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A FRAMEWORK FOR ASSESSING SUSTAINABILITY IMPACTS OF TRUCK ROUTING STRATEGIES

by

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A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in the Department of Civil and Environmental Engineering
in the College of Engineering and Computer Science
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ABSTRACT

The impact of freight on our transportation system is further accentuated by the fact that trucks consume greater roadway capacity and therefore cause more significant problems including traffic congestion, delay, crashes, air pollution, fuel consumption, and pavement damage. Assessing the actual effects of truck traffic is a growing need to support the ability to safely and efficiently move goods and people in areas where roadway expansion is not the best option. On one hand, trucks need to efficiently serve commerce and industry, while at the same time their activities need not contribute to a decline in the quality or public safety. In the current practice, to the best of the authors' knowledge, there is no framework methodology for real-time management of traffic, specifically on truck routes, to reduce travel duration and avoid truck travel delays due to non-recurring congestion (i.e. traffic incidents) and to estimate impacts on traffic flows, economy, and environment. The objective of this study is to develop a truck routing strategy and to quantify its' impacts on travel time, emissions and consequently assess the effects on the economy and environment. In order to estimate non-recurrent congestion based travel delay and fuel consumption by real-time truck routing simulation models, significant corridors with high truck percentages were selected. Furthermore, tailpipe emissions (on-site) due to traveled distance and idling are estimated via MOVES emissions simulator software. Economic Input Output-Life Cycle Assessment Model is utilized to gather fuel consumption related upstream (off-site) emissions. Simulation results of various scenarios indicated that potential annual value of time savings can reach up to $1.67 million per

selected corridor. Consistently, fuel costs and emission values are lower, even though extra miles are traveled on the alternative route. In conclusion, our study confirms that truck routing strategies in incident conditions have high economic and environmental impacts.

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CHAPTER ONE: INTRODUCTION

1.1 Overview

Traffic congestion has been an enormous problem in many aspects. In 2014, traffic congestion caused urban drivers in U.S. to travel an extra 6.9 billion hours and consume an extra 3.1 billion gallons of fuel resulting in a congestion cost of $160 billion. Trucks account for 17 percent ($28 billion) of that cost, much more than truck percentage on roads which are 7 percent of traffic (see Figure 1). Truck traffic is the largest portion among freight transport modes. Therefore, the demand of freight has been a growing source of traffic demand on the transportation network and, historically, has grown at faster rates as compare to the growth of person-travel demand. In order to meet the needs of individuals and businesses, shipment of materials and products is a primary component of travel demand on the transportation system. Trucks involved in freight transportation are third only to person travel for daily activities and tourist travel in terms of vehicle miles of travel on the roadway system. Since trucks consume greater highway capacity, thereby reduce the level of service, the impact of freight is further assessed including congestion, delay, crashes, air pollution, fuel consumption, and roadway damage in many regions. The overall impact is usually higher as compared to urban passenger vehicles due to larger sizes and heavier weights.

Florida is the fourth largest state in terms of population. Additionally, annual tourist population is over 80 million tourists in Florida. Furthermore, the state produces a number of products shipped both domestically and internationally. Consequently, Florida is a major destination and source for freight movement. In 2003, 848 million tons of freight with over $939 billion value were transported to, from, within, and through Florida via truck, rail, water modes, and air. (Florida Statewide Freight and Goods Mobility Plan). Among the freight modes, approximately 597 million tons were moved on highways via trucks. When the shipment values are considered, the portion (i.e. %80) of trucks gets even greater.

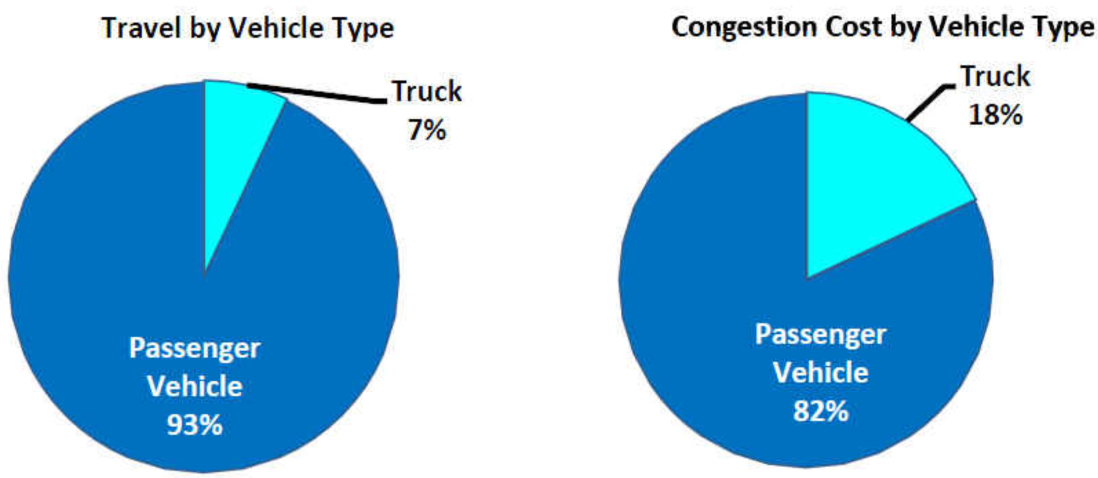

Figure 1: Cost of Congestion for Urban Passenger and Freight Vehicles in 2014
(Source: Urban Mobility Scorecard, TTI - 2015)

In Figure-2 the value and tonnage of Florida's freight shipments by mode is presented. As the figure illustrates, trucks continue to be the dominant mode of freight transportation and are predicted to increase in both value and tonnage until 2040. Moreover, there is a decrease in tonnage and value from 2007 to 2009 primarily due to the economic downturn.

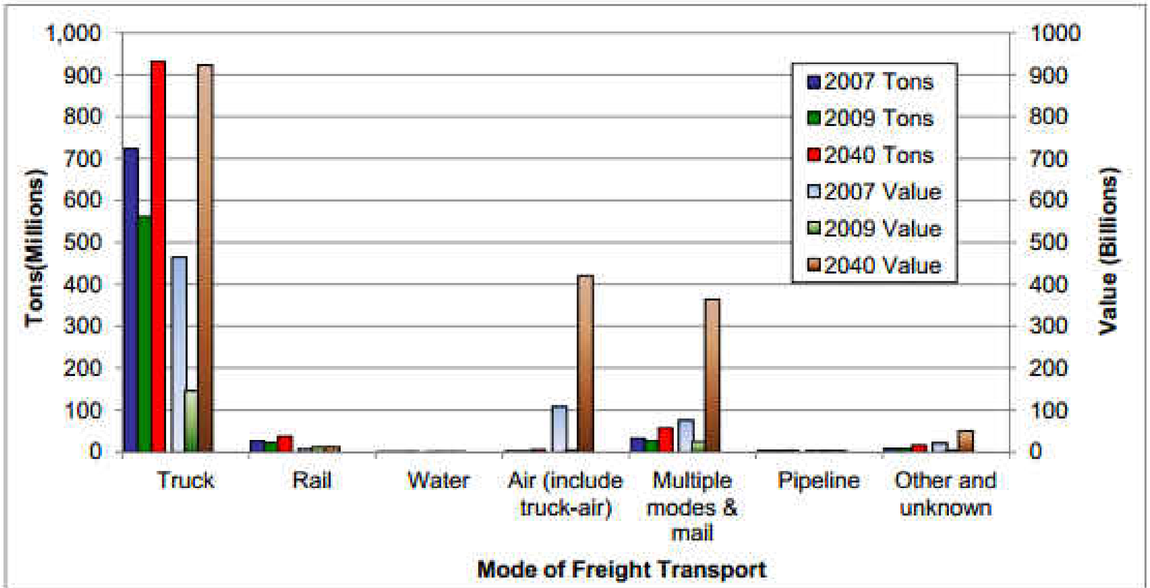

Figure 2: Florida Originating Freight Shipments by Mode (Source: FDOT, Office of Policy Planning, 2011)

1.2 Problem Statement

With the expansion of freight movements, there is a growing need to assess the actual effects of trucks on traffic to maintain safe and efficient transportation for booth goods and people, particularly in areas where roadway extension is generally not an option. Transportation decision makers, planners and engineers require more effectively assess the impacts of locating shipping intensive land uses and improve the inputs to the tools used to manage traffic. Thus, quantifying the actual impacts of truck movements is crucial for urban dynamics. On one hand, trucks need to efficiently serve commerce and industry, while at the same time their activities need not contribute to a decline in the quality of life or public safety.

There are also concerns about sustainability impacts based on truck movements. Given the majority of trucks are powered by diesel engines, the pollutants emitted by such type of engines, for example fine particulate matter (also known as PM2.5 which the average size of particles are less than 2.5 μm), NOx and CO pollution have ill effects on public health. The primary sources of PM2.5, NOx and CO pollution in the urban areas are on-road mobile sources. About 80 percent of these emissions are released into the atmosphere through the combustion of diesel fuel by trucks and they are composed of road dust, smoke, and liquid droplets (Frey 2008, Kanaroglou 2008, Fraser 1999). The increased trend of truck activity and related congestion worsen the air pollution. However, in the current practice, truck movement induced pollution assessment is not straightforwardly possible due to lack of a framework modeling methodology with applied supporting data to predict the highway section-level dynamic truck activities and corresponding emission inventory.

1.3 Research Objective

The objective of this research is to develop operational strategies on truck routes in order to enhance the travel efficiency and find the impacts of truck movements in terms of congestion cost, safety, and sustainability.

1.4 Research Methodology

In order to advance the truck travel efficiency and quantify the sustainability impacts of truck movements, a research methodology is developed. A framework of the research methodology is presented in Figure-3. The framework consists of the following five main tasks which will be detailed in this dissertation:

Task 1: Identify significant regions, facilities, and corridors in order to estimate congestion based travel delay and fuel consumption by truck routing models (i.e. microscopic operational analysis) and monetize the impacts.

Task 2: Determine the tailpipe emissions due to congestion related fuel consumption and estimate the truck re-routing scenarios emissions.

Task 3: Analyze the effects on traffic flow and possible impacts on crash rates (i.e. conflict points such as rear-end, crossing, and lane change).

Task 4: Identify the petroleum refinery savings with Economic Input Output – Life Cycle Assessment model.

Task 5: Determine the air pollution related social impacts by assessing both tailpipe and supply chain emissions.

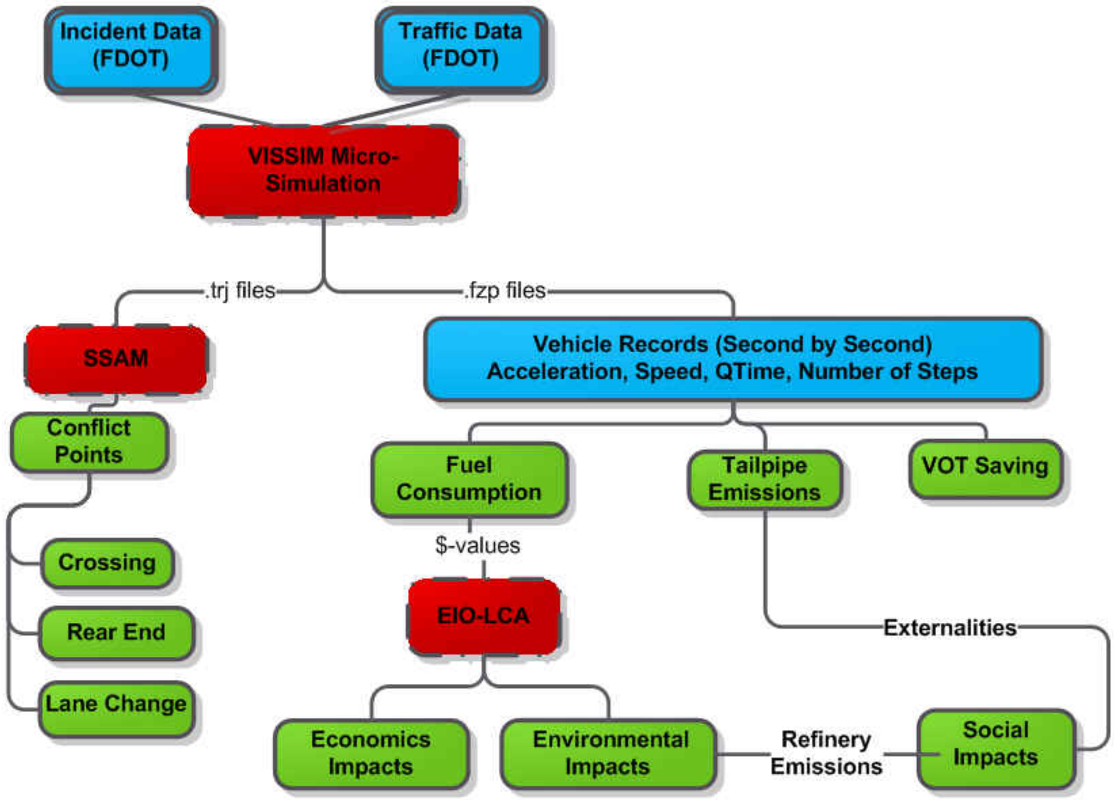

Figure 3: Framework of the Research Methodology

1.5 Dissertation Organization

The dissertation is organized as follows: Chapter two, following this chapter, summarizes the literature on previous routing and value of truck travel times as well as the sustainability impacts related studies. Chapter three provides the preliminary analysis where an undetailed truck re-routing model without using second-by-second traffic simulation is developed and the overall sustainability impacts are presented. Next chapter presents a second-by-second traffic micro-simulation model calibrated by PTV VISSIM software package including Visual Basic scripts. The following chapter number five assesses the direct impacts in terms of monetary value, fuel consumption, tailpipe emissions as well as traffic safety via a Surrogate Safety Assessment Model (SSAM). Chapter 6 provides the petroleum refinery supply chain impacts where a Triple Bottom Line – Life Cycle Assessment (TBL-LCA) approach was utilized. Last but not least, study findings including the study limitations are summarized in the conclusion chapter.

CHAPTER TWO: REVIEW OF LITERATURE

There are three sections in this chapter. A synthesis of literature on the travel delay studies is presented in the first section. The second section provides tailpipe emission analysis literature for trucks. The last section presents Economic Input-Output Life Cycle Assessment (EIO-LCA) studies.

2.1 Travel Delay Studies

Traffic congestion is classified in two main categories in literature: recurring congestion (i.e. peak hours, construction zones) and non-recurring congestion (i.e. traffic incidents induced congestion). Traffic congestion due to incidents has a large amount of impact on traffic delays on freeways. There have been numerous research efforts on minimizing the effect of the traffic incidents and many of them have studied developing different methodologies to determine the formation of incidents.

In a USDOT research project, an incident induced delay (IID) model was developed by Wang in 2008. Current methods are using either deterministic queuing theory or shock wave analysis. The queuing theory-based procedures calculate IID by using the queuing diagram formed by the cumulative vehicle arrival and departure curves. These methods examine the area among the curves to calculate the delay in units of vehicles-hours. Using the queuing diagram, Morales (1987), created a method to determine IID by implementing in Lotus 1-2 and 3. Doing so, it eases to compute the delay, time to normal flow and maximum queue in the result of freeway incidents. Similar to this method, Lindley (1987) also created a method with FREWAY model. Ten years later, another method was proposed by Sullivan (1997) by using two level approaches. It was using the queuing diagram and the FREWAY, which was called IMPACT. This method forecasts incident rate severity as well as it is duration in the level one and for the second level it forecasts the traffic delay that is caused by the incidents. While Skabardonis et al. (1998) used queuing diagram to show IID, Fu and Rilet (1997) created a model to estimate the delay on an incident region. Fu and Rilet, used real time traffic conditions to estimate the time. Soon after, Fu and Hellinga used fuzzy queuing to estimate future delay on an incident situation.

Another set of research was done in utilizing Artificial Neural Networks (ANN) (Ritchie and Cheu 1993; Ishak and Al-Deek 1998), an approach based on loop occupancy (Lin and Daganzo 1997), and wavelet technique (Teng and Qi 2003). Those methods contribute by spending less time for detection of the incidents and therefore decrease the overall negative impacts of the incidents on the traffic delays.

Cohen and Southworth (1999) utilized queuing model and developed a methodology to forecast the time delay on an incident on freeways. Li et al. (2007) introduced a model where the estimation model provides a good mean and variance model for IID and incident time.

Since the traffic model has some similarities with fluid flow, some researchers proposed to use kinematic wave theory to explain traffic flow. This idea also helped to explain shockwave effect analysis of IID. The very first attempt to explain shockwave effect was by Lighthill and Whitham (1955). At the same time, Richards (1956) created a model for traffic flow with the idea of replacing the single vehicles with continues fluid density. Thereby in the literature of traffic engineering, the first shock-wave-based model was called the LWR models.

Al-Deek et al. in 1995 introduced a new method to estimate incident delays with using loop data and incident data based on the shock wave analysis. This method divides the free way into smaller parts and calculates each parts delay individually and then sum them up for the final delay time. Mangeot and Lesort (2000) explained incident induced flow perturbation variation in his study. Estimation of delay from queuing were explained with shock effect took place with different studies. One of them was Nam and Drew (1996) came to conclusion by pointing out that "deterministic queuing analysis always underestimates the overall magnitude of delays compared to shock-wave analysis." Nonetheless, Hurdle and Son (2001) and Rakha and Zhang (2005) supposed that for better result, both methods should be used together to gain additional knowledge about traffic congestion.

Hallenbeck et al. (2003) used Seattle's metropolitan freeways to understand the nature of the traffic congestion. Comparison was made with comparing the normal use of lane versus usage at an incident occurrence. Thereby the estimation was done by looking at the difference between the two profiles. This method, later among researches, opened a door to incident detections and delay estimation in Washington State, even though the traffic congestion was questionable because of the movement from upstream to downstream locations.

Avoidable time spent in traveling, from an economic theory perspective, is a non-productive activity against which there is an cost of opportunity. For instance, travel delays in daily commute can cause work time loss. Commonly, an approach to placing a cost on the travel delay is to quantify the value of such time in terms of hours lost multiplied by a fraction of the gross hourly wage, including drivers' compensation and other benefits paid for by employees (Hensher 2001). Moreover, several studies in travel behavior have used discrete choice models to derive the travel time value, for both work-related and non-work-related purposes. The most widely used approach has been to estimate logistic regression models to explain mode or route choices of travelers. These models estimate the choices made by a sample of individuals and consider differences that travelers face in terms of travel time spent in-vehicle and out-of-vehicle. Also, various monetary costs associated with each mode or route alternative are estimated by these methodologies. The resulting parameter coefficients are assigned to the travel time versus travel cost variables in these models and thereby derive a monetary value of time savings (Hensher 2001).

The majority of travel time evaluation study efforts have based their findings on traveler responses or representative daily travel times measured by surveying techniques. However, several empirical studies have verified the significance of taking into consideration the travel time variability in the derivation of traveler cost functions as well (e.g. Jackson and Jucker 1982, Polak 1987, Black and Towriss 1993, Senna 1994, Abdel-

Aty et al. 1995, Noland and Small 1995). According to these studies, under certain circumstances, during congested peak hours travel, reducing the variability which will also reduce the uncertainties associated with travel times would result in significant traveler benefits. Typically, the major portion of benefits are found to be travel time savings on transportation and infrastructure projects (USDOT FHWA 1996). The impacts of traffic incidents are an empirically proven to have major contribution to of day-to-day variability in trip times, including severe and non-severe crashes, that block traffic lanes for extended periods and many minor incidents, such as abandoned vehicles etc. (see Lindley 1987, Giuliano 1989, Schrank et al. 1993).

2.2 Tailpipe Emissions

Numerous studies have been conducted to assess emissions due to Heavy-Duty Diesel Vehicles (HDDVs) idling, particularly from long-haul trucks, to understand the effects of diesel engine speed and accessory loading on idle emissions from these trucks and thus, to evaluate the performance of technologies that reduces idling. Mc-Cormick et al. in 2000 measured idling induced pollutants from 24 HDDV and 4 heavy-duty compressed natural gas (CNG) vehicles. Diesel engine trucks, emitted 10.2 g/hr of total HCs (THC), 70.98 g/hr of CO, 84.96 g/hr of NOx, and 1.8 g/hr of PM in average during idling, while CNG vehicle idle emissions averaged 86.1 g/hr of THC, 67.14 g/hr of CO, 16.02g/hr of NOx, and 0.18g/hr of PM. Another study effort (Brodrick et al., 2002) analyzed the effects of diesel engine speed and accessory loading on idle emissions on a

1999 model year truck powered by a 450-horsepower diesel engine. Increasing the engine speed from 600 to 1050 revolutions per minute [rpm] with air conditioning on in both cases) resulted in increased emissions of CO, NOx, and CO2 emissions by 460%, 53%, and 90%, respectively. This also raised the fuel consumption by 70%. Storey et al. examined idle emissions from five class 8 trucks, which were tested in the U.S. Army Aberdeen Test Center climate controlled chamber in 2003. Trucks were tested at high and low idling speeds with changing their loads in different weather conditions. The extreme values of emissions were found to be approximately 50–350 g/hr of NOx, 10–80 g/hr of HC, 22–295 g/hr of CO, and 0.8–20 g/hr of PM emissions. Idle fuel consumption ranged from 0.5 to 1.8 gal/hr. The study observed that ambient temperature affected Particulate Matter (PM) emissions, and data showed that PM decreased when temperature increase. This observation is expected since an increase in temperature would cause a more complete combustion of diesel droplets and less condensation of tailpipe PM. In a study effort by Pekula et al., the same data was employed to estimate the effects of ambient temperature, humidity, as well as engine speed on idle emissions in 2003. The emission rates were found to be a function of both inlet temperature and engine load. NOx emissions due to idling ranged from 97 g/hr to 181 g/hr, and CO2 emissions from idling ranged from 5170 g/hr to 11,948 g/hr at minimum and maximum idle engine speed, respectively. Additional studies have also been indicated the potential benefits of various available and forthcoming idle reduction technologies in reducing idling emissions and saving fuel (Stodolosky, F. et al., 2000), (Lutsey, N. et al., 2005).

Abou-Senna and Radwan in 2014 developed a microscopic level transportation emissions model (Micro-TEM) at limited access highways in Florida. Micro-TEM is a surrogate tailpipe CO_2 emission prediction model by integrating second-by-second microscopic traffic simulation with the traffic related (volume, truck percentage, speed limits), road geometry, and temperature parameters.

2.3 EIO - Life Cycle Assessment and Social Impacts of Air Pollution

The Economic Input-Output (EIO) analysis is a well-established methodology, which was developed by Wassily Leontief in the 1970s, for which he received the Nobel Prize (Miller and Blair, 2009). Further, the EIO-LCA model expands the environmental impact data with the EIO tables of the nation's economy to form a comprehensive system boundary.

Economic Input-Output (EIO) analysis proposed to build more powerful methodology with LCA approach to analyze the supply chain impacts including systems or products' economic and environmental impacts (Hendrickson, Lave, & Matthews, 2006).

Economic Input Output-Life Cycle Assessment (EIO-LCA) methodology, which is developed by Carnegie Mellon University, is considering any activity throughout the economic system of the U.S. (CMU, Feb-2013). Matthews et al. had a study related to the industry accounts, which indicates direct environmental emissions consist of 14 percent of total supply chain carbon emissions (HS Mathews, 2008).

In order to assess the externalities from tailpipe emissions and supply chain emissions, Muller and Mendelson developed an assessment model titled Air Pollution Emission Experiments and Policy analysis (APEEP) in 2006. APEEP model is an integrated assessment model that links environmental impacts such as emissions of air pollution to exposures, physical effects, and monetary damages in the contiguous United States (Muller and Mendelsohn 2006, 2007). This model is among one of the traditional assessment models (Mendelsohn 1980; Burtraw et al. 1998; Nordhaus 2002; EPA 1999). Sulfur dioxide (SO2), volatile organic compounds (VOCs), nitrogen oxides (NOx), fine particulate matter (PM2.5), coarse particulate matter (PM10), and ammonia (NH3) are the six pollutants that APEEP evaluate.

APEEP air-quality models utilize the emission data provided by US Environmental Protection Agency (EPA) to estimate corresponding ambient concentrations in each county in the states.

CHAPTER THREE: PRELIMINARY ANALYSIS

In this chapter, a preliminary study was conducted to simulate a real-time truck routing strategy in an incident induced congestion case on a freeway segment that can be alternated by a smooth by-pass route. Preliminary analysis of real-time truck routing strategies which are based on certain assumptions is performed to have an initial understanding of the significance level of its' possible impacts.

