THE IMPACTS OF ROAD CONSTRUCTION WORK ZONES ON THE TRANSPORTATION SYSTEM, TRAVEL BEHAVIOR OF ROAD USERS AND SURROUNDING BUSINESSES

by

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This thesis is dedicated to my parents Mr. and Mrs. Marfo and siblings.

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ABSTRACT

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Title: The Impacts of Road Construction Work Zones on the Transportation System, Travel Behavior of Road Users and Surrounding Businesses
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In our daily use of the transportation system, we are faced with several road construction workzones. These construction workzones change how road users interact with the transportation system due to the changes that occur in the system such as increased travel times, increased delay times and vehicle stopped times. A microscopic traffic simulation was developed to depict the changes that occur in the transportation system. The impacts of the changes in the transportation system on the human travel behavior was investigated using ordered probit and logit models using five independent variables; age, gender, driving experience, annual mileage and percentage of non-work trips. Finally, a business impact assessment framework was developed to assess the impact of the road construction workzones on various businesses categories such as grocery stores, pharmacy, liquor stores and fast foods. Traffic simulation results showed that the introduction of workzones in the road network introduces an increase in delay times, vehicle stopped times, and travel times. Also, the change in average travel times, delay times and vehicle stopped times differed from road link to link. The observed average changes saw an increase as high as 318 seconds per vehicle, 237 seconds per vehicle and 242 seconds per vehicle for travel time, delay time and vehicle stopped time, respectively, for the morning peak period. An average increase as high as 1607 seconds per vehicle, 258 seconds per vehicle and 265 seconds per vehicle was observed for travel time, delay time and vehicle stopped time, respectively, for the afternoon peak period. The statistical model results indicated that, on a work trip, a high driving experience, high annual mileage, and high percentage of non-work trips makes an individual more likely to change their route. The results also showed gender difference in route choice behavior. Concerning business impacts, businesses in the workzone were impacted differently with grocery and pharmacy stores having the highest and lowest total loss in revenue, respectively.

1. INTRODUCTION

1.1 Background and Problem Statement

There has been a high rise in the study of travel behavior in recent years. Most of the recent research have focused on the impacts of urban area form and social demographic variables such as age, gender, household composition, income etc. on travel behavior.

Numerous researches have been conducted to evaluate the effects of different factors on travel behavior. Studies in travel behaviors over the years have attempted to answer questions about:

- The factors that drive people to make trips
- The number of trips people make
- The destinations of these trips made
- The mode of travel by users for their trips
- The choices of route for trips
- The average vehicle occupancy when trips are being made
- The impacts of the land use and other environmental factors on trips made
- If there exist a travel pattern of people in an area
- If gender influence an individual's travel pattern

Travel behavior studies has become an important field in transportation planning, in that, it helps in the development of accurate transportation planning models so that transport analysts can make predictions about future traffic patterns. Findings from travel behavior researches serves as input for travel forecast models to help create a close representation of the real-life situation.

A comprehensive look at the studies conducted in travel behavior reveals very little work done on the impacts of work zones on road users travel behavior. With the growing use of software, that simulate conditions on road segments with work zones, it pays to properly calibrate the software to fit the changes in travel demand due to the presence of these work zones. Thus, there is a need to conduct studies about the possible changes in travel behavior due to work zones. This would help to improve the accuracy of the work zone condition simulations by these software programs.

1.2 Research Motivation

The main purpose of this research is to find out how the changes in the transportation system resulting from road construction work zones affect the travel behavior of road users in the influence area and how that impacts the revenue of neighboring businesses.

Several characteristics of a roadway can be affected due to the presence of workzones. Capacity may be reduced; noise level through the work zone may increase; risk of accidents may increase, speed limits may change, etc. These changes in roadway characteristics in turn may affect how road users respond. Some road users wouldn't mind the changes and would still use the route with the work zone since that has been their preferred route over time. On the other hand, others would decide to look for new routes for their commute due to the changes that their preferred route is experiencing.

For road users that choose to change their route, it could be due to one or more of the aforementioned factors. The extent to which a factor affects one's decision to change his or her route may also vary from one road user to another. Also, some users may change their travel destinations in other to avoid routes with work zones. For example, change their preferred grocery shop to a new one, change gas stations etc. Others may also decide to cancel trips or switch their regular modes of travel.

As it can be inferred from the previous paragraphs, a change in the roadway characteristic due to a work zone can lead to a myriad of behavioral changes in road users. This research intends to investigate the changes in roadway characteristics due to work zones and the resulting impacts on human travel behavior. Considering road user trip characteristics, the study will also seek to capture travel behavior changes due to reduction in speed, travel delays, vehicle stopped times etc.

1.3 Research Significance

This research is designed to aid planners and decision makers in the transportation industry. Using the framework developed under this study, transportation planners and decision makers would be able to quantify the impacts of road constructions on travel behavior of road users and neighboring businesses, and plan mitigation measures for the network-wide effects of roadway construction projects on transportation networks.

