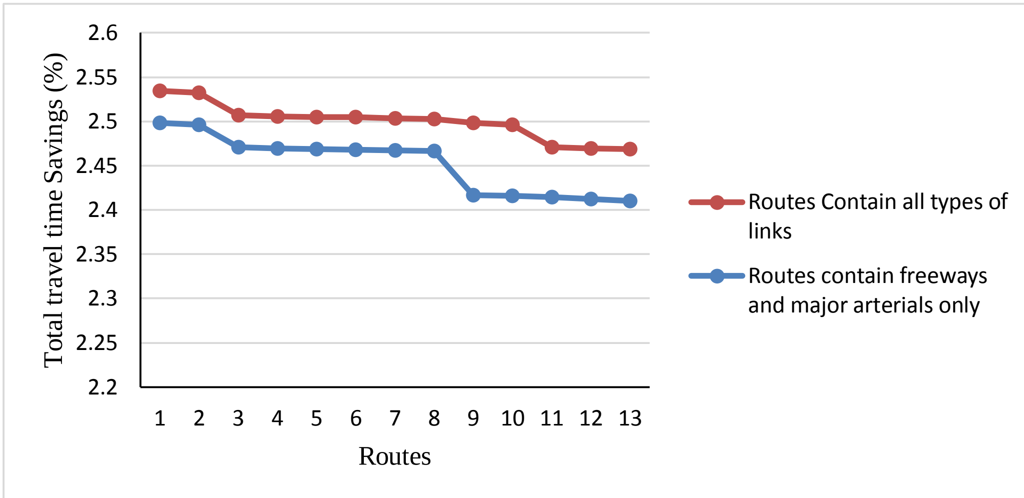

Figure 3-5. The Effect of the Links Availability in Selecting Alternate Routes

3.4 Conclusions

This paper has presented a traffic diversion model to divert travelers to optimum alternate routes around a disruption. The model estimates the current network conditions with a disruption in the network, compares the current conditions to the normal conditions, and proposes optimum alternate routes to improve the overall network performance. The travelers' route choice behavior is also considered in this model. A certain percentage of travelers is assumed to divert to the proposed alternate routes and others follow the alternate route of their choice based on UE traffic assignment. 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 a hypothetical disruption scenario.

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.

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Chapter 4. A Decision Support System for Traffic Diversion around Construction Closures

4.1 Introduction

Traffic congestion has become one of the serious problems in most urban areas. In the last three decades, vehicle miles traveled (VMT) have doubled on U.S. highways. However, the total number of highway lane miles has increased by only 5% during the same period (1). As highway infrastructure ages and road congestion increases, roads need to be expanded and reconstructed. Therefore, the federal and state government agencies have considered the maintenance, rehabilitation, and upgrading of the existing highway networks as well as constructing new ones, which results in creating many construction sites and work zones on highways. Furthermore, 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 (2). About 50% of all highway congestion is caused by non-recurrent conditions, such as traffic incidents, work zones, weather conditions, and special events. Also, about 24% of non-recurrent congestion and 10% of overall congestion resulted from work zones on freeways which led to an annual fuel loss of over $700 million (3). In 2010, there were 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). In addition to delay and safety problems, work zone activities have an adverse impact on the environment. Work zones cause additional vehicle emissions, which result from reduced speeds and queueing.

During roadway construction, when lanes or entire highway sections must be temporarily closed, it would be desirable to inform motorists of alternative routes around the construction site well in advance of the project location. This would 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 alternate routes and increase travel time of the entire network (5). The advent of personal computers with high computing power as well as readily available maps and network algorithms allow for a more systematic and optimal approach to developing diversion routes around major construction sites. The objective of the proposed study is to develop a decision support tool with a user-friendly graphical interface to allow development of optimal alternate routes around highway construction sites. This paper is organized as follows. The next section presents the overall methodology of the problem. The structure of the proposed system is then described. Next, modules, models, and algorithms of the system is presented. Finally, a summary and some conclusions are provided, along with a discussion of promising areas of future work.

4.1.1 Literature Review

Significant research efforts have been devoted to improving traffic conditions in work zone corridors. Related studies could be classified as follows: work zone traffic delay estimation, users and agencies cost optimization, and analysis of the impacts of traffic information systems on the network performance. In addition, some other studies investigated the impacts of alternative routes on the performance of the transportation network related to recurrent and non-recurrent traffic congestion.