3.1 Incident Model: What-if Scenario Analysis

Truck speed and travel-time reliability depends on a number of traffic parameters that could be listed as: roadway geometry, infrastructure design, highway capacity, weather conditions, traffic incidents, construction zones, and travel time.

Among the aforementioned factors, any type of traffic incident is a major impediment to the free flow of traffic, causing approximately 25% of the of the highway delay in U.S. roadways (USDOT FHWA 2005b). Amongst incident types, particularly severe crashes are a significant source of incident induced non-recurrent delay, however, just as important are less severe incidents such as abandoned vehicle, debris etc.

A model is developed to find the incident induced truck travel delays. A scenario site is determined by examining a truck origin-destination data from Tennessee provided by the Productivity Apex, Inc. The discrete truck origin-destination dataset contained the following variables:

- Start date & time, End date & time.
- Duration of the trip.
- Standstill. (Duration of idling).
- Start/End odometer.
- Distance of the trip.
- Start Latitude/Longitude (Origin).
- End Latitude/Longitude (Destination).

Five months of records starting from December, 2013 to April, 2014 was analyzed. Origin and destination points of trucks were spatially plotted by ArcMap software of Geographical Information Systems (GIS) platform to determine a study site which a re-routing optimization effort under congestion conditions could highlight the positive impacts. Hence, a corridor on I75 – Dalton, GA (see Figur-4) was selected as an incident site for the scenario model.

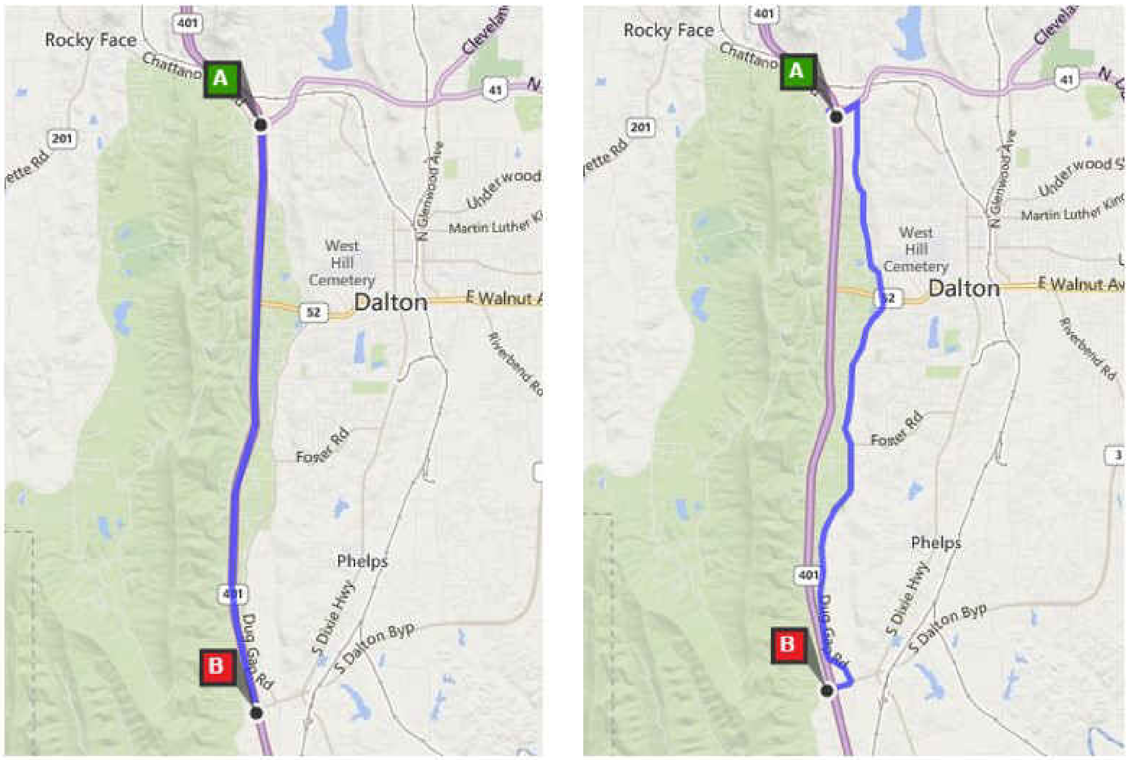

Figure 4: Truck-Trip Site, Origin-Destination Locations (A-B), Interstate-75: Shortest path (7.4 miles) and Alternative Path (9.5 miles)

The shortest path distance between Locations-A to B is 7.4 miles. The distance of the secondary option (alternative route) is 9.5 miles. For the preliminary analysis, only one alternative route is considered.

The model is generated for the southbound direction. The roadway characteristics and variables used in the model are as follows;

Number of lanes	: 3 lanes.
Capacity	: 1,500 vehicles per hour per lane.
Free-flow Speed (Shortest Path)	: 55.5 mph.
Free-flow Speed (Alternative Path)	: 38 mph.

Annual Average Daily Traffic : 40,000 vehicles. (Figure-5)

Truck Percentage : 28 percent. (Figure-6)

Truck Volume : 11,000 trucks per day. (Figure-6)

Free-flow travel time (Shortest Path) : 8 minutes.

Free-flow travel time (Alternative Path) : 15 minutes.

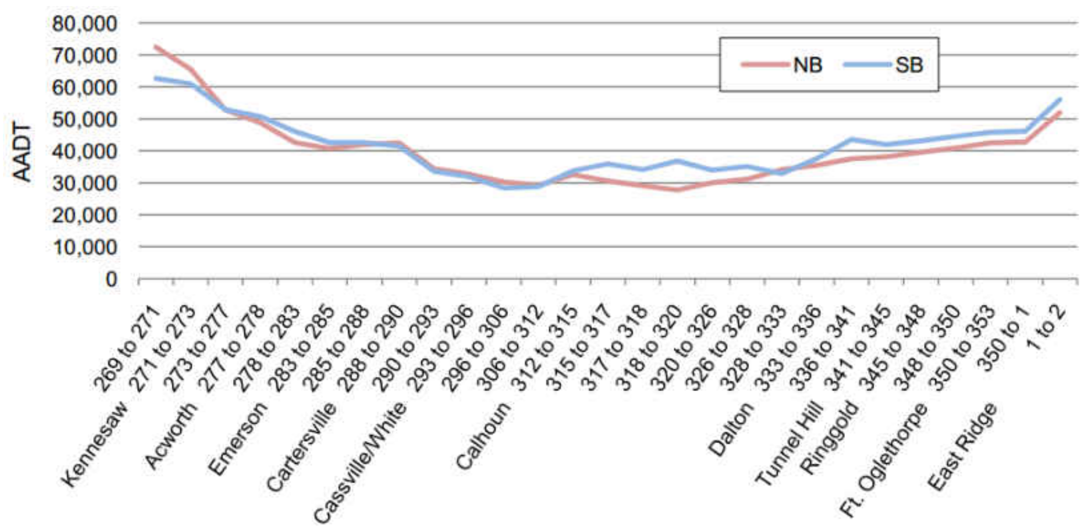

Figure 5: I-75 AADT at mileposts from 269 to 350

(Source: GDOT, TDOT, and Traffic Counts)

The Annual Average Daily Traffic (AADT) of the truck routing scenario site on I-75 North Corridor is selected from Figure-5 which was used in a Georgia DOT research project.

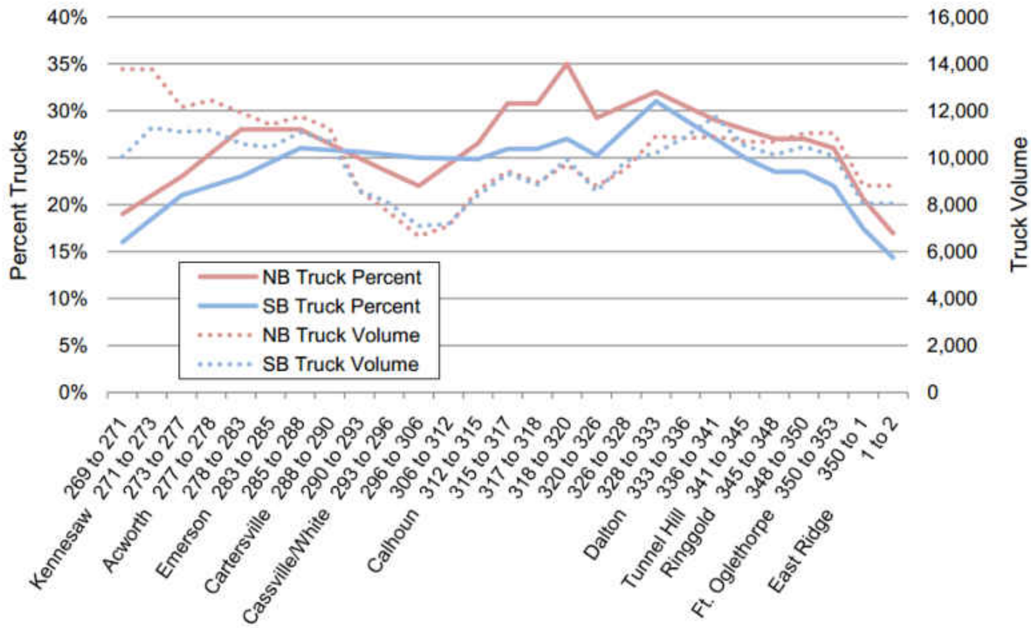

Figure 6: I-75 Truck Percentages and Volumes at mileposts from 269 to 350

(Source: GDOT and TDOT for AADT and truck percentages; traffic counts for K and D factors)

Truck volumes and truck percentages of the scenario corridor was determined from Figure-6.

There are five distribution centers for trucks in the region of the chosen segment on I-75. This is also a valuable information to show that there are several nearby production/attraction points for trucks on this corridor. In Figure-7, a geographic representation of the distribution centers near the study site is provided.

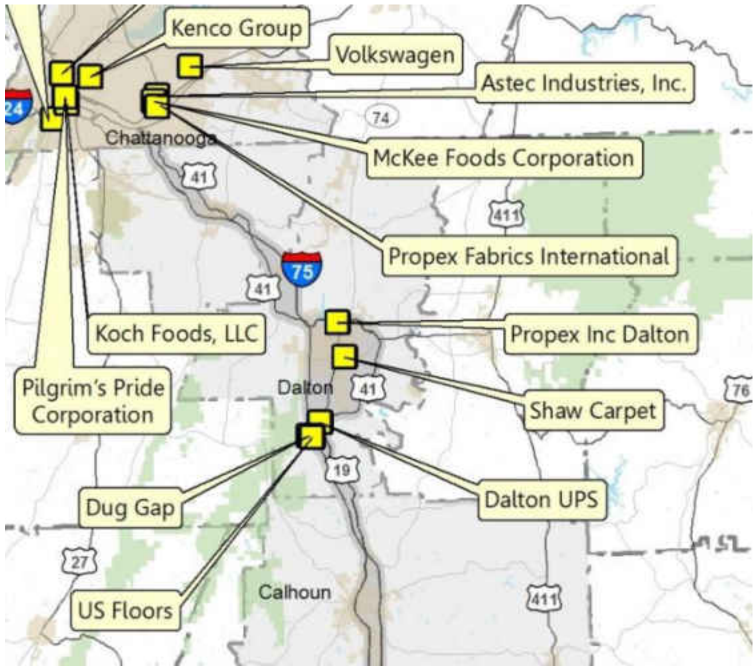

Figure 7: Major Distribution Centers (Source: I-75 North Corridor Study, GDOT, March-2013)

3.2 Methodology

Volume-delay functions is the most widely used performance measurement in route assignment methods that is able to describe the effect of road capacity on travel times. This factor explains the travel time (or cost) on a road link as a function of the traffic volume. Generally, it can also be computed as the product of the free flow time multiplied by a normalized congestion function where the argument of the delay function is the volume-to-capacity ratio.

Amongst various types of volume-delay functions proposed and used in practice in the past, the most commonly preferred volume delay functions are the *BPR* functions (Bureau of Public Roads, 1964), which are defined as;

$$T = T_0\left(1 + \alpha\left(\frac{V}{C}\right)^{\beta}\right) \qquad (3.1.)$$

Where;

T = travel time (minute)

T_0 = free flow travel time (minute)

V = traffic volume (vehicle per hour)

C = capacity (vehicle per hour)

α, β = parameter.

The coefficient, α, in the BPR function was generated by driving the curve to fit the zero volume with free speed and at level of service E. The next coefficient, β, was found by nonlinear regression statistics. α and β are selected from HCM-1985 BPR functions table shown in Table 1. In this table, three different speeds were chosen on each freeways and multilane highways. For each category, sample sizes (n), R-squared (R^2) values, and the variances (σ_v) are provided.

Table 1: BPR Functions Parameters (HCM-1985)

FACILITY		BPR FUNCTION α	β	σ_v	R^2	n
Freeways	70 mph	0.88	9.8	1.90	91.8%	31
	60 mph	0.83	5.5	1.93	91.2%	31
	50 mph	0.56	3.6	0.70	98.4%	29
Multilane	70 mph	1.00	5.4	2.78	87.3%	21
	60 mph	0.83	2.7	1.50	95.8%	21
	50 mph	0.71	2.1	0.77	98.3%	19

For this model, there are reduction factors added to the capacity and free-flow travel times in BPR functions. The capacity and free-flow (CAF) speed adjustment factors are provided in HCM-2010 as shown in Table-2. In this table incidents are grouped in five categories for a variety of roadway segments divided by number of lanes. In addition to the adjustment factors, sample occurrence probabilities of the incident groups are provided in Table-2. In addition to the adjustment factors, average durations for each incident type are provided for each level of lane closure in Table-2.

Table 2: The Default per Open Lane CAF speed adjustment factors

(Source: HCM-2010

Number of Lanes (1-Direction)	No Incident	Shoulder Closure	One Lane Closure	Two Lane Closure	Three Lane Closure	Four Lane Closure
2	1.00	0.81	0.70			
3	1.00	0.83	0.74	0.51		
4	1.00	0.85	0.77	0.50	0.52	
5	1.00	0.87	0.81	0.67	0.50	0.50
6	1.00	0.89	0.85	0.75	0.52	0.52
7	1.00	0.91	0.88	0.80	0.63	0.63
8	1.00	0.93	0.89	0.84	0.66	0.66
Average Incident Duration (min)	-	32.00	34.00	53.00	69.00	69.00
FFS adjustment factors	-	0.86	0.79	0.61	0.61	0.61
Probability of Occurrence	91.91%	5.75%	1.62%	0.40%	0.32%	0.00%

A queue will be formed by an incident when the volume V is larger than the available freeway capacity during the incident (i.e., when V>rC). The length of queue will increase until the incident scene is cleared also known as total clearance (i.e. T_i hours after the incident occurred). Further, the queue growth rate is defined as additional arriving vehicles at the end of the queue per hour (V) during the incident minus the rate at which vehicles pass the incident scene (rC). Hence, maximum length of queue occurs at the point in time when the queue is totally cleared which is calculated with following equilibrium (Harry Cohen, 1999);

$$Q = (V - rC)T_i \tag{3.2.}$$

Where;

Q = maximum queue length (vehicle)

r = capacity reduction factor due to incident

T_i = incident duration (hour)

Since the growth in queue length from zero (i.e. at the time incident occurs) to Q (i.e. at total clearance of the incident scene), the average queue length during the incident would be Q/2 accordingly (Harry Cohen, 1999).

The formula is used in calculating the travel times for a range of volume-to-capacity ratios starting from 0.3 to 1.1. If the travel cost for the shortest path exceeds the travel cost for the alternative path, then the model algorithm will make a change on the route decision and will divert the trucks via the ramp on Location-A. The route decision algorithm based on travel costs computations are as follows;

$$If\ \left((T_0)_1 + T_Q\right) * (Avg.Truck\ Value\ of\ Time) < (D_2 - D_1) * (Avg.Cost\ of\ Fuel\ per\ mile)\ then\ \text{"Keep"} \tag{3.3.}$$

$$If\ \left((T_0)_1 + T_Q\right) * (Avg.Truck\ Value\ of\ Time) > (D_2 - D_1) * (Avg.Cost\ of\ Fuel\ per\ mile)\ then\ \text{"Change"} \tag{3.4.}$$

Where;

$(T_0)_1$ = free flow travel time on shortest path (minute)

T_Q = Travel Time Delay (Time in Q) (minute)

D_1 = Shortest route distance (7.4 miles)

D_2 = Alternative route distance (9.5 miles)

Avg. Truck Value of Time = $1.55 (per min.);

$93 per hour. (TTI 2012 Urban Mobility Report)

Avg. Cost of Fuel = $0.69 (per mile);

Average miles traveled per gallon: 5.8 miles;

Yearly Average Diesel Price: $4.00 per Gallon.

Distance from the exit ramp to the incident location is also considered in this model. The variation of the distance from incident location will change the travel delays since the travel time formula changes when the truck arrives to the back of the queue. Therefore, distances starting from 1 miles to 7 miles (with 1-mile intervals) are considered in the model. Last but not least, travel time savings by changing routes are multiplied with the corresponding probabilities given in Table-2 for each type of incident.

3.3 Results

Scenarios simulated with a range of volume-to-capacity ratios from 0.3 to 1.1, length of queues at shoulder only, 1-lane closure, and 2-lane closure out of 3 total lanes are calculated and presented in Table-3.

Table 3: Q Lengths of each Scenario (miles)

(miles)	V/C Ratio								
Blocked	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**	**1.1**
Shoulder	0.00	0.00	0.00	0.00	0.00	0.00	0.28	0.68	1.07
1-Lane	0.00	0.00	0.04	0.46	0.89	1.31	1.73	2.16	2.58
2-Lane	0.86	1.52	2.17	2.83	3.49	4.15	4.81	5.47	6.13

According to the 27 scenarios generated in the above matrix, queue lengths larger than zero (highlighted in Table-3) are not all found critical by the algorithm. The re-routing decision algorithm runs for each scenario and the results (i.e. "*Keep*" or "*Change*" route) of the decisions based on travel costs are provided in Table-4.

Table 4: Decisions for Route Change Based on Travel Cost

	V/C Ratio								
Blocked	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**	**1.1**
Shoulder	*No Q*	*No Q*	*No Q*	*No Q*	*No Q*	*No Q*	*Keep*	*Keep*	*Keep*
1-Lane	*No Q*	*No Q*	*Keep*	*Keep*	*Keep*	*Keep*	*Change*	*Change*	*Change*
2-Lane	*Keep*	*Change*	*Change*	*Change*	*Change*	*Change*	*Change*	*Change*	*Change*

In Table-4, each cell is representing the decision made on an individual scenario. The decision "*Change*" refers to an incident induced congestion cost which is greater than the difference in distance of the two routes. "*Change*" route decision made scenarios are highlighted in Table-4.

The results provided in Table-5 is the travel time differences in minutes between the shortest path and alternative path based on the scenarios generated. The highlighted cells which are positive time values also means that there will be travel time savings, however, not necessarily travel cost savings.

Table 5: Travel Time Differences with the Alternative Route (minutes)

(Minutes)	V/C Ratio								
Blocked	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**	**1.1**
Shoulder	-7.00	-7.00	-7.00	-7.00	-7.00	-7.00	-6.62	-5.86	-4.77
1-Lane	-7.00	-7.00	-6.94	-6.07	-4.54	-2.15	1.35	6.20	12.66
2-Lane	-1.84	10.17	34.01	74.70	137.70	150.00	150.00	150.00	150.00

In preliminary analysis, the assumption made in travel time delay calculations is that the trucks are at Location-A exactly 5 minutes prior to the incident occurrence time for the sake of brevity in calculations. So, with this assumption the travel delays are set not to exceed "Incident duration minus 5 minutes" in order to avoid the queue length to pass the ramp at Location-A.

Probabilities of occurrence of the incident types are applied to the travel time matrix and to find the per mile travel time savings, scenario travel differences (minutes) were divided by 7.4 miles which is the distance at the shortest path. Monetary values of the delay savings were then calculated by multiplying with average loaded truck value of time which is $93.0. Daily truck vehicle miles traveled (VMT) of the section is calculated as follows;

*Avg. Daily Truck VMT= (Truck AADT) * (Distance in shortest path) * (365 days)*

The results of the travel time savings per mile matrix is multiplied by daily truck VMT and daily delay cost savings based on incident scenarios matrix is generated and provided in Table-6. Additionally, daily cost saving matrix is multiplied by 365 (days) to find the average annual delay cost savings (see Table-6).

Table 6: Individual Truck Based Travel Delay Savings for Different V/C ratios

V/C Ratio	Annual Savings	Daily Savings
0.4	$ 254,559.38	$ 697.42
0.5	$ 851,679.01	$ 2,333.37
0.6	$ 1,870,544.15	$ 5,124.78
0.7	$ 3,448,136.93	$ 9,446.95
0.8	$ 3,756,146.34	$ 10,290.81
0.9	$ 3,892,686.51	$ 10,664.89
1	$ 4,382,090.51	$ 12,005.73
1.1	$ 5,033,802.62	$ 13,791.24

In Table-6, annual and daily savings based on the incident scenarios for 7.0 miles of distance from the incident location is provided. Results indicate a range of annual travel delay cost savings from $254k to $5m and daily travel delay cost savings of $700 to $14k depending on the severity of incident (directly related to total closure time) and time-of-day (referring to volume-to-capacity ratio).

3.4 Discrete Level Incident Analysis Based on Generated Scenarios

In this section, the scenarios generated in the previous model were separately analyzed. The number of trucks effected by each incident scenario are computed using an average length of classified vehicles types. By multiplying the travel delay savings with number of trucks for each scenario, the truck delay savings per incident are estimated. Furthermore, using traffic flow calculations, traffic densities for both “in the queue” and “before the queue” are estimated. The findings for each scenario is provided in Table-7.

Table 7: Individual Incident Based Travel Delay Savings for Different V/C ratios

V/C Ratio	1-Lane	2-Lane
0.4	$ -	$ 8,051.75
0.5	$ -	$ 36,849.67
0.6	$ -	$ 117,520.72
0.7	$ -	$ 320,578.87
0.8	$ -	$ 512,430.00
0.9	$ 631.08	$ 736,792.50
1	$ 3,277.51	$ 576,832.50
1.1	$ 7,729.73	$ 1,416,622.50

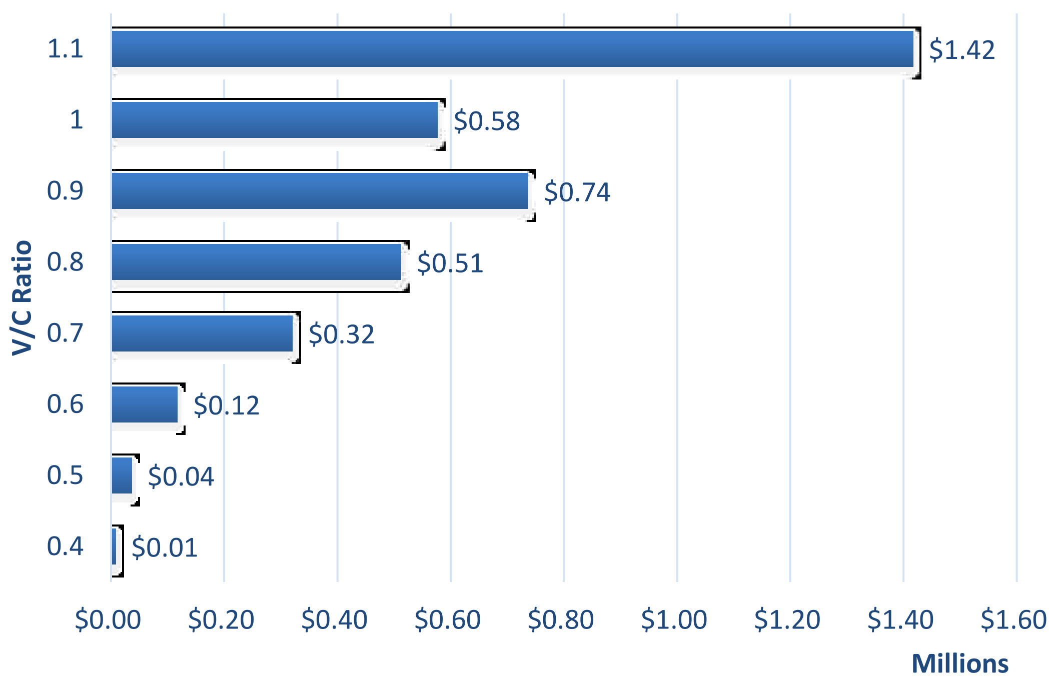

Figure 8: Travel Delay Savings due to 2-Lane Blocking Incidents at Different V/C Ratios

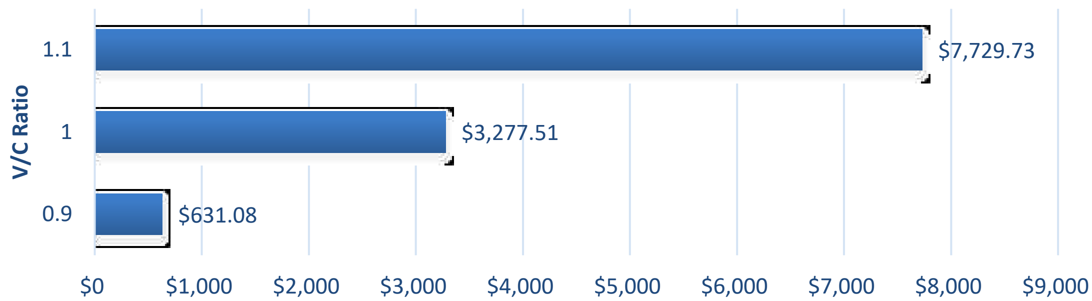

Figure 9: Travel Delay Savings due to 1-Lane Blocking Incidents at Different V/C Ratios

3.5 Fuel Consumption

The downside of changing routes from the shortest path to an alternative route which is usually relatively a longer path is the extra miles of travel which will typically result in extra fuel costs depending on the amount of idling effects and its' changes on miles per gallon. In order to find the marginal savings in cost, in this section, the output from the estimated model in the previous chapter will be further detailed by calculating the fuel consumption of extra miles traveled due to route changes on trips. Moreover, fuel consumption of idling due to travel delay savings of the incident scenarios will be determined.