1.4 Thesis Organization

The thesis is divided into eight chapters. The first chapter introduces the subject matter. Chapter two presents literature review on traffic management at work zones and human travel behavior. Chapter three describes the research study area. Chapters four through six present the research methodology on traffic simulation, statistical modeling, and business impact assessment, respectively. In Chapter Seven, the research findings are presented and discussed. Finally, in Chapter eight, summary and conclusions based on the research findings are presented.

2. LITERATURE REVIEW

2.1 Introduction

During road constructions, traffic management plans are used to control the traffic passing through the work zone or divert traffic onto a detour. Several traffic management studies have been conducted over the years to find out which combination of traffic control measures provides the most adequate way to control traffic. Human travel behavior is also hugely impacted by the changes in the transportation system. Travel behavior refers to the habits and travel patterns that road users have built over time whilst interacting with a road network.

In this chapter, we look at past literature in the areas of traffic controls employed at different types of work zones to manage traffic approaching and passing through the work zones, and past works on human travel behavior and how these travel behaviors were impacted by specific road constructions in various road networks.

2.2 Traffic Management at Work Zones

Over the years, many researches involving road reconstructions have focused on the impacts of road work zones on travel conditions (e.g. travel times, accident rates, average speed, road capacities etc.) and traffic management plans that are employed to improve the travel conditions. In his paper, Krammes (1990) presented a travel impact evaluation process based on findings from five major road reconstruction projects in the United States in the 1980's, and guidelines for selecting appropriate analysis tool for expected travel impacts. He, however, emphasized how knowledge on how motorists adjust their travel patterns in response to road reconstruction was limited at the time of his research and thus a difficult factor to capture in his research. The travel impact evaluation process focused on estimating operational and economic measures of effectiveness for decision makers to use in selecting traffic management options.

Devine et al. (1982) assessed traffic management plans that were employed during the I-195 Providence river bridge. The author concluded that employing the following measures could provide effective construction with minimal traffic disruption. These measures (also called the four E's) are engineering strategies, education of public, enforcing traffic management plans and having emergency plans in place.

Goodwin et al. (1998) in a research to find out the effect of capacity reduction on road users analyzed reports from over a hundred places from different countries on situations where capacity allocations on roadways has been changed either by new policies, maintenance works or a natural disaster. The author concludes that with the right traffic policy implementation, capacity may not necessarily cause an undue congestion as observed from the analyzed cases. On the part of capacity reduction in general, Goodwin concludes that the impacts on traffic patterns tends to be high during the early days but die out as drivers adjust to it.

Karim and Adeli (2003) designed a case-based reasoning software which was part of research for the Ohio Department of transportation for improving traffic control measures at work zones. The software works on the principle of finding similar works that have already been done and fed into the system, retrieving them, and then serving as the basis for the planner to either use it as the means of planning for the upcoming construction or modify it to improve upon user costs and other related cost. However, this tool falls short of providing the planner with any information on how the work zone can be optimized to reduce crashes, queue lengths, delays etc. At best, it may serve as a guide to the planner on how past construction works were done and the effects of the traffic control measures that were employed.

Jiang and Adeli (2003) also worked on a work zone cost optimizing model using hourly traffic volumes. The cost model considered the user delay cost, maintenance cost as well as accident cost. This optimization process considers the number of lanes closed, darkness, and seasonal demand to provide the optimum start time and work zone segment length either for short-term or long-term work zones.

Heutinck et al. (2006) conducted a research to find how traffic operations can be improved during road maintenance works using dynamic route guidance systems. A simulation of traffic flow in a work zone using this approach for distributing traffic onto detours showed an increase in the traffic flow. The simulation of different dynamic route guidance configurations identified the configuration that provided more information on the state of all detours to road users provided the highest increase in traffic flow.

Ullman and Trout (2009) conducted a research into finding how best to communicate changes at a location due to a road work zone to the visually impaired and how to best guide them through a work zone using audio messages. This research was conducted in Texas with about 50 participants. The participants were made to listen to different messages and were assessed afterwards in order to find out what should be incorporated into theses audio messages to properly guide them in and around the work zone area. This research provides a list of guidance to create good audio messages for directing the visually impaired.

Bai and Li (2011) investigated how drivers would respond to an Emergency Flasher Traffic Control Device (EFTCD) at a one-lane, two-way road work zone. This was to investigate how the EFTCD would reduce vehicle speeds in the work zone in order to reduce the number and severity of rear end collisions at work zones. The research shows up to 11% reduction in vehicle speeds from the two work zones that were used as case studies and an 82% approval from drivers when a survey was conducted to find out if it helped alert them of the change in driving conditions ahead.

Lee et al. (2012) conducted a research to investigate the effectiveness of a vehicle actuated signal on work zone operations, considering three traffic control signal types; pre-timed signal control, actuated signal with fixed all red time, and actuated signal with dynamic all red time. The man purpose was to find out which signal control mode would have the lowest work zone conflicts and vehicle delay. Using VISSUM, different work zone configurations were simulated, and of these different work zone layouts, the actuated signal with dynamic all red time provided the least delays and conflicts in most cases.

