ABSTRACT

Title of Document: A HEURISTIC FOR ROUTING HAZMAT TRANSPORT GIVEN REAL-TIME WEATHER AND TRAFFIC INFORMATION

Minseok Kim, Master of Science, 2006

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This paper addresses the problem of updating routing instructions for the transport of hazardous materials given real-time road weather and traffic information. A heuristic is proposed that explicitly considers the inherent multiobjective and dynamic nature of the problem and the need to produce updated instructions on-line. It is tested on the transportation network in the District of Columbia metropolitan region, where real-time data are received in a GIS environment. Solutions are compared to the *a posteriori* paths that could have been chosen if one could know future weather and traffic conditions exactly *a priori*.

A HEURISTIC FOR ROUTING HAZMAT TRANSPORT GIVEN REAL-TIME WEATHER AND TRAFFIC INFORMATION

By

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Thesis submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Master of Science
2006

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Chapter 1: Introduction

Access to real-time traffic and weather information along highways has increased substantially over the last decade. The ability to reroute a vehicle carrying hazardous materials (hazmat) given real-time information is crucial to avoid unexpected delay or adverse weather that could lead to increased risk of accident. That is, wet pavement or restricted visibility increases the probability of en-route hazmat accident.

If an accident causes a hazmat release or explosion, it can have catastrophic repercussions for society. This thesis addresses the problem of determining updated routing instructions to drivers of hazmat vehicles given real-time traffic and weather data and multiple objectives. Two objectives are considered: minimize travel time and minimize the potential consequence of a hazmat accident. The potential consequence that might result from a hazmat accident is referred to herein as the risk of the hazmat transport. It is assumed that risk is additive along arcs within a path. Risk along each arc in a network is computed by the product of: 1) the conditional probability of a hazmat accident given existing pavement and visibility conditions, 2) the conditional probability of a hazmat release given an accident, and 3) population exposure to a hazmat release. Risk and travel time are recalculated as real-time weather and traffic data are received.

Ideally, the set of Pareto-optimal paths that arise as the incoming real-time data is integrated with the network would be generated and a single best-compromise path would be chosen. However, generating all Pareto-optimal paths requires significant computational effort. A much quicker approach to updating the path is required for use on-line. In this thesis, a heuristic is proposed. The proposed heuristic employs a linear additive utility function, reducing the multiobjective problem to a single objective problem. Without loss of generality, each criterion is given equal weight. The technique uses the real-time information only within a neighboring area (NA) of the vehicle's current location while en-route.

The proposed heuristic seeks a pair of contiguous subpaths such that disutility is minimized within a neighboring and a non-neighboring area (NNA) of the vehicle's current location. Current traffic and weather conditions are employed only within the NA. First a least disutility subpath from the boundary of NA to a destination is found in NNA. A least disutility subpath from a current location to the boundary of NA is found then in NA. This procedure is iterated until the vehicle arrives at a destination.

A case study is conducted on a region including the District of Columbia (D.C.), Northern Virginia, and Maryland. This region is referred to as the D.C. metropolitan region. See Figure 1.1. In the case study, it is presumed that a hazmat

Figure 1.1 The District of Columbia (D.C.) Metropolitan Region

shipment of chlorine gas is to be made. Actual real-time traffic and weather data are collected for a 2 hour time period from 9:30 p.m. to 11:30 p.m. on July 12th, 2005. During this time, a thunderstorm passed through the study area. A geographic information systems (GIS) platform, ESRI's ArcGIS 9.1, is used to emulate the real-time road weather advisory system and implement to the heuristic. Traffic and weather data collected from traffic detectors and weather stations are streamed in to the transportation network in the study area.

The *a posteriori* least disutility path is determined based on realized traffic and weather condition information. Such a path provides a benchmark as it is the best path that one could have chosen, i.e. the path that would be chosen if one could know future conditions exactly *a priori*. To solve for this path, the Time-Dependent Least Time Path (TDLTP) algorithm, developed by Ziliaskopoulos and Mahmassani (1993), was modified and was applied using network states obtained from real-time weather and traffic data. A network state herein is defined as a joint realization of travel time and risk. The solutions obtained by the heuristic as used on-line were compared with the *a posteriori* solutions for several shipments, each originating at different locations and headed for different destinations. The heuristic solutions were also compared with the *a priori* solutions. *A priori* solutions assume ideal weather and traffic conditions or use the information present at time of departure.

The primary contributions of this thesis are the development of a heuristic that can quickly provide updated routing instructions to hazmat trucks in real-time considering current traffic and weather conditions, emulation of the real-time road weather advisory system in a GIS environment, and a methodology for integrating and using publicly existing real-time information. The methodologies developed herein are intended for use in actual operations centers.

1.1 Background

Quicker and safer routes can be provided to hazmat drivers by updating routing instructions given real-time weather and travel information. Official statistics (i.e., USDOT, 1998 and USDOT, 2004) show that trucks are carrying a significant portion of total daily hazmat shipments in the United States and most hazmat incidents occur along highways. In determining the optimal route of hazmat trucks, recent studies (e.g., Miller-Hooks and Mahmassani (1998) and Chang et al. (2005)) promulgate the significance of a real-time routing approach over static approaches. Some researchers (e.g., Saccomano and Chan (1985), Karkazis and Boffey (1995), and Brown and Dunn (2005)) emphasize weather impacts on risk of a hazmat accident. In this thesis, both a real-time routing approach and weather impacts on risk are explicitly considered.

1.1.1 Hazmat Shipments and Hazmat Incidents in the United States

The United States Department of Transportation (USDOT, 1998) estimates that approximately 94% of all daily hazmat shipments are shipped by truck. Table 1.1 shows the modes of transport used to ship hazardous substances. Moreover, the USDOT (2000) reports that the total tons of hazmat produced are growing by 2% per year. As society produces greater quantities of hazmat, the number of shipments is expected to continue to increase. Approximately 90% of all reported incidents in 2003

Table 1.1 Daily Hazmat Shipments by Mode (USDOT, 1998)

Mode	No of Daily Shipments	% of Total Daily Shipments
Truck	768,907	93.98%
Air	43,750	5.35%
Rail	4,315	0.53%
Pipeline	873	0.11%
Water	335	0.04%
Total	818,180	100%

Table 1.2 Annual Hazmat Incidents in U.S. by Mode (USDOT, 2004)

Mode	No. of Annual Incidents	% of Total Annual Incidents
Truck	13,595	89.6%
Rail	813	5.4%
Air	753	5.0%
Water	10	<0.01%
Total	15,171	100%

occurred along highways (USDOT, 2004). Table 1.2 shows the number of hazmat incidents reported in 2003 by mode.

The greatest concern of hazmat transport is the potential for a catastrophic event involving the shipment, as might occur should there be an accident leading to a release or explosion. Such an event could cause tremendous damage to society and could involve multiple fatalities, serious injuries, large-scale evacuations, and could require significant clean-up effort. For example, at 2:45 p.m. on Tuesday, January 13, 2004, a fuel tanker traveling south on Maryland’s I-895 (the Harbor Tunnel Thruway) veered off the overpass and landed on the northbound lanes of I-95 just south of Baltimore. The explosion involved 8,000 gallons of gasoline. The crash shut down I-95 in both directions for more than nine hours and took four lives (Buck et al., 2004).

Among hazmat incidents that occur along highways, an accident that results from a collision is of most concern to the trucking industry, because of the average cost per incident. See Table 1.3. Abkowitz et al. (2001) classified hazmat incidents by the level of transport activities using 10 years of truck incident data for the period of 1990-99 contained in the Hazardous Materials Information System (HMIS) and the Motor Carrier Management Information System (MCMIS).

Table 1.3 Costs Due to Hazmat Incidents in U.S. Highways (Abkowitz et al., 2001)

Incident Type	No. of Annual Hazmat Incidents	Total Costs of Annual Hazmat Incidents ($)	Avg. Costs of Annual Hazmat Incidents ($/incident)
En-route Accident with a release	767	415,761,858	541,609
En-route Accident without a release	1,716	616,009,408	363,377
En-route leak	1,455	72,057,730	49,524
Loading/unloading	10,746	53,466,672	4,975

1.1.2 Hazmat Shipments and Hazmat Incidents in the United States

The determination of optimal routes for trucks carrying hazmat has received significant attention in the literature. Recent studies by Sulijoadkusumo and Nozick (1998), Miller-Hooks and Mahmassani (1998), Haghani and Chen (2003), and Chang et al. (2005) address the importance of capturing time-dependent, dynamic, or stochastic problem elements that exist in the real-world transportation system in determining a path for a hazmat truck. A comprehensive review of the studies related to routing with multiple objectives, time-varying, stochastic network attributes, can be found in Chang et al. (2005). This thesis differs from these other studies in that actual real-time data are employed to capture changes in traffic and weather conditions. Most of the earlier literature, such as List and Mirchandini (1991) and Ashtakala and Eno (1996), considers only static network attributes. List et al. (1991) provides insights into static approaches with respect to risk analysis, as well as routing and scheduling of hazmat transport.

The topic of a real-time routing model for hazmat transport was pioneered by Beroggi (1994). Beroggi's approach is distinguished from a utility approach used in this thesis, in that risks and transportation costs are expressed as preferences on an ordinal scale. A human dispatcher is assumed to assess the impact of real-time events on risk and transportation cost. The dispatcher chooses the safest and most cost-effective alternative. Through an experimental setting, the author concluded that the ordinal preference model was more robust than a utility approach in the context of risk assessment and route selection. However, the performance of the ordinal preference model relies on the subjective judgment of a human dispatcher and, thus, the performance of the system may vary considerably from dispatcher to dispatcher.

The idea of applying real-time data only within a neighboring area was also employed in Miller-Hooks and Yang (2003). The authors tested a real-time routing framework with respect to three models for the arc travel time: the deterministic and time-invariant (DTI) network model, the deterministic and time-varying (DTV) network model, and the stochastic and time-varying (STV) network model. They validated that when the STV approach was employed, the routing decisions based on the information from only a small neighborhood around vehicle's current location were as good or nearly as good as decisions based on network-wide information. A similar approach is used herein and is extended for multiple attributes; specifically, travel time and risk.

The proposed heuristic also relies on concepts of the multiobjective A* (MOA*) algorithm (Stewart and White, 1991). The MOA* algorithm employs a similar concept to that employed herein. In the MOA*, actual arc costs are used to determine the next arc to traverse from a current location. A nondominated next arc outgoing from a current location is selected. A next arc outgoing from the selected arc or one of the unselected arcs, is added arbitrarily such that the cost of the accumulated path from the origin to that arc is nondominated. This procedure is repeated until all Pareto-optimal paths are found from the origin to the destination. The utility of MOA* is limited to small static networks, because finding all Pareto-optimal paths requires enormous computational effort.

GIS tools have been used by numerous researchers to support calculation, comparison, and visualization of the attributes associated with alternative routes. Miller and Shaw (2001) provide a brief review of relevant studies, including review of Lepofsky and Abkowitz (1993), Souleyrette and Sathisan (1994), and Brainard et al. (1996). The spatial decision support system (SDSS) developed by Frank et al. (2000) provided a graphical user interface for generating routing instructions. However, the SDSS sets changes in accident rates and link travel speeds by time of day based on historical data without employing real-time information.

1.1.3 Weather Impacts on Risk of Hazmat Transport

Weather can greatly affect the potential risk of incident in the transport of hazmat, because the accident rate of hazmat trucks is affected by roadway surface conditions and visibility. In the case of a release involving airborne hazmat, a measure of exposure to risk (i.e., population exposure) is affected by wind velocity or temperature. In addition, extreme weather conditions, such as heavy snow, hurricanes, thunderstorms, and tornados, can damage the transportation infrastructure requiring updated routing assistance.

Saccomano and Chan (1985) estimated conditional accident probabilities of heavy trucks given road class, pavement conditions, and visibility restrictions using heavy truck accident profiles in the Toronto area. Table 1.4 summarizes the resulting estimates. Wet pavement and restricted visibility lead to higher accident rates, especially where design speeds are higher. These rates are employed in assessing risk given weather conditions in the case study involving the D.C. metropolitan region. Estimation of risk using these rates is described in Chapter 2.

Table 1.4 Conditional Truck Accident Probabilities (Saccomano and Chan, 1985)

Conditions	Probability ($\times 10^{-6}$)	
	B	D
Dry pavement		
Unrestricted visibility	2.744	1.478
Restricted visibility	1.779	2.519
Wet pavement		
Unrestricted visibility	1.895	1.728
Restricted visibility	1.737	2.740

Note: B = arterial/collectors, Speed is higher than 31.3mph (or 50km/h)
D = expressways, Speed equals to 62.5mph (or 100km/h)

Karkazis and Boffey (1995) examined the airborne effects from the emission of pollutants that could contaminate relatively large geographical areas. A Gaussian-based pollutant dispersion model was used for representing the nuisance effects due to an accident in the presence of wind velocity. Similarly, Brown and Dunn (2005) presented a method to evaluate distances over which the public should be protected in the event of a hazmat release involving inhalation hazard. In this thesis, the impact range of a hazmat release is fixed at 5 miles from each link, as adopted by Lepofsky and Abkowitz (1993).

1.2 Working with Real-time Data

A case study involving the D.C metropolitan area is conducted. The road network in this region consists of major highways such as interstate, US, and state highways. Publicly existing real-time traffic data was collected every five minutes. Weather data was collected hourly. Arc travel times and risks must be recalculated as real-time traffic and weather data are updated. While real-time weather data are available for the entire region, real-time traffic data are provided along some segments of the major interstate highways. Real-time traffic data include total traffic volume and average spot speed estimated from each traffic detector for 5 minutes. Some arcs have a single detector along them and others have multiple detectors. Unlike traffic detectors, weather stations are scattered over the study area. Available weather data include atmospheric conditions, visibility, temperature, wind velocity, and so on. Time-dependent population data, which account for variations due to commuting trips for work, are also available by traffic analysis zone to estimate population exposure to a

Table 1.5 Data Sources Selected in the Case Study

Data Type	Data Source	Data Format
Road network	Major highways network, United States Geological Survey (USGS)	GIS shape file
Population	Census Transportation Planning Package 2000 (CTPP 2000)	GIS shape file
Real-time Weather data	AccuWeather, Inc.	GIS streaming data
Real-time Traffic data	Coordinated Highways Action Response Team (CHART) in Maryland State Highway Administration (SHA)	Text file

hazmat release. Table 1.5 contains the data sources employed in the case study. Integration of the real-time data with the network is required. Detailed descriptions of these data sources and the integration process are provided in Chapter 2.

As the hazmat truck travels and real-time data is obtained, the network state must be updated. This requires recalculation of arc travel times and risks while the vehicle is in route. It is assumed that the network state remains unchanged until the next update.

1.3 Contributions

To emulate real-time road weather advisory system and to support visualization and spatial analysis of a large problem involving real-time data, GIS tools are applied to process a variety of data resources. This thesis demonstrates the procedures to integrate publicly existing real-time data with the transportation network in a GIS environment, specifically an ArcGIS 9.1 Desktop software platform. Through the experience of integrating real-time data from multiple sources, methods for simplifying the integration process and relating databases are discussed. A heuristic is proposed that runs in ArcGIS 9.1 using Model Builder and Network Analyst extension. Model building procedures to implement the proposed heuristic are introduced.

Solutions obtained on a case study show that good routing instructions for hazmat trucks can be provided accounting for updated weather and traffic conditions only within a neighboring area of current location as compared to the a posteriori routes. Solutions obtained for different update intervals, i.e., 5 minutes, 10 minutes, and 20 minutes, indicate that the solution quality can be improved by generating updated instructions frequently. Moreover, by comparing the quality of heuristic solutions with that of the a priori solutions, the benefit of using real-time weather and traffic information to update routing instructions for hazmat transport is verified.

1.4 Organization

In the following chapter, the integration process of time-dependent population data and real-time traffic and weather data with the transportation network is provided. Data sources, the study network, and calculations of link attributes (i.e., travel time and potential risk) are described in detail. In Chapter 3, the routing heuristic is proposed and the methodology for obtaining the *a posteriori* solution is described. The experimental design used in assessing the heuristic is presented in Chapter 4. The solution quality of the heuristic solution was evaluated through comparison to the *a posteriori* solution and a best updating interval is suggested. The impact of real-time information on routing decisions is assessed by comparison between the heuristic and *a priori* solutions. Finally, findings from the case study and future considerations are summarized in Chapter 5.

Chapter 2: Data Integration with the Transportation Network

This chapter provides a detailed description of the data sources used in, and the processes required for, data integration. The provision of real-time road weather information is emulated using a combination of four data resources: 1) transportation network data, 2) population data, 3) real-time traffic data, and 4) real-time weather data. Data sources are chosen for their compatibility to aid in routing hazmat trucks or capturing changes in population, traffic, or weather conditions in the study region over time. ESRI's ArcGIS 9.1 software was used as a platform for integrating the network data with other data. Data integration processes were developed given properties (i.e., file format and update interval) of the data resources and the roles they each play in assessing link attributes (i.e., travel time and risk).

2.1 Data Source

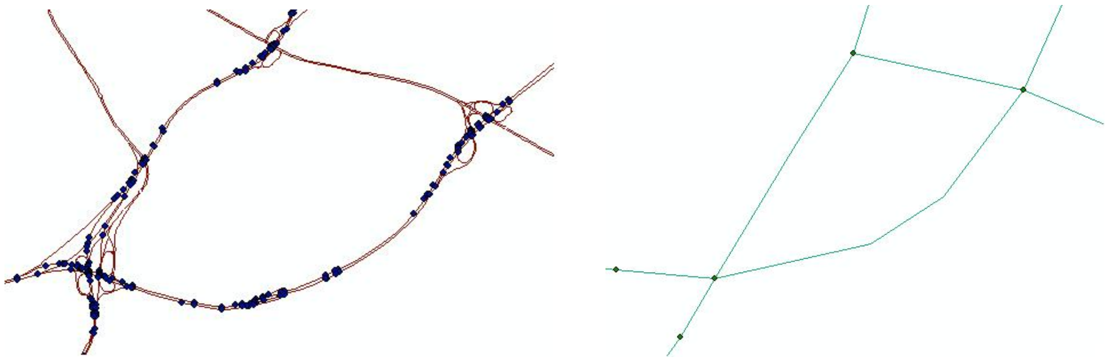
Publicly existing population data and real-time traffic and weather data for the study area were stored in a GIS transportation network. The integrated GIS transportation network includes the major freeways that can be used to carry hazmat within the study area, along with network attributes, including population, weather and traffic characteristics, along these roadways. Population and weather data play a significant role in risk assessment. Traffic data contributes to the estimation of link travel times. Estimates of link travel times are made from spot speeds and traffic volumes collected from traffic detectors.

2.1.1 GIS Transportation Network

There are numerous potential sources of GIS data that are provided by public agencies (e.g., Census 2000 TIGER/Line Data) and private companies (e.g., GDT Dynamap). Many of these data sources have been developed with high resolution to support georeferencing functions (i.e., address-matching). Their line features consist of relatively short road segments, making the data amenable for use in routing vehicles. However, hazmat trucks can only travel on certain types of roads, including interstate, U.S. and state highways. In selecting a route for a hazmat truck, a very detailed road network, with local streets, may not be required. While such detailed data can be very useful for matching locations on a map or providing directions for passenger cars, the added computation time required to work with such detailed maps is not warranted for use in this context. Thus, GIS data with lower resolution (i.e., major roadway data from the U.S. Geological Survey (USGS)) would be preferred.