Major highway construction projects result in traffic congestion, which causes driver dissatisfaction, road user delay, and traffic crashes. Relevant studies such as (6) and (7) investigated the issue of work zone traffic delay and used their results to develop an intelligent decision support system. Jiang and Adeli used neural network and optimization techniques to present a macroscopic computational model for estimating traffic delays in freeway work zones based on traffic flow theory (6). The model can be used as an intelligent decision support system to investigate the impact of various factors, such as number of lane closures and darkness, and find the optimum work zone segment length and optimum starting time. In another study, they developed an object-oriented (OO) model for freeway work zone capacity, queue delay and length estimation (8). This model also was applied to an advanced intelligent decision support system, called IntelliZone (intelligent support system for work zone traffic management). In addition, Karim and Adeli presented an adaptive computational model for work zone capacity and delay estimation (7). Their model considered several parameters such as the number of open lanes and truck percentage. A radial-basis function neural network model was used to estimate the work zone capacity, and a deterministic traffic flow model based on the estimated work zone capacity was used to compute queue delays and lengths. However, they did not discuss about the alternative routes or diversion plans in their models.

Some other studies investigated simulation and optimization cost methods to optimize various controllable aspects of work zones. Lee proposed a scheduling model based on the route-changing behavior of road users (9). Their model was capable of computing the traffic delay of vehicles via microscopic simulation, and applying team ant colony optimization to find a near-optimal schedule. Moreover, Chen and Schonfeld developed a methodology to optimize work zone length for four alternative zone configurations with and without alternate route while considering the characteristics of the detour route bypassing the work zone (10). Their objective was to minimize the total cost, including agency cost, user cost, and crash cost. A total cost objective function was formulated and used to optimize work zone length for four alternatives. Moreover, Gallo et al. evaluated the effectiveness of a forced detour strategy and compared it to other traffic control strategies (11). Different strategies such as no suggested detour (all vehicles merge to one lane), a suggested detour (a choice was given to drivers to divert), and a full detour (all vehicle diverted) were considered. VISSIM microscopic simulation models were developed based on the traffic data collected from the work zone and parallel detour route.

The models estimated the impact of different strategies on drivers in terms of delay through the work zone. Their results suggested that the forced detour strategy decreased travel times and queue lengths in comparison to other strategies.

With the development of Intelligent Transportation Systems (ITS), Automated Work Zone Information Systems (AWIS) have been employed along the construction sites to provide traffic information to the travelers and improve work zone conditions. Lee and Kim investigated the design, performance, and validation of AWIS, which provided road users real time travel information to avoid traffic delays in the construction corridor (12). Travel times were estimated from speed data and disseminated through portable and permanent changeable message signs on site and through the project website. Their results showed that implementation of the AWIS caused a 17.5% reduction in the peak hour traffic demand through the work zone with a significant volume increase on the detour freeways. Chu et al. also evaluated the effectiveness of an AWIS system, called CHIPS (Computerized Highway Information Processing System) (13). Traffic diversion, safety effects, and driver's responses were studied to evaluate the effectiveness of the system. The driver survey indicated that most drivers liked the system. Also, the results showed the effectiveness of diverting traffic and promoting smoother traffic flow during congested periods. These systems only provide travel time information along the work zone corridors and do not inform motorists about alternate routes and related travel times around the construction sites. However, a system that provides both information would be more effective.

Traffic diversion and offering alternate routes is one of the traffic network management strategies for recurrent and non-recurrent traffic congestion. Relevant studies have investigated the effectiveness of traffic diversion on the performance of the transportation network. Bhavsar et al. developed a generic decision support system that could predict the effects of the traffic diversion on transportation networks (14). A support vector regression (SVR), which is a set of regression algorithms based on the underlying theory of support vector machines, was used for this purpose. To train the SVR model, two highway networks in southern California were used, and then the model was tested on a third new network in Vermont. The results indicated that based on the size of the training data set and the number of transportation networks used in training, the SVR was capable of predicting the traffic diversion impacts with a reasonable degree of accuracy. In addition, Govind et al. developed a PC tool known as TEMPO (Transportation Emergency Management Post-Incident Operations) (15). TEMPO was capable of identifying traffic diversion strategies around the disruption in an urban area network. TEMPO used heuristic approach to estimate the origin-destinations (OD) of the traffic on the closed links and then reassigned the estimated ODs to the remainder of the network based on an incremental assignment procedure. 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 variable message signs (VMS) (16). They applied Dynasmart-P to conduct relevant simulation experiments. Their framework was based on traffic assignment under the user equilibrium principle. Moreover, Aved et al. presented the Real-Time Route Diversion System (RTRDS) (17). Dynasmart-P traffic simulator was used by RTRDS 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 studies, the framework is based on the traffic assignment under user equilibrium or system optimal and do not consider both at the same time. In addition, some researchers implemented both user equilibrium and system optimal 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 system optimum traffic assignment (18). They proposed a model, which implements a system optimum approach, but considers the individual needs by adding additional constraints to ensure that users are assigned to the acceptable routes. However, the application of their models on the network with a disruption have not been discussed. A network with a closed link due to an unexpected incident has a different traffic pattern and minimizing the total effects of the disruption is investigated in the proposed system in this study.