Dickerson et al. (2016) in their research, developed a web-based tool for the department of transportation (DOT) for the District of Columbia. This tool is designed to help improve the safety at work zones and reduce the work zone impact on traffic operations by serving as a planning tool for the DOT. It tracks all planned work zones that are issued permits to find if there are conflicts on road closures and detours, and with the embedded traffic simulation tool, it is also able to show congestion hotspots in the entire district's network coordinating all the planned and ongoing work zones that have been provided as input. The tool provides the bases for the creation of a citywide traffic management plan.

Zhang and Gambatese (2017) recently conducted a study in Oregon to find out the effectiveness of the different temporary Traffic Control Measures (TCM) used at work zones. Four different combination of TCM combinations were used: stop signs only; stop signs with a portable changeable message signs; stop signs with a radar speed display; and stop signs, portable changeable message signs and a radar speed display. The author concludes that the fourth combination (stop signs, portable changeable message signs and a radar speed display) offers the highest speed reduction compared to the other TCM combinations.

Pesti and Brydia (2017) used Bluetooth sensors to capture the daily post event impacts on the I-35 ongoing road reconstruction in Texas, using the Bluetooth MAC address matching technique to measure the travel time, delays, average speeds and queue length at work zone. Also, together with an excel based program, a tool for finding the best times for scheduling lane closures for minimum impacts on queue length was developed. This technique, according to the author, provides a very cost-effective means of monitoring the performance of the work zone.

Abdelmohsen and El-Rayes (2018) developed an optimization tool for work zone management planning. Providing the tool with the necessary data on the highway characteristics, work zone layout and characteristics, etc., the developed program uses a four-stage optimization process to provide the user with an optimal work zone traffic control plan based on the acceptable traffic delay and crash index. It also provides a means to analyze the impact of different traffic control measures on traffic delays and crash index at work zones.

2.3 Travel Behavior

Studies in travel behavior dates back as far as the 1940s but began to really take shape in the 1980s. M. G. Boarnet & Sarmiento (1998) conducted a research on the effect of land use on non- work trips in Southern California. The research concludes there is no significant link between the land use variable and travel behavior. This research uses data collected over a two-day period of the non-work trips recorded by about 769 individuals in the last quarter of 1993.

A research by same author later on in M. Boarnet & Crane (2001), reveals a more complex relationship between travel behavior and land use. The author states that land use drives up the price of travel and that in turn affect travel behavior. The research also emphasizes on the role the geographical scale plays in showing a link between travel behavior and land use. Data for this research was from a travel behavior survey from 1986 in San Diego providing about 4199 non-work trips for the research.

Snellen et al. (2001) conducted a research to find the relationship between urban city shapes, different road networks and travel behavior. No clear link was established between these variables in order to show any influence urban shape and road networks have on activity-based travel patterns. This research was conducted using eight Dutch cities.

Cao et al. (2009) looked for a link between the built environment and non- work travel behavior. The results of the research show that mixed land use neighborhood promotes the use of transits based on their availability. Also, non- motorized trips such as walking are fueled by the aesthetics of the neighborhood. The research also found a link between an individual's neighborhood selection and their trip making habits.

Nasri and Zhang (2012) assessed the effect of the built environment on travel behavior at a metropolitan level of six metropolitan areas in the US. A mixed-effect model was generated using data on the Vehicle Miles travelled (VMT) in these six areas. The authors conclude that households in places with higher population, employment densities, better-mixed land development, and shorter distances to city centers provides the least VMT.

Christiansen et al. (2017) investigated the effects of parking facilities on travel behavior using data from the Norwegian national travel survey. The authors conclude that, having a combination of parking restrictions and a daily parking fee can considerably reduce car use for work related trips. For parking in residential areas, the authors report that the farther the parking area from one's home reduced the number of driven trips although it may not reduce the number of trips in general. Finally pairing good standards of public transit with parking restrictions at city centers increases the patronage for public transits.

2.4 Work Zone Impacts on Travel Behavior

Changes in roadway characteristics due to a road construction or maintenance work zone may lead a myriad of changes in the behavior of road users. Several researchers have conducted studies to investigate the different behavioral changes that occurred during some road reconstruction period. Although little has been done to investigate the factors that causes people to reroute when there is an ongoing road construction, some research has been done to assess road users travel behavior before and after road reconstructions.

Very little can be found in literature in the 1980's and 90's on work zone related travel behavior changes research. In the 1980's, Hendrickson et al. (1982) assessed the changes in travel pattern from the I-376 reconstruction in Pittsburg, United States. In this paper, using volume counts, vehicle occupancy counts, travel time measurements and travel survey, the authors concluded there was very little observance in changes to mode choice. Route choice, however substantially changed in response to the restrictions on the freeway due to the road reconstruction. Also, averagely, road users' departure time was twenty minutes earlier than the pre-construction time.

Nam et al. (1999) investigated the impact of a freeway reconstruction in Seattle on travel patterns of the people there. The research concluded the socioeconomics of individuals played a major role to the extent to which their travel patterns changed with people of different age groups, income, household size and marital status expressing opposing views on the extent to with the freeway closures affected their travel behavior.