Two sources of roadway data were considered for use in creating the study transportation network: USGS data GDT Dynamap. Since USGS data are intended for geographic display and analysis at the national level and for large regional areas. This data provide attributes related to interstate, U.S., and state highways, but excludes data related to local streets. In GDT Dynamap, roadway segments contain nodes where two segments are not intersecting each other; whereas, in a USGS network, nodes only exist where two roadways intersect.

For the purpose of matching locations on the map, a network with high resolution can provide more precision than a network with low resolution. From the perspective of routing a hazmat truck, however, nodes do not need to be placed where a truck cannot make a change in direction. Therefore, the USGS network is selected



(a) GDT Dynamap (b) USGS Network

Figure 2.1 GDT Dynamap vs USGS Network

for use in this work. Figure 2.1 shows the difference between GDT Dynamap and USGS data in terms of resolution.

The Washington D.C. metropolitan region network, consisting of major (interstate, U.S., state) highways, was extracted from the USGS data set. The network is composed of 587 undirected links and 382 nodes as shown in Figure 2.2. The link

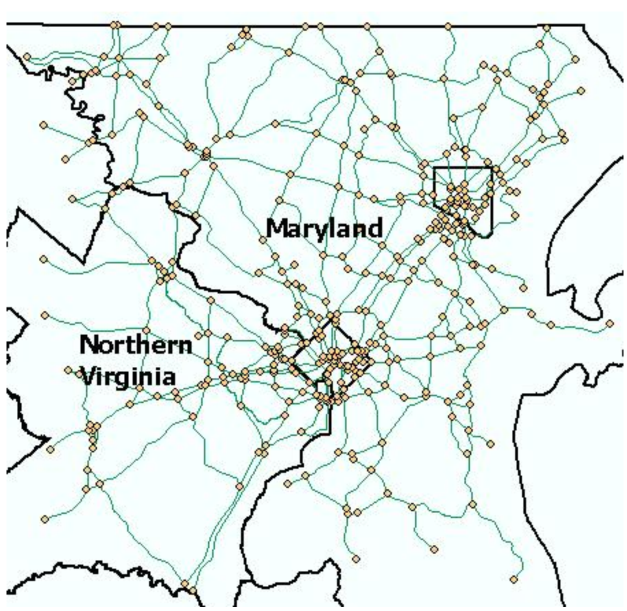


Figure 2.2 Washington D.C. Metropolitan Region Network (USGS Data)

attributes of the extracted network, including end node IDs, road names, road classification, and length, as they appear within the GIS platform, are presented for the first five links in Figure 2.3. Network attributes for routing a hazmat truck are represented by adding columns (or fields) corresponding to population, traffic and weather conditions to the attribute table as shown in Figure 2.3.

Attributes of Network

OBJECTID*	Shape*	FNODE_	TNODE_	MILES	FEATURE	NAME	STATE
1	Polyline	10744	10600	2.86	Other Highway	State Route 1	MD
2	Polyline	10773	10600	7.58	Other Through Highway	State Route 1	MD
3	Polyline	10966	10773	6.71	Principal Highway	US Route 1	MD
4	Polyline	10966	10744	6.65	Other Highway	State Route 5	MD
5	Polyline	10974	10744	8.7	Other Highway	State Route 1	MD

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Figure 2.3 Link Attributes of the Extracted Network (USGS Data)

Note that there are restricted links and preferred (i.e. government suggested) routes for hazmat transport in the study area. Three links, marked “x” in Figure 2.4,

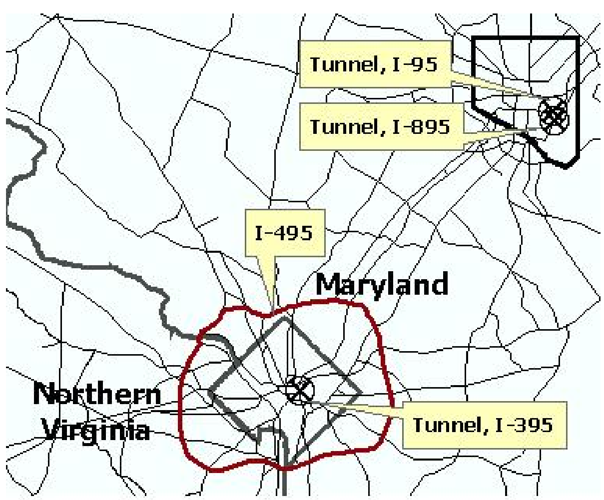


Figure 2.4 Restricted Links and a Designated Route for Hazmat Transport (NHMRR)

represent tunnels in the District and the City of Baltimore. These tunnels are restricted for hazmat transport by the National Hazardous Material Route Registry (NHMRR). On the other hand, Interstate Highway 495, a beltway that goes around the District, is suggested over other highways. This study considers three restricted links in selecting a path. The preferred routes are not explicitly applied in this work.

2.1.2 Population Data

In this thesis, population exposure to a hazmat release given an accident is the principal measurement used in estimating the risk imposed on society from hazmat transport. Changes in potentially affected population by time of day are explicitly considered. Estimation of changes in population by time of day is possible using the Census Transportation Planning Package 2000 (CTPP 2000) data. The CTPP consists of three parts that summarize information by place of residence, place of work, and worker-flows between home and work. Tables, including the number of residents (table #1-047), the number of people leaving home to go to work (table #1-001), and the number of people arriving at work (table #2-001), were extracted from part 1 and 2 by traffic analysis zone (TAZ).

Figure 2.5 illustrates the process required to extract a table of the number of people leaving home to go to work from the CTPP 2000 (part 1). Time is split into 40 time periods with 15-minute, 1-hour, and 5-hour intervals of time for three time frames: 5:00 a.m.-10:00 a.m., 10:00 a.m.-12:00 a.m., and 12:00 a.m.-5:00 a.m., respectively. Since, real-time data were collected from 9:30 p.m. to 11:30 p.m. in the case study, hourly population data between 9:00 p.m. and 12:00 a.m. were used.

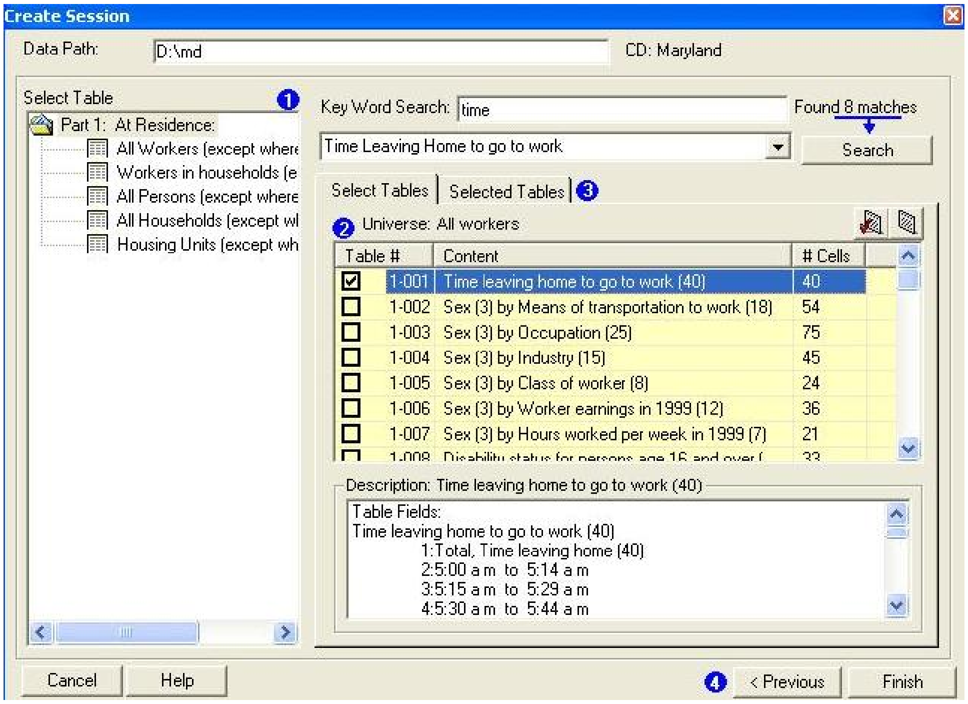


Figure 2.5 Data Extraction from CTPP 2000 (Part 1, Table #1-001)

Population is estimated by adding the number of residents to the difference between the number of people leaving home and the number arriving at work by TAZ. It is assumed that work places are not located within the same TAZ as the residential area for each individual. Changes in population due to other trip purposes, such as shopping and school, are not captured in the CTPP 2000 data. In this study, it is assumed that population changes due to such trips are negligible.

2.1.3 Traffic Data

CHART (Coordinated Highways Action Response Team) provides real-time traffic data along major interstate highways in Maryland. Figure 2.6 shows the locations of radar traffic detectors along the links in the study area. Traffic detectors collect data on traffic volume and spot speed every 5 minutes. The Center for Advanced

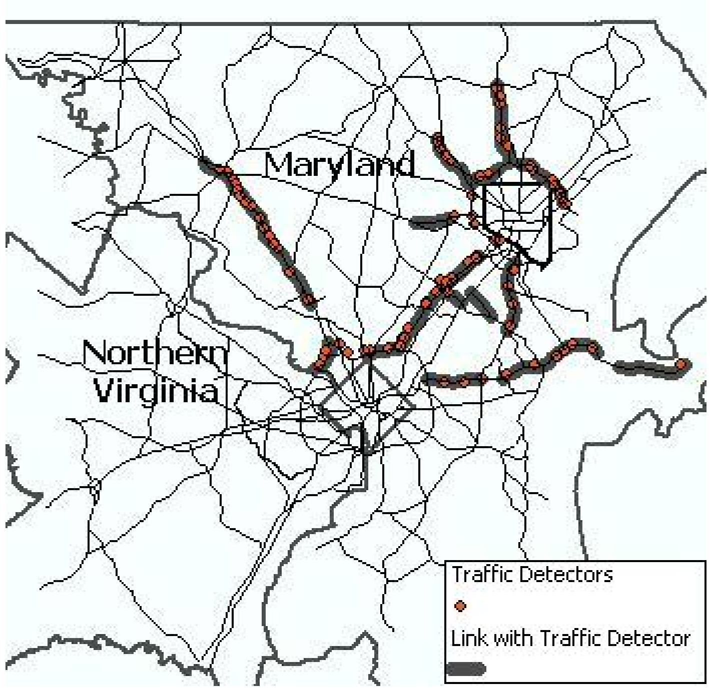
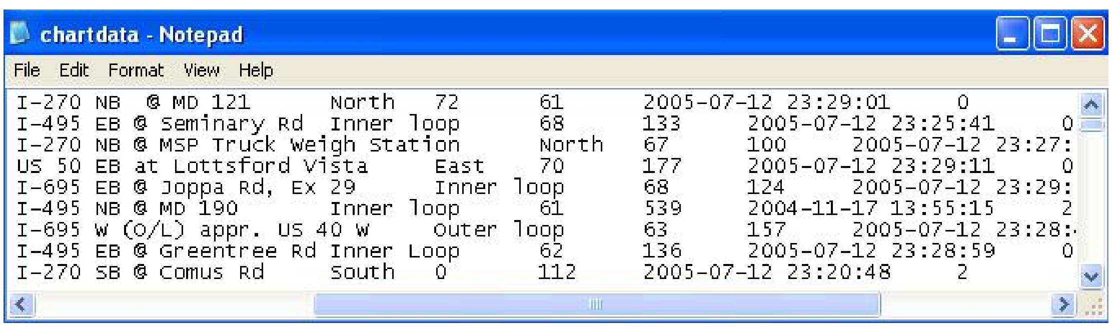