For the changed routes highlighted in Table-3, trucks will be traveling extra miles since the alternative route is 2.1 miles longer in distance than the shortest route. Therefore, the difference in fuel consumption from alternative path with free-flow and shortest path at congestion conditions needs be evaluated. In other words, the travelling on alternative routes during the incident induced congestion conditions on the shortest path is saving travel time for those scenarios where the algorithm calculated sufficient amount of difference and made a ”*Change*” decision. The delays due to the incident based congestion are considered as savings in terms of idling fuel consumption.

3.5.1 Methodology and Results

The number of “*Change*” decisions in each incident category in Table-3 are considered as 2.1 miles of fuel consumption by a diesel truck engine. The extra miles of travel matrix cells are multiplied by the incident category probabilities. This matrix is also divided by the distance of shortest path to find a unit of extra miles traveled per mile. Average miles traveled per gallon for diesel trucks is recorded as 5.8 mpg. So, each is divided by 5.8 and multiplied with the annual truck vehicle miles traveled to find annual fuel consumption in gallons due to extra miles traveled. Results are represented by the chart Figure-10.

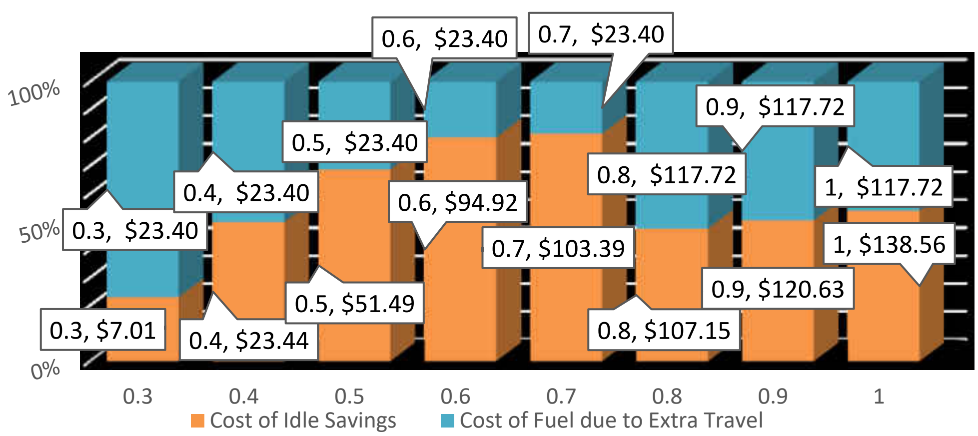

Figure 10: Annual Individual Truck-Based Cost of Fuels

In discrete level incident based analysis, we also estimated the fuel consumption and monetary values were found. Calculated fuel cost differences (i.e. both negative and positive values) between idle and extra traveled miles due to route changing are presented in Table-8, Figure-11 and 12.

Table 8: Fuel Cost Differences in Incident Based Results

V/C Ratio	1-Lane	2-Lane
0.4	$ -	$ (342.18)
0.5	$ -	$ 809.82
0.6	$ -	$ 4,342.12
0.7	$ -	$ 13,680.19
0.8	$ -	$ 22,152.40
0.9	$ (404.93)	$ 31,851.62
1	$ (332.00)	$ 24,936.53
1.1	$ (188.58)	$ 61,240.74

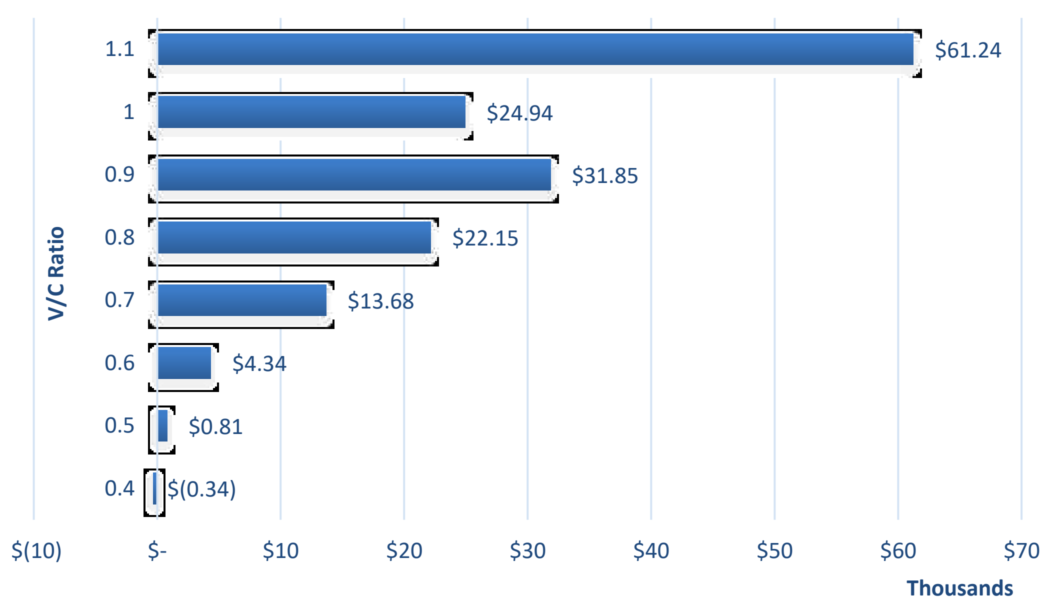

Figure 11: Fuel Cost Differences for 2-Lane Blocked Incidents

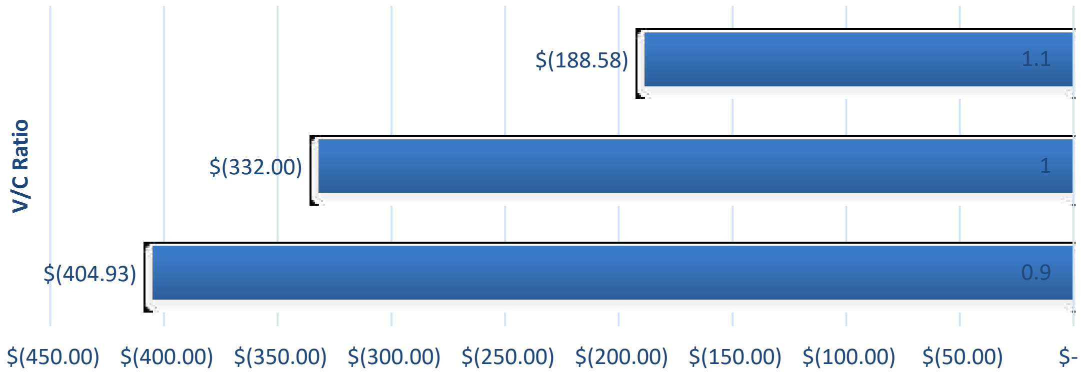

Figure 12: Fuel Cost Differences for 1-Lane Blocked Incidents

Travel delay savings are assumed to be idling savings to be able to convert them in to fuel costs. Fuel consumption due to idling are found from US Department of Energy Argonne National Laboratory. Loaded diesel trucks were found to be 1.15 gal/hr. In addition to 1.15 gal/hr, annual truck vehicle miles traveled are multiplied by the travel delay savings matrix cells in order to find the annual cost of idling savings.

According to the fuel consumption costs analysis, idling costs dominate the total fuel consumptions costs at a range of V/C ratios from 0.5 to 0.7, however, in the remaining V/C ratios fuel consumption due to miles traveled are becoming higher as compared to idling. In addition, 2 out of three lane closure scenarios fuel cost differences extremely rise at over 1.0 V/C ratio due to the increase in number of vehicles in system. On the other hand, in 1-lane closure scenarios, the difference reduces while V/C increases.

3.6 Environmental Impacts

In this section, the environmental impacts of the truck routing based incident simulation model are provided. The environmental impacts considered in preliminary analysis can be presented in two categories. First category is the on-site impacts which are tailpipe emissions and the second category is the off-site impacts which are also known as the emissions from the supply chain of petroleum refineries.

3.6.1 Tailpipe Emissions

Air pollutants emitted by vehicle tailpipes have been shown to have variety of negative effects on public health as well as the natural environment. In particular, diesel engine emissions are a significant air-quality issue which is about 30 to 35% of the nation's NOx emissions and 25% of the PM emissions out of mobile sources.

In this section, tailpipe emissions of vehicles will be calculated before and after the operational strategies in order to make a comparison and assess the air quality improvements in terms of exhaust emissions. Motor Vehicle Emission Simulator (MOVES) will be used for the analysis. The latest version is MOVES2010b. This is a computer modeling tool that was designed to estimate emissions from on-road or highway vehicles. It is used for evaluating transportation conformity analyses, CO, NO_x, PM10 (particles less than 10 micrometers in diameter), and PM2.5 hot spot and project level analysis, and the benefits from different mobile source control strategies.

The analysis calibrated with MOVES simulation software provides the tailpipe emissions for idling in gr/sec units while for the extra miles traveled it provides values in gr/mile units. The idling emission rates found from the simulation software are presented in Table-9.

Table 9: Idling Emission Rates

[gr/sec]	**National**
Carbon Monoxide (CO)	2.53E-02
Oxides of Nitrogen (NOx)	7.24E-02
Primary Exhaust PM10 - Total	1.01E-04
Primary Exhaust PM2.5 -Total	9.79E-05

Emission factors due to traveled miles found from the simulation software are provided in Table-10. In preliminary analysis, we use constant speed fuel consumptions and emissions.

Table 10: Traveled Miles Emission Factors

[gr/mile]	**National**
CO	1.589
NOx	4.347
PM10	0.108
PM2.5	0.0496

3.6.2 Petroleum Refinery Supply Chain Emissions

In order to identify the off-site (i.e. supply chain) impacts due to the reduction of average travel time, Economic Input Output Model – Life Cycle Assessment (EIO-LCA) approach will be applied.

Life Cycle Assessment (LCA) is a tool that was developed in early 1990s in order to investigate potential environmental impacts in system base. In other words, it is a powerful method which has been used widely in literature for providing the results of production or process's impacts from cradle to grave. This cradle to grave approach starts from raw material extraction and continues with production, transportation, use phases and finally concludes with end-of-life phase (Finnveden et al., 2009). The LCA methodology basically consists of goal and scope definition, life-cycle inventory analysis, life-cycle impact assessment, and interpretation sections (Graedel and Allenby, 2009).

Economic Input-Output (EIO) analysis proposed to build more powerful methodology with LCA approach to analyze the supply chain impacts including systems or products' economic and environmental impacts (Hendrickson, Lave, & Matthews, 2006).

In this study the input for the EIO-LCA model is the cost difference among the idling savings and extra travel costs. For 0.6 volume to capacity ratio, differences are positive, therefore, there are savings in terms of fuel. This saving in fuel can be analyzed in EIO-LCA tool and will give the savings in supply chain of the petroleum refineries. The results are shown in Table-11.

Table 11: EIO-LCA Results – Emissions from Petroleum Refineries

[tons]	GHG CO2e	CO	NOx	PM10	PM2.5
2 miles	32.2	0.06	0.051	0.007	0.003
3 miles	78.8	0.147	0.124	0.018	0.008
4 miles	80.9	0.151	0.127	0.018	0.008
5 miles	83	0.155	0.13	0.018	0.008
6 miles	72.7	0.159	0.134	0.019	0.009
7 miles	87.1	0.163	0.137	0.019	0.009

In Table-11, first column represents the greenhouse gases which is also known as the CO_2 equivalent value of the other remaining types of tailpipe emissions pollutants.

3.6.3 Tailpipe and Off-Site Emission Analysis Results

The results of both tailpipe emissions and petroleum refinery supply chain emissions are provided in this section. Figure-13 is the annual carbon monoxide emissions differences as well as the off-site emissions found due to fuel consumption savings. The emissions at each V/C ratio from 0.4 to 1.1 is provided in the below chart. Blue parts represent the emission derived from petroleum refineries while the orange parts of columns denote the tailpipe emissions.

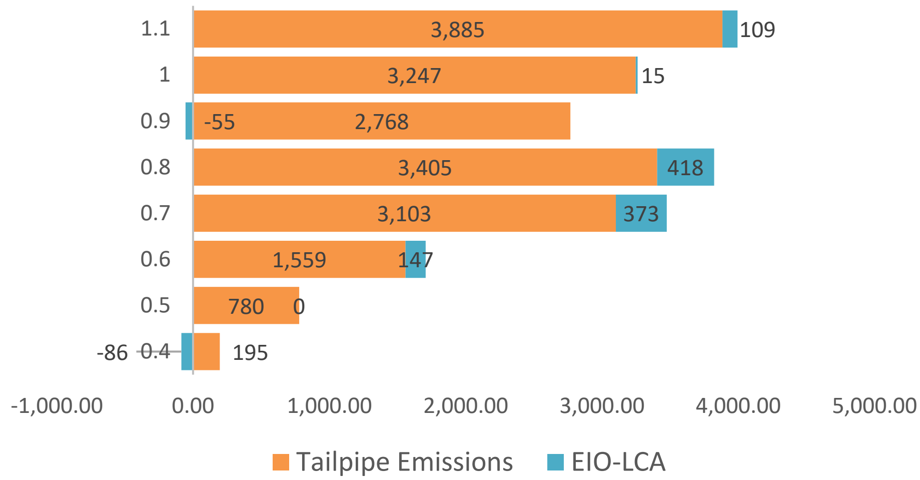

Figure 13: CO Annual Emission (kg)

The results in Figure13 indicates an optimal level at V/C ratio of 0.9. Then, it significantly rises at 1.0 and higher volume-to-capacity ratios.

In Figure14, the total annual emissions of nitrogen oxide is provided.

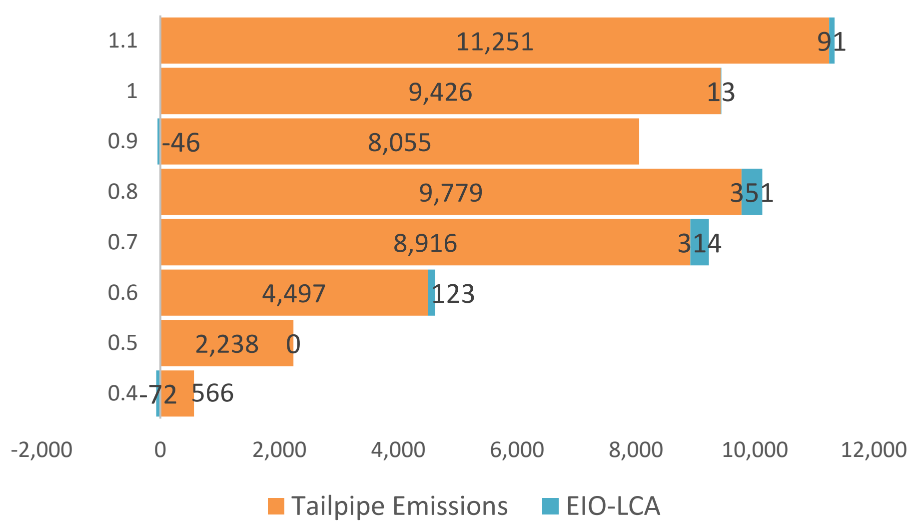

Figure 14: NO_x Annual Emissions (kg)

Figure15 provides the particulate matters smaller than 10 micrometers in diameter for both tailpipe and supply chain emissions.

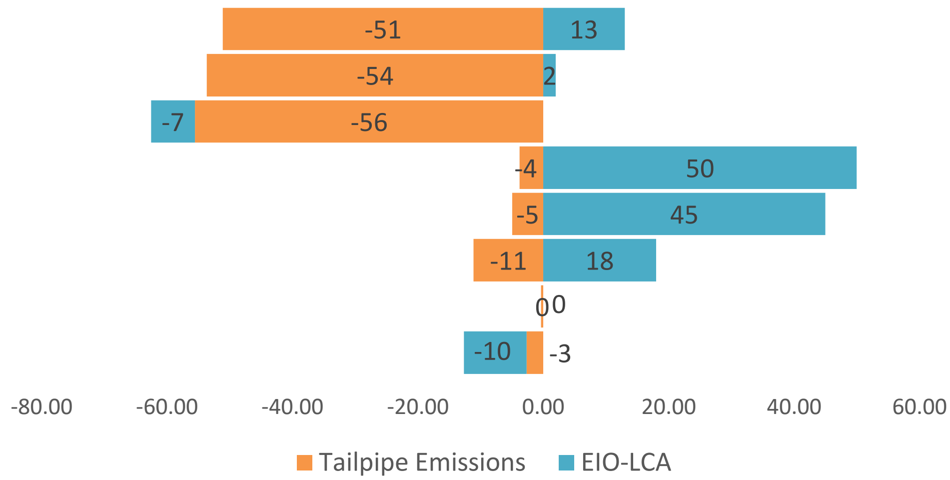

Figure 15: PM_{10} Annual Emissions (kg)

Last but not least, Figure16 presents the annual savings in terms of particulate matters smaller than 2.5 micrometers in diameter.

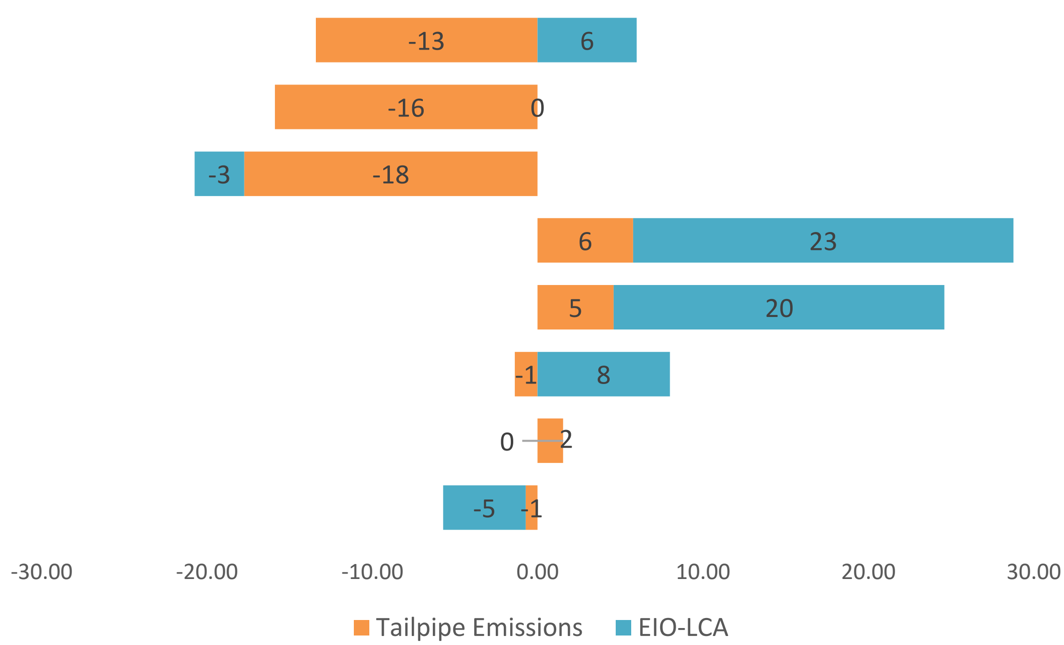

Figure 16: PM2.5 Annual Emissions (kg)

3.6.4 Discussion

In this section, a preliminary study was conducted under certain assumptions to simulate a real-time truck routing strategy in a congestion caused by an incident on a pre-selected corridor at I-75 that has an alternative route between two exit ramps for trucks to divert if needed. Analysis with a BPR function determining the travel delays at different type of incidents (levels determined by number of lane closure at three lanes freeway) on a range of volume-to-capacity ratios from 0.3 to 1.1. Monetary values of travel delay savings including fuel consumption and emissions are presented. To summarize, preliminary analysis results indicate a need of a route decision making algorithm for trucks at incident induced congestions.

CHAPTER FOUR: TRAFFIC MICRO-SIMULATION MODEL

4.1 Background

In this chapter, the first task of the framework methodology is performed. This task includes selection of testbed corridor, input data mining/preparation for the corresponding traffic parameters for the selected corridor, calibrating second-by-second car following model based traffic microsimulation models and data analysis of the simulation model output to find delay savings, monetary values of travel time savings, fuel consumption costs. In order to study the non-recurrent incident induced truck travel delays, a busy freeway corridor with high truck percentages an I-75 was selected as a testbed network. This procedure includes examining the truck percentages as well as AADT's on both Interstate-75 and Interstate-95. The other criteria in choosing the best corridor for this study was the occurrence of an easy by-pass route.

After many dynamic routing trials with busy corridors at high truck percentages, the testbed corridor was selected on I-75 at approximately 1-mile north of US-27 from MP 17.603 to MP 22.265 located in Marion County and City of Ocala. In Figure 17, a geographic representation of the truck percentage categories on Florida highways heat map is provided. Figure 18 also illustrates the high-volume sections of I-75 highway. The site location's truck percentage (T factor) is 24.2% while the AADT is 65,500 (see Table 12 source: FDOT online traffic information: http://www2.dot.state.fl.us/FloridaTrafficOnline/viewer.html)

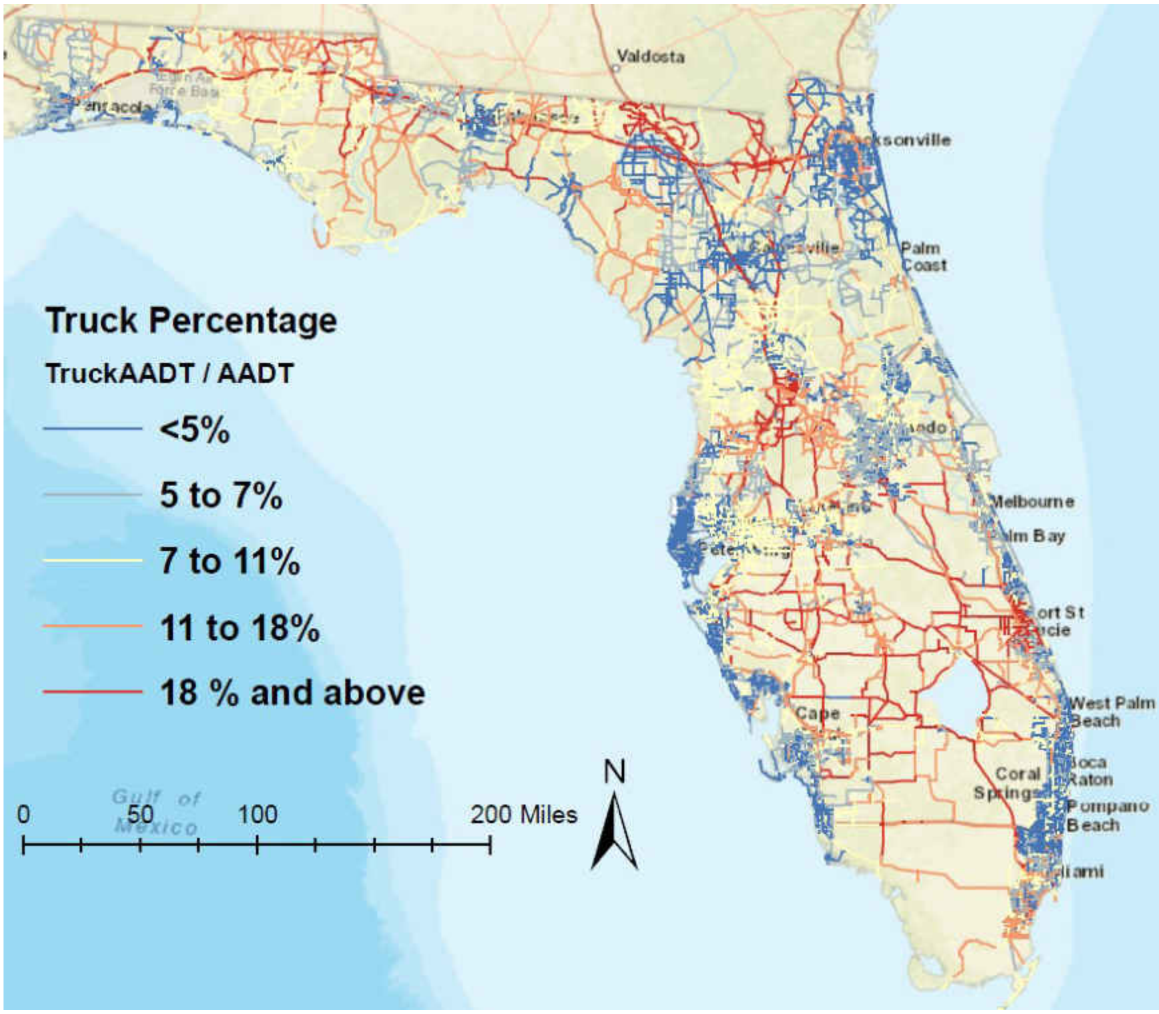

Figure 17 Truck Percentages in Florida Highways (GIS Map)

Truck percentages are calculated by dividing the annual average daily truck traffic by total annual average daily traffic. In Figure 17, a GIS map is generated with truck percentages on Florida highways are classified in five ordered categories: Less than 5%, 5 to 7%, 7 to 11%, 11 to 18%, and 18% and above. Classification thresholds were estimated by the median and variances of the overall Florida highway truck percentages. In this map, the study site region can be seen as one of the truck traffic hot spots in the State of Florida.