A little more research on travel behavior of road users in responds to road work zones is seen in literature from the 2000's. Fujii et al. (2001) researched on how frequent automobile drivers were impacted by a freeway closure in Japan. The author noticed a slight increase in public transportation patronage during the road closure period. Also, it was noticed that most drivers that used their private vehicle for commuting were reluctant to switch to public transportation due to an over estimation of the travel times using the public transport to commute. Once this erroneous overestimation was corrected some drivers were less reluctant to switch modes, but the research could not establish how long that behavior was going to last after the expressway reopens.

Hunt et al. (2002) also worked on capturing the responses of automobile drivers change in travel behavior due to the closure of a bridge in Calgary, Alberta in Canada for repairs and were forced to find alternate ways to the downtown area. It was observed that, there was no major decline in vehicle trips to the downtown area however, there was a significant number of drivers that reported shifting travel times to avoid congested peak periods. There was an increase in transit patronage by about 3.6% and 0.8% increase in cycling and walking.

Zhu et al. (2010) analyzes how traffic behavior is affected by disasters such as the I-35W Mississippi River bridge collapse in 2007. From the research, it is noted that it took several weeks for road users to adjust after the unexpected interference. The author concludes the travel demand was however not significantly impacted and due to the available of alternate roads with unused capacities. Travel times and congestion during peak periods also went up significantly. In terms of patronage for public transit, there was no visible increase.

Yang and Schonfeld (2011) used three different simulation models to simulate the diversion fraction of drivers at a road work zone. The simulation further proved that the attractiveness of the detour (i.e. the speed limit and length) played a major role in drivers choosing to reroute.

A number of travel behavior research was also conduction on a freeway reconstruction in downtown Sacramento, in 2008. Yun et al. (2011) analyzed the impacts of the I-5 freeway reconstruction in Sacramento, California in 2008 on non-work travel behavior of road users. Two surveys were conducted six months apart to find out how many times motorists made changes to their non-work travels under seven broad areas. Namely, route change, day change, location change, day change, mode change, activity change and activity forgone. The paper further discusses a binary and multivariate logit model that was used to determine whether a user made at least one of the non-work travel changes. It concluded that route change was the most common non-work travel behavior change which represented about 44% of their survey respondents and mode change being the least non-work travel change behavior representing 8.8% of the survey respondents.

Mokhtarian et al. (2011) also worked on assessing how travel behaviors of both genders were affected due reconstruction of the I-5 freeway and concluded that women were more likely to make at least one change in travel behavior (64%) than men (53%). The travel behavior changes reviewed in the research included route changing and mode changing such as public transit, carpooling, walking, biking, and telecommuting. L. Ye et al. (2012) addressed the impact of the I-5 reconstruction on the passive (factors outside road users control e.g. travel conditions) and active (strategies adopted by road users) actions. The paper concluded that there appeared no excessive impact on passive actions as more than half of the responses from survey said travel conditions remained the same or even better during the reconstruction period. On the active actions, the paper noted that changing departure times to avoid peak hours and routes were the two high strategies adopted by road users (48% and 44% of the survey responses respectively). Also travel modes such as walking and biking, carpooling and transits showed little increase in usage.

H. M. Zhang et al. (2012) also examined the impact the reconstruction of the I-5 freeway had on the travel demand to the downtown area. From this research it was noticed that there was a high travel demand reduction in the area close to the closure as more traffic diverted to major arterials to the downtown area. The inbound flow saw a major decrease about 3%-7% compared to the outbound flow from downtown Sacramento that recorded a 1%-4% decrease in travel demand.

Newer research in road user response to road work zones includes Kattan et al. (2013) and Tanvir (2017). Kattan et al. (2013) in their paper analyzed the response of travelers to real-time information provided on road closures and advisory detours from the construction of a light rail line in the city of Calgary, Canada. From the paper the author noted that, during the construction, the major changes in travel behavior resulted from route changing, followed by mode changing and then finally destination changing. Also, motorists preferred radio followed by Variable Message Signs (VMS) for en-route messages on traffic updates and the TV the most for pre-trip updates. Interestingly, it was noted that most users (43%) who changed routes due to information from VMS did not follow the suggested route from the VMS and 27% did follow the suggested route given.

Tanvir (2017) analyzed driver diversion rates from road work zones on using Bluetooth devices. Although the paper could not provide a conclusive diversion rate from their case study of the reconstruction work zone at I-40 in Raleigh, NC, it provided a useful insight into the major challenges that come with using Bluetooth devices to capture traffic data; mainly the reliability of the wireless communication technology.

2.5 Chapter Summary

This chapter presented past literature on traffic management at work zones and how human travel behavior are impacted by these work zones during road reconstructions. It can be noted that different combinations of traffic managements provided different levels of results in the studies analyzed. Human travel impacts due to road construction projects are also place specific and differed from one place of construction to the other. The next chapter with describe the case study area for this research.

3. CASE STUDY

3.1 Introduction

To capture the impacts of road construction on travelling behavior of road users a three-step methodology was developed.