4.1.2 Contribution

The objective of this study is to develop a decision support system with a user-friendly graphical interface to identify optimum alternate routes around highway construction sites. The resulting tool is named TDS (Traffic Diversion System). TDS is capable of identifying alternate routes upstream of single or multiple lane closures. Models and algorithms applied in this system allow assessment of alternate routes that optimize network performance. While some travelers utilize the new alternate routes proposed by TDS to reach their destination, other travelers follow the UE traffic assignment in the network. This system is of interest to construction agencies and traffic network managers to help them divert traffic from the congested area and reduce traffic demand through the construction sites. An easy to use Graphical User Interface (GUI) that allows users to work easily with the system and a graphical representation of the roadway network around the construction sites are the advantages of using this system. While the developed system has application in diverting traffic around work zones, its proposed models, algorithms and features could be useful in other areas related to the intelligent transportation systems.

4.2 Methodology

The TDS package has many modules to help traffic network managers reduce congestion around construction closures and improve network performance. The software requires input data for a number of network variables to make recommendations about traffic diversions due to construction activities on any links in the network (The input data is discussed in the next section). The traffic diversion module of TDS is based on an optimization model (Chapter 3). Initially, the entire network and its data are loaded. The user equilibrium assignment is applied in the next step to generate the path flow pattern in the normal network (network without any closure). The user then specifies and reduces the capacity of the links that are disrupted by construction activities. This capacity reduction could be by closing the entire link or just one or more lanes on that link. A subnetwork that includes all the affected links around the closed links is defined to reduce the complexity of the prediction model by considering only the affected links and not the entire network (Subnetwork is discussed in section 4.4.3). Next, the user equilibrium assignment is applied again on the affected network (with a closed link) to show the significant traffic volume changes on the links and identify possible alternate routes. Therefore, the traffic diversion model evaluates these alternate routes to minimize the total travel time of the network and recommends the optimum alternate routes.

4.3 TDS Structure

TDS is a decision support system, which is implemented in Java. TDS requires information about the roadway network around the construction site including nodes and links. In addition, Origin-Destination (OD) zones and the OD demand information is required for use in TDS. The input data are set up in four DAT files, a node file, a link file, a demand file, and a zone file. In the node file, each line represents a node in the network that could be an intersection or a centroid, and it has four fields, as follows:

1- Node ID, an integer number assigned to the node by user.

2- X coordinate, a number that represents node longitude.

3- Y coordinate, a number that represents node latitude.

4- Centroid indicator, is one if the node is a centroid and zero otherwise.

In the link file, each line represents a segment of the road between two nodes. Two-way streets are considered as two separate links. Each line has 12 fields, as follows:

1- Link ID, an integer number assigned to the link by user.
2- Start node, the node ID from which the link is started.
3- End node, the node ID at which the link is ended.
4- Length, a number that indicates the length of the link (miles or kilometers).
5- Direction, is one if the link is a one-way street and two if the link is a two-way street.
6- Functional classification, is a number between one to eight that indicates the type of the link (1= Freeway, 2= Principal Arterial, 3= Minor Arterial, 4= Collectors, 6= Freeway Ramp, 7= Frontage Road, and 8= HOV)
7- Number of lanes, an integer number that indicates the total number of lanes available in one direction of the link.
8- Free-flow Speed, the estimated speed under free-flow conditions (mph or kph).
9- Link Capacity, capacity of the street (vehicles per hour per lane)
10- Free-flow travel time, the estimated travel time under free-flow condition (minutes).
11- Link Volume, a number that indicates the total peak hour traffic volume on the link (vehicles per hour).
12- Area Type, is a number between one to five, which is a function of population and employment (1= Central Business District, 2= Outer Business District, 3= Urban Residential, 4= Suburban Residential, and 5= Rural).

In the zone file, each line represents a zone in the network. Each zone contains a centroid node. The zone file includes two fields, as follows:

1- Zone ID, an integer number assigned to the zone by user.
2- Centroid node, the node ID of the centroid node in the zone.