Figure 2.6 Locations of Traffic Detectors



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I-270 NB  @ MD 121        North   72      61      2005-07-12 23:29:01     0
I-495 EB @ Seminary Rd  Inner loop      68      133     2005-07-12 23:25:41     0
I-270 NB @ MSP Truck Weigh Station      North   67      100     2005-07-12 23:27:
US 50 EB at Lottsford Vista     East    70      177     2005-07-12 23:29:11     0
I-695 EB @ Joppa Rd, Ex 29      Inner loop      68      124     2005-07-12 23:29:
I-495 NB @ MD 190       Inner loop      61      539     2004-11-17 13:55:15     2
I-695 W (O/L) appr. US 40 W     Outer loop      63      157     2005-07-12 23:28:
I-495 EB @ Greentree Rd Inner Loop      62      136     2005-07-12 23:28:59     0
I-270 SB @ Comus Rd     South   0       112     2005-07-12 23:20:48     2
```

Figure 2.7 CHART Traffic Data

Transportation Technology (CATT) at the University of Maryland manages database systems for CHART. To support this study, CATT provided real-time traffic data every 5 minutes from their server into a personal ftp account in a text format. The text file provides the location, traffic volumes, spot speeds, last update time, and a reliability index (0 for good and 2 for bad) for each detector ID, as captured in Figure 2.7.

2.1.4 Weather Data

Two data sources were considered as sources of real-time weather information: Road Weather Information System (RWIS) managed by CHART and AccuWeather service provided by AccuWeather, Inc.

RWIS data are usually updated every 10 minutes and weather stations are located along highways. However, RWIS data could not be used in this thesis, because there are restrictions on obtaining the data in real-time. Only historical weather data is available for Maryland. Moreover, information on visibility is missing at many weather stations.

Real-time weather data are also available through the web-based data streaming service of AccuWeather, Inc. AccuWeather data are provided in a GIS layer format that can be directly imported into ArcGIS. The layer contains data on the current weather conditions of each weather station. Weather stations are scattered in all directions over the study area as shown in Figure 2.8. Temperature, wind velocity,

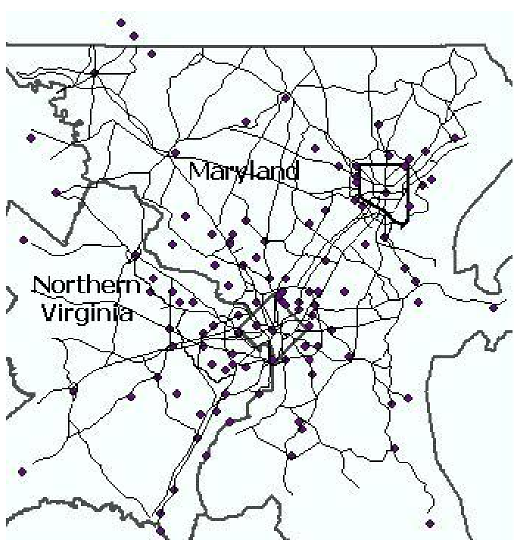

Figure 2.8 Locations of Weather Stations

Attributes of Weather at 0930PM, July 12, 2005

OID	StationID	Latitude	Longitude	Atmosphere	Visibility	Temparatur	WindDirec	WindSpeed
0	2G4	39.42	-76.88	P/CLOUDY	9	86	SW	5
1	5VA5	38.3	-77.46	CLEAR	10	86	CLM	0
2	MD09	38.67	-76.59	CLOUDY	7	81	SSE	4
3	MD10	39.39	-76.52	P/CLOUDY	6	84	N	4
4	MD11	39.34	-76.72	M/CLOUDY	12	87	SSW	5

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Figure 2.9 AccuWeather Data

atmospheric status (i.e., rain, thunderstorm, fog, haze, clear, etc.), and visibility are included. See Figure 2.9. This data is available on a nationwide scale, but unfortunately is updated only hourly. For lack of a better alternative, the AccuWeather data were used in this study.

2.2 Data Integration

The first task in preparing the network representation for the study area is to extract the transportation network from USGS GIS data set. The network must then be integrated with the CTPP 2000 population data, CHART traffic data, and AccuWeather data. This section describes how the data were combined from their multiple sources within a GIS platform through an integration process consisting of three phases.

In the first phase, the population data were integrated with the topological network by associating each link with the population along that link (extracted from TAZ) within a 5-mile radius of the vehicle's location. In this study, the affected range of a hazmat release is assumed to be 5 miles from the location of an accident, as discussed in Lepofsky and Abkowitz (1993) and Chapter 1. In the second phase, real-time traffic data was downloaded from an ftp account every 5 minutes from 9:30 p.m. to 11:30 p.m. on July 12th, 2005, when a thunder storm passed through the study region. Link travel speeds were calculated from the downloaded data. Travel times were calculated using link travel speeds and link lengths. In the third phase, current weather conditions (e.g., atmospheric status and visibility) for the same 2-hour time period were integrated with the network by assigning each link to the closest weather station from the mid-point of the line feature. Network attributes of atmospheric status and visibility were used to determine the conditional probability of a hazmat accident given weather conditions, as presented by Saccomano and Chan (1985). Risk was calculated using this conditional probability, the conditional probability of a hazmat release, and population exposure. Additional details concerning these three phases of the data integration process are given next.

2.2.1 Integration of Population Data

As discussed in section 2.1, the number of residents (table #1-047), people leaving home to go to work (table #1-001), and people arriving at work (table #2-001) in the study area were extracted from the CTPP 2000 data on a GIS layer format. While the number of residents does not change over the period of study, the number of people leaving for work and those arriving at work vary by time of day. The actual population remaining within each TAZ was calculated by adding numbers in table #1-047 to the difference between those in table #1-001 and table #2-001 for each time period for each relevant TAZ. Since the spatial scope of data extraction in CTPP 2000

Attributes of PopulationByTAZ

FID	Shape	LONGLAB	AM500	AM515	AM530	AM545	AM600	AM615	AM630	AM645
0	Polygon	TAZ 51510:430A0	1790	1830	1870	1915	1855	1920	1885	2050
1	Polygon	TAZ 51510:430B0	1945	1945	1970	1945	1920	2000	2015	2005
2	Polygon	TAZ 51510:430C0	1690	1695	1710	1755	1670	1710	1700	1816
3	Polygon	TAZ 51510:430D0	1855	1829	1830	1840	1765	1840	1840	1810
4	Polygon	TAZ 51510:430E0	1395	1395	1360	1391	1365	1395	1315	1360

Record: 1 Show: All Selected Records (0 out of 5475 Selected.) Options

Figure 2.10 Populations by TAZ

is limited by state, this procedure was repeated for Northern Virginia, the District, and Maryland. These data were then combined using the merge function in ArcGIS. Figure 2.10 presents the resulting populations of the first five TAZs for the time periods split in subsection 2.1.2. There are 5,475 TAZs in the study area as shown in Figure 2.11. Population density by TAZ is presented in Figure 2.12 for one of the time periods, i.e. from 9:00 p.m. to 10:00 p.m. Urban areas around the District and the City of Baltimore show higher density than other areas.

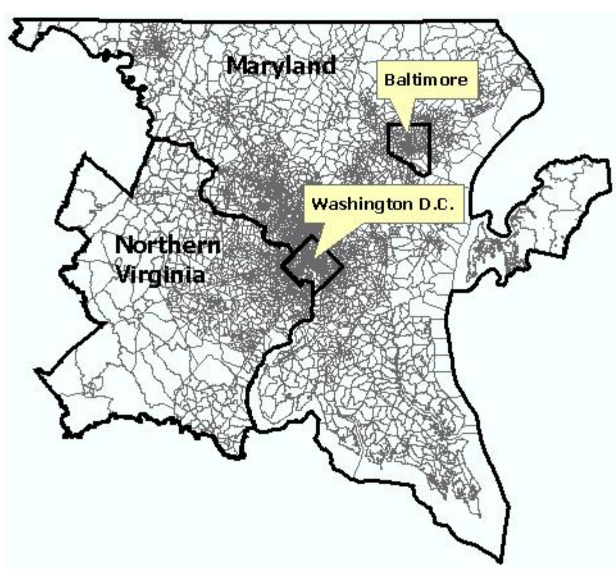


Figure 2.11 Traffic Analysis Zone

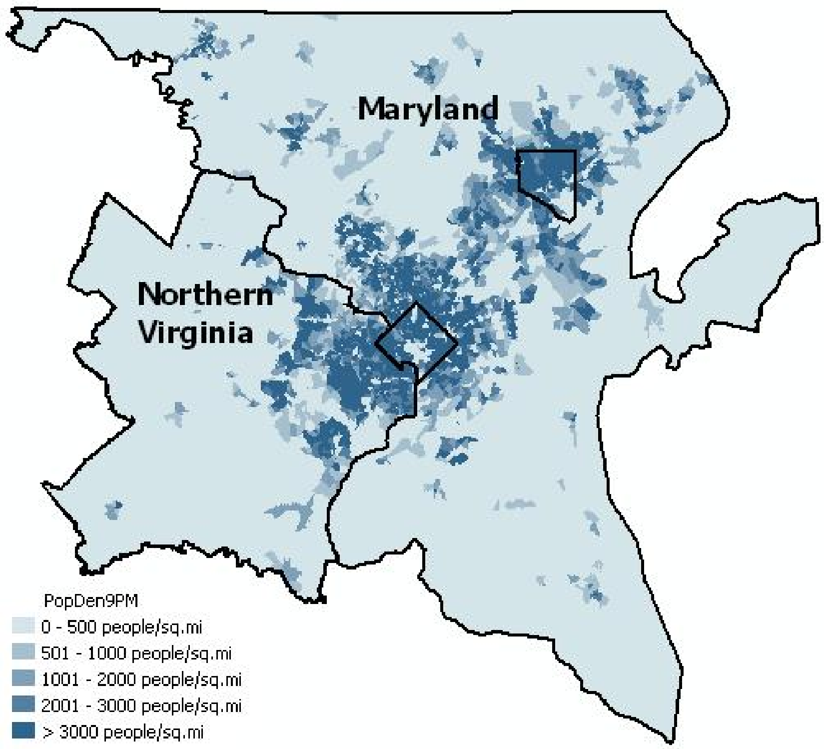


Figure 2.12 Population Density by TAZ (9:00 p.m.-10:00 p.m.)

To associate the affected populations by TAZ with links in the network, TAZs within 5 miles of each link were grouped, as discussed previously. One might consider a more sophisticated model of the impact area in the event of an airborne release, where the direction and the speed of wind significantly affect the size and the spatial distributions of the impact area (Karkazis and Boffey, 1995).

The buffering function in ArcGIS was used in identifying TAZs affected by a hazmat release, i.e. the impact area. Those TAZs whose centers are located within the 5-mile buffer of a link are considered to be within the impact area. It is recommended that the shape of buffer be chosen as flat, which creates rectangular line endings coincident with the end point of the link. A round type of buffer may result in double counting of populations in buffers when considering the population along multiple consecutive links. Frank et al. (2000) pointed out this issue in their study, as well.

Figure 2.13 shows 5 miles of flat buffers over the network and an example of two buffers of adjacent links. Total population in the TAZs whose centers are within the 5- mile buffer, is associated with the corresponding link of each buffer. Network attributes, integrated with population in an impact area, are presented for the first five links in Figure 2.14 for the time period between 9:00 p.m. and 10:00 p.m.

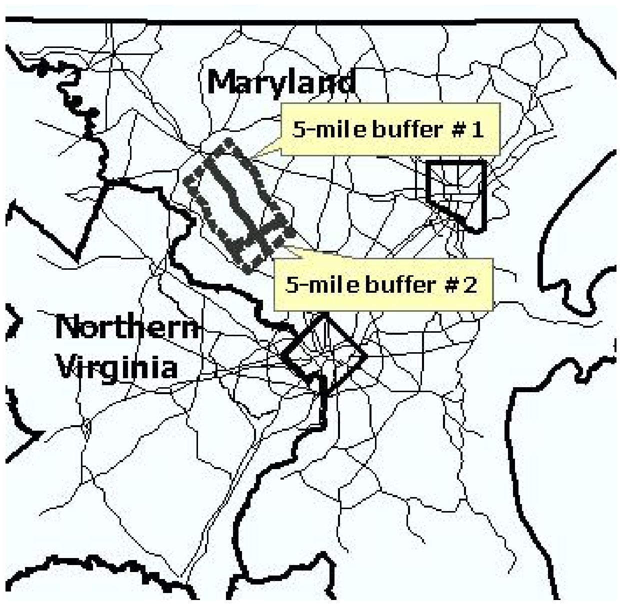
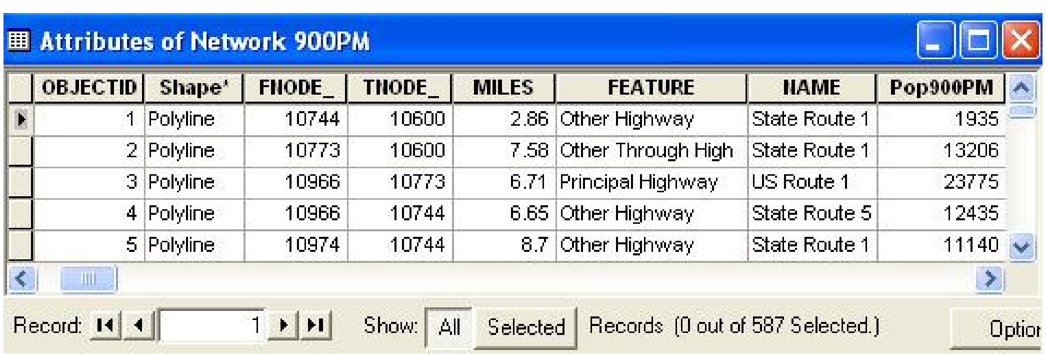


Figure 2.13 5-mile Buffers of Two Adjacent Links



Attributes of Network 900PM

OBJECTID	Shape*	FNODE_	TNODE_	MILES	FEATURE	NAME	Pop900PM
1	Polyline	10744	10600	2.86	Other Highway	State Route 1	1935
2	Polyline	10773	10600	7.58	Other Through High	State Route 1	13206
3	Polyline	10966	10773	6.71	Principal Highway	US Route 1	23775
4	Polyline	10966	10744	6.65	Other Highway	State Route 5	12435
5	Polyline	10974	10744	8.7	Other Highway	State Route 1	11140

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Figure 2.14 Network Attributes with Population in an Impact Area (9:00 p.m.-10:00 p.m.)

2.2.2 Integration of Traffic Data

An overview of phase two, traffic data integration, is provided in Figure 2.15. The CHART traffic data must first be downloaded. Downloading was scheduled at 5-minute intervals through ftp software, WSFTP Pro 9.0. As raw data were downloaded into a local desktop computer, they were read into Microsoft Excel to convert a text file into a database file (DBF), a required format to join traffic data with the GIS transportation network. A macro was programmed to sort out obsolete numbers (i.e., numbers that have not been recently updated due to hardware problems on traffic detectors), calculate travel speeds, and generate a DBF file. Obsolete data are indexed by the number ‘2’ in the last column, as shown in Figure 2.7. The processes of downloading the data through generating a DBF file are completed on-line.

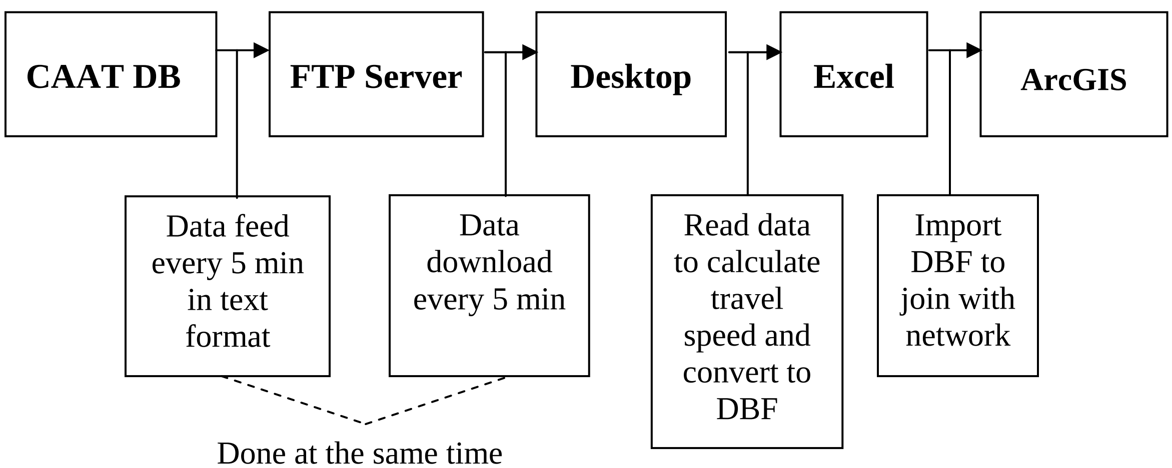

Figure 2.15 Integration Processes of Traffic Data

Spot speeds in the raw data cannot provide travel speed along an entire street segment. If multiple detectors exist along the same street segment, spot speeds from those detectors must to be aggregated to assess average speed for the segment. In this work, link travel speeds were estimated by the linear combination of spot speeds at multiple detectors. The weights of spot speeds were calculated by dividing the traffic volume at each detector by the total traffic volumes counted at relevant detectors, as shown in Equation 2.1. If there is only one detector along a link, a spot speed from a single detector will represent the link travel speed.

$$TS_i = \frac{\sum_{k=1}^{n} Q_k \cdot V_k}{\sum_{k=1}^{n} Q_k}, \qquad \text{(Eq. 2.1)}$$

Where, TS_i = Travel speed of link *i* (mph),

n = Number of traffic detectors along link *i*,

Q_k = Traffic volume at traffic detector *k*, and

V_k = Spot speed at traffic detector *k*.

Cortes et al. (2002) presented a method for estimating link travel time from multiple point detectors. In their methodology, spot speeds of individual vehicles must be collected during the time interval of data collection (i.e., 5 minutes for the CHART traffic data). However, spot speeds obtained from the CHART data are averaged estimates for each 5-minute time interval. If required data is available in the future, their methodology could provide a good alternative to estimate link travel times.