1. Two sets of questionnaires were developed. The first survey was to collect the information on how road construction work zones impact road users travel patterns and which factors affects their decision to change their travel behavior the most. The second survey was sent to businesses in the study area to assess the impacts of road constructions on these businesses
2. A traffic simulation was developed to show the changes that results in the system because of a road construction work zone
3. A statistical model was modeled to analyze the results collected from the road user survey and predict how the travel behavior of users change in response to road construction work zones

3.2 Study Area

The city of Hammond, located in Northwest Indiana, was used as our case study. The city of Hammond is part of the Lake County and had a population of about 77,134 as of 2016. It is most noticeably known for being home to the Purdue University Northwest campus which has a population of approximately 12000 students. Hammond, Indiana is ideally located on the outskirts of Chicago, just about 40 minutes' drive to downtown Chicago.
A map of the city of Hammond is shown in Figure 3.1.

Figure 3.1 A map showing the boundaries of the city of Hammond

The aerial map of the study area for the case study is also shown in Figure 2. The bright red line areas on the aerial map indicates the boundaries of the case study area. The study area is bounded at the top by the Michigan Street, on the right by Kennedy Avenue, on the left by Hohman Street and at the bottom by 173rd Street.

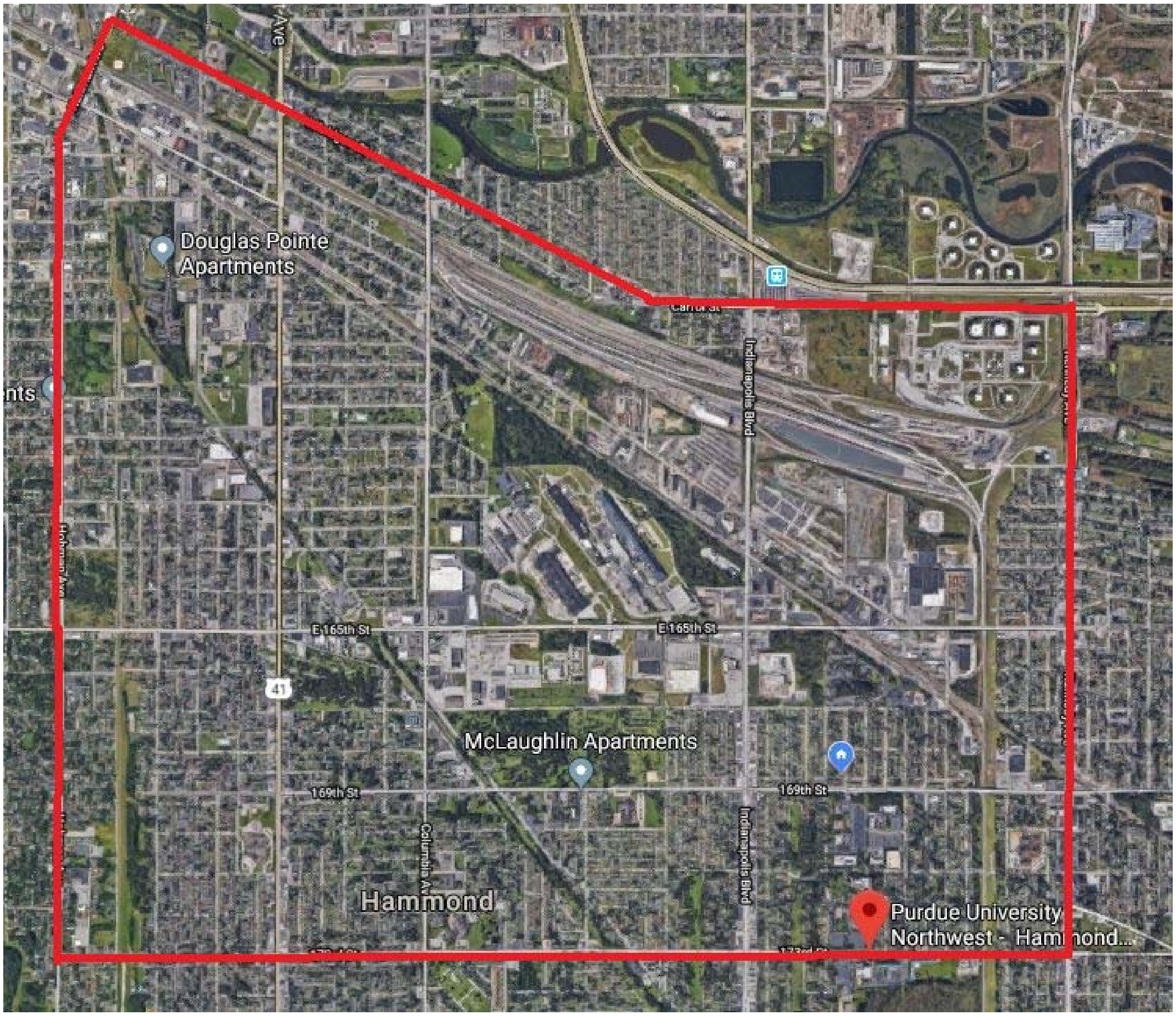


Figure 3.2 An aerial view of the Case study area within the city of Hammond

3.3 Chapter Summary

This chapter provides the description of the case study area that was used to demonstrate the framework developed in this study. The next chapter presents traffic simulation related information that was applied to estimate the impacts of the work zones on the road network.