In the demand file, each line represents an OD demand between an origin and a destination, and it contains three fields, as follows:

1- Origin node, the node ID of the origin node.

2- Destination node, the node ID of the destination node.

3- Demand, a number that indicates the total demand between an origin and destination (vehicles).

The data described above is used for a graphical representation of the network as well as in models and algorithms. In this study, the Tarrant County network in north Texas is used as a test network with 7500 nodes, 2000 links, and 400 zones.

4.4 TDS's Modules, Models and Algorithms

TDS is a user-friendly graphical interface software developed in Java to be used by construction firms and traffic network managers. TDS is designed to improve traffic conditions in the disrupted network, especially around the construction activities. The system includes, graphical user interface, subnetwork extraction, vehicle routing, and a traffic diversion model. Once the system is open in Java, a graphical representation of the network, which is a map of links and nodes is displayed.

4.4.1 Graphical User Interface

The TDS tool has an easy-to-use GUI including a graphical representation of the roadway network around the construction site. The network representation is similar to a Google or Yahoo map (Figure 4-1), with one notable difference. Each link of the network is a dynamic link. A dynamic link has two properties. First, when a cursor is clicked on the link (after selecting the "Select Link" button), detailed information about the link is displayed, including link ID, link length, number of lanes, link capacity, etc. Second, the above information can be edited as illustrated in Figure 4-2. For example, the number of links could be reduced from the existing three lanes to two, one or even zero, i.e. full closure. This would allow rapid editing of link properties and the network in general. Once the network is edited, various modules of TDS such as vehicle routing and traffic diversion could be performed based on the latest roadway conditions. The GUI of TDS is capable of zooming and displaying the set of nodes, links, and node and link IDs by clicking on the related buttons. The system is also capable of displaying an affected area (subnetwork) and optimum alternate routes around the closed link, as well as the shortest paths with lowest travel time between two selected nodes.