Many links exist for which there are no traffic sensors. Travel speeds on these links for both directions were set to the roadway speed limits: 65mph for interstate highway or 55mph for U.S. or state highways. Figure 2.16 shows the attribute table of the integrated network with directional travel speeds for five links at 9:30 p.m. on July 12th, 2005. Travel times were calculated using the link lengths and directional travel speeds estimated from detector data or set to the given speed limit. Figure 2.17 presents travel speeds along links. Travel speeds on the links that are highlighted based on data from traffic detectors are not significantly different from those on the other links. Speeds marked on the map are FT_SPEED shown in Figure 2.16. Characters in front of FT_SPEED of the highlighted links imply the direction corresponding to travel from a From-node to a To-node. For example, 'w 65' means link travel speed is 65 mph westbound.

Attributes of Network at 9:30 p.m. on July 12th, 2005

OBJECTID	NAME	FT_SPEED	TF_SPEED	FT_Minute	TF_Minute
347	Interstate Route 95, Interst	65	65	3.4	3.4
348	State Route 27	55	55	7.7	7.7
349	Interstate Route 270	45	64	20.2	14.2
350	State Route 295	65	65	8.2	8.2
351	US Route 50, US Route 30	66	70	10.8	10.2

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Figure 2.16 Network Attributes with Traffic Data (9:30 p.m. on July 12th, 2005)

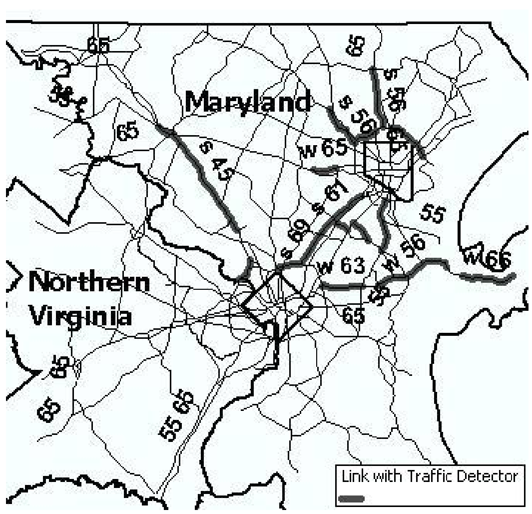
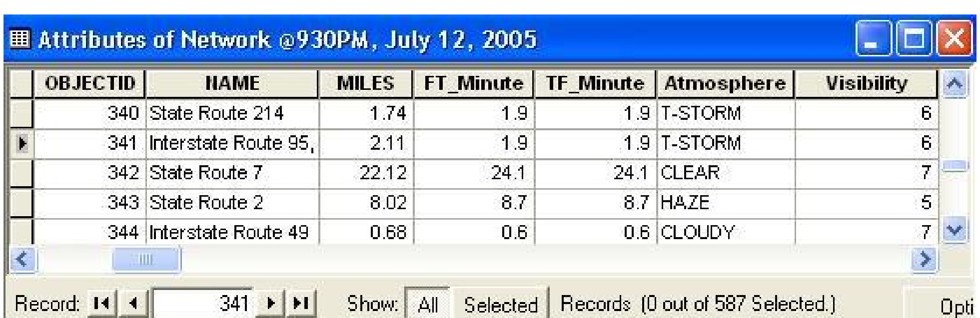


Figure 2.17 Travel Speeds (FT_Speed, 9:30 p.m. on July 12th, 2005)

2.2.3 Integration of Weather Data

Since AccuWeather data are in a GIS layer format, they can be directly retrieved in ArcGIS. Thus, while necessary for phase two, the third phase of integrating weather data with a network does not require a complicated process for importing data into ArcGIS. As introduced in Figures 2.8 and 2.9, data on the current weather conditions are stored in a GIS layer with point features that represent weather stations on a nationwide scale.

AccuWeather, Inc. describes the update frequency of their data as continuous. However, it appears that AccuWeather data is only updated hourly on the 30's. The extracted weather data on point features were joined to the links by applying the spatial join function in ArcGIS. By this join process, links are paired with the closest weather station from their mid-points. The results of spatial join is presented for five links in Figure 2.18. Links were labeled in terms of atmospheric conditions and visibility, as shown in Figure 2.19. It is noted that areas southwest and east of the District incurred thunderstorms and most other areas were cloudy or hazy at 9:30 p.m. on July 12th, 2005. Visibility was relatively low under the thunderstorm or haze as compared with areas that were cloudy or clear. Note that no unit of measurement for visibility was provided by AccuWeather, Inc.


Attributes of Network @930PM, July 12, 2005

OBJECTID	NAME	MILES	FT_Minute	TF_Minute	Atmosphere	Visibility
340	State Route 214	1.74	1.9	1.9	T-STORM	6
341	Interstate Route 95,	2.11	1.9	1.9	T-STORM	6
342	State Route 7	22.12	24.1	24.1	CLEAR	7
343	State Route 2	8.02	8.7	8.7	HAZE	5
344	Interstate Route 49	0.68	0.6	0.6	CLOUDY	7

Record: 341 Show: All Selected Records (0 out of 587 Selected.) Opti

Figure 2.18 Network Attributes with Weather Data (9:30 p.m. on July 12th, 2005)

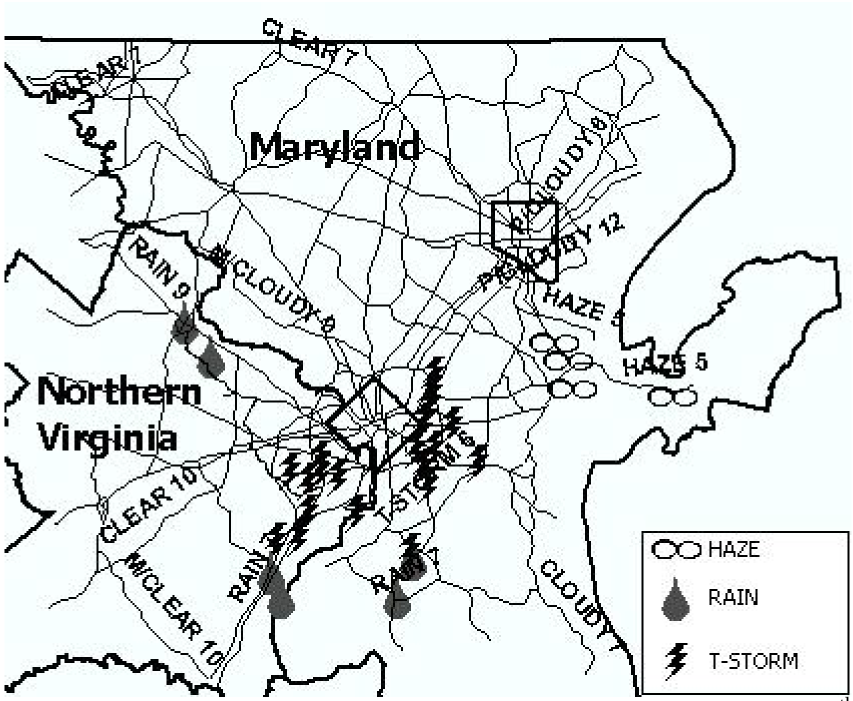


Figure 2.19 Atmospheric Conditions and Visibility (9:30 p.m. on July 12th, 2005)

Risk was calculated by multiplying three elements: 1) the conditional probability of a truck accident given pavement conditions and visibility restrictions, 2) the conditional probability of a hazmat release given a truck accident, and 3) population exposure. The first conditional probability was determined referring to Table 1.4 presented by Saccomano and Chan (1985). It is assumed that pavement is wet when the link is under rain or thunderstorm. Visibility is considered restricted when the visibility value is less than or equal to 6. Links whose features are named as limited access highways in USGS data were associated with road classification D (expressways with speed = 62.5 mph) defined in Table 1.4 and the other links were related to road classification B (arterial/collectors with speed > 31.3 mph). Due to limitations on the number of digits permitted in each field within the GIS software, the first conditional probability was split into two fields (i.e., ProbOfAcc1 and ProbOfAcc2), as shown in Figure 2.20.

The second conditional probability was developed directly from estimates given in (Subramanian, 1998). In his dissertation, Subramanian estimated the conditional probability of a hazmat release given a truck accident by roadway classification (Interstate highways (0.093), US/state highways (0.106), county roads (0.105), and city streets (0.027)). The focus of this earlier work was on the transport of chlorine gas. This second conditional probability was stored in a field called ProbOfRel, as shown in Figure 2.20. The third element required to estimate risk, i.e. population exposure, relies on the results (i.e., Pop900PM shown in Figure 2.21) of the first phase of data integration described in subsection 2.2.1.

Figure 2.21 shows risk values that result from the product of the three components for five links. Subsection 3.1.1 in the next chapter provides an equation for estimating risk and for computing the path's disutility.

Attributes of Network @930PM, July 12, 2005

OBJECTID	NAME	Atmosphere	Visibility	ProbOfAcc1	ProbOfAcc2	ProbOfRel
340	State Route 214	T-STORM	6	1.737	0.000001	0.106000
341	Interstate Route 95,	T-STORM	6	2.74	0.000001	0.093000
342	State Route 7	CLEAR	7	2.744	0.000001	0.106000
343	State Route 2	HAZE	5	1.779	0.000001	0.106000
344	Interstate Route 49	CLOUDY	7	1.478	0.000001	0.093000

Record: 0 Show: All Selected Records (0 out of 587 Selected.)

Figure 2.20 Conditional Probabilities of a Hazmat Accident and a Hazmat Release (9:30 p.m. on July 12th, 2005)

Attributes of Network @930PM, July 12, 2005

OBJECTID	MILES	Pop900PM	ProbOfAcc1	ProbOfAcc2	ProbOfRel	Cons_Acc
340	1.74	22481	1.737	0.000001	0.106000	0.00414
341	2.11	94502	2.74	0.000001	0.093000	0.02408
342	22.12	23512	2.744	0.000001	0.106000	0.00684
343	8.02	14206	1.779	0.000001	0.106000	0.00268
344	0.68	16886	1.478	0.000001	0.093000	0.00232

Record: 340 Show: All Selected Records (0 out of 587 Selected.)

Figure 2.21 Potential Consequences of a Hazmat Accident (9:30 p.m. on July 12th, 2005)

2.3 Overview of the Integrated Network

Changes in population exposure by time of day and traffic and weather conditions during the 2-hour time period (from 9:30 p.m. to 11:30 p.m.) during which time the real-time data were collected are examined for a particular location or time.

To illustrate changes in population exposure by time of day, a link within an urban area northeast of the District (i.e. Link ID 567 given in the USGS data) was selected. Figure 2.23 presents the location of the selected link and the release impact area. Distributions of population exposure on this link were plotted over 1-hour time intervals. Note that population exposures of four 15-minute time intervals, as split in the CTPP2000, were averaged by hour for the time period between 5:00 a.m. and 11:00 a.m. The distributions of population exposure on this link indicate that significant variations in population occur in the morning from 6:00 a.m. to 9:00 a.m., as shown in Figure 2.24. To capture these significant changes in population for routing a hazmat truck, it would have been interesting if real-time data had been

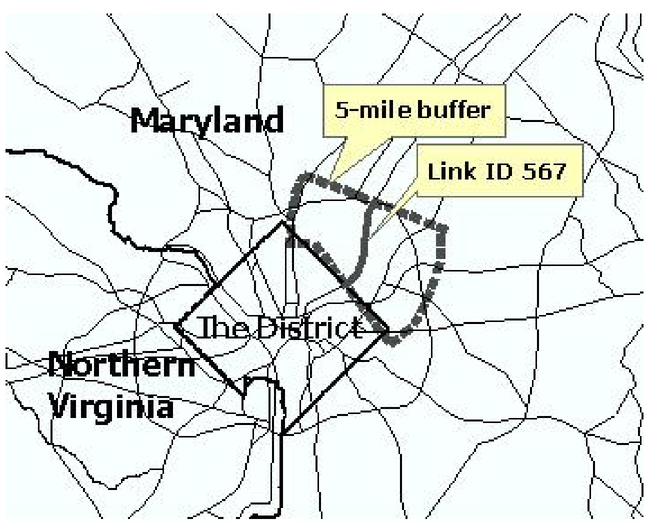


Figure 2.23 Impact Area of Link ID 567

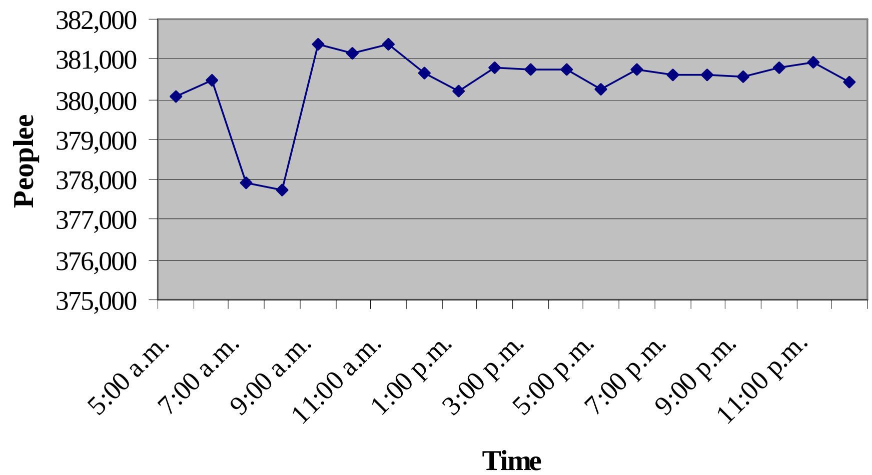


Figure 2.24 Population Exposure of Link ID 567 by Hour

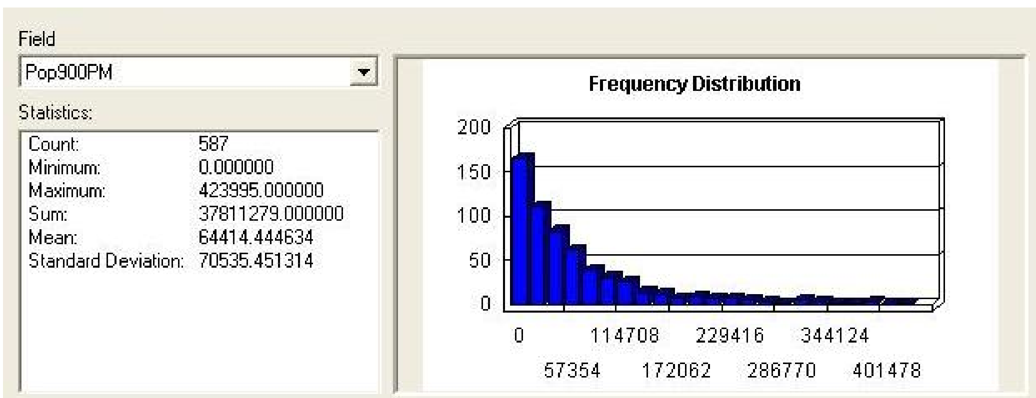


Figure 2.25 Statistics of Population Exposure by Link (9:00 p.m.–10:00 p.m.)

collected in the morning. However, as was typical in the summer of 2005, severe weather conditions (i.e., thunderstorm, rain, and haze) arose most often in the late evening within the study region. Figure 2.25 shows statistics of population exposure by link at a time period from 9:00 p.m. to 10:00 p.m. The maximum population exposure is approximately 424,000 people within 5 miles of a link and the mean value is approximately 64,400 people. Most population exposures by link range from 0 to 172,062 people.

Figures 2.26 and 2.27 present travel speeds in both directions at 9:30 p.m. and 10:30 p.m. on July 12th, 2005, respectively. Travel speeds along links without traffic detectors do not change, because they were set to the roadway's speed limit. Those travel speeds along links with traffic detectors changed slightly over time. As discussed in subsection 2.2.3, AccuWeather data are updated hourly on the 30s. At 9:30 p.m., a thunderstorm was passing through Northern Virginia, just southwest of the District, and Maryland, just east of the District. Areas surrounding the thunderstorm were rainy or hazy. Figures 2.28 and 2.29 indicate that the storm diminished over the time period of interest, but haze persisted in much of the region.

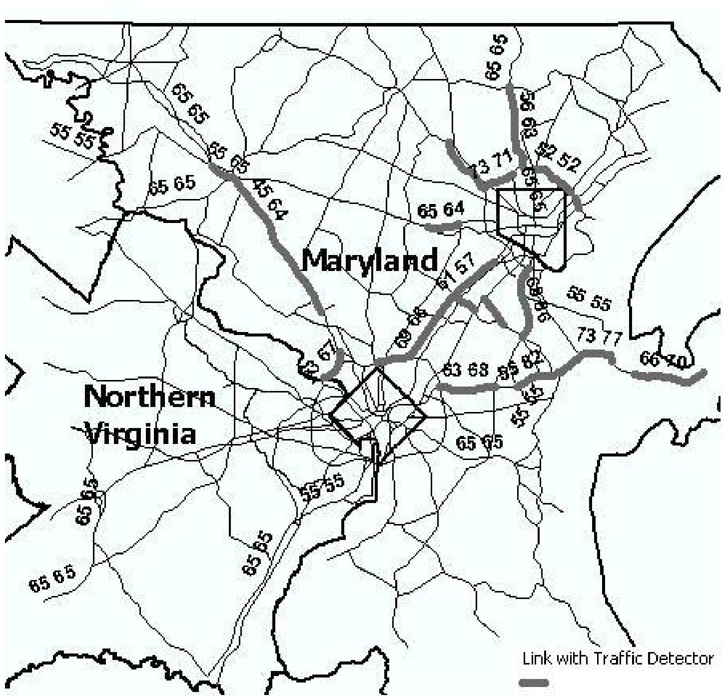


Figure 2.26 Travel Speeds at 9:30 p.m. on July 12th, 2005 (Both Directions)

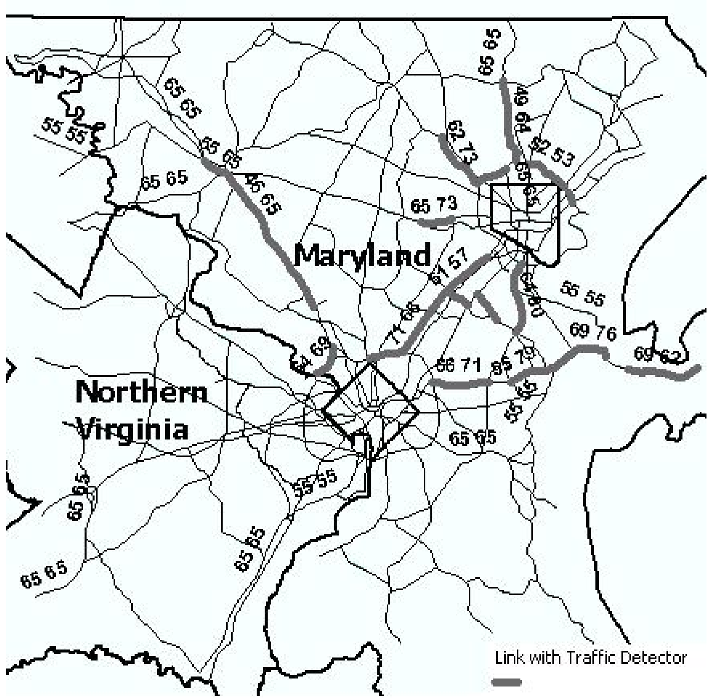


Figure 2.27 Travel Speeds at 10:30 p.m. on July 12th, 2005 (Both Directions)

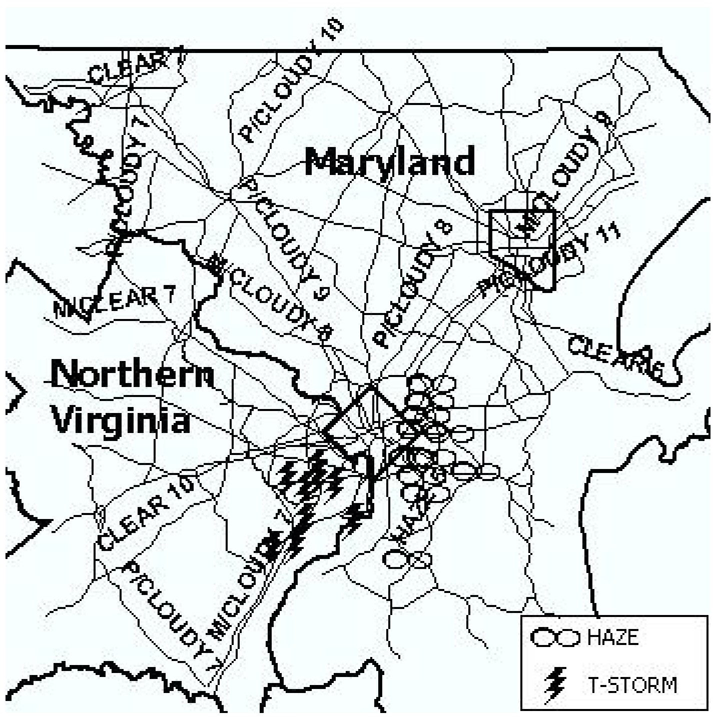


Figure 2.28 Atmospheric Conditions and Visibility at 9:35 p.m. on July 12th, 2005

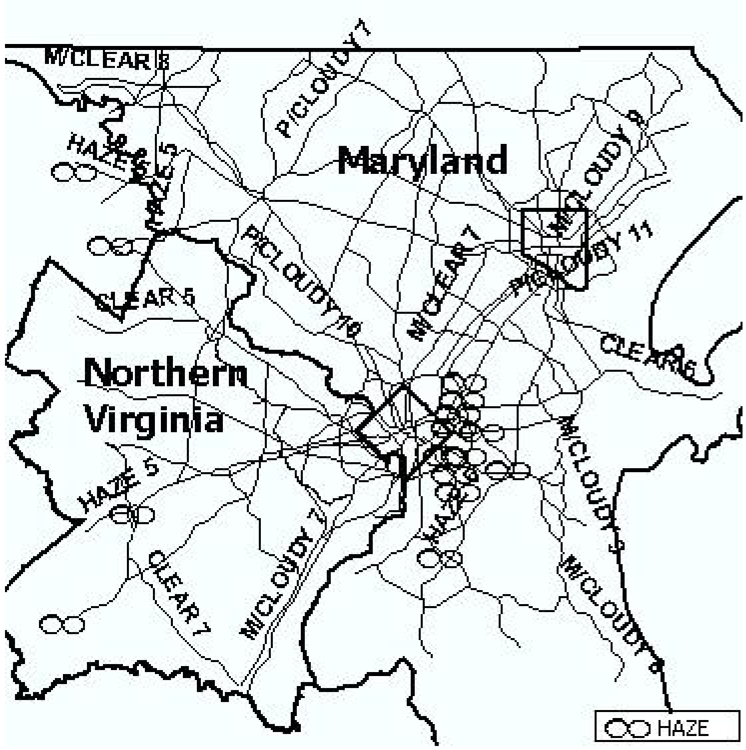


Figure 2.29 Atmospheric Conditions and Visibility at 10:35 p.m. on July 12th, 2005

Chapter 3: Solution Techniques

In dealing with the multiobjective problem of determining a best path for a hazmat truck that seeks to minimize both travel time and risk, it would be ideal to develop a solution technique that finds all Pareto-optimal paths from the origin to the vehicle's destination. However, a solution technique that generates all Pareto-optimal paths requires enormous computational effort and updated paths based on real-time traffic and weather information cannot be generated in real-time. Additionally, significant computational time is required to integrate the real-time data with the transportation network. In this work, a heuristic is developed that can remarkably reduce computational effort required for both real-time data integration and path determination.

Solution paths developed by the proposed technique are compared to the *a posteriori* least disutility path, i.e. the optimal solution given 20/20 hindsight, based on the same disutility function used to generate the heuristic solutions. Note that one could also generate all *a posteriori* Pareto-optimal solutions for this comparison.

3.1 A Heuristic Solution Technique

Several techniques are employed in developing the heuristic to reduce the required computational effort. First, the multiobjective problem is reduced to a single objective problem. Second, some elements (i.e., arc travel time, travel distance from the origin to the destination, the longest travel time, and the highest risk) in the disutility function are only approximated. Third, real-time information is employed only within a neighboring area of the vehicle's current location and only up-to-date historical data is used outside of this neighborhood, reducing the number of links for which real-time data must be integrated. The proposed heuristic is implemented in a GIS environment using Model Builder and Network Analyst in ArcGIS 9.1.

3.1.1 The Concept of the Proposed Heuristic

A utility approach is employed to reduce the multiobjective problem of minimizing both travel time and risk to a single objective problem. A linearly additive disutility function is assumed with equal weight given to each objective:

$$U_i = 0.5\left(\frac{TT_i}{\left(\frac{L_{AVG}}{20}\right)\times 60} + \frac{P(A|W)_i \times P(R|A)_i \times Pop_i}{P^*(A|W)_i \times P^*(R|A)_i \times Pop_{AVG} \times L_{AVG}} \right) \quad \text{(Eq. 3.1)}$$