4. TRAFFIC SIMULATION

4.1 Introduction

Several years ago, Bruce Greenshields a prolific traffic researcher developed the traffic flow models, and since then many traffic models have been developed to assess what happens to traffic in a transportation system. Many years after that, and with the advancement of technology traffic simulations have taken the transportation industry by a storm. Particularly due to its usefulness in mirroring what is happening in real life in our transportation systems to provide predictions for both long-term and short-term transportation planning using data collected about the current system.

4.2 Types of Traffic Simulation

Traffic simulation models can be classified under three broad headings. Namely;

- Macroscopic Traffic Simulation Models
- Mesoscopic Traffic Simulation Models
- Microscopic Traffic Simulation Models

Macroscopic traffic simulation models describe traffic flow as a continuous flow. Thus, all vehicles in the traffic streams are aggregated and aggregated variables such as average speeds and average densities are used to describe the traffic flow. Macroscopic models include models such as kinematic wave models and higher-order flow models which describe the dynamics in the traffic stream with a partial differential equation (Van Wageningen-Kessels, van Lint, Vuik, & Hoogendoorn, 2015).

Mesoscopic traffic simulation models combine properties of the micro and macro simulation. The mesoscopic simulation models traffic behavior in aggregate terms such as probability distributions but vehicle behavior rules are described for each vehicle individually. Popular mesoscopic simulation models include gas-kinetic models, cluster models and headway distribution models (Van Wageningen-Kessels et al., 2015).

Microscopic traffic simulation models provide a very high level of fidelity. This is due to the fact that it models vehicle behavior in the traffic stream individually. The microscopic models work on the assumption that a driver of a vehicle adjusts its behavior to that of the vehicle it is following. This simulation describes the vehicles behavior laterally (i.e. lane changing) and longitudinally (i.e. car-following). They are good for evaluating congested corridors, roads with complex geometric design etc. Popular examples of the microscopic simulation models includes action point models, safe-distance models, cellular automata models and stimulus response models (Van Wageningen-Kessels et al., 2015).

4.3 Traffic Simulation Methodology

A microscopic simulation of traffic in the study area was made possible by the use of a commercial traffic simulation software, namely, TransModeler. TransModeler provides the ability to model all types of the road network and analyze the traffic behavior in the traffic system. This visualization is very powerful and can be achieved in either 2-dimensional or 3-dimensional space.

Also, TransModeler provides a system to model the presence of a work zone on a road network. This function is known as incident modeling. These incidents are placed into the road network to show a reduction in capacity in the road network. The start time and duration of the work zone can also be specified to better simulate the road work zone on the road. With all the proper input, the impacts of the work zones on the road network can be visualized and analyzed. Figure 4.7 at the end of the chapter shows the complete methodology applied in this research.

4.3.1 Data collection for building Simulation Database

To be able to build and run a simulation smoothly, firstly, data about the road network in the case study area had to be collected. Data on traffic signal timings at intersections, turning movements at intersections and traffic demand was collected to be able to mimic as closely as possible the reality on the roads to the simulation to be created.

4.3.1.1 Collecting traffic signal timing at intersections

Signal timing is an important aspect in traffic simulation. To create a traffic signal plan for the simulation that closely represents the signal timings on the roads in the study area, signal timings at selected intersections on the roads were collected. Collecting signal timings of all signalized intersections in the road network was always going to be a long and tedious task, hence signal timings at signalized intersections on similar road types with similar traffic were assumed to be the same. Signal timings at six different intersections were collected by physical being present at the intersections and timing the different phases with a stop watch. Average values were then tabulated. A sample signal timing table is shown in Table 4.1. The complete data on intersection signal times can be found in Appendix D.

Table 4.1 Intersection signal times at 169th Street – Indianapolis Blvd.

Signal Times in Seconds			
169th	Straight	Right Turn	Left Turn
Green	31	14.12	14.4
Red	70	17	87.3
Yellow	4	3.11	2.5
Indianapolis	Straight	Right Turn	Left Turn
Green	66.5	14.7	14.5
Red	67	16.8	87
Yellow	3.5	3.4	3.5

4.3.1.2 Collecting data on turning movements at intersections

Collecting data on turning movements at intersections are needed to create a turning movement tables in the simulation database that are used to generate the simulation trip matrix. To have a representative of realistic traffic stream in the road network for the simulation, cameras were mounted at different intersections within the road network to capture vehicle turning movements at intersections at peak periods. At each selected intersection, at peak periods, vehicle movements through the intersection for sixty continuous minutes were recorded. A sample table showing turn movements in each direction as documented is shown in Table 4.2. The complete data on intersection turning movements can be found in Appendix C.