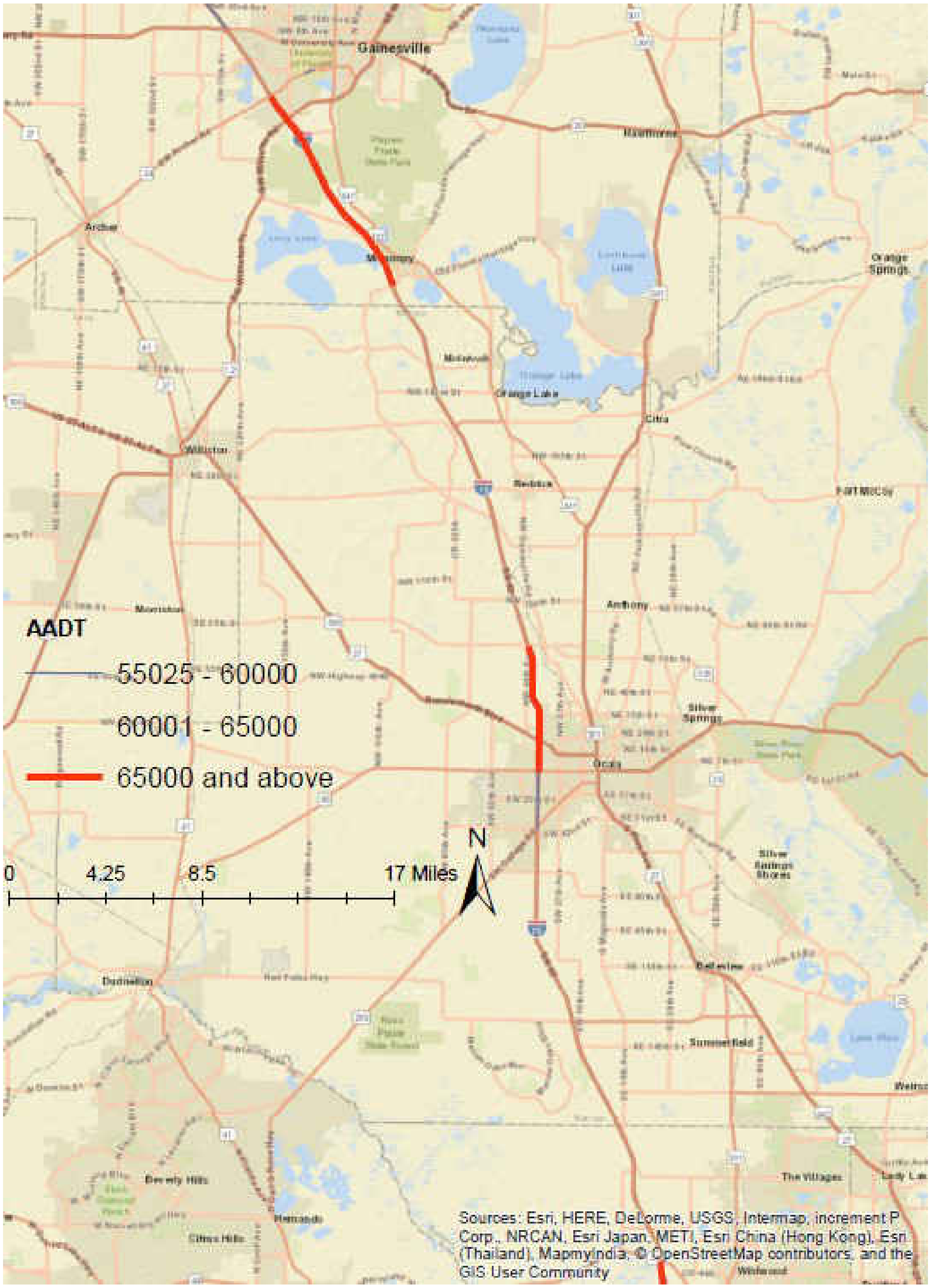

Figure 18 AADT levels on sections at I-75 Corridor

Figure 18 illustrates the level of AADT's at the busiest sections of I-75 highway. High volumes are further categorized in 3 groups in this map: AADT from 55,025 to 60,000, AADT above 60,000 to 65,000, and AADT at 65,000 and above which is represented with red colored line.

Table 12 Site Information from FDOT Traffic Reports

Site Information	
Feature	**1**
Site	360438
Description	ON I-75, 0.986 MI. N OF US-27 (RCLP)
Section	36210000
Milepoint	18.809
AADT	**65500**
Site Type	Portable
Class Data	No
K Factor	10.6
D Factor	54.5
T Factor	24.2
TRAFFIC REPORTS (provided in format)	
Marion County	**Annual Average Daily Traffic**
	Historical AADT Data
	No Synopsis Report Available

Table 12 presents general traffic parameters of the site location. Site number at FDOT inventory database, description of the portable traffic monitoring site location (which falls into the study corridor), milepost, annual average daily traffic recorded and estimated during 2015, type of monitoring device, K-factor (i.e. the 30th highest hourly volume of the year expressed as a percentage of the AADT), D-factor (i.e. is the 30th highest hourly volume of the year), and T-factor (i.e. the percentage of the AADT volume generated by trucks or commercial vehicles) are provided in this table.

The selected corridor has an alternative route of 5.8 miles while the main route is 5.4 miles. The travel time difference is approximately 5 minutes in non-congestion (at free-flow speed) conditions. For this study, second-by-second car following micro-simulation models based on incident scenarios were calibrated only on the southbound direction of the study corridor. Main and alternative routes are illustrated in Figure 19.

At MP 22.265 which is determined as point A, an exit ramp connects to the alternative route that is mainly on NW 44th Ave. the diverted truck traffic enters back to the I-75 corridor at MP 17.603 (plotted as point B on the map). The shortest path corridor has three southbound and three northbound lanes while the alternative path is two-lane on each directions.

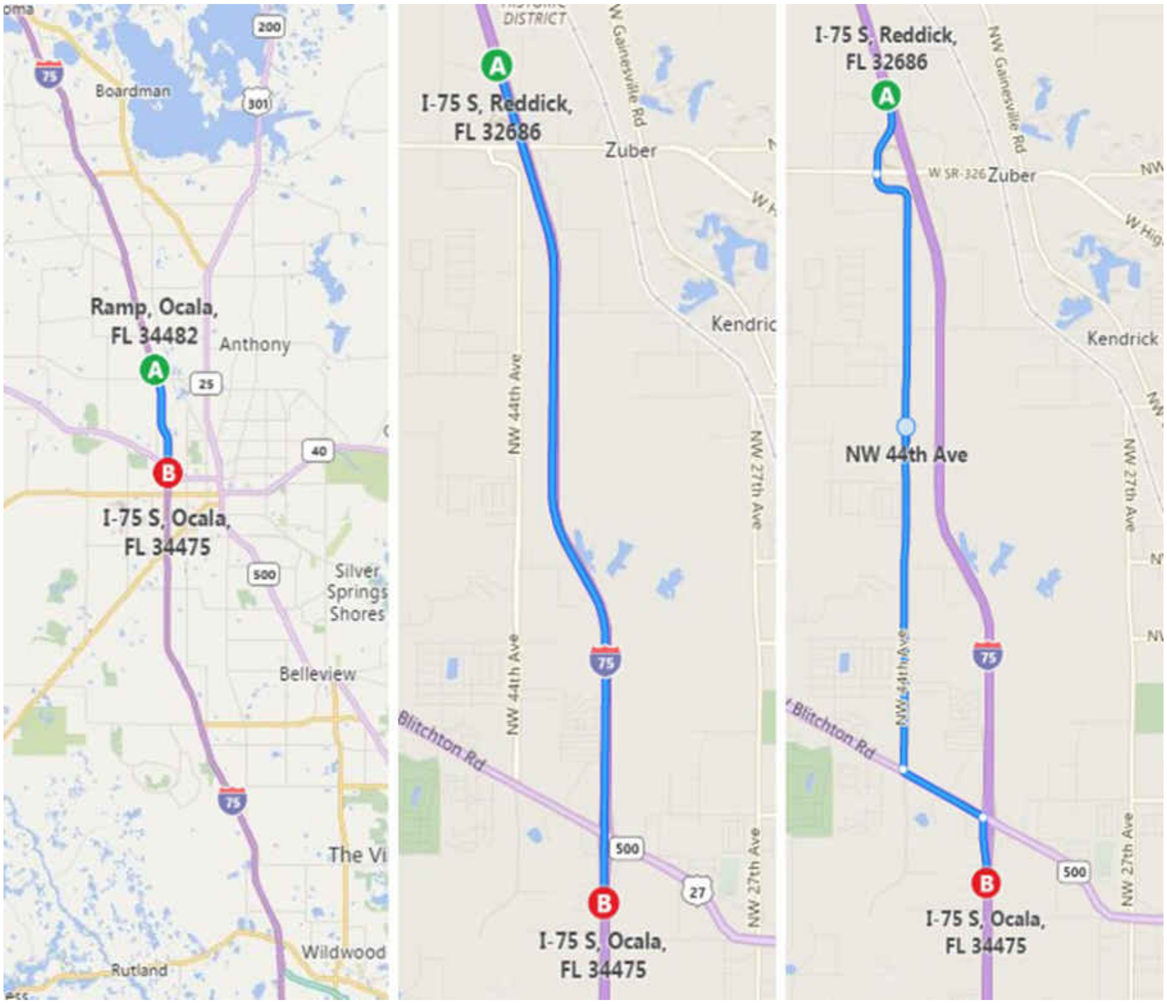

Figure 19 Study Corridor

4.2 Incident Data (FDOT)

Traffic incident data of Central Florida Area collected by Florida Department of Transportation is utilized to assess traffic event history of the study corridor. Traffic events dataset was collected from October 2009 to February 2016. The data features include but not limited to type of event, level of closure, incident duration, date and time, geo-location etc. Given the aforementioned information, traffic incidents were categorized by their level of lane closures. Events that caused at least a shoulder closure and above were selected for the evaluation. Annual incident frequency and mean durations are illustrated in Figure 20 and 21. As mentioned earlier, years 2009 and 2016 are not complete due to the data collection time period.

Incident mean durations where employed in choosing the best possible simulation period. In addition, the incident history of the study corridor is utilized to compute the annual impacts of the micro-simulation scenario models output.

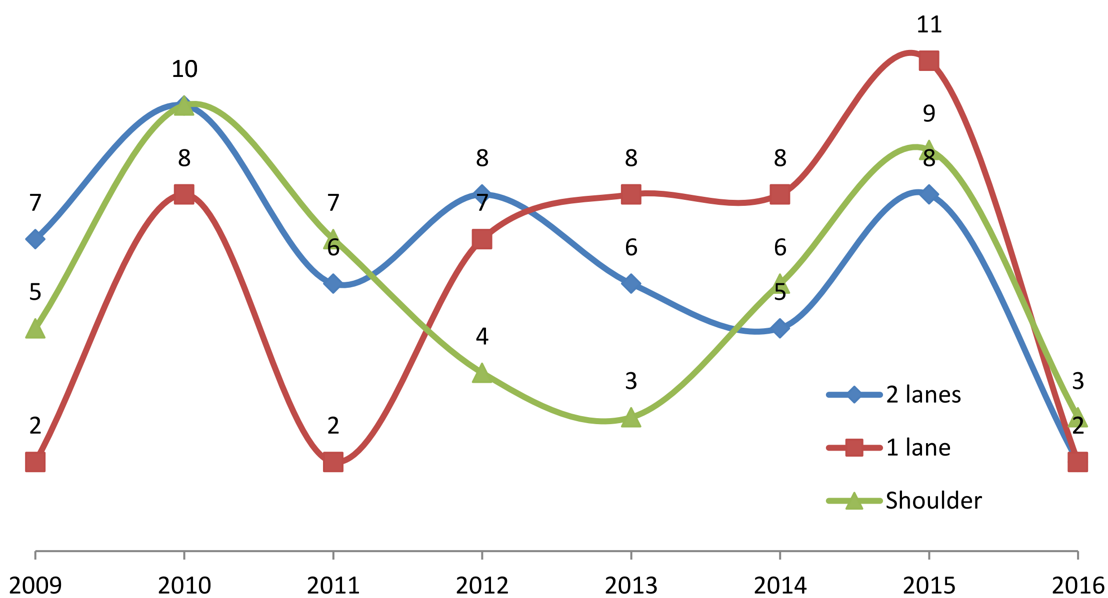

Figure 20 Annual Number of Incidents (Frequency)

In Figure 20, the annual number of incidents from year 2009 to 2016 are provided. Since there are only a few months' worth of data points on the first and last year of the chart, number of incidents are lower as compared to other years in between. Highest number of incidents occurred in 2010 and 2015 according to Figure 20.

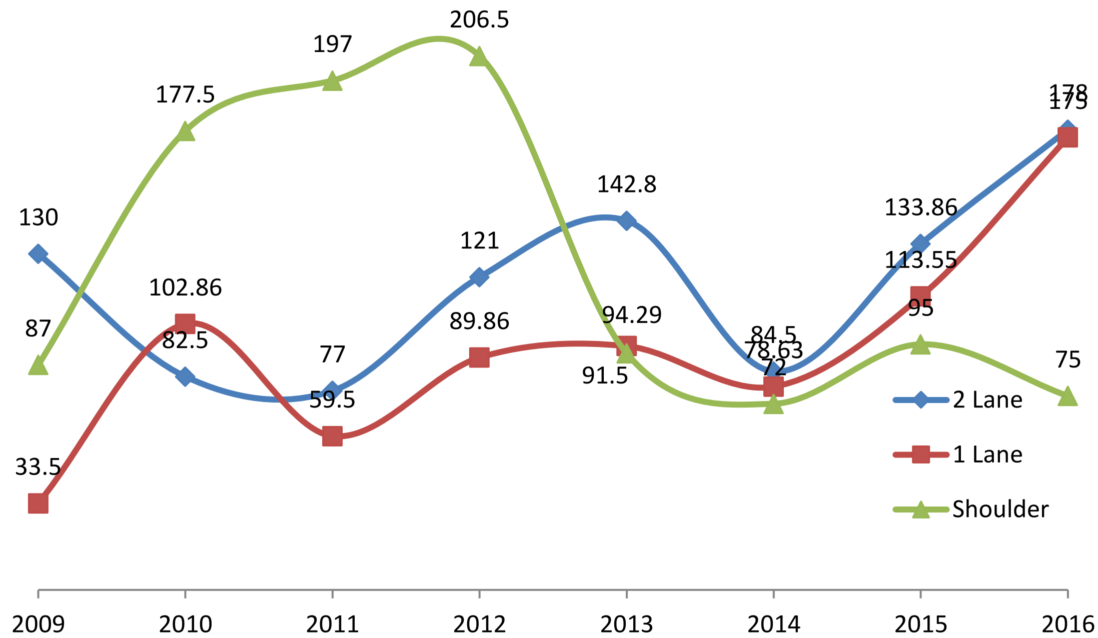

Figure 21 Annually Mean Incident Durations (Minutes)

In Figure 21, the annual mean of incident durations in minutes from year 2009 to 2016 are provided. Again, since there are only a few months' worth of data points on the first and last year of the chart, mean of incident durations are estimated by much lower frequency of incidents which may result in misrepresentation of the average incident durations in the corresponding years. Highest mean of incident duration occurred in 2012 in shoulder closures while in 1 or 2 lane closure incidents 2016 (first two months) average has the highest durations according to Figure 21.

4.3 Micro-Simulation Model Development with VISSIM

VISSIM 7.0 is a stochastic and driver behavior based micro-simulation tool developed by PTV Group to model any type of traffic operations, including highways, public transit, pedestrians etc. VISSIM is well-thought-out as a powerful tool due to its' capabilities of taking into consideration the stochastic nature of the transportation problem settings for modelling multimodal transport operations. There are many modules of analyzing traffic operations under constraints, including, but not limited to lane configuration, traffic signals, traffic composition, etc. Hence, it is a pretty useful tool for the evaluation of performance measures of diverse alternatives based on ITS-based transportation engineering and planning measures of effectiveness. (www.ptvamerica.com). There are three types of scenarios to simulate non-recurrent congestion (i.e. incident induced) used in this model. First one is a "shoulder-only" closure scenario, second one is "one out of three lanes closure" scenario and the last scenario is "two out of three lanes closure". Truck de-routing (diversion) was applied depending on second-by-second travel delay decision algorithms. In order to find the impacts of truck diversion strategies, each of these scenarios has a base case where no truck routing strategy was applied (also considered as normal conditions).

In the micro-simulation calibration process, network geometry including horizontal curves, grades and ramp locations is a critical step. Geometric boundaries of the I-75 corridor were coded in VISSIM as shown in Figure 22. Based on southbound traffic data and incident statistics, time of day of the study period (7,500 seconds) was chosen to be a Wednesday evening peak-hour (i.e. 6:00 pm to 8:05 pm).

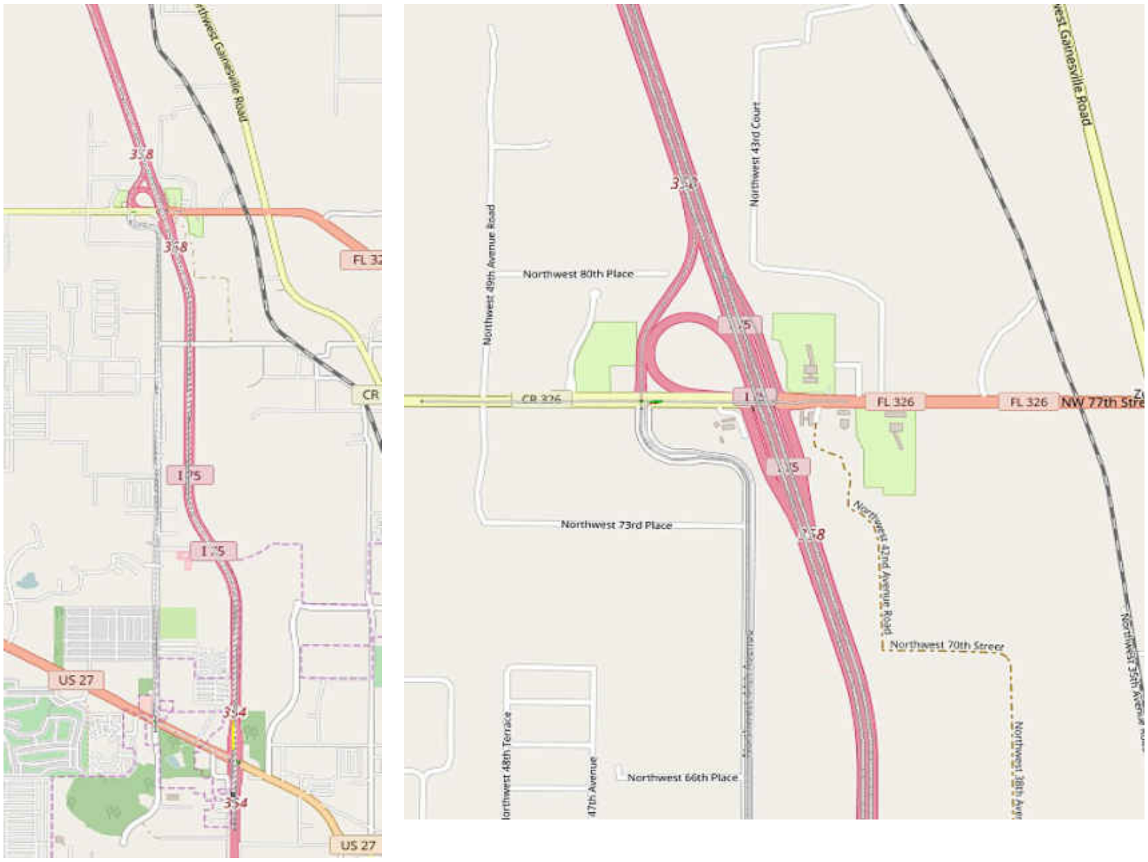

Figure 22 Corridor Representation in VISSIM

Parameter calibration is performed to minimize the misfit between observed data and simulated data as much as possible from the actual network. The program user can assess the results from a visual or from a numerical point of view while the simulation is running. Accordingly, the visual inspection can be made to observe the movements on the screen visualization, to be able to check for network geometry which reflects that the traffic movements are realistically simulated. For example, unexpected decelerations can cause shockwaves leading to disruption in the traffic flow. This highlights the importance of geometry coding.

Traffic simulation models consist of various numbers of parameters and variables to define. VISSIM uses two main models; first one is car following models and the second one is lane change models. Car following models are related with the vehicle following behavior that affect the flow rates depending on the selected car following model. These models are as follows: Wiedemann 74, which is mainly suitable for urban traffic (arterials) and Wiedemann 99 that is primarily applicable for freeways. The lane changing models affect the driving behavior based on an extensive range of parameters. These parameters are presented in Figure 23. The driving behavior parameters can be defined for each link as well as for each vehicle class.

The first step in the calibration process was to make a set of runs with different seed numbers. Since VISSIM is a stochastic model, a random number generator is used for all type of parameters. The seed number is a starting point for the generator which called by the program and used to analyze many different parameters for the simulation.

The parameter classes that use random number generator include car following, lane changing, driver‘s behavior, and release of demand volume.