where, U_i = Disutility of arc *i*

$P(A|W)_i$ = Conditional probability of a truck accident given pavement conditions and visibility restrictions (Saccomano and Chan, 1985)

$P(R|A)_i$ = Conditional probability of a release of Chlorine gas given an accident (Subramanian, 1998)

$P^*(A|W)_i$ = Max { $P(A|W)_i$ } (i.e., 2.744E-6)

$P^*(R|A)_i$ = Max { $P(R|A)_i$ } (i.e., 0.106)

Pop_i = Population exposure to a hazmat release on arc *i* (people)

Pop_{AVG} = Average population exposure to a hazmat release over an entire network (i.e., 16,000 people/mile)

TT_i = Travel time on arc *i* (minutes)

L_{AVG} = Average of Euclidean and grid distance given origin and destination (miles)

The disutility function consists of two components. The first component is travel time on link *i* normalized to the total travel time between the origin and the destination (O-D) under very bad traffic conditions (i.e. travel speeds of only 20 mph are assumed). The trip length (L_{AVG}) between the origin and destination is defined as the average of Euclidean and grid distance. Figure 3.1 shows an example of estimating L_{AVG}. The numerator of the second component provides estimate of risk along each arc for given weather conditions on the arc. The denominator provides the estimate of the highest risk that results from the highest conditional probability of a truck accident for the given weather conditions, the highest conditional probability of a hazmat release given a truck accident, and average population exposure (i.e., Pop_{AVG}) over the entire trip. Pop_{AVG} is estimated by dividing the total population exposure along all links in the network by the total link length. The resulting arc disutility is presented for five links in Figure 3.2. As travel time is directional, disutility is also directional.

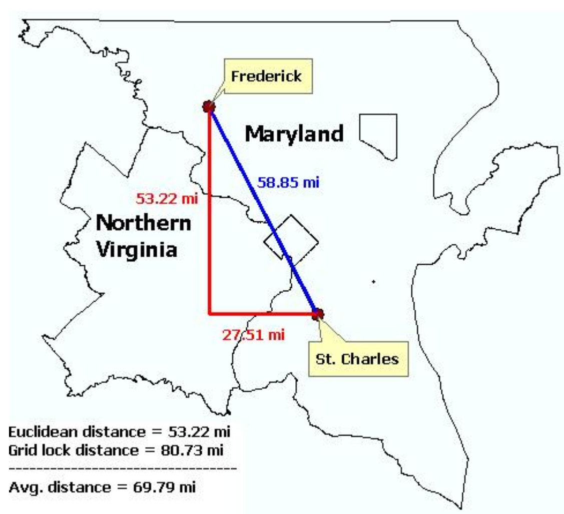
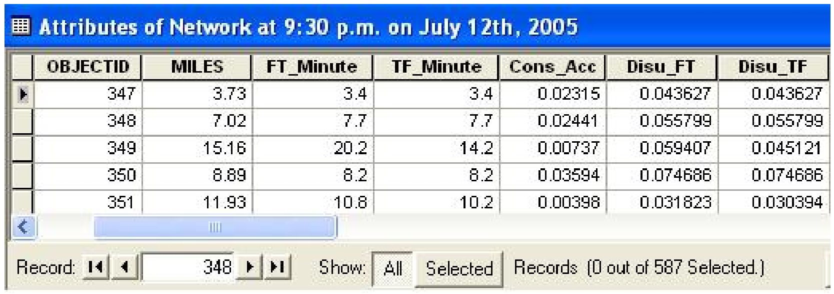


Figure 3.1 An Example of Estimating an Entire Trip Length



Attributes of Network at 9:30 p.m. on July 12th, 2005

OBJECTID	MILES	FT_Minute	TF_Minute	Cons_Acc	Disu_FT	Disu_TF
347	3.73	3.4	3.4	0.02315	0.043627	0.043627
348	7.02	7.7	7.7	0.02441	0.055799	0.055799
349	15.16	20.2	14.2	0.00737	0.059407	0.045121
350	8.89	8.2	8.2	0.03594	0.074686	0.074686
351	11.93	10.8	10.2	0.00398	0.031823	0.030394

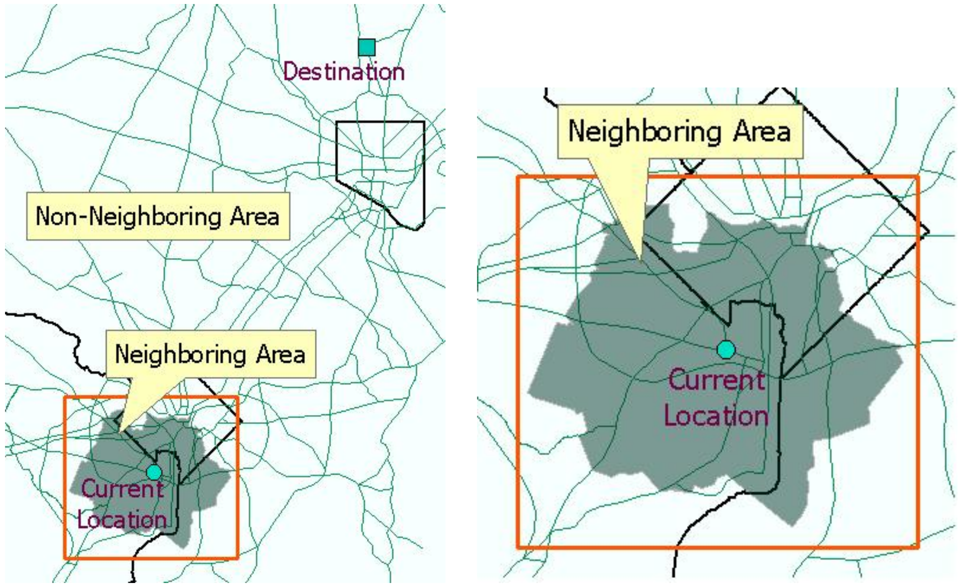
Record: 348 Show: All Selected Records (0 out of 587 Selected.)

Figure 3.2 Arc Disutility at 9:30 p.m. on July 12th, 2005

The proposed heuristic seeks a pair of contiguous subpaths (one to the edge of the neighboring area of the vehicle’s current location and a second from the edge of the neighboring area to the destination) such that disutility is minimized. Remaining path computation is repeated at intermediate locations as updated real-time information is received.

The neighboring area (NA) is the area surrounding the vehicle’s current location. It is defined as the area within X minutes travel time from the current location given current traffic conditions. Without loss of generality, X is also taken to be the update interval of a network state (or routing instructions). The vehicle is expected to arrive at the boundary of NA in X minutes. However, if the vehicle arrives earlier or later than expected, the NA is generated where the vehicle is at X minutes from the last update. The non-neighboring area (NNA) is the remaining portion of the network, i.e. those areas outside the NA. Figure 3.3 shows an example of NA within 10 minutes from the current location and its corresponding NNA. Current traffic and weather conditions are employed only within the NA and only the most recent past network state is employed within the NNA.

The most recent past network state is obtained by employing the up-to-date



(a) NA and NNA (b) Zoomed-in NA

Figure 3.3 An Example of a Neighboring and Non-neighboring Area

historical data, i.e. the real-time data that were not integrated within the NNA of the last intermediate (or current) location to save computational effort. While the vehicle is traveling from the last intermediate location to the current location during X minutes, the previously incomplete data integration for the NNA X minutes ago is completed. The network state that results from this completion of data integration is used as the network state, referred to as the most recent past network state, to find a subpath in NNA at the current vehicle's location. Suppose the network state is updated every 10 minutes (i.e., 9:30 pm., 9:40 p.m., 9:50 p.m., etc.) and the last intermediate location of the vehicle is where it arrived at 9:31 p.m. At time of 9:31 p.m., the data collected at 9:30 p.m. were employed only within the NA of the last intermediate location. While the vehicle was in route to the current location where it arrives at 9:41 p.m., the real-time data of 9:30 p.m. are integrated with the NNA of the last intermediate location. The resulting network state of this integration is used as the most recent past network state in finding a subpath in the NNA of the current location at 9:41 p.m.

First a subpath in NNA, whose least disutility is the minimum among all least disutility subpaths from boundary nodes of NA to a destination, is selected based on the most recent past network state. In the process of determining the least disutility path by the proposed heuristic, a set of boundary nodes of the NA is defined. This set is the set of nodes that represent intersections between the boundary of NA and the line features of the network. A subpath in NA is found based on the current network state (i.e. the most updated network state) such that disutility is minimized from an origin to the boundary node of NA, from which the selected path through the NNA region begins.

An example of two subpaths found by the proposed heuristic is shown in Figure 3.4. First subpath 1 is selected and the boundary node labeled "2" is chosen.

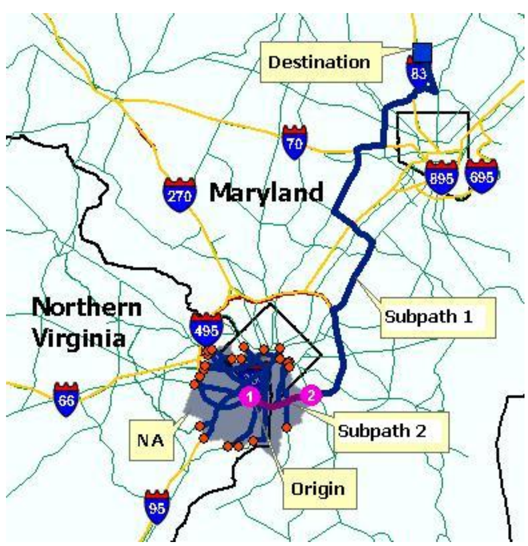


Figure 3.4 An Example of Two Subpaths Found by the Proposed Heuristic

Next the subpath between the current location and node 2 is determined. When the network state is updated next, another pair of subpaths is found in the same manner. This procedure is iterated until the vehicle arrives at the destination. The following two subsections provide detailed information on this procedure.

3.1.2 The Procedure to Implement the Proposed Heuristic

The heuristic is composed of four steps:

Step 1.

Find the NA within X minutes (i.e., the update interval for collecting of real-time data) of the current location. Consider current traffic conditions. Identify or generate boundary nodes of the NA.

Step 2.

If the destination is within the NA, go to Step 4; otherwise, find the subpath from boundary nodes of NA to the destination that minimizes disutility based on the most recent past network state. Identify the boundary node along the chosen subpath.

Step 3.

Find a subpath from the current location to the boundary node of NA chosen in Step 2 that minimizes disutility based on the current network state (i.e., the most updated network state). The most recent past network state is updated during X minutes. The location where the vehicle arrives in X minutes is defined as the new current location. The current network state is updated in X minutes for the arcs expected to be within Y (i.e., Y>X) minutes of travel distance from the new current location. Go to Step 1.

Step 4.

Find a subpath from the current location to the destination such that disutility is minimized given the current network data. Stop.

The problem of determining the least disutility path addressed in Step 3 is formulated as a shortest path problem in which cost is taken as disutility. The solution of this problem provides the subpath in NA from the current vehicle's location to the boundary node of the NA. Let G = (N, A) be a finite digraph, where N is the set of nodes and A is the set of directed arcs.

$$\text{Min } \sum_{i=1}^{N}\sum_{j=1}^{N} X_{ij} \cdot U_{ij}$$

Subject to:

$$\sum_{\{j:(i.j)\in A\}}^{N} X_{ij} - \sum_{\{j:(j,i)\in A\}}^{N} X_{ji} = \begin{cases} 1 & \text{if } i = \text{origin} \\ -1 & \text{if } i = \text{destination} \\ 0 & \text{otherwise} \end{cases}, \qquad i = 1, 2, ..., N$$

$$X_{ij} \in \{0, 1\} \qquad \text{for } \forall i,\ j = 1, 2, ..., N$$

where,

U_{ij} = Disutility on arc (i, j) based on the current network state

$$X_{ij} = \begin{cases} 1 & \text{if arc } (i, j) \text{ is in the path} \\ 0 & \text{otherwise} \end{cases}$$

3.1.3 Implementation of the Proposed Heuristic

The proposed heuristic was implemented in the GIS environment using Model Builder and Network Analyst in ArcGIS 9.1. Model Builder provides users with the interface to create models in ArcGIS. A new model can be created within the Model Builder window by building a sequence of required tools and specifying input and output data for each. Figure 3.5 shows an example of model creation in this environment. Input and output data are drawn in ovals. A tool is expressed as a rectangle with a hammer. Any existing or created tools in ArcGIS 9.1 can be imported as an element of the model to execute their functions.

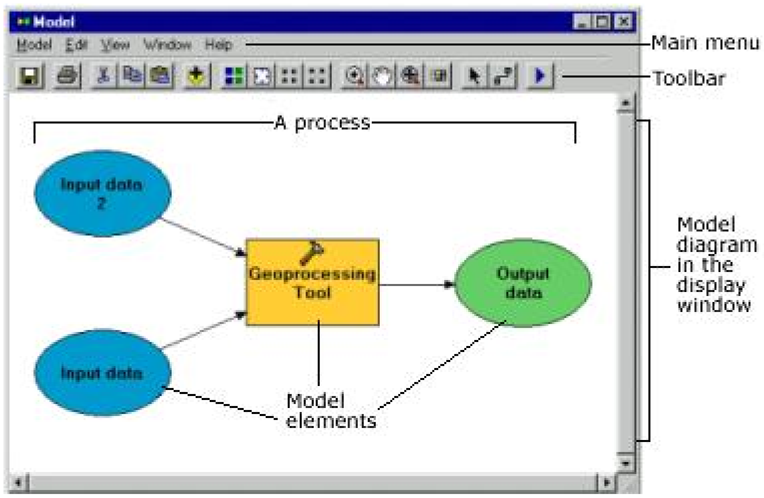


Figure 3.5 Model Builder Window (Source: Help in ArcGIS 9.1)

In this study, the Network Analyst extension provides the principal tools used in building the models used to implement the proposed heuristic. The ArcGIS Network Analyst extension allows users to build a network dataset and perform analysis on it. A network dataset is constructed by specifying fields (or columns) of the attribute table of the integrated network that will be used as cost attributes. Figure 3.6 shows a process of cost specification in building a network dataset. The Travel Time attribute is specified to use it as the impedance in implementing Step 1 (i.e., finding the NA within X minutes) of the heuristic. It is not necessary to specify the Risk attribute in implementing the heuristic. However, this attribute aids in tracing the

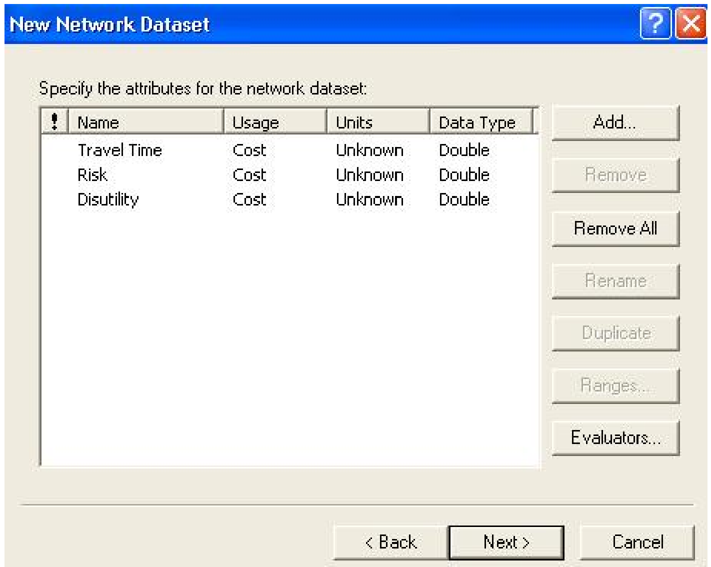


Figure 3.6 Specification of Network Attributes in Building a Network Data Set

risk values of paths that result from Step 2 and Step 3 of the heuristic. Thus, the Risk attribute was specified in this work. The Travel Time attribute is also useful to trace travel times given paths. The Disutility attribute is specified to consider it in finding two contiguous subpaths in NA and NNA.

Each attribute is associated with a field (or column) in the attribute table of the integrated network using the Evaluators window shown in Figure 3.7. This window is opened by clicking the Evaluators button shown in Figure 3.6. For example, the

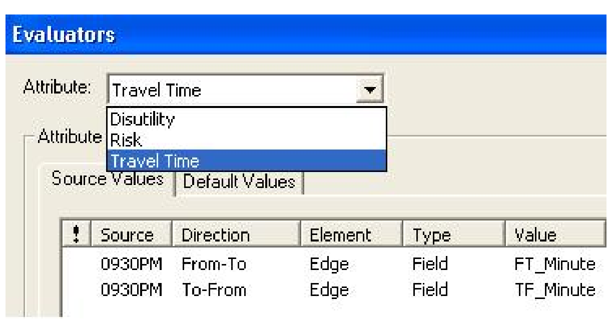


Figure 3.7 An Example of Fields Set as Input of Network Attributes

Travel Time attribute is linked with two fields,FT_Minute and TF_Minute, that contain travel times calculated from traffic conditions at 9:30 p.m. Similarly, the Risk attribute is set to use values in the Cons_Acc field, presented in Figure 3.2, by selecting the Risk attribute in the drag-down list. The Disutility attribute is set to use Disu_FT and Disu_TF fields, shown in Figure 3.7, as its input.

In this work, 24 network data sets were constructed with a 5-minute time interval from 9:30 p.m. to 11:30 p.m. on July 12th, 2005. Though collection of real-time data was successfully completed, estimation of disutility and construction of network data sets could not be done in real-time. Thus, the real-time operation was emulated by constructing network data sets *a priori*. As presented in Chapter 2, traffic conditions change every 5 minutes and weather conditions vary hourly.