Table 4.2 Intersection Turning Movements at Kennedy Avenue – 173rd Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	3	114	5	31	14	0	26	107	17	5	8	27
2nd 15mins	5	138	9	35	16	0	47	113	11	5	12	15
3rd 15mins	6	114	3	32	18	5	41	101	14	11	17	20
4th 15mins	7	100	6	42	16	3	33	101	17	6	8	13

4.3.2 Building the Traffic Simulation

TransModeler provides a nice and intuitive user-friendly interface that allows the user to build a simulation of a road network from scratch. Its GIS based interface makes it easy to build the road network on top of existing maps in the software database. The steps involved in building and successfully running the simulation included:

- Designing the road layout of the study area
- Designing the intersections (both signalized and unsignalized intersections)
- Developing vehicle trips and paths using data from turning movements at intersections
- Designing work zones in the road network
- Checking simulation database for errors and selecting simulation output

4.3.2.1 Designing the road layout of the study area

TransModeler has an in-built GIS interface that allows you to search for addresses in the in-built map. Using the in-built map, the study area was located, and a road layout drawn on top of it using the road editor toolbox. The road editor toolbox, provides all the necessary functionalities to generate a road layout as closely as possible to the existing roadway. In this study, only the major streets in the study area were used. This was so because, the research aimed to assess the impacts of road construction work zones on major roads in the network. Also, almost all major constructions in a road network happens on major streets. After creating the layout, the link characteristics and fidelity level for simulation are also specified. For the purposes of this research, all road segments are simulated using microscopic fidelity. Figure 4.1 shows the roadway generated for the study area.

Figure 4.1 Road layout with link names as designed in simulation software

4.3.2.2 Designing the Intersections (Traffic Signalization)

In the generated case study network, there are a total of 27 intersections, all of which are signalized. Data collected at intersections were used to create traffic signal plans at these intersections using the intersection toolbox in TransModeler. The toolbox provides access to an intersection control editor where the signal phases at a selected intersection is created. For this study, pre-timed phases were created for the signalized intersections as is the case on the existing roads. The intersection control editor also allows for turning movements at the intersections to be created. A turning movement table for all intersections in the road network was created using turning movements data collected from intersections in the case study road network.