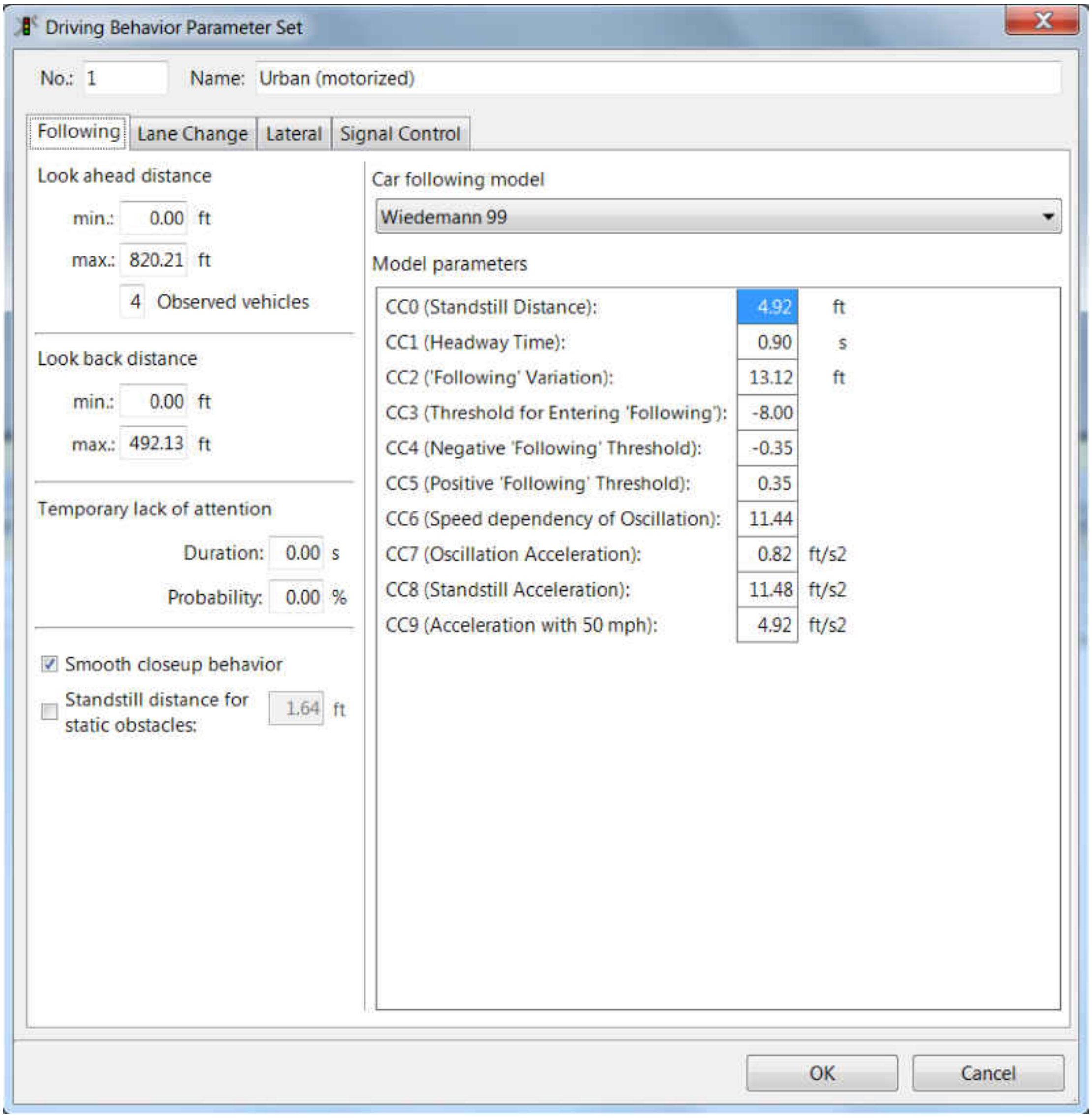

Figure 23 Wiedemann 99 Car Following Model Parameters

In the driving behavior parameters of Wiedemann 99 car following model shown in Figure 23, maximum lookahead distance was set to 820.21 ft and 4 observed vehicles while the lookback distance was set to 492.13 ft. Due to congestion conditions caused by an incident, the smooth closeup behavior option is selected. Standstill distance, headway time, “following” variation, threshold for entering “following”, negative “following” threshold, positive “following” threshold, speed dependency of oscillation, oscillation acceleration, standstill acceleration, and acceleration with 50 mph are the other parameters set based on the Wiedemann 99 car following model.

Three incident simulation scenarios as opposed to the base scenario (normal conditions / no non-recurrent congestion) are proposed based on the roadway level of closure. Table 13 provides the volumes, speed distributions, link types, truck percentages, simulation duration, and incident period during the simulation. Each type of scenarios are presented in two columns, firstly the main path (shortest route) and secondly the alternate path.

Table 13 Simulation Scenario Characteristics

Level of Closure	**Shoulder Closure**		**1-Lane Closure**		**2-Lane Closure**	
Routes	Main	Alternate	Main	Alternate	Main	Alternate
Vehicle Inputs (Volume)	4500	930	3450	930	3450	930
Desired Speed Distributions	70 mph	45 mph	70 mph	45 mph	70 mph	45 mph
Link Types	Freeway	Urban	Freeway	Urban	Freeway	Urban
Truck Percentage	20%	5%	20%	5%	20%	5%
Simulation Period (sec)	7500	7501	7500	7500	7500	7500
Incident Period	6500		5500		5500	

Incidents were simulated using reduced speed areas on the affected lanes. According to the Highway Capacity Manual (HCM) published in 2010, the capacity reduction factor due to shoulder closure is provided as 81% and free-flow speed reduction factor is 86%. Due to high volume (V/C = 1) in shoulder closure scenarios, a reduced speed area with 55 mph was placed towards the end of the main route to imitate (simulate) shoulder blockage conditions (see Figure 24).

To simulate a one lane closure, a reduced speed area with zero mph speed on right lane was coded. Since HCM suggests 79% free-flow speed reduction factor, reduced speed areas of 55 mph for the remaining two lanes also placed. Finally, two lane closures were simulated by implementing zero mph reduced speed areas for the right two lanes for 5500 seconds. Left lane speed was also reduced to 40 mph to follow HCM's 61% free-flow speed reduction factor.

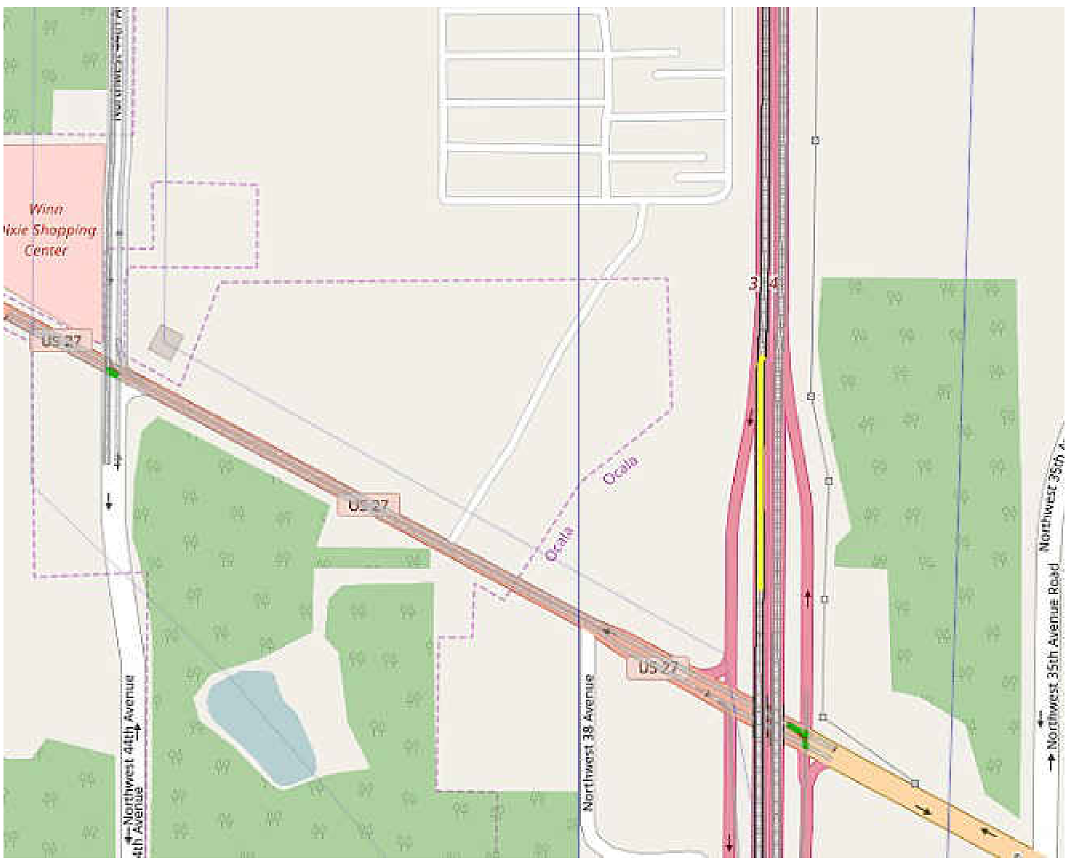

Figure 24 Reduced Speed Areas for Shoulder Closure

The routing decision algorithm was generated by writing a Visual Basic (VB) code based on incident induced travel delay comparisons between main and alternative routes of each scenario. For base scenarios, the script was not applied. However, in incident scenario runs, the script was set to run at every time step start. VB code is illustrated in Figure 25. When the VB script is activated for each time step; a decision is made at each simulation second based on the travel times comparison of both routes.

```vb
Option Explicit



Dim Veh_TT_measurement_number
Dim Veh_TT_measurement_1
Dim Veh_TT_measurement_2
Dim Veh_TT_measurement_3
Dim Veh_TT_measurement_4
Dim Veh_TT_measurement_5

Dim TT_Main1
Dim TT_Alternate1
Dim TT_Main2
Dim TT_Alternate2
Dim TT_Initial
Dim SVRC11
Dim SVRC21
Dim Lane1
Dim Lane2

Set Veh_TT_measurement_1 = Vissim.Net.VehicleTravelTimeMeasurements.ItemByKey(2)
Set Veh_TT_measurement_2 = Vissim.Net.VehicleTravelTimeMeasurements.ItemByKey(1)
Set Veh_TT_measurement_3 = Vissim.Net.VehicleTravelTimeMeasurements.ItemByKey(3)
Set Veh_TT_measurement_4 = Vissim.Net.VehicleTravelTimeMeasurements.ItemByKey(4)
Set Veh_TT_measurement_5 = Vissim.Net.VehicleTravelTimeMeasurements.ItemByKey(6)

'SVRC11 = Vissim.Net.VehicleRoutingDecisionsStatic.ItemByKey(1).VehRoutSta.ItemByKey(1).AttValue("RelFlow(1)")
'SVRC21 = Vissim.Net.VehicleRoutingDecisionsStatic.ItemByKey(2).VehRoutSta.ItemByKey(1).AttValue("RelFlow(1)")


TT_Main1 = Veh_TT_measurement_1.AttValue("TravTm(Current,Last,All)")
TT_Alternate1 = Veh_TT_measurement_2.AttValue("TravTm(Current,Last,All)")
TT_Initial = Veh_TT_measurement_5.AttValue("TravTm(Current,Last,All)")
if TT_Main1 > 540 then
    Vissim.Net.VehicleRoutingDecisionsStatic.ItemByKey(1).VehRoutSta.ItemByKey(1).AttValue("RelFlow(1)") = 0
    If TT_Main1 < TT_Alternate1  then
    Vissim.Net.VehicleRoutingDecisionsStatic.ItemByKey(1).VehRoutSta.ItemByKey(1).AttValue("RelFlow(1)") = 1000
    end if
end if
if TT_Initial > 30 then
Vissim.Net.VehicleRoutingDecisionsStatic.ItemByKey(1).VehRoutSta.ItemByKey(1).AttValue("RelFlow(1)") = 1000
end if

TT_Main2 = Veh_TT_measurement_3.AttValue("TravTm(Current,Last,All)")
TT_Alternate2 = Veh_TT_measurement_4.AttValue("TravTm(Current,Avg,All)")
TT_Initial = Veh_TT_measurement_5.AttValue("TravTm(Current,Last,All)")
If TT_Main2 > TT_Alternate2 and TT_Initial < 50 then
SVRC21 = 0
else
SVRC21 = 1000
end if
```

Figure 25 Visual Basic Code for Truck Routing Decision Algorithm

4.4 Vehicle Records Outputs

As a result of the second-by second micro-simulation model runs, one of VISSIM's direct output datasets is the vehicle record file with an fzp extension. The attributes included in this raw output dataset are presented in Table 14.

Table 14 Vehicle Record (.fzp) File Attributes

Attributes	Description
@$VEHICLESIMSEC	Simulation Seconds
NO	ID Number of Vehicle
LANELINKNO	Lane Link ID
LANEINDEX	Lane Index
POS	Position
POSLAT	Latitude
DELAYTM	Delay Time
DISTTRAVTOTAL	Total Distance Traveled
QTIME	Time spent in queue
SPEED	Speed
WEIGHT	Weight of Vehicle
VEHTYPE	Vehicle type
ACCELERATION	Acceleration
NUMSTOPS	Number of Stops
POWER	Power
FUELCONSUMPTION	Fuel Consumption
DWELLTM	Dwell Time for PT
COSTTOT	Total Cost
TotalTime	Total Travel Time

Vehicle records file attributes provide a second-by-second record of each vehicle in the network. Therefore, the savings in terms of value of time is accurately computed by aggregating the total travel times or travel delays by vehicle ID as well as the link ID's. Randomly selected vehicles from the main routes of each scenario were plotted by for evaluation purposes. Second-by-second accelerations, speeds, and number of stops are provided in these plots (see Figures 26 to 31). Comparisons between the base scenarios versus the incident case scenarios can be observed via these charts.

Three charts (speed, acceleration, and number of stops) for both base and incident case scenarios for all three type of incident scenarios (shoulder closure, one and two-lane closures) are provided in Figures 26 to 31.

As a result, the incident scenarios where a routing decision algorithm is applied, a significant reduction in acceleration-deceleration, number of stops, and deviation in speed is can be observed in all three scenarios.