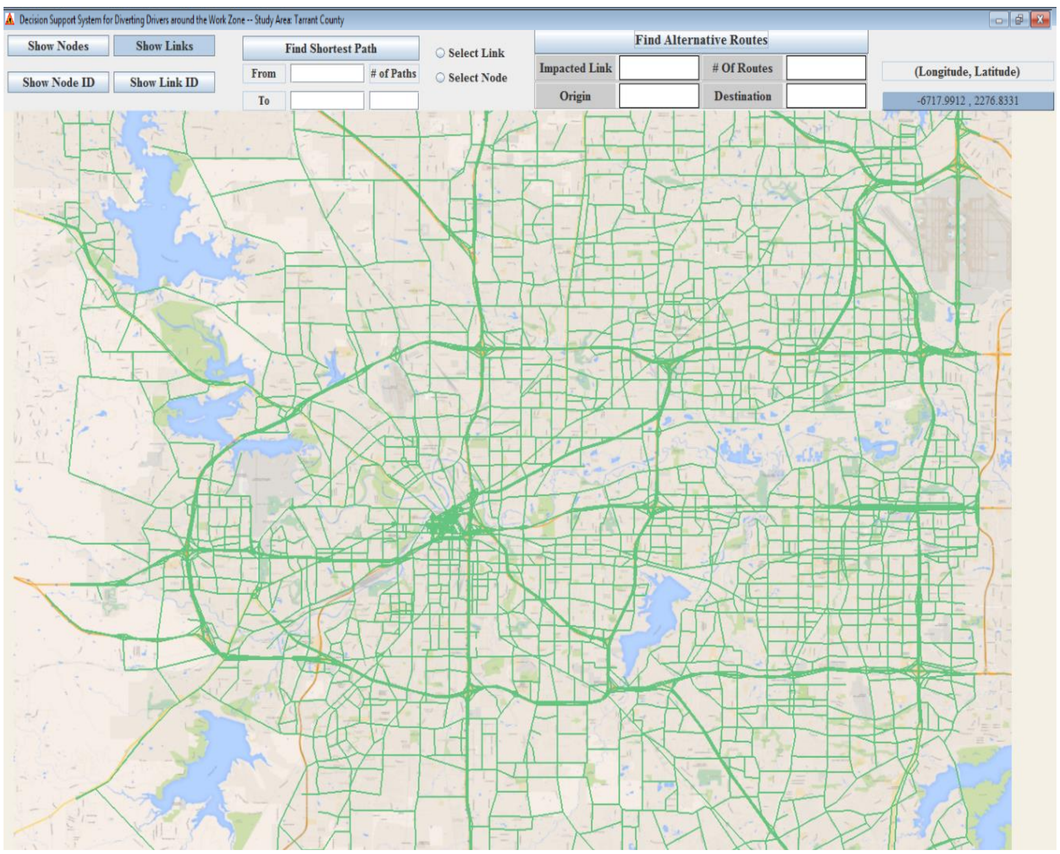

Figure 4-1. Loading the Network in TDS

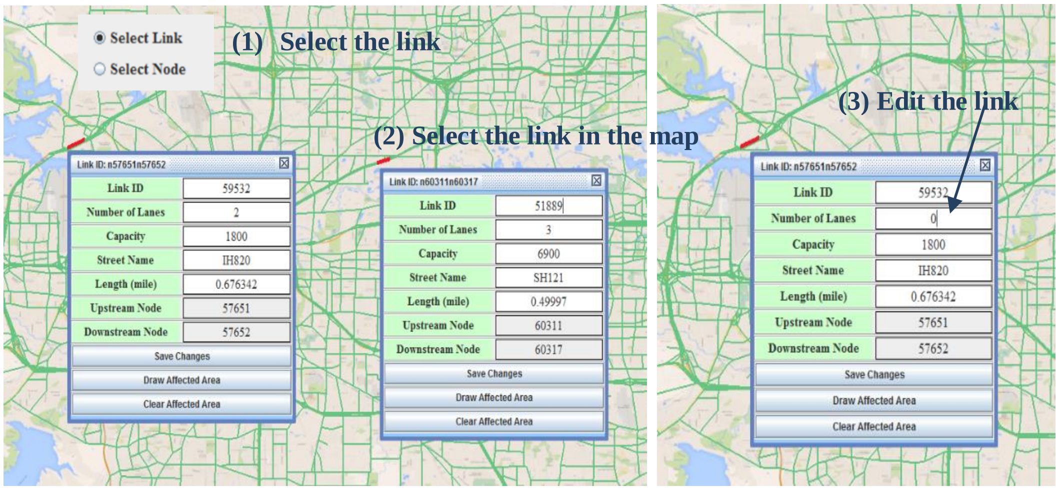

Figure 4-2. Displaying and Editing Link information

4.4.2 Vehicle Routing

The vehicle routing module is the k-shortest path approach implemented in TDS. The routing module identifies k-number of shortest paths with the lowest travel time connecting any pair of nodes in the network. The first step is to specify the closed links in the network by clicking on links. To perform vehicle routing, “Find Shortest Path” button and then the origin and destination nodes are to be selected by the user. Origin and destination nodes can be selected on the map, by selecting the “Select Node” button and then selecting nodes in the network. Nodes also can be selected by entering the node IDs in the “From” and “To” boxes. In the next step, the user specifies the desired number of shortest paths (k). Once the node selection is made and number of shortest paths (k) is specified, the shortest paths are promptly highlighted on the screen. Any changes made in the network, such as closure of certain links or reduction in link capacities are considered in finding the shortest paths. Steps to perform vehicle routing are shown in Figure 4-3. The resulting links along the shortest path and the travel time of the path also display in a tabulated format for printing or saving as an Excel file.