The first three steps of the proposed heuristic (i.e., finding NA, finding a subpath in NNA, and finding a subpath in NA) were implemented using the 24 network data sets. Three Network Analysis tools (i.e., Finding a Service Area, Finding the Closest Facility, and Finding a Route) played a significant role in implementing the first three steps. The model building process for each step is described next.

The implementation of Step 1 requires the use of two models shown in Figure 3.8 and Figure 3.9. The 1st model identifies the NA and the 2nd model generates the boundary nodes of the NA. The NA found by the first model is used as input data to the second model. The first model runs the tool of Finding a Service Area based on the current network state, current location, and restricted links for hazmat transport. The update interval of real-time data is specified. The current network state, current

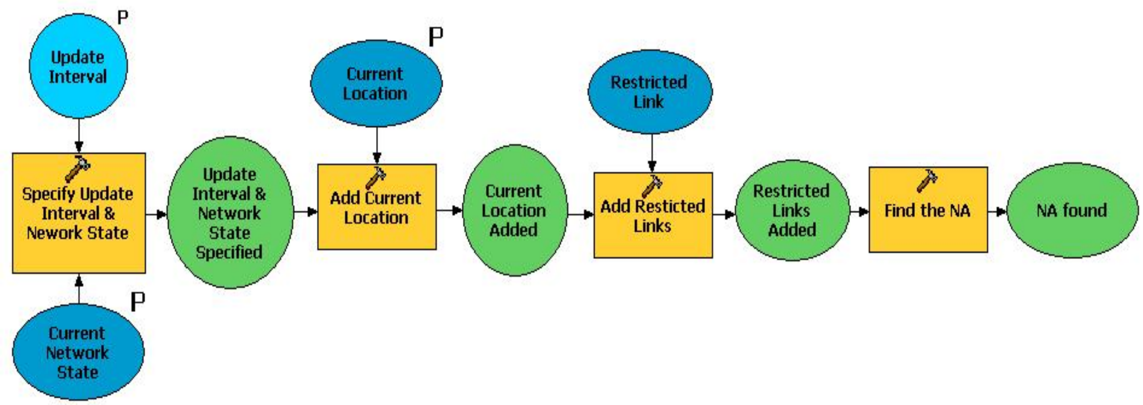


Figure 3.8 A Model to Find NA

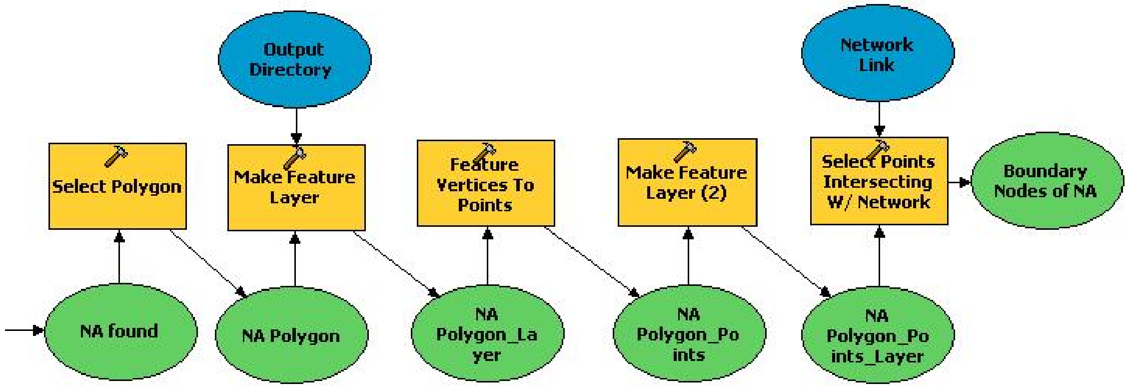
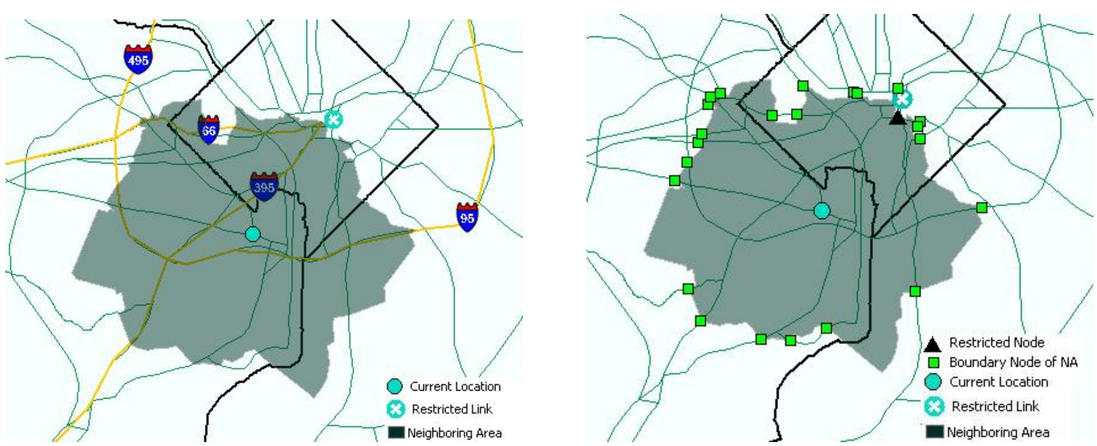


Figure 3.9 A Model to Generate the Boundary-Nodes of NA



(a) NA (b) The Boundary-nodes of NA

Figure 3.10 An example of the Result of the Implementation of Step 1 location, and the update interval are set as model parameters. The Travel Time attribute is specified as the impedance in finding the NA. The second model converts the polygon feature of the NA to points and selects those points that intersect with the line features of the network. These selected points are identified as the boundary nodes of NA. Figure 3.10 shows an example of NA and the boundary nodes of NA resulting from implementation of the first and second models.

Step 2 of the proposed heuristic is implemented by creating a model that applies the tool of Finding the Closest Facility to select a subpath within NNA. Figure 3.11 shows the implementation in Model Builder. Input data include the boundary nodes of NA found in Step 1, the most recent past network state, the destination, and restricted links. The number of boundary nodes (i.e. subpaths) to be found is set to one. The most recent past network state and the destination are set as model parameters. The disutility attribute of the network attribute of the network data set is specified as the impedance to determine the least disutility subpath. Figure 3.12

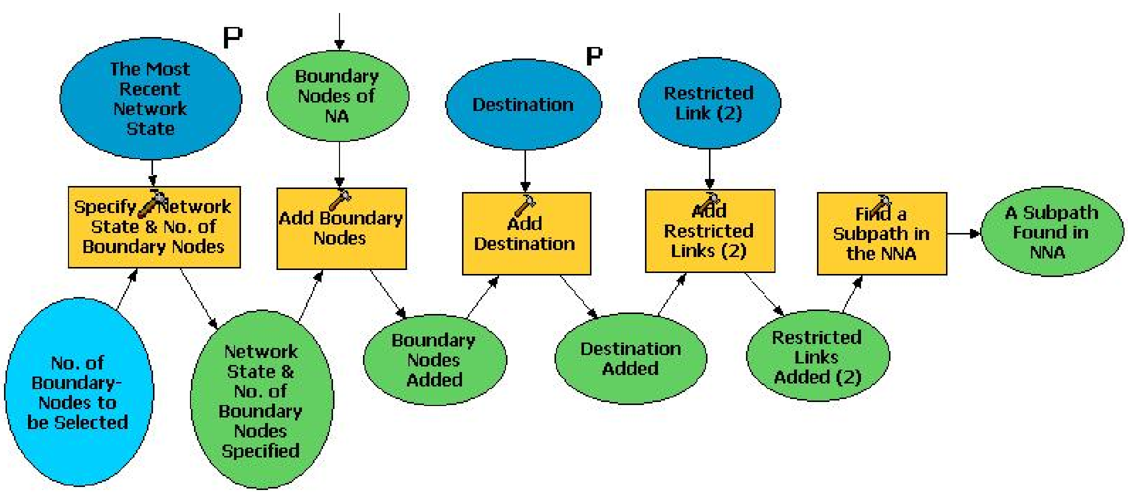


Figure 3.11 A Model to Find a Subpath in NNA

provides an example of a subpath found in NNA. While the model is running, ArcGIS 9.1 indexes the boundary nodes (e.g., location 1, location 2, etc.) of NA. The subpath, selected from one of the boundary nodes to the destination, is also indexed (e.g., location 5 – destination).

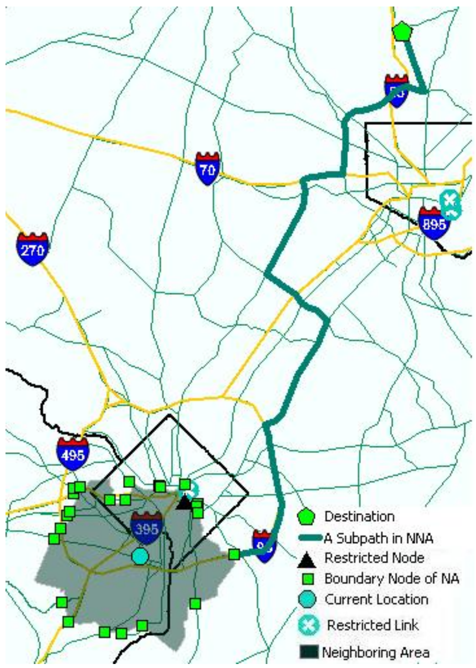


Figure 3.12 An Example of a Subpath Found in NNA

The implementation of Step 3 is made by employing the tool of Finding a Route as shown in Figure 3.13. The current network state, current location, the boundary node of NA selected in Step 2, and restricted links are used as input data. To specify the selected boundary-node of NA, the index of the boundary node (e.g., location 5) is entered in a query. The current network state and the query are set as model parameters. The Disutility attribute of the network data set is set as the impedance to find a subpath in NA. Figure 3.14 shows the resulting subpath in NA that is connected to the subpath found in Step 2.

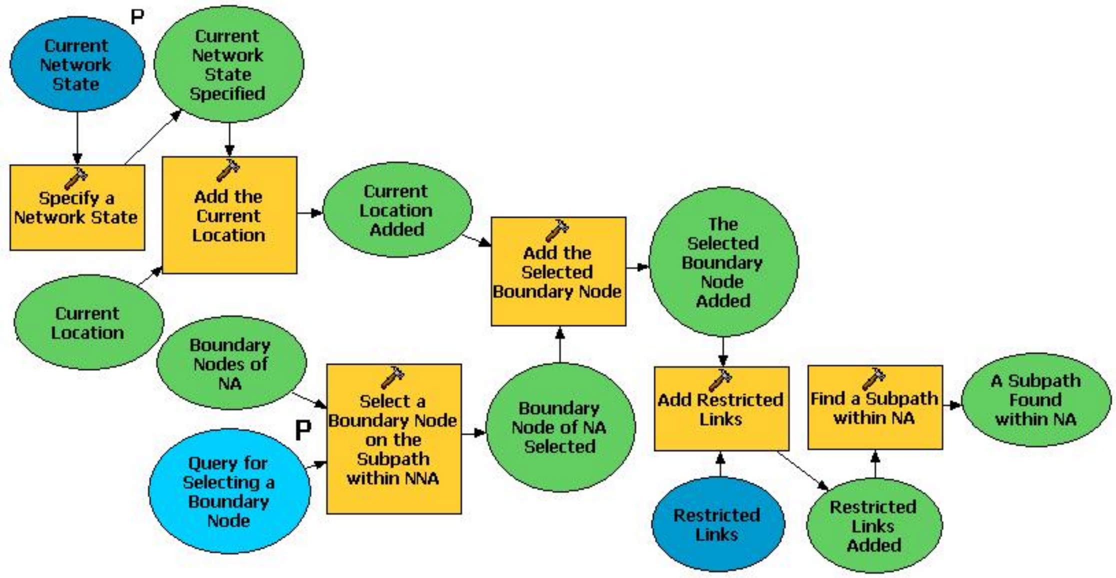


Figure 3.13 A Model to Find a Subpath in NA

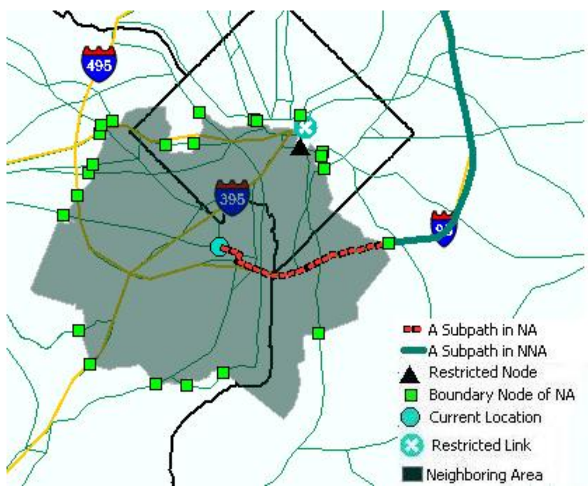
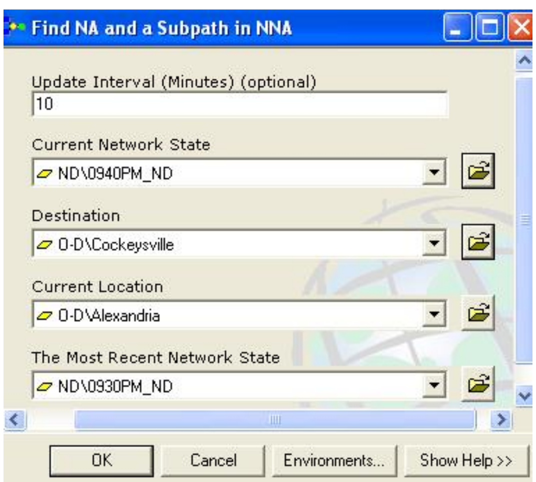
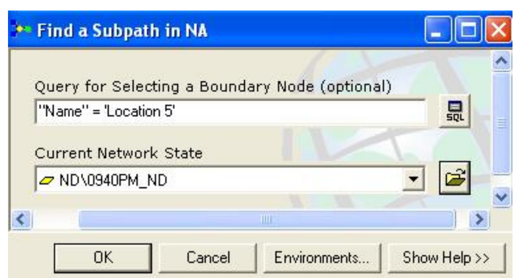


Figure 3.14 An Example of a Subpath Found in NA

The three models of Figures 3.8, 3.9, and 3.11 were combined as shown in Figure 3.15 (a). A dialog box in the figure provides the user interface to run a combined model. The combined model is executed by clicking the OK button after specifying the model parameters (i.e., the update interval of real-time data, the current network state, the most recent past network state, current location, and the destination). The model that implements Step 3 runs separately because the query to specify the selected boundary node of NA in Step 2 makes its inclusion difficult. Figure 3.15 (b) presents a dialog box used to run this model. There are two model parameters: the query for specifying the boundary node and the current network state that will be used. A single iteration of the proposed heuristic is finished by sequentially running code through these two dialog boxes.



(a) Find NA and a Subpath in NNA



(b) Find a Subpath in NA

Figure 3.15 Dialog Boxes to Implement the Proposed Heuristic

3.2 The a Posteriori Solution Technique

The *a posteriori* solution is defined as the best path that one could have chosen if one could know future traffic and weather conditions exactly *a priori*. To solve for this path, the Time-Dependent Least Time Path (TDLTP) algorithm of Ziliaskopoulos and Mahmassani (1993) was modified such that the objective minimizes disutility instead of travel time. It is assumed that the vehicle cannot wait at any intermediate node.

The TDLTP algorithm was implemented in C++. The GIS transportation network, including 24 network states based on real-time data that was updated every 5 minutes, was converted to a text file. This file also includes the forward star network representation of the transportation network. Specifically, arc travel time (i.e., FT_Minute and TF_Minute) and arc disutility (i.e., Disu_FT and Disu_TF) in the attribute table of the integrated network were extracted as arc attributes. The dialog box in Figure 3.16 illustrates a process used in converting the GIS network that contains the network state at 9:30 p.m. on July 12th, 2005 to a text file. The resulting forward star network representation was converted to the backward star network representation as required by the TDLTP algorithm.

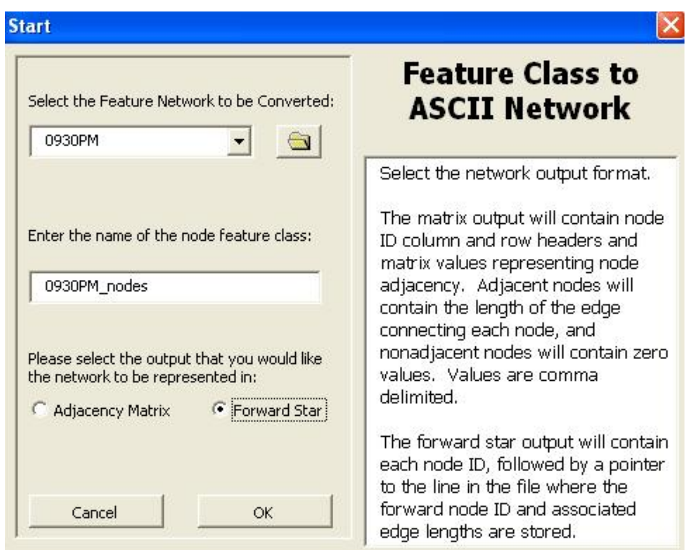


Figure 3.16 A Dialog Box to Convert the GIS Transportation Network to a Text File

Chapter 4: Experimental Design and Analysis of Results

A case study was conducted in which the proposed heuristic was implemented on the integrated Washington D.C. Metropolitan Area network described in Chapter 1. Five test runs were made on three pairs of origins and destinations (O-D) for two departure times. Each test run applied two versions of *a priori* routing and three implementations of heuristic routing for a single O-D pair and departure time. The *a priori* routing methods provided the hazmat truck with routing instructions planned upon departure time and never updated thereafter. The first of the *a priori* routing methods does not use real-time information. The second method employs the real-time data that is available for the entire network at the time of planning the route. The heuristic was used to generate the updated routing instructions as the network state was updated based on real-time data arriving at fixed time intervals of constant duration. The proposed heuristic is implemented for 3 update intervals for which real-time information is collected and updated.

The results of the five test runs were analyzed. For each test run, routes obtained from the *a priori* and heuristic methods were compared with the corresponding *a posteriori* route in terms of the resulting route and travel impedance (i.e., travel time, risk, and disutility). The resulting routes were drawn on the map with adverse atmospheric status (i.e. thunderstorm and haze) along them that the vehicle encountered en route. Variations in the optimality of the resulting routes were examined over the five routing types by test run.

4.1 Experimental Design

Two versions of *a priori* routing were implemented: *a priori* – ideal and *a priori* – depart. In *a priori* – ideal routing, the ideal static network is employed. That is, all travel speeds are set to roadway speed limits and dry pavement and unrestricted visibility are assumed. The optimal path based on ideal conditions is determined before the vehicle departs from the origin and is never updated. Table 1.4 in Chapter 1 indicates that on expressways (i.e. interstate highways), the conditional probability of truck accident given pavement condition and visibility restriction is lower under the ideal condition (i.e. dry pavement and unrestricted visibility) than non-ideal conditions (i.e. either wet or restricted visibility. On arterials or collectors (i.e. U.S. or state highways), however, the conditional probability is highest under ideal conditions than non-ideal conditions. Thus, ideal conditions do not ensure lower risk and disutility than non-ideal conditions for all road classes.

In *a priori* – depart routing, the current network state at the time of departure based on recent information on roadway conditions is employed in determining a route. The route, like *a priori* – ideal route, is not updated en route. It may not be feasible to use the most recent real-time information for the entire network if the network is vary large as to integrate real-time data with the network in such limited time.

Three update intervals of real-time data were considered in implementing the heuristic: 5 minutes, 10 minutes, and 20 minutes. It is assumed that it takes as long as update intervals for the vehicle to arrive at next intermediate location departing from a current location. These routing types are referred to as heuristic- 5 minutes, heuristic – 10 minutes, and heuristic – 20 minutes. As described in Chapter 3, the current (or most updated) network state is applied only within a neighboring area (NA) of the current vehicle's location. For the non-neighboring area (NNA), the most recent past network state is employed. The most recent past network state that will be used to find a subpath in NNA is determined by the update interval of the heuristic of interest.

Suppose a hazmat shipment departs at 9:31 p.m. and the network state is updated every 5 minutes (i.e., 9:00 p.m., 9:05 p.m., 9:10 p.m., etc.). For this case, the network states updated at 9:30 p.m. and 9:25 p.m. are used as the current and the most recent past network state, respectively, in the first iteration of heuristic – 5 minutes. At the second iteration, network states updated at 9:35 p.m. and 9:30 p.m. are used as the current and most recent past network state. Table 4.1 provides an example of the pairs of current and most recent past network states that are used in the first two iterations of the heuristic for a shipment departing from the origin at 9:31 p.m. It is assumed that the vehicle does not arrive at the destination during these first two iterations.

Table 4.1 An Example of the Pairs of Network States Used by the Heuristic

Iteration / Heuristic	Iteration 1		Iteration 2	
	Time of Update	Pair of Network States*	Time of Update	Pair of Network States*
Heuristic – 5 Minutes	9:31 p.m.	(9:30 p.m., 9:25 p.m.)	9:36 p.m.	(9:35 p.m., 9:30 p.m.)
Heuristic – 10 Minutes	9:31 p.m.	(9:30 p.m., 9:20 p.m.)	9:41 p.m.	(9:40 p.m., 9:30 p.m.)
Heuristic – 20 Minutes	9:31 p.m.	(9:30 p.m., 9:10 p.m.)	9:51 p.m.	(9:50 p.m., 9:30 p.m.)

Note: pair of network states* = (current network state, most recent past network state)