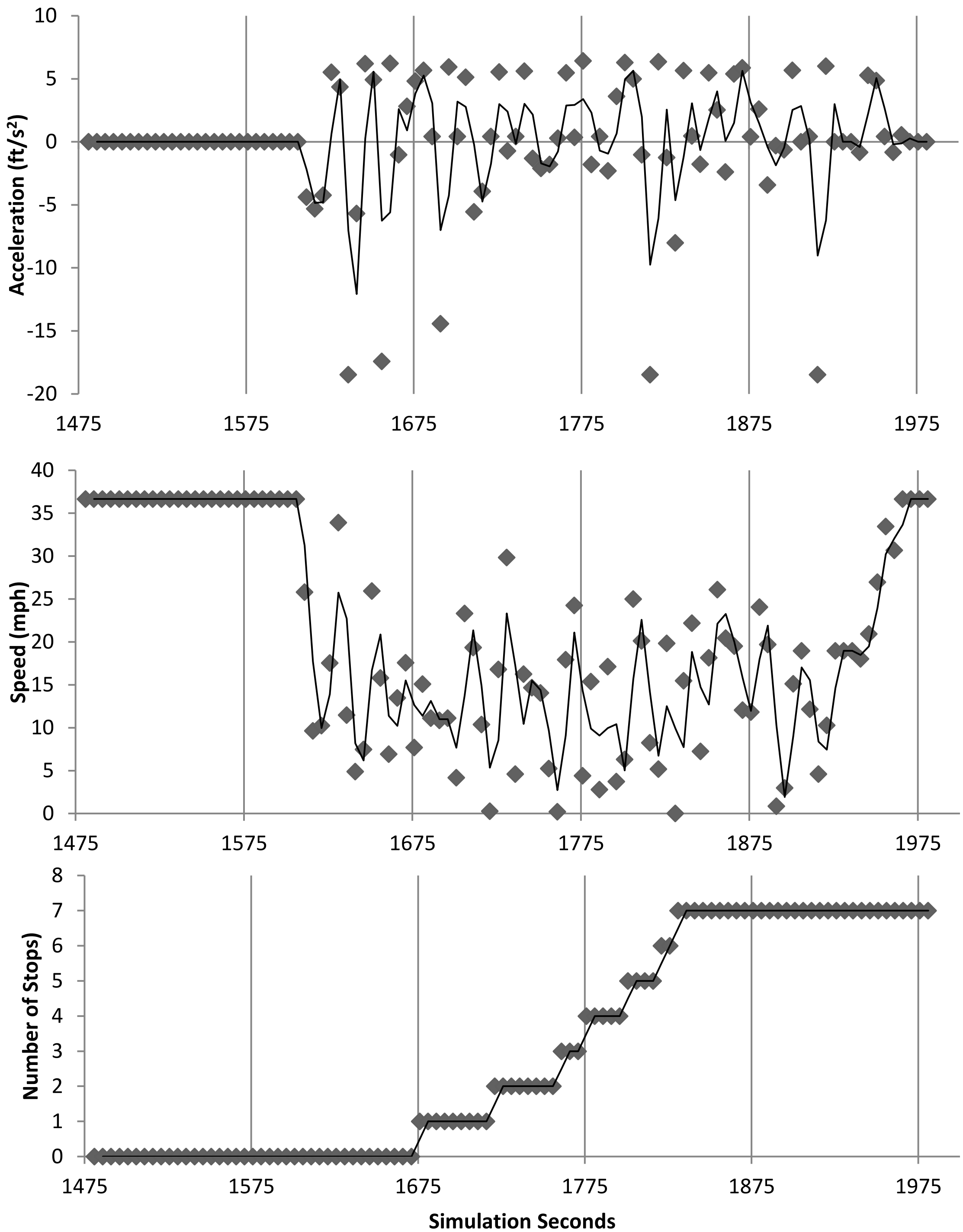

Figure 26 Shoulder Base Scenario Vehicle Record

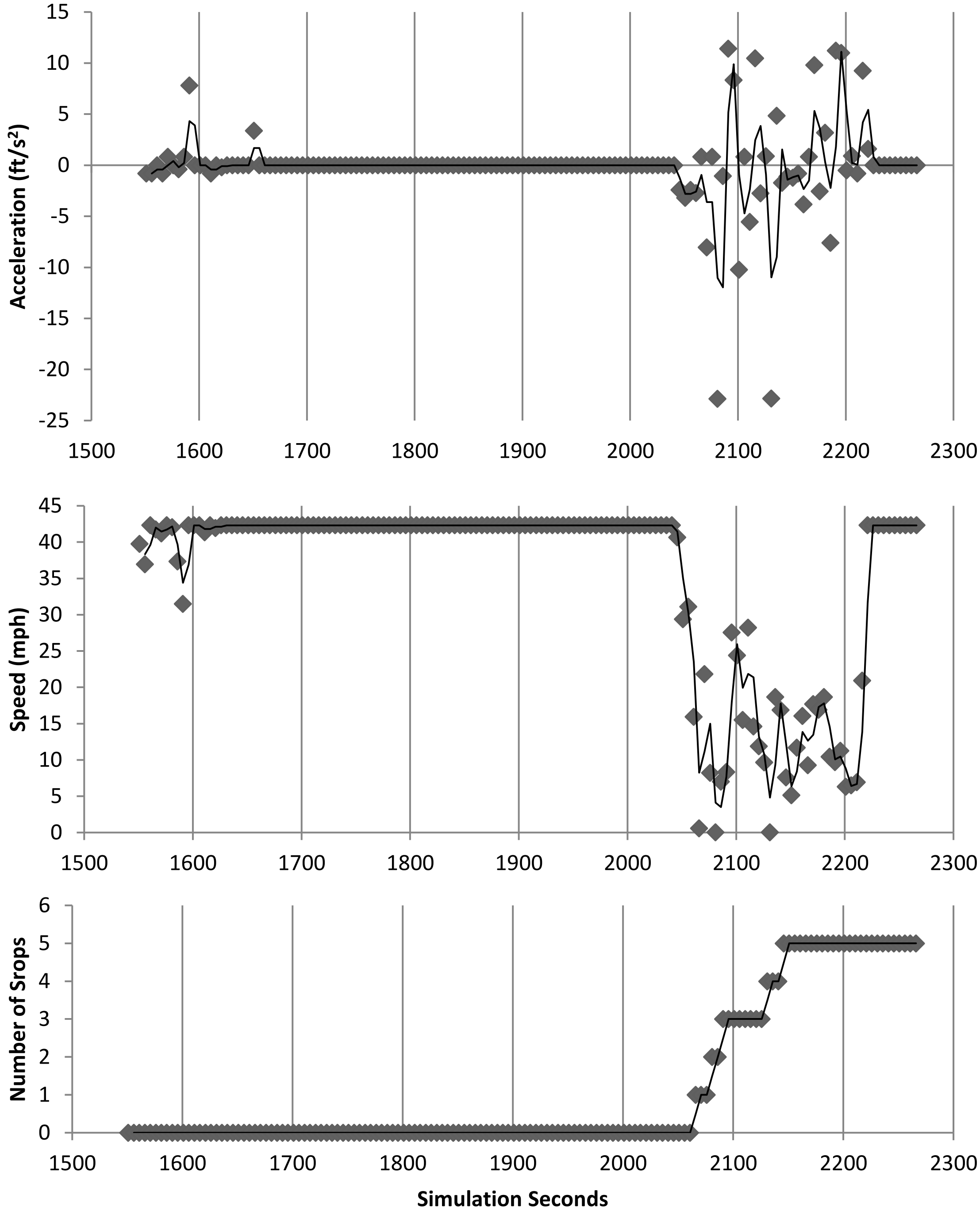

Figure 27 Shoulder Incident Case - Routing Scenario Vehicle Record

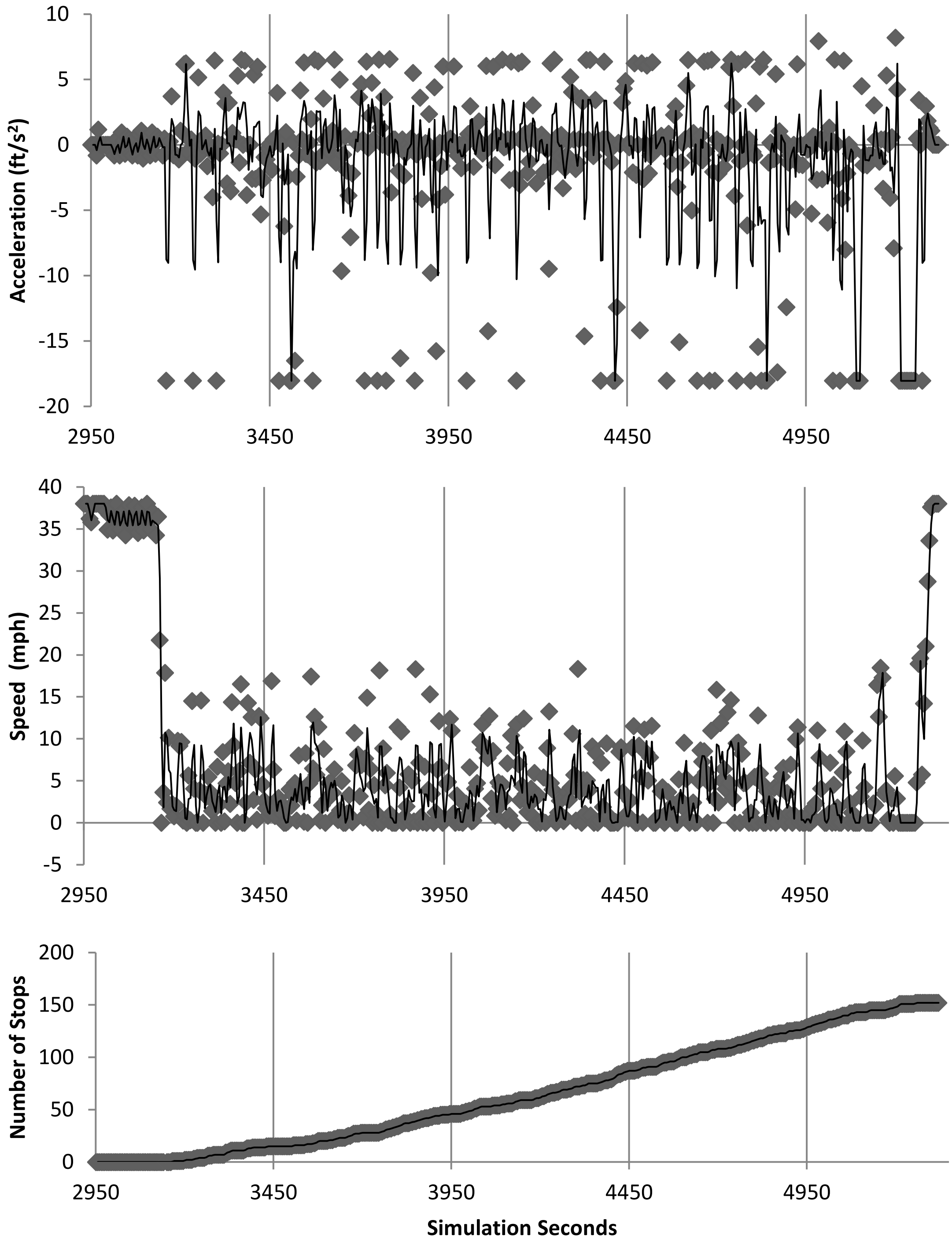

Figure 28 One Lane Base Scenario Vehicle Records

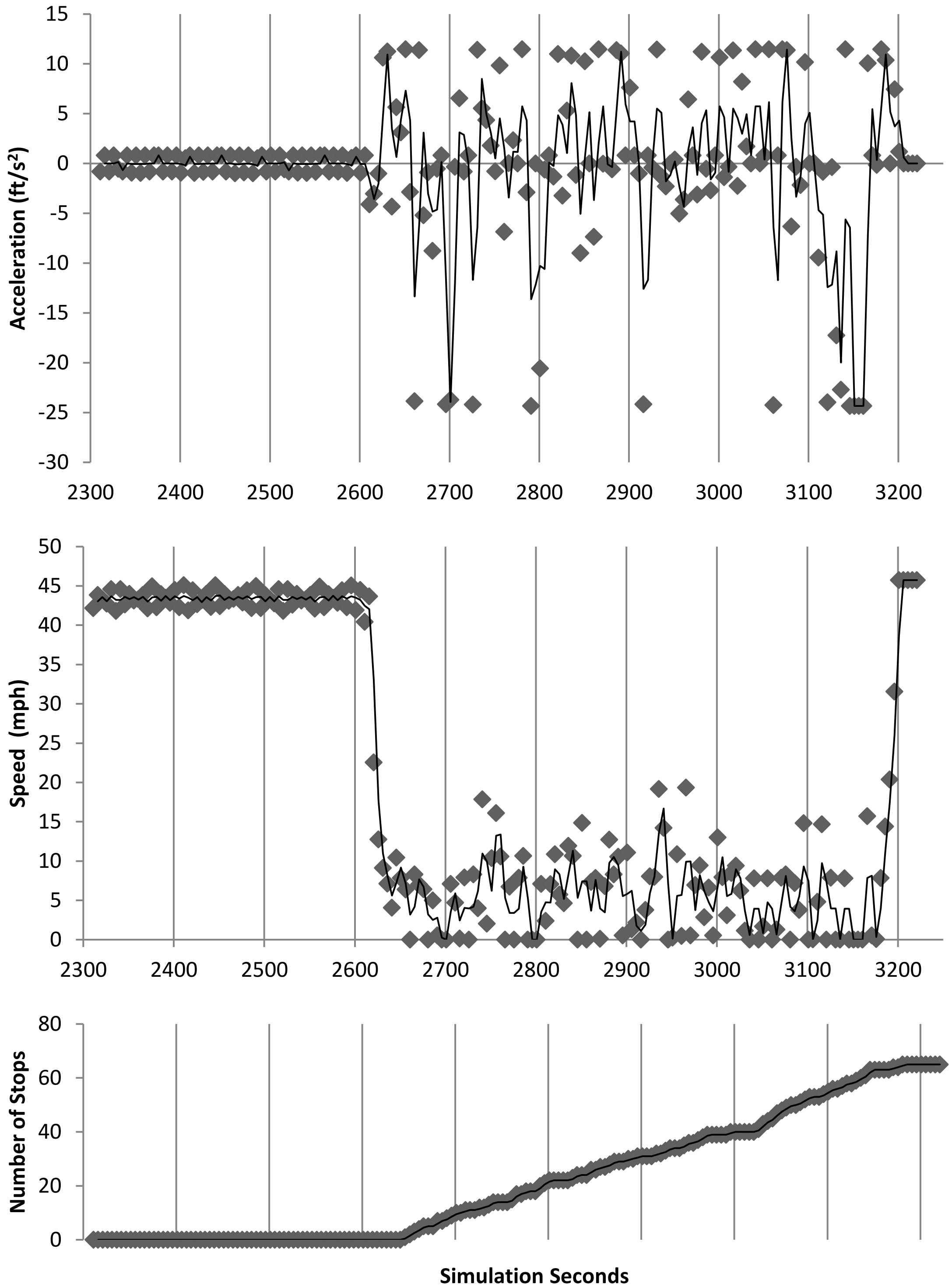

Figure 29 One Lane Incident Case - Routing Scenario Vehicle Records

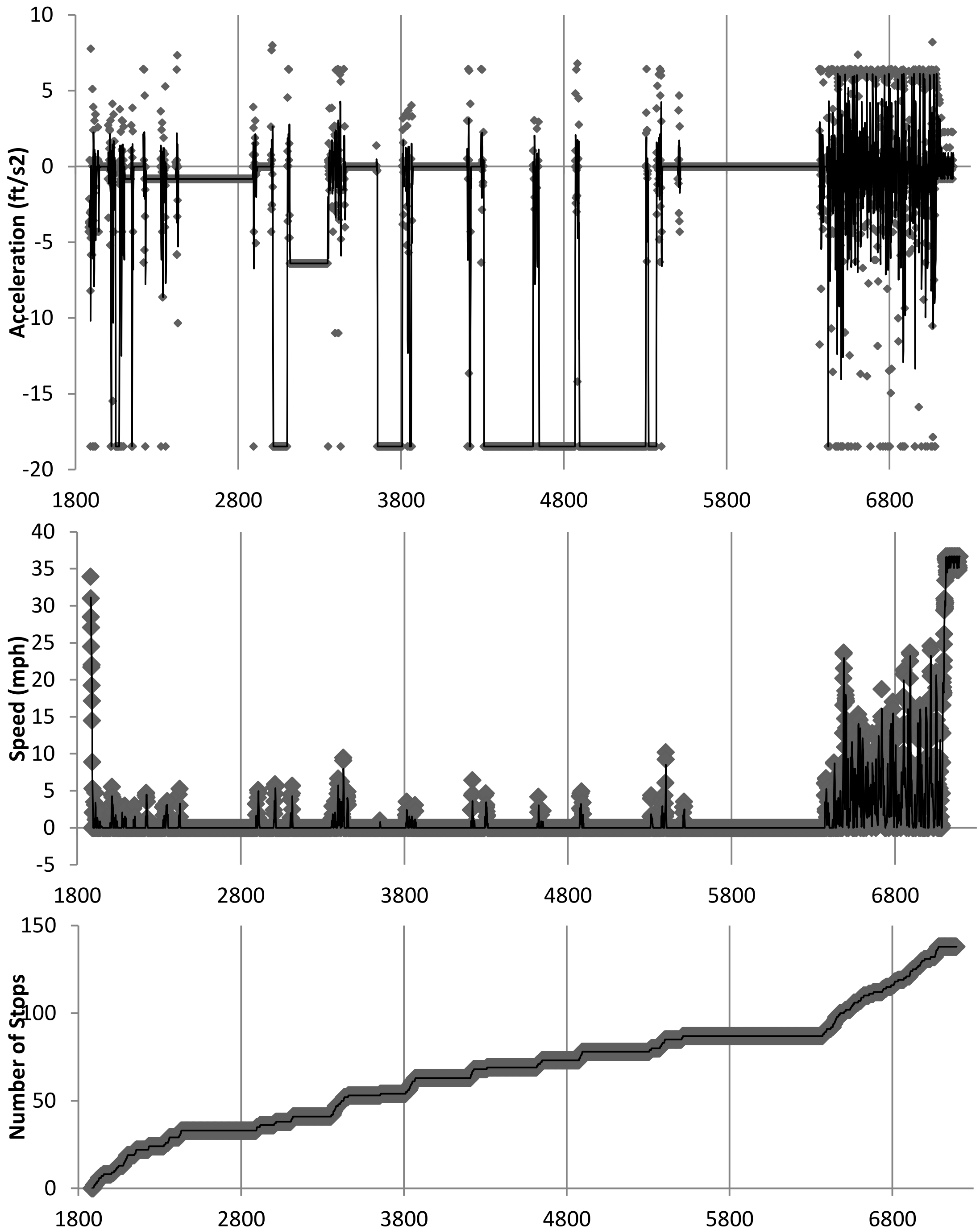

Figure 30 Two Lane Base Scenario Vehicle Records

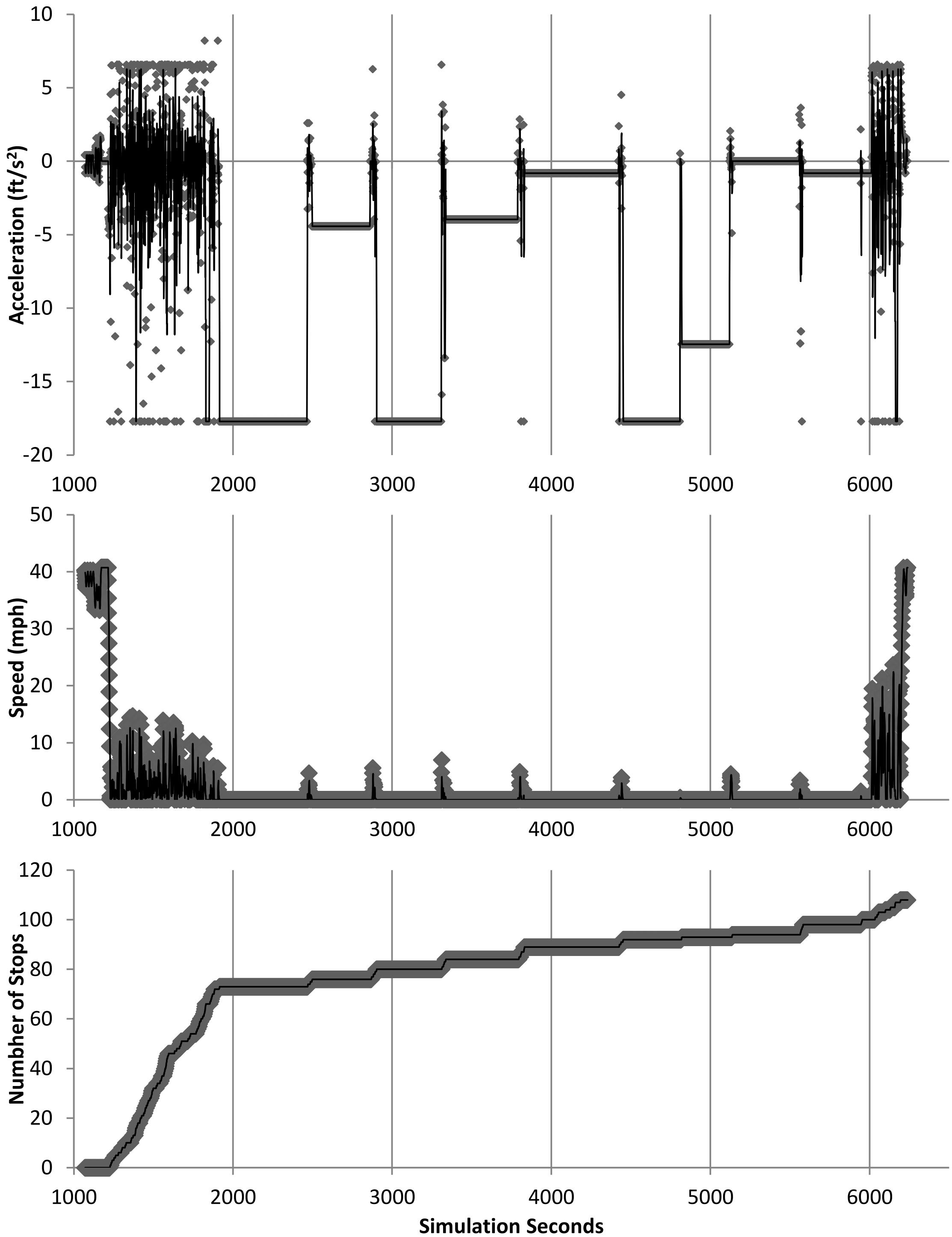

Figure 31 Two Lane Incident Case - Routing Scenario Vehicle Records

CHAPTER FIVE: DIRECT IMPACT RESULTS

In this chapter, real-time routing strategies at incident induced congestion conditions are further evaluated by assessing the monetary value of delay savings for each vehicle type, fuel consumption savings and thus reduction in tailpipe emissions due to less congestion and safety impacts such as number of conflict points are assessed and presented.

5.1 Value of Time (VOT) Savings

In Chapter 4, a VISSIM output called vehicle record was described in detail. As mentioned in the aforementioned section, one of the attributes of fzp files is travel time. Total travel times are compared between base and incident case scenarios. The differences are considered as travel delay savings. Aggregation of total travel times by vehicle types provides the total times of each vehicle type spent on the main route.

According to Texas A&M Transportation Institute (TTI), cost of congestions are provided as follows; $17.67 per person-hour and $94.04 per truck. Travel time monetary values were multiplied by the travel times of each scenario and provided in Figure 32. Value of time savings for each year from 2009 to 2016 is also presented in Figure 33.

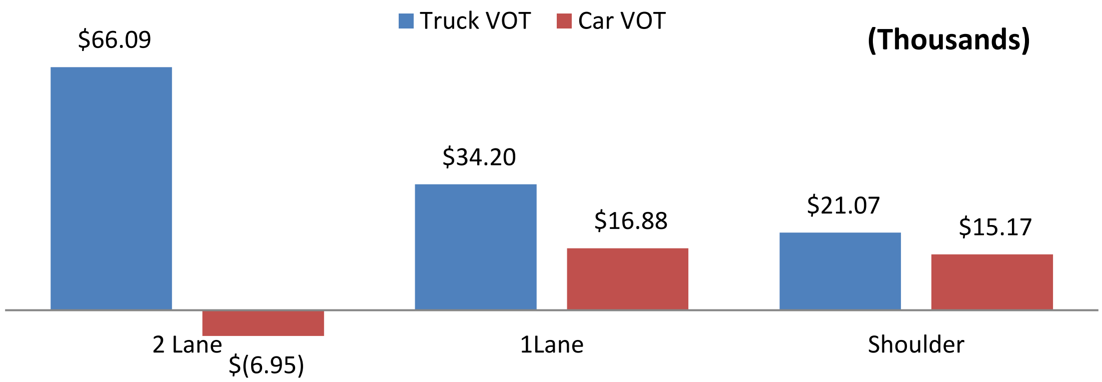

Figure 32 Value of Time Savings

For each of the three incident case scenarios calibrated in the previous section; travel time differences from the base scenarios for both vehicle classes (trucks and passenger cars) are summarized and their monetary values are provided in Figure 32. For two lane closure scenarios, the dollar values of truck delay savings are $66k in total, however, for passenger cars, the base scenario with two-lane blocked and trucks travel on the congested main route outperforms the routing algorithm scenario by approximately $7k. the reason behind this result is that actually the number of passenger cars served by the main route increases significantly while the trucks leave the section (number of passenger cars increase at the simulation period); thus results with bias in interpreting the value of time.

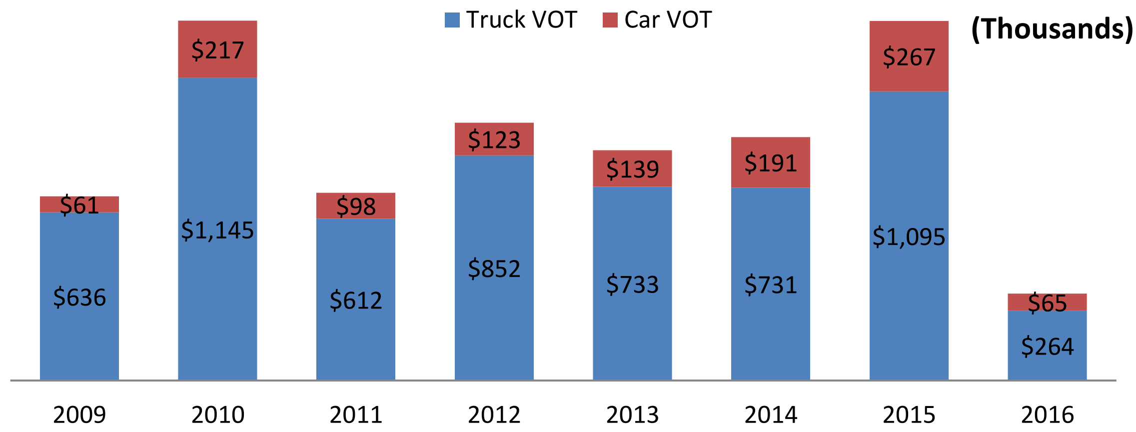

Figure 33 Annual Value of Time Savings

By applying the previously utilized incident data, the annual value of time savings are estimated and presented in Figure 33. As mentioned earlier, 2009 and 2016 consists of two months of data, thus, does not represent the entire year. Both car and truck value of time savings were found to be highest in year 2015.

5.2 Fuel Consumption and Emissions

In order to analyze the tailpipe emissions from traffic micro simulation model outputs, a microscopic transportation emissions model (Micro-TEM) that was developed by Abou-Senna and Radwan in 2014 is utilized in this section. Carbon dioxide (CO_2) transportation emissions predictions on limited access highways can be done using this surrogate model. The prediction expression of the model equation is provided in Eq. (5.1.).

$$\ln(CO2) = 10.407 - 0.268\,(\text{Volume}^2) + 0.073\,(\text{Speed}^2) + 0.55\,(\text{Volume}) - 0.084\,(\text{Speed}) + 0.31\,(\text{Truck\%}) + 0.298\,(\text{Grade\%}) + 0.057\,(\text{Speed*Grade}) + 0.054\,(\text{Truck\%*Grade\%}) \quad (5.1.)$$

The parameters for each scenario of VISSIM micro simulation models output that are fed into Micro-TEM model are listed in Table 15. The CO_2 emissions results are also attached to Table 14. Output volumes differ from input volumes due to congestion induced flow reductions.

Tailpipe CO2 emissions of scenarios are provided in Figure 36 and annual exhaust CO2 emissions are presented in Figure 37 by the secondary axis.

Fuel consumption of each of the simulation scenarios were determined by converting the CO2 emissions. Eq. (5.2.) and (5.3.) are the conversion methods for both diesel and gasoline that are provided by EPA in 2006. The Code of Federal Regulations (40 CFR 600.113) provides carbon content per gallon of gasoline and diesel fuel values which EPA also utilizes in estimating the fuel economy of vehicles: gasoline carbon content per gallon is 2,421 grams and diesel carbon content per gallon is 2,778 grams.

Table 15 Micro-TEM Inputs

Scenario	Input Volume	Output Avg Volume	Input Truck %	Output Truck %	Avg Speed	CO2 Emissions (kg)
Shoulder Base	4500	4176	20	19.6%	19.23	43,376
Shoulder w/routing	4500	3640	20	3.0%	39.5	17,456
2 lanes Base	3450	2458	20	17.5%	7.1	41,852
2 lanes w/routing	3450	2672	20	3.0%	9.12	17,326
1 lane Base	3450	3418	20	19.7%	14.67	37,382
1 lane w/routing	3450	2771	20	2.7%	33.5	13,693

In order to calculate the CO_2 emissions from a gallon of fuel is computed by the carbon emissions multiplied by the molecular weight ratio of CO_2 which is 44 and the molecular weight of carbon.

Thus, CO_2 emissions from a gallon of gasoline = 2,421 grams x 0.99 x (44/12) = 8,788 grams = 8.8 kg/gallon = 19.4 pounds/gallon (5.2.)

CO2 emissions from a gallon of diesel = 2,778 grams x 0.99 x (44/12) =10,084 grams = 10.1 kg/gallon = 22.2 pounds/gallon (5.3.)

Consequently, a reverse calculation was made to find gallons per a kg of CO_2 emission at each fuel type. The fuel savings in gallons at each simulation scenario for both diesel and gasoline fuel types are illustrated in Figure 34 and annual savings by fuel types are presented in Figure 35. (Fuel prices are obtained from U.S. Energy Information Administration, http://www.eia.gov/petroleum/gasdiesel/)

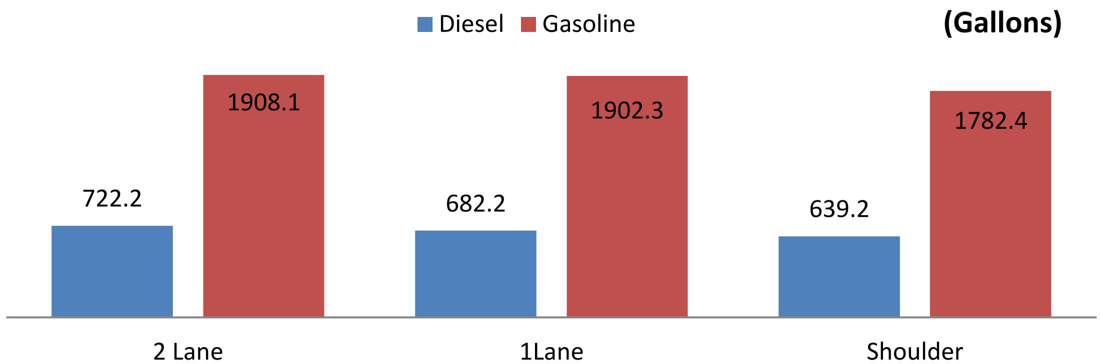

Figure 34 Fuel Savings (Gallons)

For each of the three incident case scenarios calibrated; fuel consumption for both vehicle classes (diesel and gasoline) are summarized in Figure 34 in gallons. For two lane closure scenarios, the fuel consumption for passenger cars is 1,908 gallons where diesel engine trucks consumption was estimated as 723 gallons.

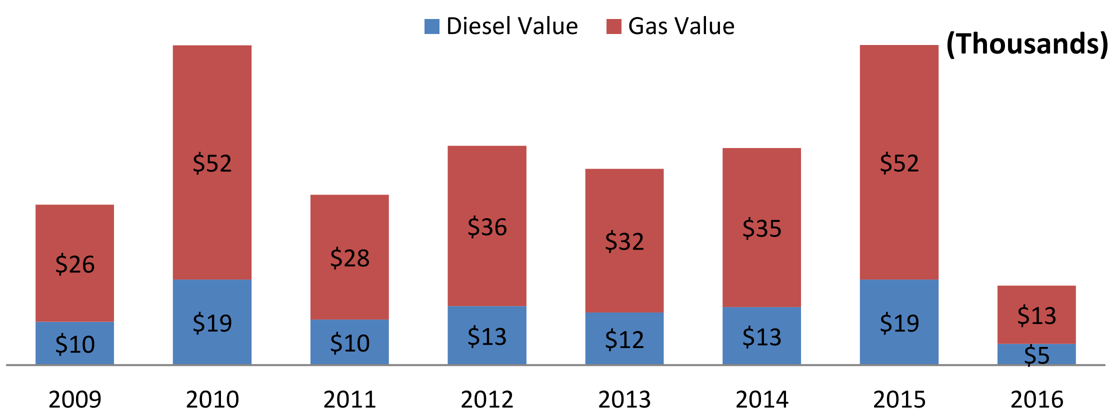

Figure 35 Annual Fuel Savings ($-value)

When incident data is applied, the annual value of time savings are estimated and presented in Figure 35. As mentioned, 2009 and 2016 consists of two months of data, thus, does not represent the entire year. Both diesel and gasoline engine vehicles' fuel consumption were found to be highest in year 2010 and 2015.

Argonne National Laboratory releases an updated GREET (The Greenhouse gases, Regulated Emissions, and Energy use in Transportation) Model every year. GREET 2016 model provides conversion factors from fuel to pollutants such as CO, NOx, VOC, PM10, PM2.5 that are essential for especially in diesel engines. The factors obtained from GREET 2016 model is provided in Table 16.

Table 16 GREET Model Pollutants from Fuel Consumption

gr/gallon	**VOC**	**CO**	**NOx**	**PM10**	**PM2.5**
Diesel	2.5784	10.3298	25.7568	0.2969	0.2725
Gasoline	4.0397	88.1153	3.8066	0.1817	0.1613

Volatile Organic Compounds (VOCs) represent hundreds of different compounds. They come from incomplete fuel combustion. Other VOC emissions originate from evaporation of fuel especially during refueling. Gasoline engines produce higher amounts of VOCs than diesel engines due to the greater volatility of fuel.

NO, NO2 and other oxides of nitrogen is called as NOx that play a major role in the formation of ozone. They are mainly created during fuel combustion especially when engines burn a small amount of the nitrogen in the air along with nitrogen compounds from the vehicle fuels. Diesel engines generally emit greater amounts of NOx than gasoline engines due to their higher combustion temperatures.

According to National Air Quality in 2002, Carbon Monoxide (CO) results from the vehicle ‘s incomplete combustion of fuels especially at low temperatures. Carbon monoxide has the impact of decreasing the amount of oxygen in the blood. Motor vehicle exhaust produces about 60 percent of all CO emissions nationwide. Gasoline engines produce higher amounts of CO than diesel engines, due to their lower combustion temperature as compare to diesel engines

Last but not least, particulate Matter (PM) can be a primary or secondary pollutant. "Primary" particles, such as dust or black carbon come from number of sources such as vehicles, factories and construction sites. "Secondary" particles are formed from chemical reactions with other emissions. PM2.5 is the "fine" particles that are less than or equal to 2.5 μm in diameter while PM10 is particles less than or equal to 10 μm in diameter. Diesel engines produce significantly more PM than gasoline engines. Fine particulate matter can be inhaled in the lungs which can intensify symptoms in individuals that are suffering from respiratory illnesses.

Estimated annual pollutants are provided in Figure 36 and 37.