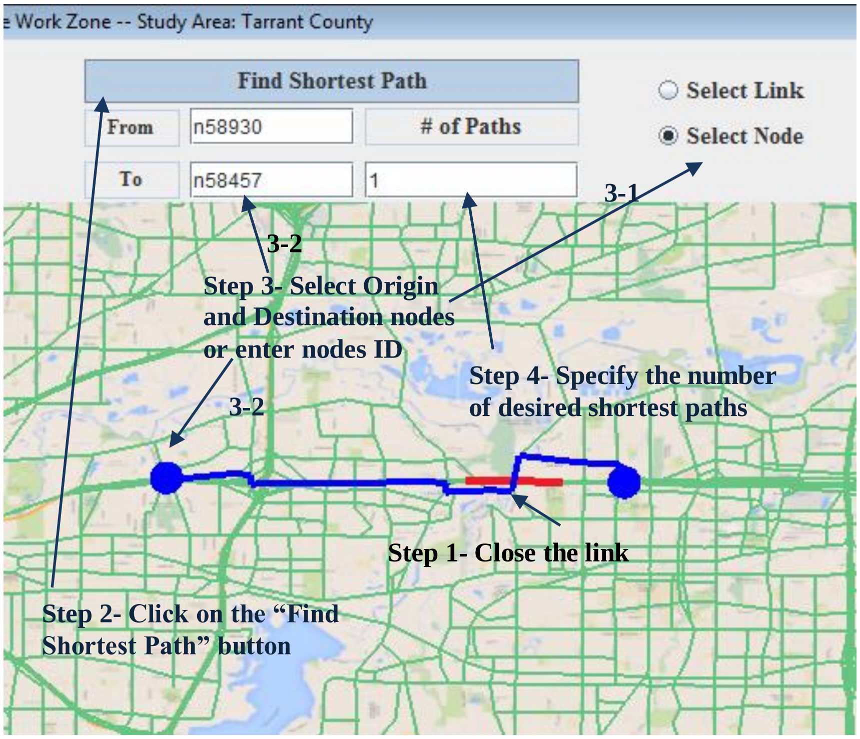

Figure 4-3. Steps to perfume Vehicle Routing module

4.4.3 Subnetwork

The subnetwork, which is defined as the affected area around the closure, is used in the traffic diversion model in TDS instead of the entire network. Defining a subnetwork around the closed links, which covers all the affected areas, helps reduce the complexity of the model and ensures that the results are achieved in a timely manner (19). Once the closed link is specified by the user, a subnetwork is displayed and extracted from the complete network by clicking on the "Draw Affected Area" button available on the link information box as illustrated in Figure 4-4. Closed links are identified and highlighted in the network by clicking on the links by the user. Therefore, a modeling framework, which was proposed in chapter 2, is used to define the subnetwork radius. The general form of the model to estimate the subnetwork radius is as follows:

$$R = A + B * AT_4 + C * d^{Ac} + D * SPT_1 + E * SPT_2 \qquad (4.1)$$

where R is the radius of the subnetwork from the middle of the closed link, AT_4 is one if the closed link is in area type 4 which is a suburban residential area and zero otherwise, d^{Ac} is the closed links traffic volume, and SPT_1 and SPT_2 are travel times on the alternate routes with the first and second lowest travel time around the closure. Parameters A, B, C, D, and E are model's coefficients with different values based on a selected significant level increase in link travel times to define the affected links in the network. Once a subnetwork is extracted, the origin-destination (OD) matrix of the subnetwork and OD matrix for the traffic on the closed links are then estimated. The process of estimating these OD matrices is explained in chapter3.

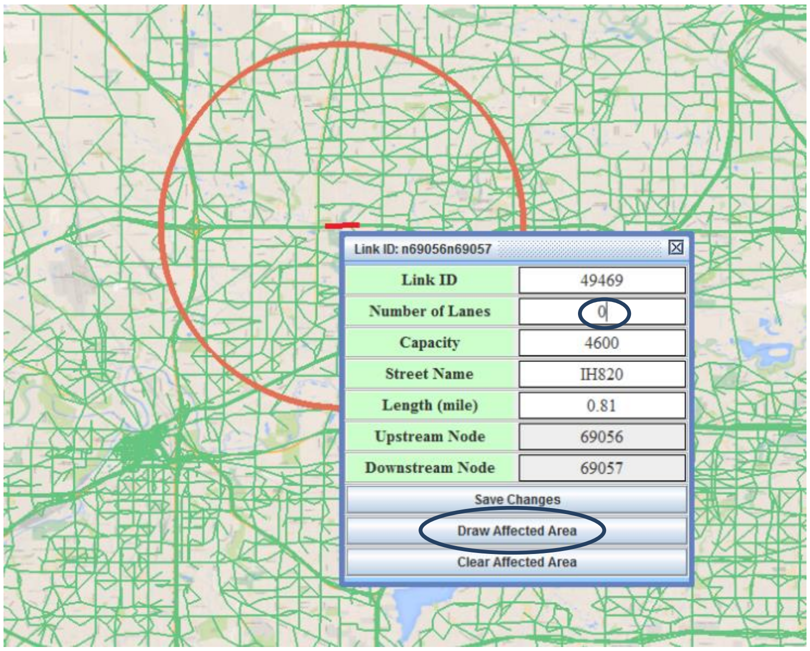

Figure 4-4. Subnetwork Extraction

4.4.4 Traffic Diversion Model

The traffic diversion model in TDS provides optimum alternate routes for the user around the closed links to divert traffic and mitigate traffic congestion. Travelers are assumed to follow their historical user equilibrium routes before the closure. Closed links are identified in the network and a subnetwork, which contains all significant affected links around the closure, is extracted from the complete network. OD matrices for the subnetwork and for the traffic on the closed links are then estimated (section 4.3). Next, the user equilibrium model assigns travelers to the routes in the subnetwork with a closed link. Links with significant increases in traffic volume after the closure are then identified. Possible alternate routes between a set of start and end nodes upstream and downstream of the closed links are considered. The alternate routes are then ranked based on the total traffic volume increases after the closure. Traffic diversion model evaluates these routes and the optimum alternate routes are proposed, which minimize the total travel time of the subnetwork. During roadway construction, when a lane or an entire freeway section must be temporarily closed, variable message signs are assumed to inform travelers of alternate routes before the closure location. A certain percentage of travelers is assumed to divert to the proposed alternate routes and others decide to divert to the alternate route of their choice based on their congestion perception (UE assignment). Traffic diversion algorithms are explained in more detail in chapter3.