Three origin - destination (O-D) pairs were selected such that either the origin or the destination was under a thunderstorm at the time of departure and the trip length, defined in subsection 3.1.1, was approximately 70 miles. In case that one considers O-D pairs that incur different trip lengths between them, the 24 network states for the time of interest (i.e. from 9:30 p.m. to 11:30 p.m. on July 12th, 2005) must be constructed for each O-D pair. This is because the disutility function defined in Chapter 3 depends on the estimated trip length. In this work, O-D pairs with identical trip lengths are only considered. One might consider selecting O-D pairs with various trip lengths. Figure 4.1 provides the selected three O-D pairs in the case study, i.e., (Alexandria, Virginia; Cockeysville, Maryland), (Boonsboro, Maryland; Alexandria, Virginia), and (Dale City, Virginia; Baltimore, Maryland). Alexandria and Dale City were under a thunderstorm between 9:30 p.m. and 10:30 p.m. on the date of departure.

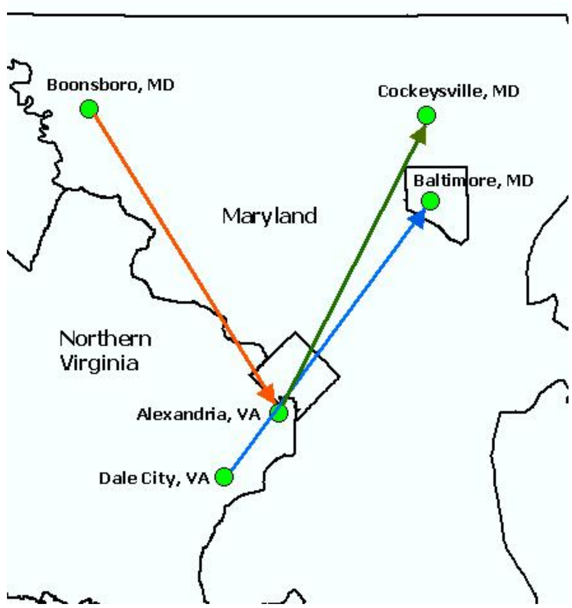


Figure 4.1 Selected O-D Pairs in the Case Study

Two departure times were considered: 9:31 p.m. and 9:51 p.m. Since real-time data were collected beginning at 9:30 p.m., the most recent past network state was not available at 9:31 p.m. when it was required. Thus, for the shipment departing at 9:31 p.m., the ideal static network state was used instead of the most recent past network state in finding a subpath in NNA during only the first iteration of the heuristic.

4.2 Analysis of Results

Routes that result from the five routing methods and *a posteriori* route were visualized in ArcGIS and their travel impedance was compared for five test runs. Travel impedance includes travel time and risk that correspond to (least) disutility along each route. These three cost attributes are actual values that the resulting routes would incur based on traffic and weather conditions revealed for the time period of interest in the case study. Figures 4.1 through 4.5 show the results of five test runs. Each figure includes the locations of O-D, departure and arrival time at O-D, the resulting route, and adverse weather conditions (i.e., thunderstorm, rain, or haze) in route.

4.2.1 Test Run 1

An origin is Alexandria, Virginia and a destination is Cockeysville, Maryland. Departure time is 9:31 p.m. The origin is under a thunderstorm at the time of departure. While the vehicle was in route the thunderstorm diminished to haze. The ideal static network state was used instead of the most recent past network state in finding a subpath in NNA during the first iteration of the heuristic, as remarked in section 4.1. Table 4.2 summarizes travel impedance (i.e., travel time, risk, and disutility) of resulting routes in test run 1. Figure 4.2 provides resulting routes drawn on the map.

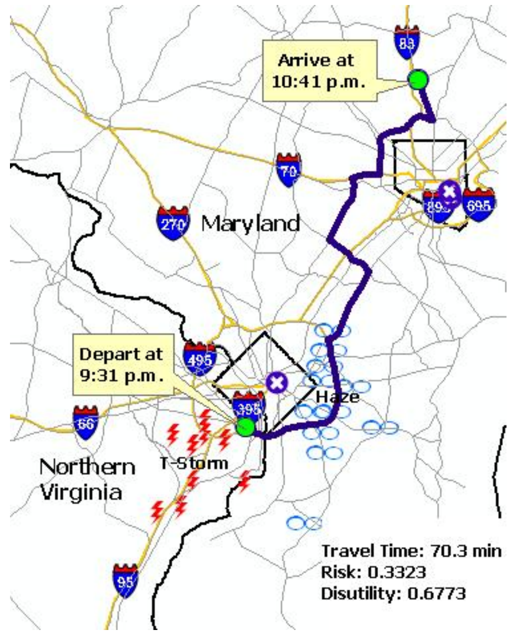
Table 4.2 Travel Impedance of Resulting Routes by Routing Method; Test Run 1

<table>
<tr><th colspan="2" rowspan="2">Routing Method</th><th colspan="3">Travel Impedance</th><th rowspan="2">Performance* on Disutility (%)</th></tr>
<tr><th>Time (min)</th><th>Risk</th><th>Disutility</th></tr>
<tr><td colspan="2">A Posteriori</td><td>79.0</td><td>0.2952</td><td>0.6411</td><td>-</td></tr>
<tr><td rowspan="2">A Priori – Ideal</td><td>Planned</td><td>70.0</td><td>0.2755</td><td>0.5897</td><td>-8.02</td></tr>
<tr><td>Actual</td><td>70.3</td><td>0.3323</td><td>0.6773</td><td>5.65</td></tr>
<tr><td rowspan="2">A Priori – Depart</td><td>Planned</td><td>78.6</td><td>0.2973</td><td>0.6434</td><td>0.36</td></tr>
<tr><td>Actual</td><td>79.0</td><td>0.2952</td><td>0.6411</td><td>0.00</td></tr>
<tr><td rowspan="2">Heuristic – 5 Minutes</td><td>Planned</td><td>79.0</td><td>0.2952</td><td>0.6411</td><td>0.00</td></tr>
<tr><td>Actual</td><td>79.0</td><td>0.2952</td><td>0.6411</td><td>0.00</td></tr>
<tr><td rowspan="2">Heuristic – 10 Minutes</td><td>Planned</td><td>73.4</td><td>0.3267</td><td>0.6762</td><td>5.48</td></tr>
<tr><td>Actual</td><td>73.4</td><td>0.3267</td><td>0.6762</td><td>5.48</td></tr>
<tr><td rowspan="2">Heuristic – 20 Minutes</td><td>Planned</td><td>73.3</td><td>0.3304</td><td>0.6816</td><td>6.32</td></tr>
<tr><td>Actual</td><td>73.4</td><td>0.3267</td><td>0.6762</td><td>5.48</td></tr>
</table>

Note: Performance* = difference from *a posteriori* route

A posteriori route (Figure 4.2 (a)) avoids haze. *A priori* – depart (Figure 4.2 (c)) and heuristic – 5 minutes (Figure 4.2 (d)) routes are identical with *a posteriori* route. Though the resulting route is the same, the weather conditions that were considered by these two routing methods are different. Since atmospheric status over links that are under haze in Figure 4.2 (c) was a thunderstorm at the time of departure (i.e. 9:30 p.m.) as presented in Chapter 2, actually *a priori* – depart routing considered a thunderstorm not haze. If there had been no adverse weather conditions at 9:30 p.m. where haze existed in Figure 4.2 (c), *a priori* – depart route would have

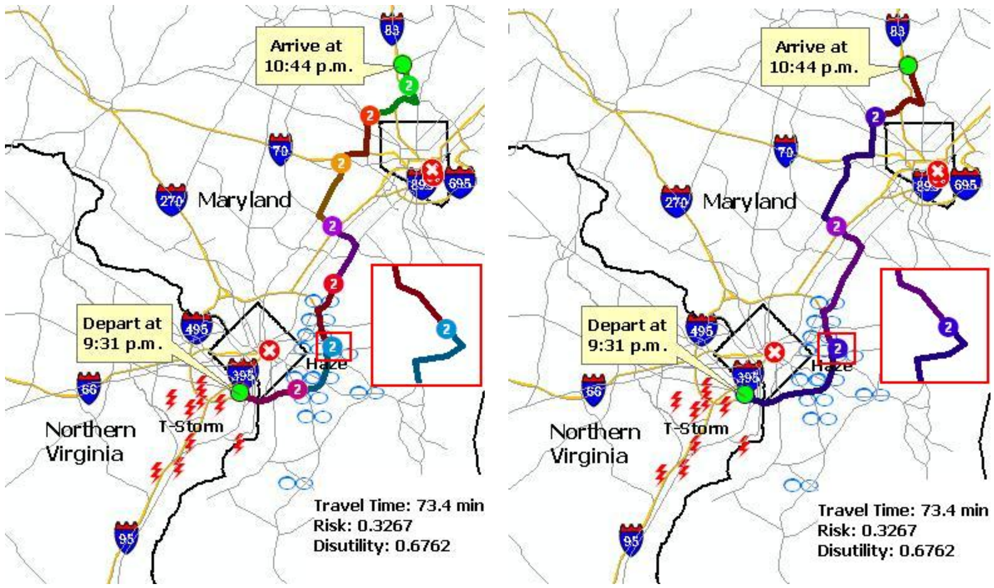
(a) *A Posteriori* Route



(b) *A Priori* – Ideal Route

(c) *A Priori* – Depart Route

(d) Heuristic – 5 Minutes Route



(e) Heuristic – 10 Minutes Route (f) Heuristic – 20 Minutes Route

Figure 4.2 Results of Test Run 1

passed through haze. In terms of disutility, however, *a priori* – depart route is not quite bad compared with *a posteriori* route due to significant reduction (i.e. 8.7 minutes) in travel time. Though the ideal static network state was used in Step 2 of the first iteration, the direction of the first subpath, outgoing from the origin, of heuristic – 5 minutes route (Figure 4.2 (d)) was the same as that of *a posteriori* route that considered adverse weather conditions.

Routing methods of *a priori* – ideal, heuristic – 10 minutes and heuristic – 20 minutes also generate routes that pass through haze. Resulting routes of these three routing methods reduce travel time but increase both risk and disutility compared with *a posteriori* route. *A priori* – ideal route becomes to pass through haze because it assumes ideal weather conditions of dry pavement and unrestricted visibility. In heuristic – 10 minutes and 20 minutes routing, increase in the size of the neighboring area (NA) causes to ignore adverse weather conditions within NA in determining a subpath through the non-neighboring area. Such ignorance eventually led the vehicle to encounter haze within NA. This result implies that it is desirable that the update interval of real-time data is as short as less than 10 minutes to avoid them when adverse weather conditions exist over the network.

4.2.2 Test Run 2

An origin is Boonsboro, Maryland and a destination is Alexandria, Maryland. Departure time is 9:31 p.m. The destination is under a thunderstorm at the time of departure. While the vehicle was in route, the thunderstorm disappeared. The ideal static network state was used in Step 2 of the heuristic during the first iteration. Table 4.3 summarizes travel impedance (i.e., travel time, risk, and disutility) of resulting routes in test run 2. Figure 4.3 provides resulting routes drawn on the map.

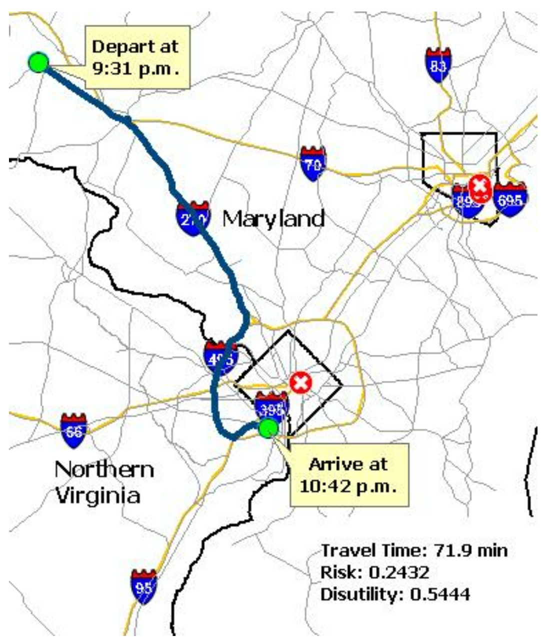
Table 4.3 Travel Impedance of Resulting Routes by Routing Method; Test Run 2

Routing Method		Travel Impedance			Performance* on Disutility (%)
		Time (min)	Risk	Disutility	
A Posteriori		85.3	0.1938	0.5005	-
A Priori – Ideal	Planned	66.2	0.2155	0.4878	-2.54
	Actual	71.9	0.2432	0.5444	8.77
A Priori – Depart	Planned	82.7	0.1927	0.4927	-1.56
	Actual	82.7	0.2266	0.5448	8.85
Heuristic – 5 Minutes	Planned	81.2	0.2103	0.5161	3.12
	Actual	81.2	0.2103	0.5161	3.12
Heuristic – 10 Minutes	Planned	80.4	0.2136	0.5192	3.74
	Actual	81.2	0.2103	0.5161	3.12
Heuristic – 20 Minutes	Planned	71.5	0.2197	0.5076	1.42
	Actual	71.5	0.2515	0.5561	11.11

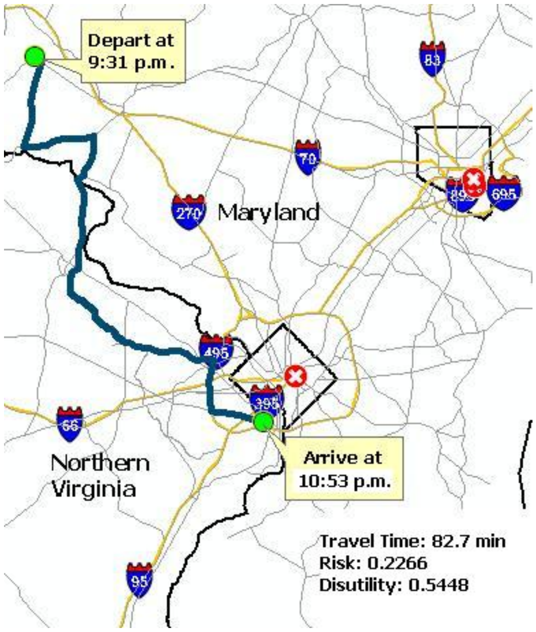
Note: Performance* = difference from *a posteriori* route

Routes that result from *a priori* – depart, heuristic – 5 minutes, and heuristic – 10 minutes (Figures 4.3 (c), (d), and (e)) are similar with *a posteriori* route (Figure 4.3 (a)). Routes of heuristic – 5 minutes and 10 minutes are equally good (i.e. 3.12% difference) as *a posteriori* route on disutility. However, *a priori* – depart route incurs 8.85% higher disutility than *a posteriori* route though it is most similar with *a posteriori* route among three routes. This is because it enforces the vehicle to take state highway rather than interstate highway for several segments near by the destination considering the thunderstorm that existed around the destination at the time of departure. Given dry pavement and unrestricted visibility, the conditional probability of a truck accident is approximately 50% lower on interstate highways than that on state highways as noted in Table 1.4 in Chapter 1. This result implies that *a priori* – depart routing method can unnecessarily consider them when adverse weather conditions around the destination disappear while the vehicle is in route.

(a) *A Posteriori* Route

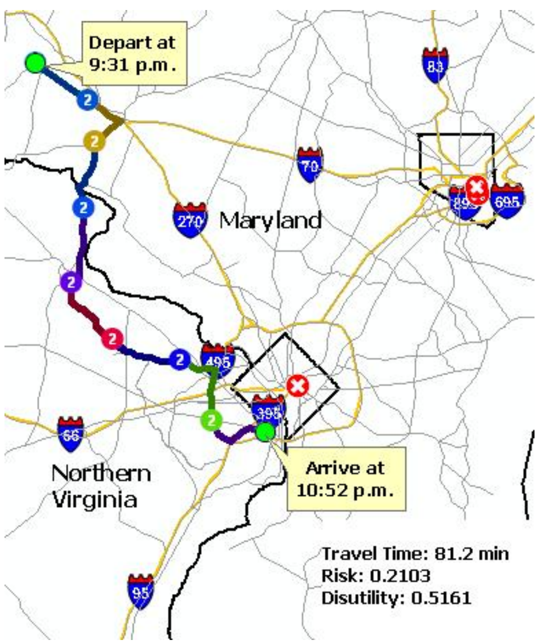


(b) *A Priori* – Ideal Route

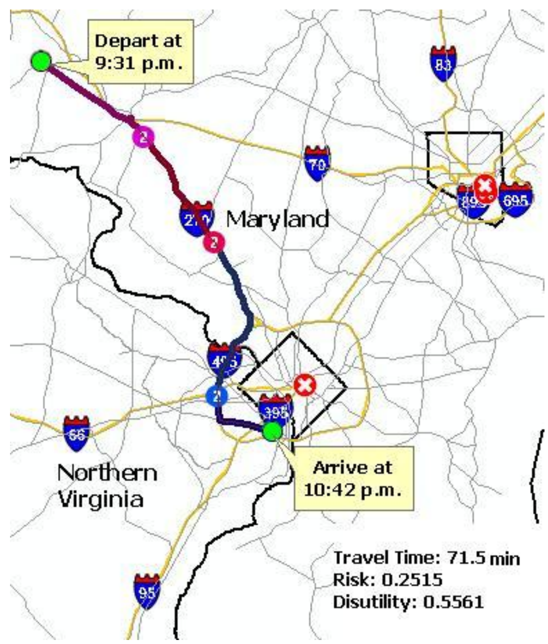


(c) *A Priori* – Depart Route

(d) Heuristic – 5 Minutes Route



(e) Heuristic – 10 Minutes Route



(f) Heuristic – 20 Minutes Route

Figure 4.3 Results of Test Run 2

A priori – ideal route (Figure 4.3 (b)) and heuristic – 20 minutes route (Figure 4.3 (f)) also incur much higher (i.e. 8.77% and 11.11%) disutility than *a posteriori* route. Planned disutility of *a priori* – ideal route is 2.54% less than disutility of *a posteriori* route, but it turned out the actual disutility is 8.77% higher than disutility of *a posteriori* route. Heuristic – 20 minutes route becomes to be similar with *a priori* – ideal route by using the ideal static network state in Step 2 of the first iteration.

4.2.3 Test Run 3

An origin is Dale City, Maryland and a destination is City of Baltimore, Maryland. Departure time is 9:31 p.m. The origin is under a thunderstorm at the time of departure. The thunderstorm was moving in the direction of the destination. While the vehicle was in route, the thunderstorm disappeared around the origin and diminished to haze in east of Washington D.C. The ideal static network state was used in Step 2

Table 4.4 Travel Impedance of Resulting Routes by Routing Method; Test Run 3

Routing Method		Travel Impedance			Performance* on Disutility (%)
		Time (min)	Risk	Disutility	
A Posteriori		74.0	0.2207	0.5149	-
A Priori – Ideal	Planned	63.6	0.2538	0.5420	5.26
	Actual	63.6	0.2840	0.5874	14.08
A Priori – Depart	Planned	73.8	0.2226	0.5173	0.47
	Actual	74.0	0.2207	0.5149	0.00
Heuristic – 5 Minutes	Planned	71.1	0.2396	0.5369	4.27
	Actual	71.1	0.2396	0.5369	4.27
Heuristic – 10 Minutes	Planned	62.8	0.3778	0.7294	41.66
	Actual	62.8	0.3778	0.7294	41.66
Heuristic – 20 Minutes	Planned	66.7	0.2787	0.5865	13.91
	Actual	66.7	0.2785	0.5862	13.85

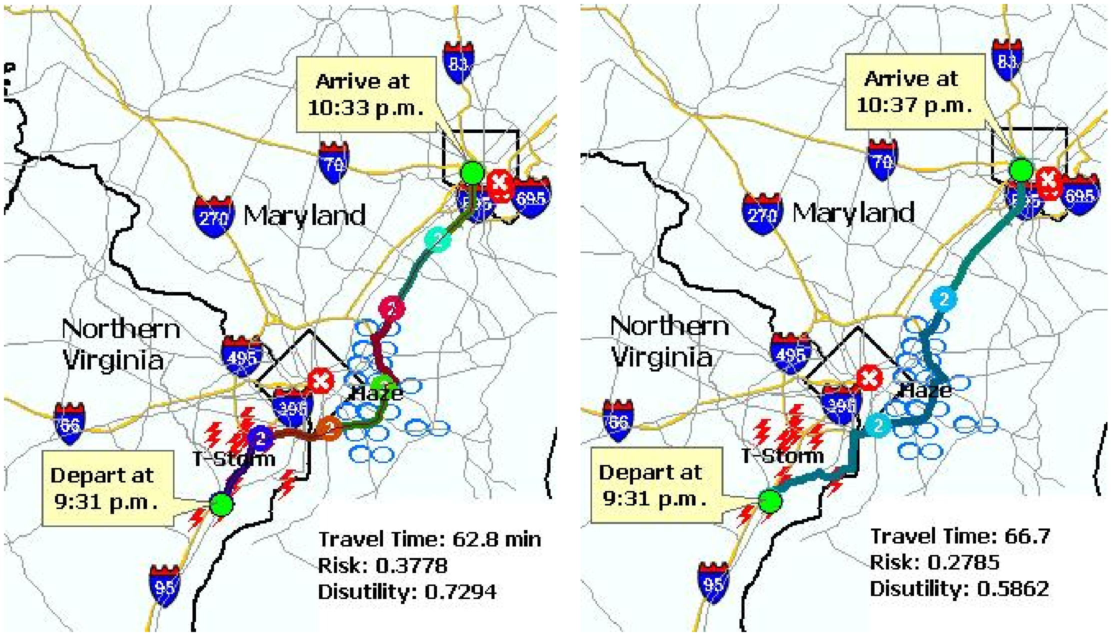
Note: Performance* = difference from *a posteriori* route of the heuristic during the first iteration. Table 4.4 summarizes travel impedance (i.e., travel time, risk, and disutility) of resulting routes in test run 3. Figure 4.4 presents resulting routes.

(a) *A Posteriori* Route

(b) *A Priori* – Ideal Route

(c) *A Priori* – Depart Route

(d) Heuristic – 5 Minutes Route



(e) Heuristic – 10 Minutes Route (f) Heuristic – 20 Minutes Route

Figure 4.4 Results of Test Run 3