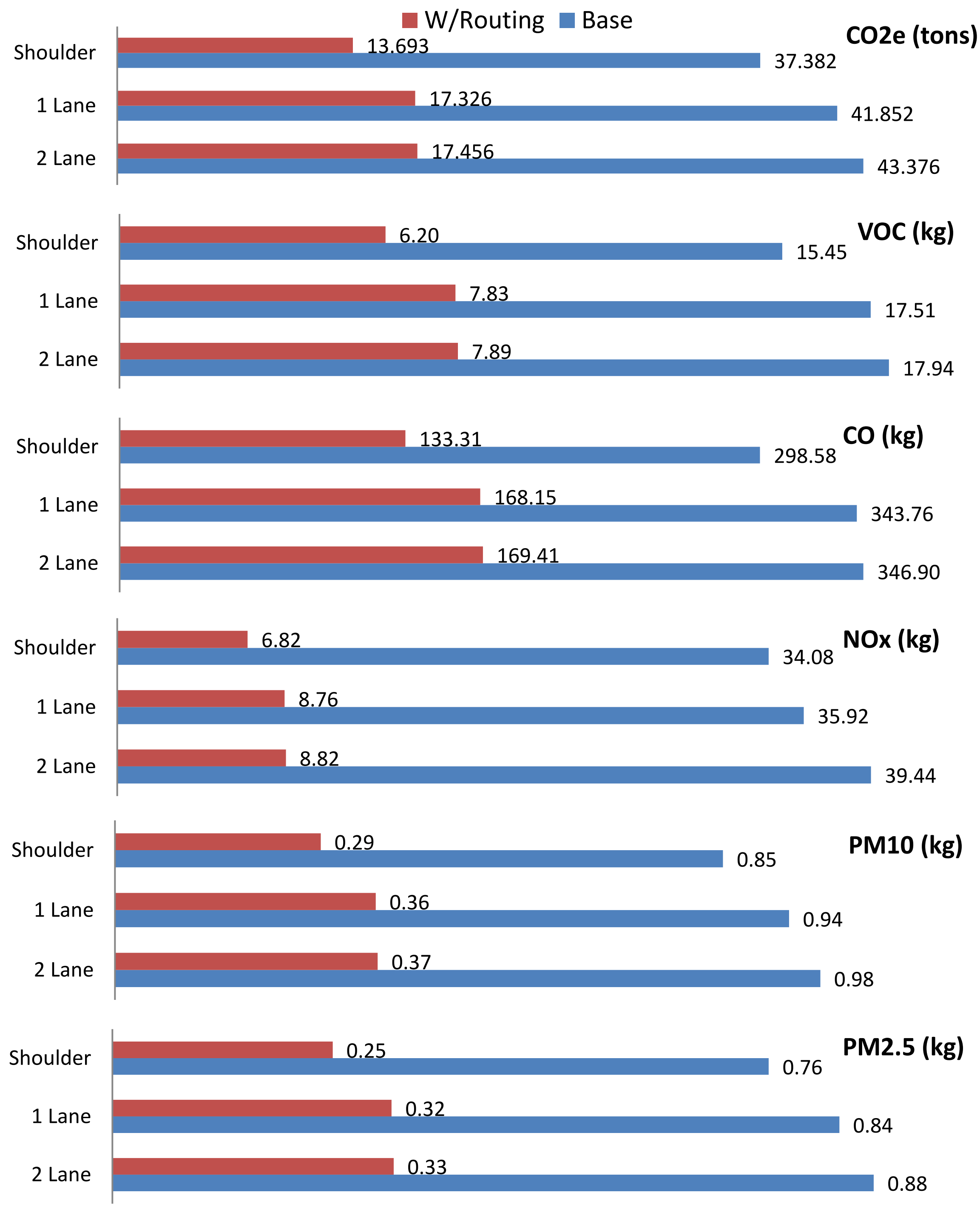

Figure 36 Tailpipe Emission Comparisons

In Figure 36, although the CO_2 emissions seems the highest in quantity, the health and social impacts of PM's were found to be higher in literature. In one 2-lanes closure event, PM2.5 emissions could reach to 1.2 kg within a few hours.

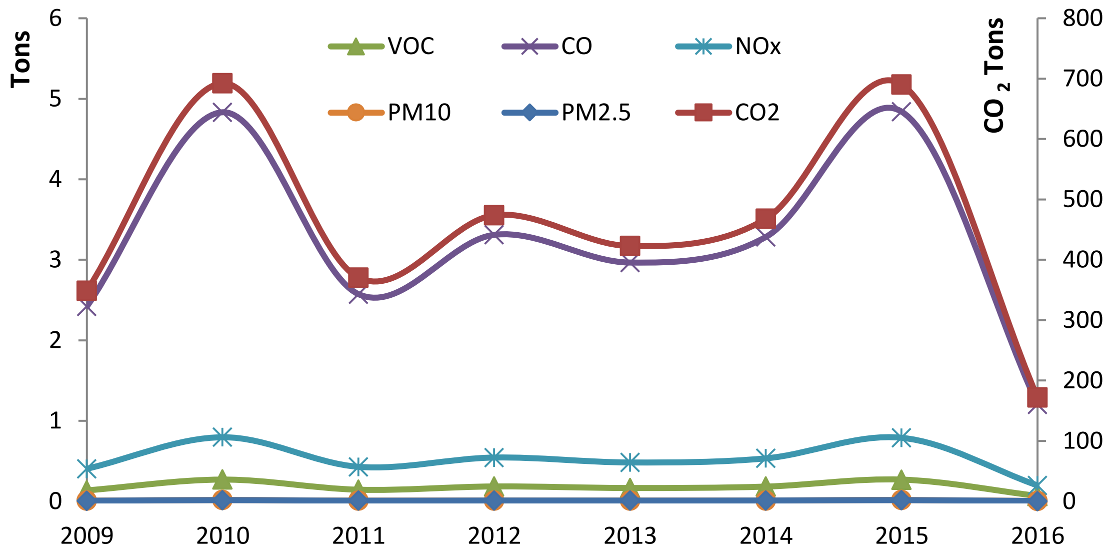

Figure 37 Tailpipe Emissions (tons)

<u>5.3 Surrogate Safety Assessment Model (SSAM)</u>

Traffic conflict points have been studied and analyzed since the late 1960s as a surrogate measurement to estimate the safety of a location, under the assumption of conflict frequency is directly related with the actual risk of crashes. The safety of traffic facilities is usually analyzed by tracking and evaluating motor vehicle crash reports over time. Collecting crash data is mostly slow due to lack of records and random nature of crashes. Therefore, to reveal the need for remediation of either the roadway design or the flow-control strategy becomes durable. Additionally, the traditional methods is usually not applicable to analyze the safety aspects of roadway designs that have not been built or traffic flow-control/operational strategies that have yet to be applied in the field.

Surrogate Safety Assessment Model (SSAM) is a technique that further analyzes the micro-simulation output and also the frequency and character of barely avoided vehicle-to-vehicle collisions in traffic via automated conflict analysis. Accordingly, it is capable of assessing the safety aspects of transportation facilities bypassing the wait for statistically significant sample sizes of crashes, injuries, or fatalities to occur.

A conflict in traffic can be described as a scenario where the likelihood of two vehicles being collided is estimated without elusive action. An illustration of a conflict can be seen in Figure 38. In this conflict; a vehicle is angling across two lanes to the left-turn inlet and has shortly cut in front of another vehicle that must make a sudden brake to avoid a collision.

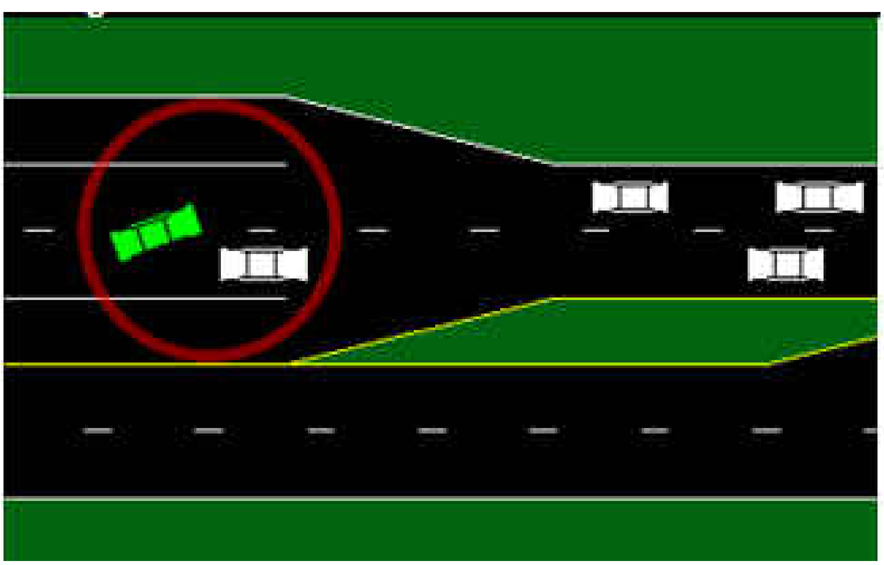

Figure 38 Sample Conflict Illustration

Traditionally, conflict studies utilize laborers that are trained to detect and record conflicts observed at a traffic facility such as an intersection. However, the application of SSAM software was developed to automate conflict analysis via processing the vehicle trajectory data. The trajectory file is an output generated by four traffic micro-simulation software packages which all use stochastic computational methods: VISSIM, Paramics, AIMSUN, and TEXAS. In other words, SSAM is a post-processor that analyzes the dataset of TRJ files produced by second-by-second traffic micro-simulation models.

VISSIM TRJ files for five random seed numbers for each scenario where fed in to SSAM. Vehicle-to-vehicle interaction was analyzed to identify conflict events and records and all possible events are found. SSAM also generates several surrogate safety performance measures for these events, including the followings:

- Minimum time-to-collision (TTC).
- Minimum post-encroachment (PET).
- Initial deceleration rate (DR).
- Maximum deceleration rate (MaxD).
- Maximum speed (MaxS).
- Maximum speed differential (DeltaS).
- Classification as lane-change, rear-end, or path-crossing event type.
- Vehicle velocity change had the event proceeded to a crash (DeltaV).

The angle of conflict is estimated as an approximate angle of a hypothetical collision between conflicting vehicles, according to the measured heading of each vehicle. The conflict angle used in SSAM ranges from -180 ° to +180 °. A positive angle is indicating approach from the right and a negative angle is indicating left approach. An angle of 180 ° (or -180 °) referring to a direct crossing crash (also known as direct head-on collision), and an angle of 0 ° (or -0 °) indicates a direct rear-end crash. (see Figure 39)

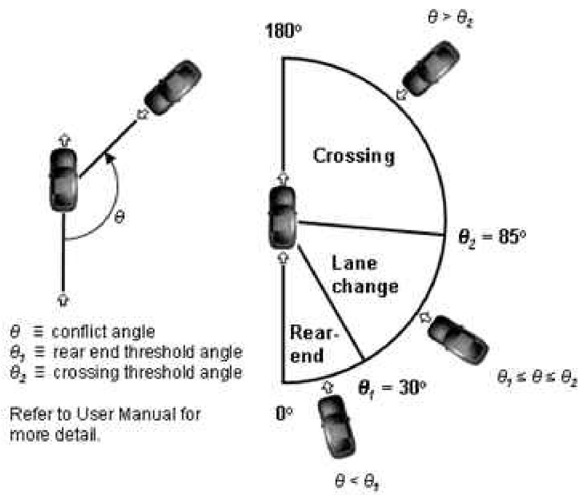

Figure 39 Conflict Angle Illustration

Surrogate safety measure thresholds estimated by SSAM are presented in Figure 40. Definitions of the measures were previously listed.

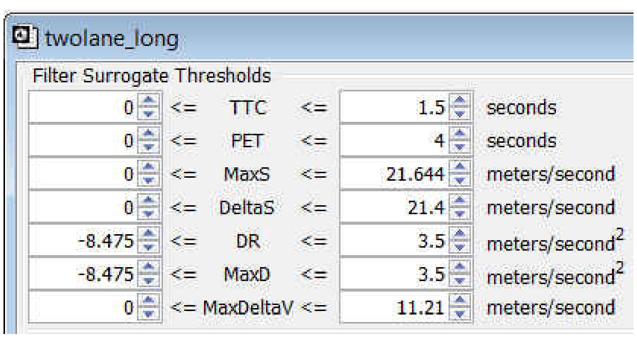

Figure 40 Surrogate Safety Measures Thresholds

After analyzing each scenario in VISSIM second-by-second simulation model software, the generated trajectory files were used as an input for the SSAM analysis and results of crossing, rear end, and lane change conflict points are provided in Table 17. In addition, comparison bar charts from the base scenario for each conflict points are presented in Figure 41.

Table 17 Number of Conflicts

Conflict Frequency	Crossing	Rear-End	Lane Change	Total	Decrease in Risk
Shoulder Base	15	137,020	7,144	144,179	-
Shoulder w/routing	86	10,240	803	11,129	5.06%
One lane Base	13	210,275	3,103	213,391	-
One lane w/routing	123	43,894	1,489	45,506	78.67%
Two lane Base	13	243,741	1,603	245,357	-
Two lane w/routing	175	230,937	1,826	232,938	92.28%

Findings in this section can be summarized as follows: To assess the safety impacts of the routing strategies, an automated conflict analysis tool SSAM was employed. Decrease in risk of collisions at shoulder closure are around 5%, whereas at one-lane closure scenarios the difference becomes 78 % and reaches up to 95% on 2-lane closure scenarios.

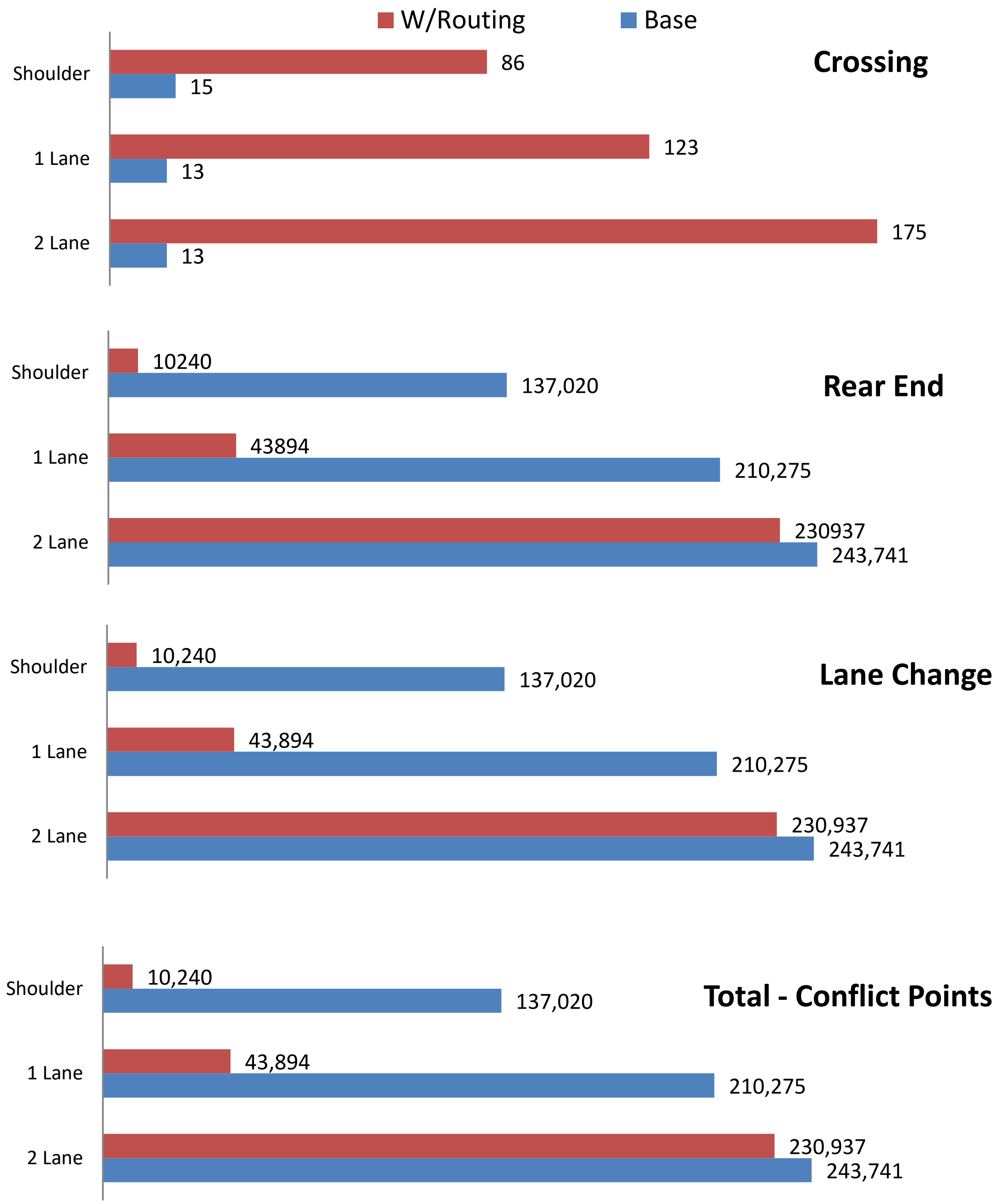

Figure 41 SSAM Results

CHAPTER SIX: SUPPLY CHAIN IMPACTS FROM PETROLEUM REFINERIES

6.1 Background

In order to identify the supply chain (i.e. off-site) impacts due to the reduction of total travel time from both vehicle types, Economic Input Output Model – Life Cycle Assessment (EIO-LCA) approach will be applied.

Life Cycle Assessment (LCA) is a tool that was developed in early 1990s in order to investigate potential environmental impacts in system base. In other words, it is a powerful method which has been used widely in literature for providing the results of production or process's impacts from cradle to grave. This approach starts from raw material extraction and continues with production, transportation, uses phases and finally concludes with end-of-life phase (Finnveden et al., 2009). The LCA methodology basically consists of goal and scope definition, life-cycle inventory analysis, life-cycle impact assessment, and interpretation sections (Graedel and Allenby, 2010).

Economic Input-Output (EIO) analysis proposed to build more powerful methodology with LCA approach to analyze the supply chain impacts including systems or products' economic and environmental impacts (Hendrickson, Lave, & Matthews, 2006).

In this chapter, EIO-LCA tool is utilized to assess the off-site impacts of fuel consumption (monetary value in dollars) by selecting the petroleum refinery industries.

Savings in fuel can be analyzed in EIO-LCA tool and will give the secondary savings in supply chain of the petroleum refineries. The input for the EIO-LCA model was the cost difference among the routing savings from the base scenarios. Annual petroleum refinery economic impacts are provided in Figure 42. Besides the economic activities in the supply industries, the tool provides a variety of environmental impacts. The environmental impacts provided are represented by the following emissions produced by the petroleum refinery supply chain; CO, VOC, NO_x, PM10, PM2.5, and CO_2 equivalent GHG gases. Figure 43 present the annual emission outputs from the EIO-LCA tool. CO_2 equivalent GHG gases range between 50 to 250 tons while other pollutants range from 0 to 400 kg annual emissions.

6.2 Petroleum Refinery Supply Chain Economic Savings

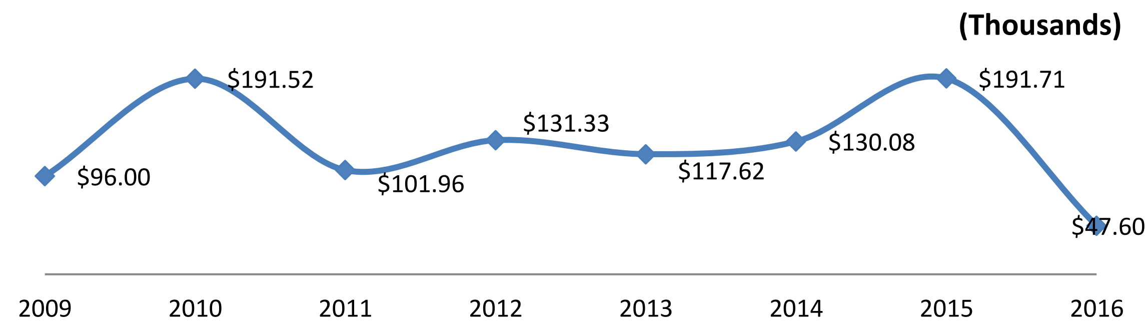

Figure 42 Petroleum Refinery Economic Impacts

6.3 Petroleum Refinery Supply Chain Emissions

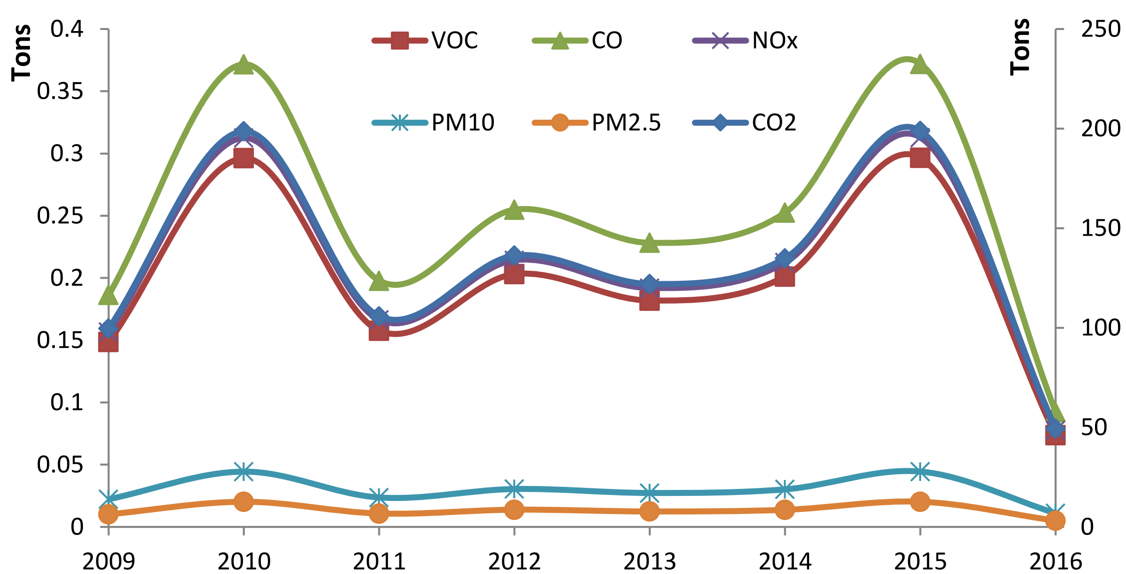

Figure 43 Petroleum Refinery Emissions

6.4 Social Impacts of Emissions (APEEP Model)

In this section, emissions are further evaluated by assessing their social impacts to the society. The Air Pollution Emission Experiments and Policy analysis (APEEP) model is an integrated assessment model that links environmental impacts such as emissions of air pollution to exposures, physical effects, and monetary damages in the contiguous United States (Muller and Mendelsohn 2006, 2007). This model is among one of the traditional assessment models (Mendelsohn 1980; Nordhaus 1992; Burtraw et al. 1998; EPA 1999). Sulfur dioxide (SO_2), volatile organic compounds (VOCs), nitrogen oxides (NOx), fine particulate matter (PM2.5), coarse particulate matter (PM10), and ammonia (NH_3) are the six pollutants that APEEP evaluate.

APEEP air-quality models utilize the emission data provided by US Environmental Protection Agency (EPA) to estimate corresponding ambient concentrations in each county in the states.

APEEP can be used to describe marginal damage of pollutants on a source specific basis. The algorithm used to compute the emission induced marginal damages is; first it estimates the total damages due to all sources in the model, producing its baseline by the observed emissions (EPA 2011); second, APEEP adds 1 ton of each pollutant from one source and redo the computation for total damages. The marginal damage can be described as the difference from the damage that arises after adding 1 ton of pollutant the damages due to the baseline emissions. The algorithm segregates the contribution of a single ton of emissions from each source to total national damages. This method also captures the formation of secondary pollutants. These pollutants are sulfates and nitrates (considered as PM2.5) as well as tropospheric ozone (O_3). APEEP ascribes the marginal damage due to such secondary pollutants back to the source of emissions. Eq. (6.1.) expresses the marginal damage that is calculated by adding the differences in damages across the complete set of counties that receive emissions from a source. (Muller and Mendelsohn 2006, 2007)

$$MD_{i,p} = \sum r\, Dr, ep - \sum r\, Dr, bp \qquad (6.1.)$$

where

$MD_{i,p}$ = damage per ton of an emission of pollutant (p) from the source (i).

D_r = total dollar damage that occurs at receptor county (r).

bp = 2002 baseline emissions of p.

ep = 2002 baseline emissions plus 1 ton of p from i.