To perform the traffic diversion model, first, the “Find Alternate Routes” button is to be selected by the user. On activating the diversion module, the user is asked to identify the closed links. Closed links can be selected by clicking on the links in the map or by entering link IDs in the “Impacted Link” box. The number of desired alternate routes is then specified by the user. This can be done by adding a number in the “# of Routes” box. Once these selections are made, alternate routes are promptly highlighted in the map. Traffic diversion module evaluates and recommends optimum start and end nodes for the alternate paths. However, the user can also specify the start and end nodes in the “Origin” and “Destination” boxes after activating the module. Figure 4-5 shows the steps to find the optimum alternate routes. The results are also displayed in a tabulated format and can be saved as an Excel file (Figure 4-6).

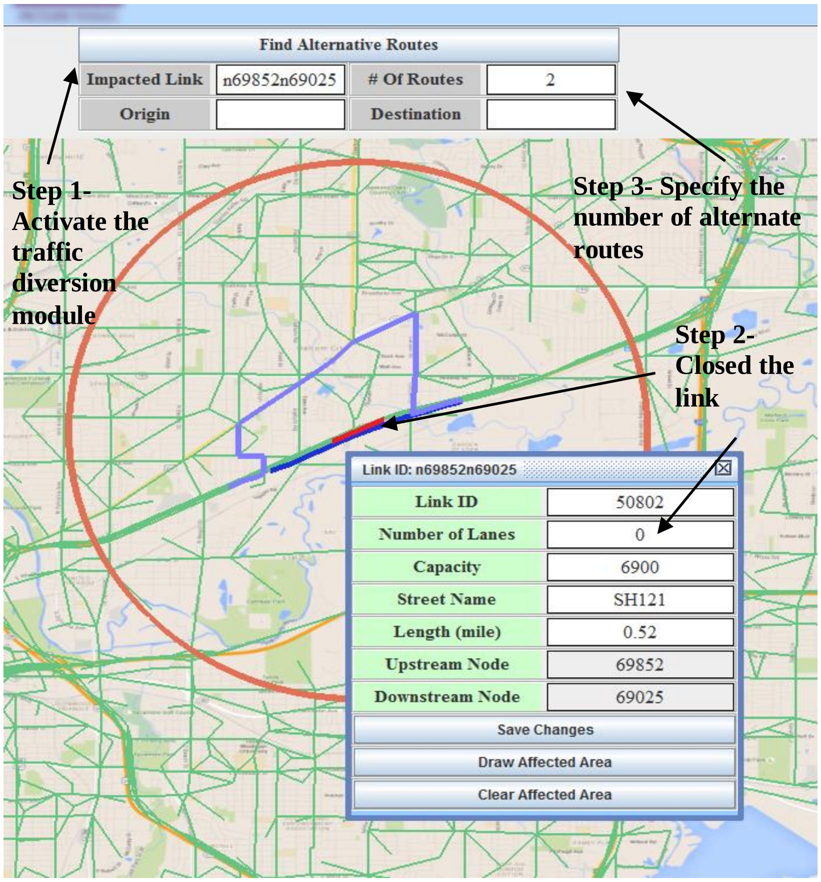

Figure 4-5. Traffic Diversion Model

Scenarios	Total Travel Time (minutes)	Route Description
Before Closure	321,642	-
Do-nothing	328,197	-
Alternate Route #1	321,603	SH121 OFFRAMP EB-SH121 FRTG EB-SH121 ONRAMP EB
Alternate Route #2	321,645	SH121 OFFRAMP EB- US377 SH183-CARSON ST-EB-SH121 ONRAMP EB