A priori – depart route (Figure 4.4 (c)) is identical with *a posteriori* route that goes around haze. Heuristic – 5 minutes route (Figure 4.4 (d)) is similar with *a posteriori* route in terms of both directions and disutility. Routes of *a priori* – ideal, heuristic – 10 minutes, and heuristic – 20 minutes (Figures 4.4 (b), (e), and (f)) incur much higher disutility than the *a posteriori* route because they pass through the thunderstorm or haze. Of note is that the resulting route of heuristic – 10 minutes incurs 41.66% higher disutility than *a posteriori* route by routing the vehicle to both a thunderstorm and haze. This case may happen if the origin is located at the boundary of a severe weather in the direction that is away from the destination and the update interval of real-time data is relatively long (i.e. longer than 10 minutes).

4.2.4 Test Run 4

The O-D pair is the same as in Case Study 2. Departure time is 9:51 p.m. The destination is located between a thunderstorm and haze at the time of departure. While the vehicle is in route, the thunderstorm disappeared. The most recent past network state was used in finding a subpath in NNA for all iterations of the heuristic. That is, this test run is more faithful to the original experimental design presented in Table 4.1. Table 4.5 summarizes travel impedance (i.e., travel time, risk, and disutility) of resulting routes in test run 4. Figure 4.5 presents resulting routes.

Table 4.5 Travel Impedance of Resulting Routes by Routing Method; Test Run 4

Routing Method		Travel Impedance			Performance* on Disutility (%)
		Time (min)	Risk	Disutility	
A Posteriori		83.1	0.1931	0.4942	-
A Priori – Ideal	Planned	66.2	0.2155	0.4878	-1.30
	Actual	73.2	0.2182	0.5093	3.06
A Priori – Depart	Planned	82.7	0.1928	0.4928	-0.28
	Actual	82.7	0.2267	0.5448	10.24
Heuristic – 5 Minutes	Planned	83.1	0.1931	0.4942	0.00
	Actual	83.1	0.1931	0.4942	0.00
Heuristic – 10 Minutes	Planned	84.6	0.1958	0.5019	1.56
	Actual	83.1	0.1931	0.4942	0.00
Heuristic – 20 Minutes	Planned	83.5	0.1933	0.4954	0.24
	Actual	83.1	0.1931	0.4942	0.00

Note: Performance* = difference from *a posteriori* route

All three heuristic routes (Figures 4.5 (d), (e), and (f)) are identical with *a posteriori* route (Figure 4.5 (a)). This improvement on the heuristic routing, as compared to the first three test runs, is made by considering the most recent past network state in finding a subpath in NNA for all iterations of the heuristic. *A priori* –

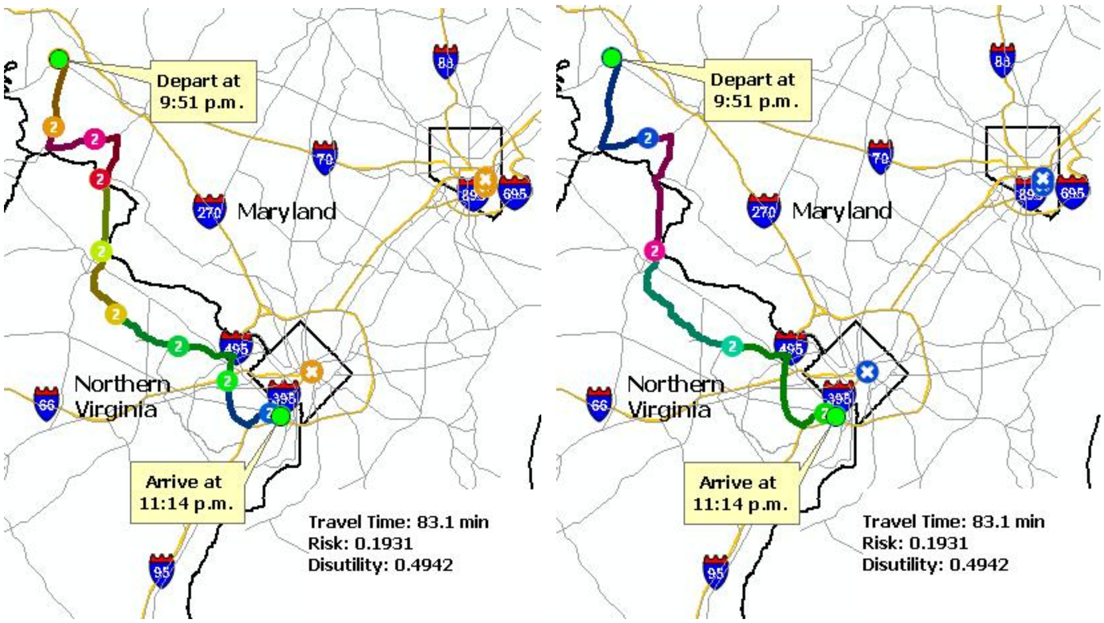
ideal route (Figure 4.5 (b)) is dissimilar with *a posteriori* route but its disutility is equally good (i.e. 3.06%) as *a posteriori* route. This is because there were no significant changes in traffic and weather conditions along *a priori* – ideal route. This

(a) *A Posteriori* Route

(b) *A Priori* – Ideal Route

(c) *A Priori* – Depart Route

(d) Heuristic – 5 Minutes Route



(e) Heuristic – 10 Minutes Route (f) Heuristic – 20 Minutes Route

Figure 4.5 Results of Test Run 4

result implies that the benefit of using real-time information is not significant when traffic and weather conditions do not change remarkably. On the other hand, *a priori* – depart route incurs the highest disutility among all routing methods because it unnecessarily considered a severe weather condition, i.e. the thunderstorm diminished while the vehicle was in route, at the destination at the time of departure.

4.2.5 Test Run 5

The O-D pair is the same as in test run 3. Departure time is 9:51 p.m. At the time of departure, the origin is located at the boundary of a thunderstorm and there is haze in the direction of the destination. The thunderstorm disappeared but haze persisted while the vehicle was in route. The most recent past network state was used in finding a subpath in NNA for all iterations of the heuristic. Thus, this test run is also faithful to the original experimental design, described in Table 4.1, like test run 4. Table 4.6 summarizes travel impedance (i.e., travel time, risk, and disutility) of resulting routes in test run 5. Figure 4.6 presents resulting routes.

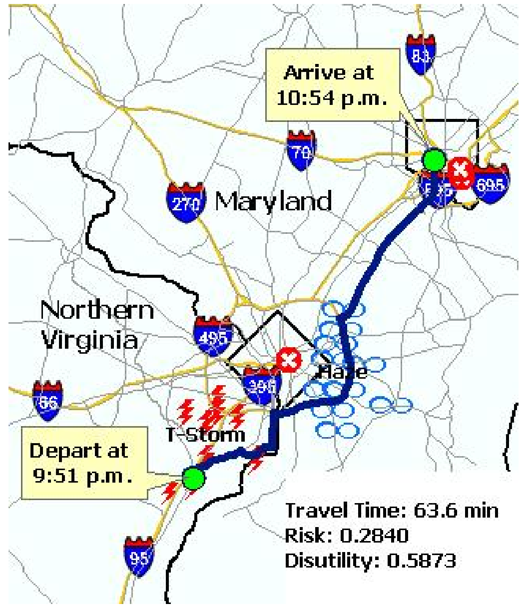
Table 4.6 Travel Impedance of Resulting Routes by Routing Method; Test Run 5

Routing Method		Travel Impedance			Performance* on Disutility (%)
		Time (min)	Risk	Disutility	
A Posteriori		74.2	0.2206	0.5153	-
A Priori – Ideal	Planned	63.6	0.2538	0.5420	5.18
	Actual	63.6	0.2840	0.5873	13.97
A Priori – Depart	Planned	74.0	0.2205	0.5147	-0.12
	Actual	74.2	0.2206	0.5153	0.00
Heuristic – 5 Minutes	Planned	71.1	0.2394	0.5353	3.88
	Actual	71.1	0.2394	0.5353	3.88
Heuristic – 10 Minutes	Planned	67.5	0.2798	0.5902	14.54
	Actual	66.7	0.2784	0.5861	13.74
Heuristic – 20 Minutes	Planned	66.7	0.2785	0.5863	13.78
	Actual	66.7	0.2784	0.5861	13.74

Note: Performance* = difference from *a posteriori* route

The difference from *a posteriori* route of heuristic – 10 minutes route (Figure 4.6 (e)) was reduced significantly by considering the most recent past network state in finding a subpath in NNA for all iterations of the heuristic, as compared with that in test run 3. The results on other routing methods are approximately the same as those obtained from test run 3.

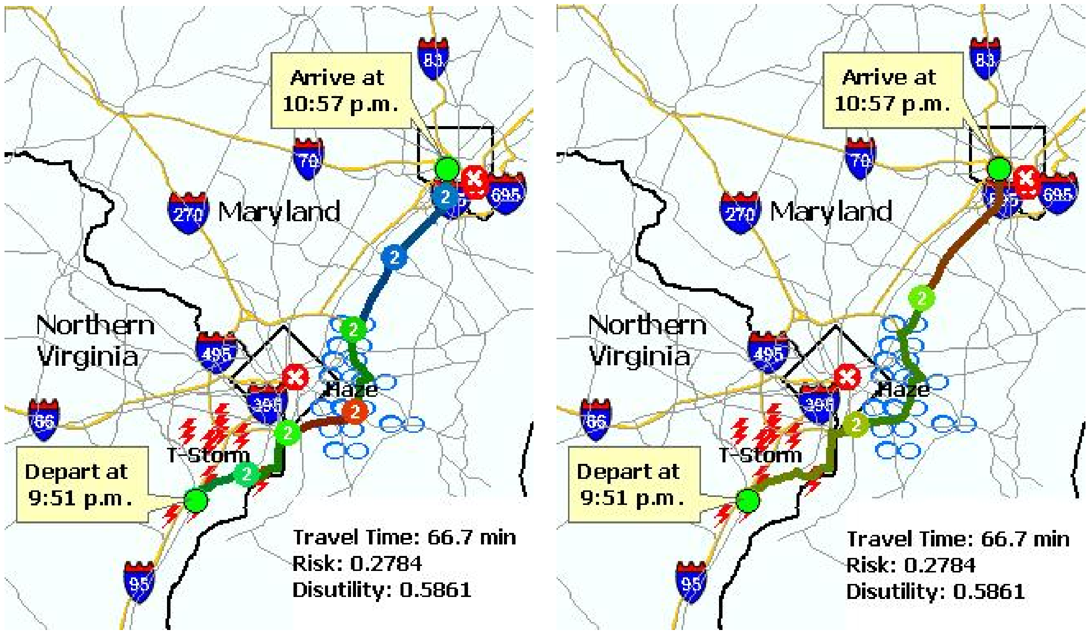
(a) *A Posteriori* Route



(b) *A Priori* – Ideal Route

(c) *A Priori* – Depart Route

(d) Heuristic – 5 Minutes Route



(e) Heuristic – 10 Minutes Route (f) Heuristic – 20 Minutes Route

Figure 4.6 Results of Test Run 5

4.2.6 Summary of Results

Table 4.7 summarizes optimality of resulting routes by routing method for the five test runs. Disutility of *a posteriori* route is considered as 100% optimal value. Figure

Table 4.7 Optimality of Resulting Routes by Routing Method (Unit: %)

Routing Method	Test Run 1	Test Run 2	Test Run 3	Test Run 4	Test Run 5
A Priori – Ideal	94.35	91.23	85.92	96.94	86.03
A Priori – Depart	100.00	91.15	100.00	89.76	100.00
Heuristic – 5 Minutes	100.00	96.88	95.73	100.00	96.12
Heuristic – 10 Minutes	94.52	96.88	58.34	100.00	86.26
Heuristic – 20 Minutes	94.52	88.89	86.15	100.00	86.26

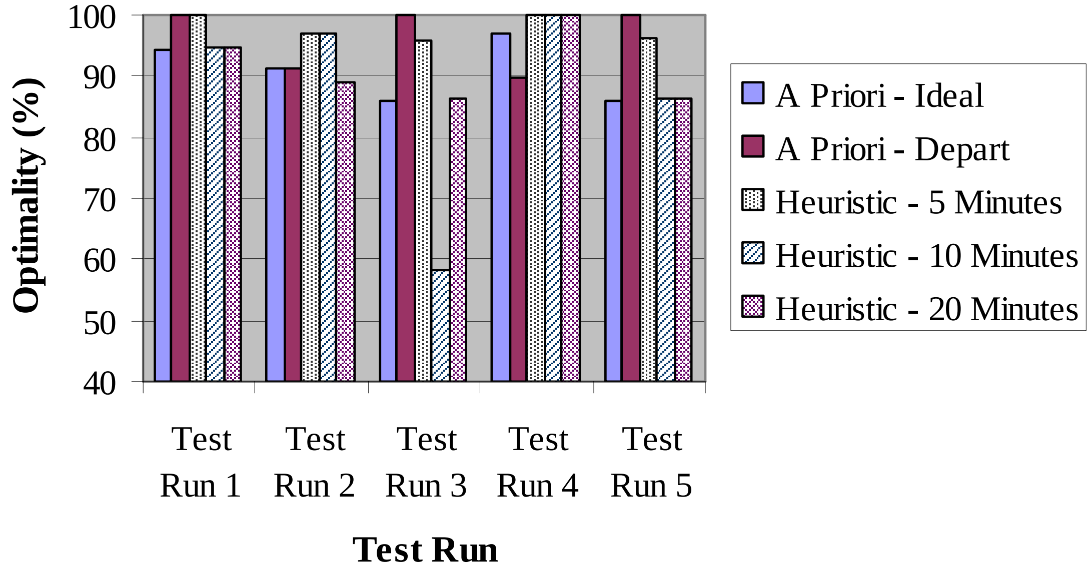


Figure 4.7 Optimality of Resulting Routes by Routing Method

4.7 presents a chart drawn based on the optimality values in Table 4.7.

In the perspective of verifying the benefit of use of real-time information in rerouting the hazmat truck, test runs 3 and 5 can be stated as well designed experiments than others. *A priori* – ideal routing method shows relatively poor performance, i.e. less than 90% optimality, in these two test runs. The origin was under adverse weather conditions such as a thunderstorm or haze at the time of departure in these test runs. Test run 1 also has a similar property on the origin but significant reduction in travel time of *a priori* – ideal route compensates increase in risk. Thus, the optimality of *a priori* – ideal route in test run 1 is greater than 90%.

A priori – depart routing method shows relatively poor optimality (i.e. about 90%) in test runs 2 and 4. For these two test runs, the destination was under adverse weather conditions at the time of departure. While the vehicle was in route, adverse weather conditions disappeared. By its routing mechanism, *a priori* – depart routing unnecessarily considers, bad weather conditions around the destination. On the other hand, a priori – depart routing provides good performances (i.e. 100% optimality) when the origin is located under adverse weather conditions at the time of departure as set in test runs 1, 3, and 5.

Heuristic – 5 minutes routing shows the best performance among all routing methods such that the optimality of resulting routes is consistently greater than 95%. This result indicates that though real-time information is employed only within the neighboring area of the current vehicle's location, the heuristic solution can be equally as good as *a posteriori* solution when the network state is frequently updated.

In general, routing methods of heuristic – 10 minutes and 20 minutes provide routing instructions that are slightly better or equally good as *a priori* – ideal routing method. However, as the size of the neighboring area (NA) becomes large as compared to heuristic – 5 minutes routing, the extent to ignore adverse weather conditions within the NA can increase and it can cause very low optimality. The optimality of heuristic – 10 minutes route in test 3 that is less than 60% shows an example of this situation.

Chapter 5: Conclusions and Future Considerations

In this thesis, the problem of rerouting a hazmat truck given real-time traffic and weather information was addressed. The real-time road weather advisory system was emulated in a GIS environment by integrating actual real-time data with the transportation network for the District of Columbia metropolitan region. Real-time traffic and weather data were collected for two hours between 9:30 p.m. and 11:30 p.m. on July 12th, 2005. In addition to real-time data, population data in the study area were combined with the network.

A heuristic that can quickly generate updated routing instructions is proposed. The heuristic reduces the multiobjective problem of minimizing travel time and minimizing risk to a single objective problem assuming a linear additive utility function. The heuristic only requires real-time information within a neighboring area of the vehicle's current location.

The proposed heuristic was tested on the Washington D.C. metropolitan region network. Real-time data is integrated with the network in ArcGIS 9.1. Five runs of the heuristic were made for three origin and destination pairs and two departure times. Heuristic solutions were compared with *a posteriori* solutions obtained from the implementation of a modified TDLTP algorithm in C++ environment and *a priori* solutions to assess the benefit using real-time information in routing hazmat vehicles.

Results from the case study imply that one can provide better routing instructions than would be obtained if planned *a priori* by rerouting a hazmat truck adapting to real-time traffic and weather conditions. Though real-time information is employed only within a neighboring area of current location, the heuristic solution can be equally as good as the *a posteriori* solution when the network state is updated frequently (i.e., every 5 minutes). When the network state is not significantly changed due to adverse weather conditions, the heuristic routing with a relatively long time interval (i.e., 10 minutes and 20 minutes) also ensures higher quality solutions than the *a priori* routing that assumes non-congested traffic and clear weather conditions without using real-time information.

The best available sources of data at the time of the case study development were employed in this study. Enhancements to these data sources and how the data is used within the heuristic could lead to improved results. First, both traffic and weather data should be updated frequently. This study applied hourly updated weather data due to the lack of a better alternative. In the future, Road Weather Information System (RWIS) has promise as a good source of real-time weather data. For example, the RWIS managed by Maryland State Highway Administration is now providing real-time weather information at 10 minute intervals or less. Though these data could not be obtained in real-time for this study, operations centers that provide routing instructions to hazmat trucks may be able to use the RWIS data. Second, one might use a more sophisticated model to estimate population exposure to hazards by inhalation than the model used herein that fixes an impact radius to 5 miles. Identification of the impact area based on a dispersion model could provide better exposure estimates. Third, one might consider the use of existing weather forecasts to predict the network state. Fourth, individual vehicle-based traffic data could be helpful in better estimating arc travel times.

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