GHG emissions' social impacts are districted in three categories by level of damage such as; low, medium and high where low representing less populated rural areas to high population urban areas. In this study, medium level of social impacts are used (i.e. medium GHG = $42 per ton).

The social impacts of other pollutants that are considered mostly diesel engine related pollutants are provided in Table 17.

Table 18 Tailpipe Emissions' Social Impact Factors

Tailpipe Emissions	CO	NOx	PM10	PM2.5	VOC
Weighted Average	$886	$3,445	$11,644	$75,850	$7,159
Best rural - low damage	$298	$1,160	$786	$3,729	$364
Worst urban - high damage	$2,374	$9,232	$25,812	$171,208	$16,110

The social impact factors seen in Table 17 are applied to the tailpipe emissions of both passenger cars and trucks that are evaluated in the micro-simulation models. The results are illustrated in Figure 44.

APEEP model has altered social impact factors that can be applied to the supply chain refinery emissions. These factors are listed in Table 18.

Table 19 Supply Chain Emissions' Social Impact Factors

Refinery Emissions	CO	NOx	PM10	PM2.5	VOC
Weighted Average	$648	$2,006	$6,712	$43,844	$4,136
Low	$45	$951	$552	$2,807	$273
High	$3,828	$667	$39,578	$235,784	$21,860

The EIO-LCA results of supply chain emissions are also further analyzed by using the APEEP model by using the weighted average factors from Table 18. The social impacts are presented in Figure 45.

In summary, the annual total air pollution induced social impacts are aggregated and provided in Figure 46.

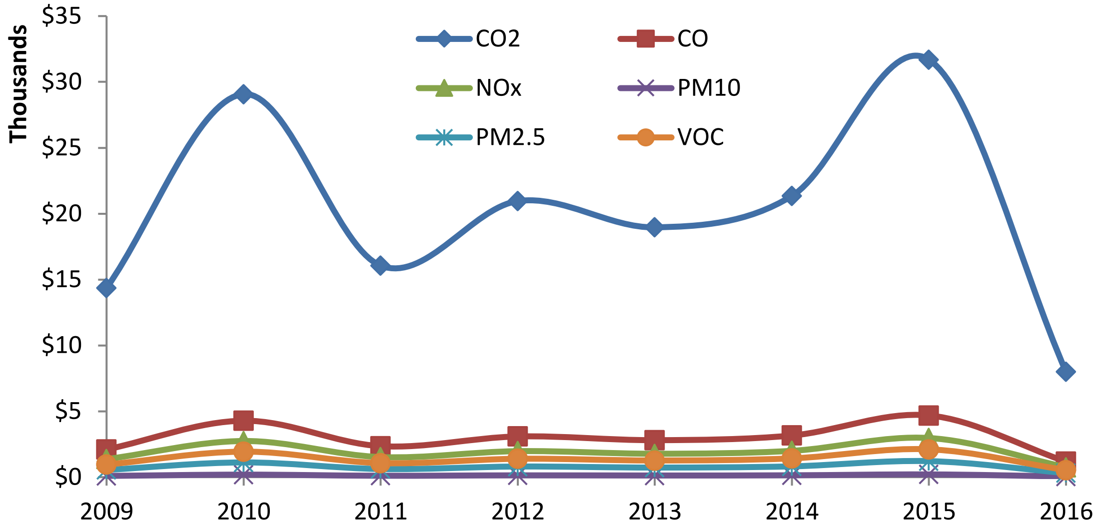

Figure 44 Social Impacts of Tailpipe Emissions

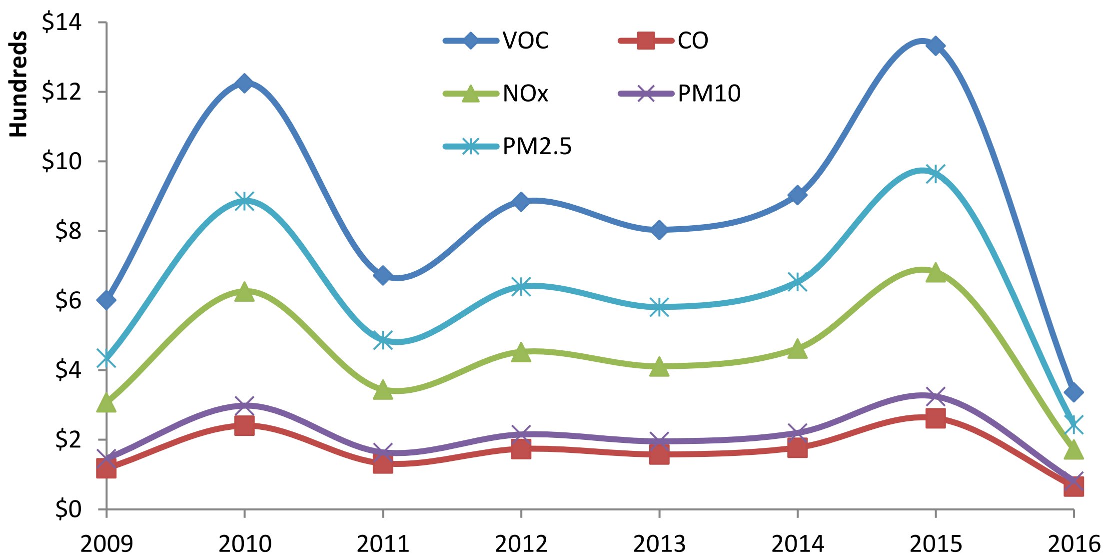

Figure 45 Social Impacts of Supply Chain Refinery Emissions

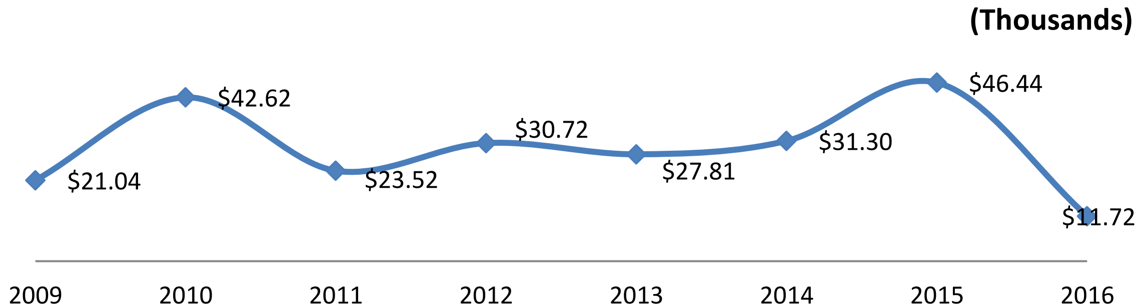

Figure 46 Social Impacts of Total Emissions

6.5 Discussion

In this study, three types of impacts of truck real-time routing strategy are accentuated. These are economic, environmental, and social impacts. The monetarized impacts can be listed as; value of time, off-site economic activities from the supply chain and air pollution induced social impacts. The annual summary of total savings can be seen in Figure 47.

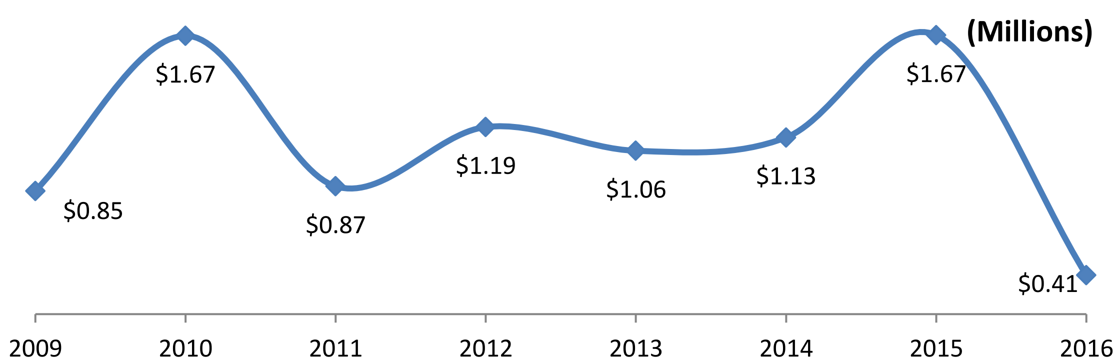

Figure 47 Total Annual Monetary Values

CHAPTER SEVEN: CONCLUSION

There is a growing need to effectively assess the impacts of locating shipping intensive land uses and improve the inputs to the tools used to manage traffic. On one hand, trucks need to efficiently serve commerce and industry, while at the same time their activities need not contribute to a decline in the quality of life or public safety. In the current practice there is no methodology for a real-time management specifically on truck routes to reduce travel duration and avoid truck travel delays due to unexpected events (i.e. traffic incidents) and estimate the impacts on traffic flows, traffic safety, pavement, and sustainability.

The impact of freight on our transportation system is further accentuated by the fact that trucks consume greater roadway capacity and therefore cause more significant problems including traffic congestion, delay, crashes, air pollution, fuel consumption, and pavement damage. There is a growing need to quantify the actual effects of truck traffic to support the ability to safely and efficiently move goods and people in areas where expansion of roadways is not an option. On one hand, trucks need to efficiently serve commerce and industry, while at the same time their activities need not contribute to a decline in the quality or public safety. In the current practice, to the best of our knowledge, there is no methodology for real time management of traffic, specifically on truck routes, to reduce travel duration and avoid truck travel delays due to non-recurring congestion (i.e. traffic incidents) and to estimate impacts on traffic flows, economy, and environment. The objective of this study is to develop a truck routing strategy and to quantify its' impact on travel time, emissions and consequently assess the effects on the economy and environment. In order to estimate non-recurrent congestion based travel delay and fuel consumption by real time truck routing simulation models, significant corridors with high truck percentage were selected. According to the cost of congestion studies, the value of travel time of passenger cars and trucks are determined as $17.67 and $94.04, respectively in 2015. Simulation results of various scenarios indicated that potential annual value of time savings can reach up to $1.67 million per selected corridor. Furthermore, tailpipe emissions (on-site) due to traveled distance and idling are determined with Micro-TEM regression tool and MOVES emissions simulator program. In addition, to assess the safety impacts of the routing strategies, an automated conflict analysis tool Surrogate Safety Assessment Model (SSAM) was employed. Decrease in risk of collisions reach up to 95% on 2-lane closure scenarios. Last but not least, the Economic Input Output-Life Cycle Assessment Model is then utilized to gather fuel consumption related upstream (off-site) emissions. Consistently, fuel costs and emission values are lower, even though extra miles are traveled on the alternative route. In conclusion, our study confirms that truck routing strategies on traffic incident induced congestion conditions have high economic and environmental impacts. And the framework methodology developed in this study can be applied to quantify these impacts at any limited access highway section that has an alternative route.

LIST OF REFERENCES

Abdel-Aty, M. A., Kitamura, R., & Jovanis, P. P. (1995). Investigating effect of travel time variability on route choice using repeated-measurement stated preference data (No. 1493).

Abou-Senna, H., & Radwan, E. (2013). VISSIM/MOVES integration to investigate the effect of major key parameters on CO2 emissions. Transportation Research Part D: Transport and Environment, 21, 39–46. doi:10.1016/j.trd.2013.02.003

Abou-Senna, H., & Radwan, E. (2014). Developing a Microscopic Transportation Emissions Model to Estimate Carbon Dioxide Emissions on Limited-Access Highways. Transportation Research Record, 2428(1), 44-53.

Abou-Senna, H., Radwan, E., Westerlund, K., & Cooper, C. D. (2013). Using a traffic simulation model (VISSIM) with an emissions model (MOVES) to predict emissions from vehicles on a limited-access highway. Journal of the Air & Waste Management Association, 63(7), 819–831. doi:10.1080/10962247.2013.795918

Al-Deek, H., Garib, A., & Radwan, A. E. (1995). New method for estimating freeway incident congestion. Transportation Research Record, 30-39.

Black, I. G., & Towriss, J. G. (1993). Demand effects of travel time reliability. Centre for Transport Studies, Cranfield Institute of Technology.

Brodrick, C. J., Dwyer, H. A., Farshchi, M., Harris, D. B., & King Jr, F. G. (2002). Effects of engine speed and accessory load on idling emissions from heavy-duty diesel truck engines. Journal of the Air & Waste Management Association, 52(9), 1026-1031.

Bureau, U. S. C. (2012). Table 1103. Motor Vehicle Accidents — Number and Deaths: 1990 to 2009 Table 1104. Traffic Fatalities by State: 1990 to 2009 Transportation 693, 2012.

Burtraw, D., Krupnick, A., Mansur, E., Austin, D., & Farrell, D. (1998). Costs and benefits of reducing air pollutants related to acid rain. Contemporary Economic Policy, 16(4), 379-400.

Codes, A. (2014). American National Standard. Retrieved from http://www.nema.org/Standards/ComplimentaryDocuments/Contents and Scope ANSI C78.50-2014.pdf

Cohen, H., & Southworth, F. (1999). On the measurement and valuation of travel time variability due to incidents on freeways. Journal of Transportation and Statistics, 2(2), 123-131.

Data, T. T. G. (2001). A Synthesis of Highway Practice, NCHRP Synthesis 298. Transportation Research Board, National Academy Press, Washington, DC.

Elderly, L. (2003). State of Florida. The Florida Geography, (April). Retrieved from http://www.science.fau.edu/geo/fsg/fl_geog/The Florida Geographer 1991 Vol. 25.pdf#page=6

EPA, A. (2011). Inventory of US greenhouse gas emissions and sinks: 1990-2009. US Environmental Protection Agency, Washington, DC.

Facts, T. S. (2012). Data (2014). National Highway Traffic Safety Administration.

Finnveden, G., Hauschild, M. Z., Ekvall, T., Guinée, J., Heijungs, R., Hellweg, S., ... & Suh, S. (2009). Recent developments in life cycle assessment. Journal of environmental management, 91(1), 1-21.

Florida Seaport Transportation and Economic Development Council. (2013). The Five-Year Florida Seaport Mission Plan.

Fu, L., & Rilett, L. (1997). Real-time estimation of incident delay in dynamic and stochastic networks. Transportation Research Record: Journal of the Transportation Research Board, (1603), 99-105.

Gibby, A. R., Ryuichi Kitamura, Huichun Zhao (1990) Evaluation of Truck Impacts on Pavement Maintenance Costs. *Transportation Research Record* (1262), 48 - 56

Gillett, J. C. (2011). Monetizing Truck Freight and The Cost of Delay For Major by, (December).

Giuliano, G. (1989). Incident characteristics, frequency, and duration on a high volume urban freeway. Transportation Research Part A: General, 23(5), 387-396.

Graedel, T. E., & Allenby, B. (2009). Industrial Ecology and Sustainable Engineering (2nd ed.). Prentice Hall.

Graham, L. a., Rideout, G., Rosenblatt, D., & Hendren, J. (2008). Greenhouse gas emissions from heavy-duty vehicles. Atmospheric Environment, 42(19), 4665–4681. doi:10.1016/j.atmosenv.2008.01.049

Hallenbeck, M. E., Carlson, D., & Simmons, J. (2003). The possibilities of transportation concurrency: Proposal and evaluation of measurement alternatives. Washington State Transportation Research Center, Seattle.

Hendrickson, C. T., Lave, L. B., & Matthews, H. S. (2006). Environmental Life Cycle Assessment of Goods and Services: An Input-Output Approach (Vol. 3). Washington DC: RFF Press. doi:10.2307/302397

Hensher, D. A. (2001). The valuation of commuter travel time savings for car drivers: evaluating alternative model specifications. Transportation, 28(2), 101-118.

Hurdle, V., & Son, B. (2001). Shock wave and cumulative arrival and departure models: Partners without conflict. Transportation Research Record: Journal of the Transportation Research Board, (1776), 159-166.

Ishak, S., & Al-Deek, H. (1998). Fuzzy ART neural network model for automated detection of freeway incidents. Transportation Research Record: Journal of the Transportation Research Board, (1634), 56-63.

Jackson, W. B., & Jucker, J. V. (1982). An empirical study of travel time variability and travel choice behavior. Transportation Science, 16(4), 460-475.

Jansuwan, S. (2013). A Quantitative Framework for Assessing Vulnerability and Redundancy of Freight Transportation Networks, 2013.

Kay, L. (2000). Remember the Past, Protect the Future: EPA 1999 Annual Report.

Khan, A. S., Clark, N. N., Thompson, G. J., Wayne, W. S., Gautam, M., Lyon, D. W., & Hawelti, D. (2006). Idle Emissions from Heavy-Duty Diesel Vehicles: Review and Recent Data. Journal of the Air & Waste Management Association, 56(10), 1404–1419. doi:10.1080/10473289.2006.10464551

Khattak, A. J., & Rouphail, N. (2005). Incident Management Assistance Patrols: Assessment of Investment Benefits and Costs (No. FHWA/NC/2005-02). NC Department of Transportation, Research and Analysis Group.

Klodzinski, J., & Al-Deek, H. (2002). Using seaport freight transportation data to distribute heavy truck trips on adjacent highways. Proceedings of the 82 nd Transportation …. Retrieved from http://www.ltrc.lsu.edu/TRB_82/TRB2003-000851.pdf

Klodzinski, J., & Al-Deek, H. (2003). Transferability of an intermodal freight transportation forecasting model to major Florida seaports. … Record: Journal of the Transportation …. Retrieved from http://trb.metapress.com/index/x3055705g406451v.pdf

Li, X., Han, J., Lee, J. G., & Gonzalez, H. (2007, July). Traffic density-based discovery of hot routes in road networks. In International Symposium on Spatial and Temporal Databases (pp. 441-459). Springer, Berlin, Heidelberg.

Lighthill, M. J., & Whitham, G. B. (1955). On kinematic waves II. A theory of traffic flow on long crowded roads. Proc. R. Soc. Lond. A, 229(1178), 317-345.

Lin, W. H., & Daganzo, C. F. (1997). A simple detection scheme for delay-inducing freeway incidents. Transportation Research Part A: Policy and Practice, 31(2), 141-155.

Lindley, J. A. (1987). Urban freeway congestion: quantification of the problem and effectiveness of potential solutions. ITE journal, 57(1), 27-32.

Lutsey, N., & Sperling, D. (2005). Energy efficiency, fuel economy, and policy implications. Transportation Research Record, 1941(1), 8-17.

Marlina, S. (2012). Understanding the dynamics of truck traffic on freeways by evaluating truck passenger car equivalent (PCE) in the Highway Capacity Manual (HCM) 2010.

Matthews, H. S., Hendrickson, C. T., & Weber, C. L. (2008). The importance of carbon footprint estimation boundaries.

McCormick, R. L., Graboski, M. S., Alleman, T. L., & Yanowitz, J. (2000). Idle Emissions from Heavy-Duty Diesel and Natural Gas Vehicles at High Altitude. Journal of the Air & Waste Management Association, 50(11), 1992–1998. doi:10.1080/10473289.2000.10464229

McCormick, R. L., Graboski, M. S., Alleman, T. L., & Yanowitz, J. (2000). Idle emissions from heavy-duty diesel and natural gas vehicles at high altitude. Journal of the Air & Waste Management Association, 50(11), 1992-1998.

Mendelsohn, R. (1980). An economic analysis of air pollution from coal-fired power plants. Journal of Environmental Economics and Management, 7(1), 30-43.

Miller, R. E., & Blair, P. D. (2009). Input-output analysis: foundations and extensions. Cambridge University Press.

Model, F., Force, T., Committee, F., Short, J., Park, L., Mysore, V., … Zanjani, A. (2012). Truck GPS Data for Freight Performance Measurement and Planning: Applications, Issues, and Opportunities, 1–19.

Mohamed, A., Laman, H., Oloufa, A., & Abou-Senna, H. (2018). A Framework for Assessing the Impacts of State Level Platooning Truck Only Lane Strategies in Florida (No. 18-05914).

Morales, J. M. (1987). Analytical procedures for estimating freeway traffic congestion. ITE journal, 57(1), 45-49.

Muller, N. Z., & Mendelsohn, R. (2006). The Air Pollution Emission Experiments and Policy Analysis Model (APEEP) Technical Appendix. Yale University: New Haven, CT, USA, 1.

Muller, N. Z., & Mendelsohn, R. (2007). Measuring the damages of air pollution in the United States. Journal of Environmental Economics and Management, 54(1), 1-14.

Nam, D. H., & Drew, D. R. (1998). Analyzing freeway traffic under congestion: Traffic dynamics approach. Journal of Transportation Engineering, 124(3), 208-212.

Noland, R. B., & Small, K. A. (1995). Travel-time uncertainty, departure time choice, and the cost of the morning commute (p. 32). Institute of Transportation Studies, University of California, Irvine.

Nordhaus, W. D. (2002). The health of nations: the contribution of improved health to living standards (No. w8818). National Bureau of Economic Research.

Ozbay, K. M. A., & Tech, V. (n.d.). Evaluation of incident management strategies and technologies using an integrated traffic / incident management simulation Pushkin Kachroo Melike Baykal-Gursoy, *X*.

Pan, B., Demiryurek, U., Shahabi, C., & Gupta, C. (2013). Forecasting Spatiotemporal Impact of Traffic Incidents on Road Networks. *2013 IEEE 13th International Conference on Data Mining*, 587–596. doi:10.1109/ICDM.2013.44

Pekula, N., Kuritz, B., Hearne, J., Marchese, A. J., & Hesketh, R. P. (2003). The effect of ambient temperature, humidity, and engine speed on idling emissions from heavy-duty diesel trucks (No. 2003-01-0290). SAE Technical Paper.

Polak, E. (1987). On the mathematical foundations of nondifferentiable optimization in engineering design. SIAM review, 29(1), 21-89.

Rakha, H., & Zhang, W. (2005). Estimating traffic stream space mean speed and reliability from dual-and single-loop detectors. Transportation Research Record: Journal of the Transportation Research Board, (1925), 38-47.

Richards, P. I. (1956). Shock waves on the highway. Operations research, 4(1), 42-51.

Ritchie, S. G., & Cheu, R. L. (1993). Simulation of freeway incident detection using artificial neural networks. Transportation Research Part C: Emerging Technologies, 1(3), 203-217.

Schrank, D. (2008). Urban Mobility Report (2004) (Vol. 771). Retrieved from http://books.google.com/books?hl=en&lr=&id=uDQlad4_qy0C&oi=fnd&pg=PA1&dq=Urban+Mobility+Report&ots=kXSUGKJfC3&sig=JPOeMHpVpfie9ndeBrRDldUEGF4

Schrank, D. L., Turner, S., & Lomax, T. J. (1993). Estimates of urban roadway congestion, 1990.

Senna, L. A. (1994). The influence of travel time variability on the value of time. Transportation, 21(2), 203-228.

Skabardonis, A., Petty, K., Varaiya, P., & Bertini, R. (1998). Evaluation of the freeway service patrol (FSP) in Los Angeles.

States, U. (2002). Study of Exhaust Emissions from Idling Heavy-Duty Diesel Trucks and Commercially Available Idle-Reducing.

Stodola, J. (2007). Possibilities of traffic accidents and risk crash evaluation. Journal of Polish Safety and Reliability Association, 2.

Stodolsky, F., Gaines, L., & Vyas, A. (2000). Analysis of technology options to reduce the fuel consumption of idling trucks (No. ANL/ESD-43). Argonne National Lab., IL (US).

Sullivan, E. C. (1997). New model for predicting freeway incidents and incident delays. Journal of Transportation Engineering, 123(4), 267-275

Teng, H., & Qi, Y. (2003). Application of wavelet technique to freeway incident detection. Transportation Research Part C: Emerging Technologies, 11(3-4), 289-308.

Tia, M., & Kumara, W. (2005). Evaluation of Early Strength Requirement of Concrete for Slab Replacement Using APT, (March), 49104504972–12. Retrieved from http://trid.trb.org/view.aspx?id=755084

Tong, H. Y., Hung, W. T., & Cheung, C. S. (2000). On-Road Motor Vehicle Emissions and Fuel Consumption in Urban Driving Conditions. Journal of the Air & Waste Management Association, 50(4), 543–554. doi:10.1080/10473289.2000.10464041

U.S. Bureau of Economic Analysis. (2002). 2002 Benchmark Input-Output Data. Retrieved from http://www.bea.gov/industry/io_benchmark.htm

Wang, Y., Hallenbeck, M., Cheevarunothai, P., & Northwest, T. (2008). Quantifying incident-induced travel delays on freeways using traffic sensor data, (61). Retrieved from http://www.wsdot.wa.gov/research/reports/fullreports/700.1.pdf

Young, P., Notis, K., Feuerberg, G., & Nguyen, L. (2013). Bureau of Transportation Statistics.