Figure 4-6. The TDS Results in the Tabulated Format

4.5 Discussion and Conclusions

The TDS package is developed in this study to generate optimum alternate routes around a disruption in the network. TDS is capable of network editing, vehicle routing (find the shortest paths between two specified nodes), defining and extracting a subnetwork around a disrupted link, and finally identifying optimum alternate routes to improve network performance (based on traffic diversion model). TDS has a high speed of execution over real size networks. This capability can be attributed to its programming language (Java), an efficient management structure, and the heuristic traffic diversion algorithms employed. Several assumptions are made in the traffic diversion methodology to simplify the model and obtain the results with a shorter computing time. For example, the deterministic user equilibrium assignment is applied for the OD demand traffic assignment before and after the closure, except for the traffic assignment on the alternate routes. In the deterministic user equilibrium assignment, it is assumed that drivers have a perfect knowledge of travel cost on each link. This assumption can be relaxed by using stochastic user equilibrium assignment. Stochastic user equilibrium considers more realistic drivers' behavior by introducing a random perception error term for the travel cost on each link. However, the use of stochastic user equilibrium will make the calculations too time consuming. To investigate the degree of accuracy of the deterministic approach, TDS results can be evaluated with results from the stochastic assignment procedure used in a planning software such as TransCAD. This evaluation can be an extension for this study.

In addition, various parameters are used in the traffic diversion methodology to identify the alternate routes. These include the size of the subnetwork, percentage of driver's diversion to alternate routes, number of start and end nodes upstream and downstream of the closed link, and the number of paths between start and end nodes. Users are allowed to change these TDS parameters in the system to try to improve the results. Therefore, another extension to this study is a sensitivity analysis on the above parameters. Sensitivity analysis allows users to identify the optimum value for these parameters to use in the model.

4.6 References

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Chapter 5. Conclusion

A decision support system is developed in this research to identify the optimum alternate routes around highway construction sites. The developed system, TDS (Traffic Diversion System), helps traffic network managers divert traffic from the disrupted area and reduce the traffic demand through the congested region. TDS's modules, models, and algorithms allow assessment of alternate routes that optimize network performance. The network editing module of TDS provides a user-friendly graphical interface for users to work easily with the system. Displaying network information, editing this information, searching for nodes or links, displaying the results in a map, and displaying and saving the results in a tabulated format are among key capabilities of this module of TDS.

Moreover, a traffic diversion model is implemented in TDS to determine the optimum alternate routes around construction activities. To simplify computations, a subnetwork is extracted from the complete network to use in the diversion model instead of the entire network. The size of the subnetwork, which covers all the significant affected links around the disrupted link, is estimated based on the modeling framework proposed in this research. Linear regression models, which are functions of the closed link demand and network topology, are developed to estimate the size of the subnetwork around the disruption. This size is defined based on the distance between the closed link and the farthest link with significant increase in travel time after the closure. The closed link's area type, traffic volume on the closed link, and travel time on the first and second alternative paths with lowest travel times are significant variables that influence the size of the subnetwork.

An optimization traffic diversion model, deployed in TDS, assesses the optimum alternate routes to improve network performance. Available alternate routes around the disrupted links are evaluated and ranked to minimize the total travel time of the network.

Travelers are assumed to follow their historical user equilibrium routes before and after the closure while a certain percentage of them is assumed to divert to the proposed alternate routes. The performance of the model is examined using a case study based on the Tarrant County network in north Texas. The application of the traffic diversion model is compared to a do-nothing scenario by a set of simulation experiments. The results show the effectiveness of the model in mitigating the traffic congestion and improving the total travel time of the network.

Several possible extensions for this study exist. A major extension is to improve the developed traffic diversion model by incorporating dynamic traffic assignment (DTA). A dynamic model interacts between network congestion and travel behavior. Traffic networks are highly dynamic with numerous sources of uncertainties on both the demand and supply sides. Travel behavior depends on the congestion conditions on the current time and it changes periodically. Therefore, travel behavior changes frequently in a traffic network due to current and non-recurrent circumstances. The proposed traffic diversion methodology would adopt a DTA model, which is relatively consistent with travelers' behavior and incorporates temporal changes in the demand and supply in the traffic network.

Another extension to this study is to evaluate the TDS results with the results from a planning software such as TransCAD. The degree of accuracy of the results can be estimated with comparing the deterministic approach that is used in TDS with a stochastic assignment procedure in TransCAD. Stochastic user equilibrium considers more realistic drivers behavior by introducing a random perception error term for the travel cost on each link, however, it makes the calculations too time consuming. Sensitivity analysis on the model's parameters could be another extension to this study. The size of the subnetwork, percentage of drivers diverting to alternate routes, number of start and end nodes upstream and downstream of a closed link, and number of paths between start and end nodes are parameters that TDS does allow the user to change to improve the results. Finally, more experiments can be used to improve the proposed regression models to estimate the size of the subnetwork. Volumes in other peak periods such as AM peak and off peak can also be considered to select the closed link samples to develop these models more generally.