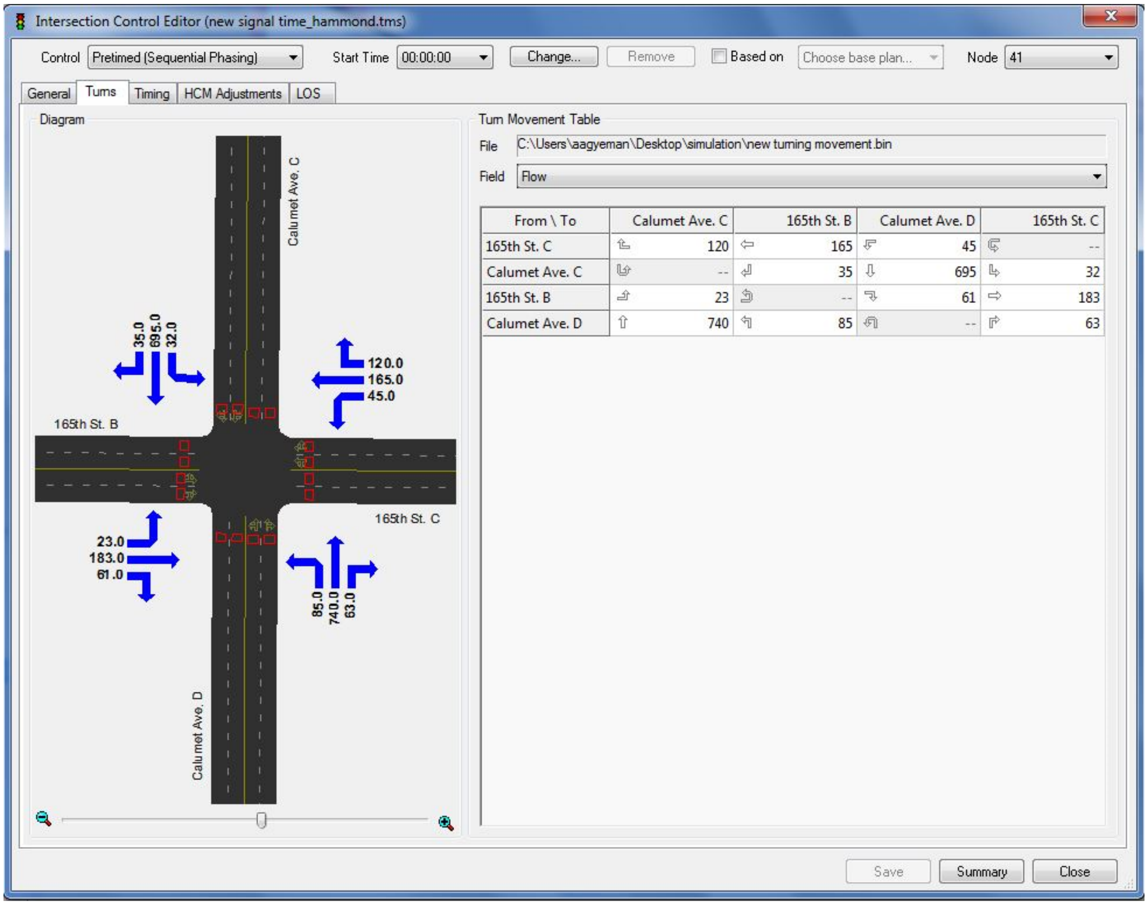


Figure 4.2 The turning movements created in the intersection control editor

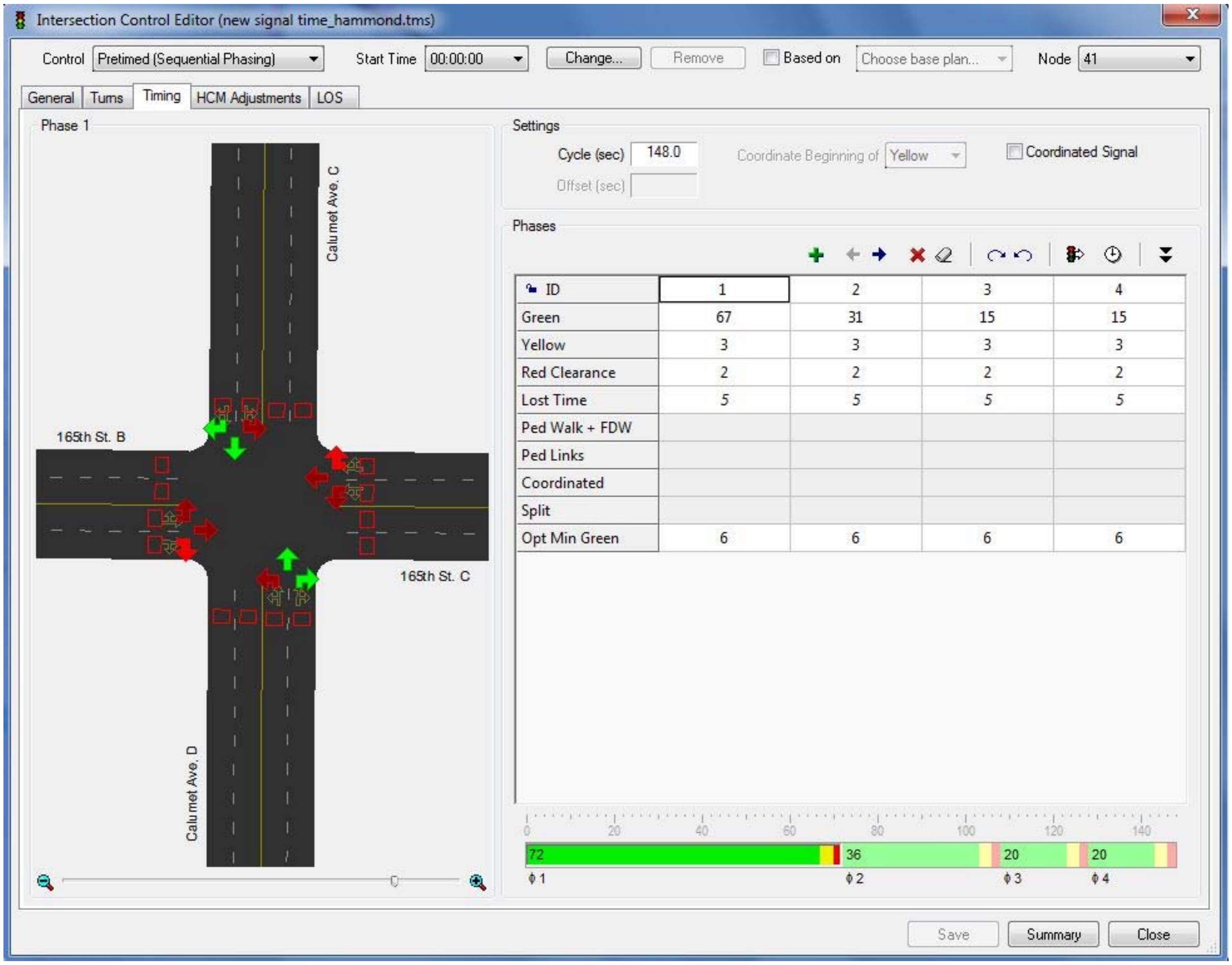


Figure 4.3 Signal timing creation using the intersection control editor.

4.3.2.3 Developing vehicle trips and paths using data from turning movements at intersections

Using the intersection turning movement data in the case study area, a trip matrix for all nodes in the road network can be estimated using the in-built feature in TransModeler that populates a set of origins and destinations from the movements of vehicles in the system using path cost for each origin-destination pair. These paths, although assigned prior to the start of the simulation are updated during simulation. The vehicle path costs are a function of travel times on segments, delays at intersections, tolls at toll plazas if any etc. and the perception of these cost depends on the driver characteristics assigned to the driver.

4.3.2.4 Designing work zones in the road network

Road construction work zones on the lanes of the roadway can be simulated in TransModeler using the incident or work zone toolbox. Using the toolbox, incidents are placed into the road network to show a reduction in capacity in the road network. The start time and duration of the work zone can also be specified to better simulate the road work zone on the road. In this research both temporary (work zones that lasted some hours in a typical day) and permanent (work zones that lasted the entire day) work zones were selectively placed in the road network and the network wide effects were evaluated. The effects of these work zones on travel times, travel speeds, queue lengths etc. were subsequently measured. A traffic simulation of three cases was thus conducted. The first case had no work zones in the road network, the second case had permanent work zones in the network and the third case had both permanent and temporary work zones in the road network. In all, six (6) permanent work zones were introduced into the system in the second case and two (2) more temporary work zones were added in the third case.

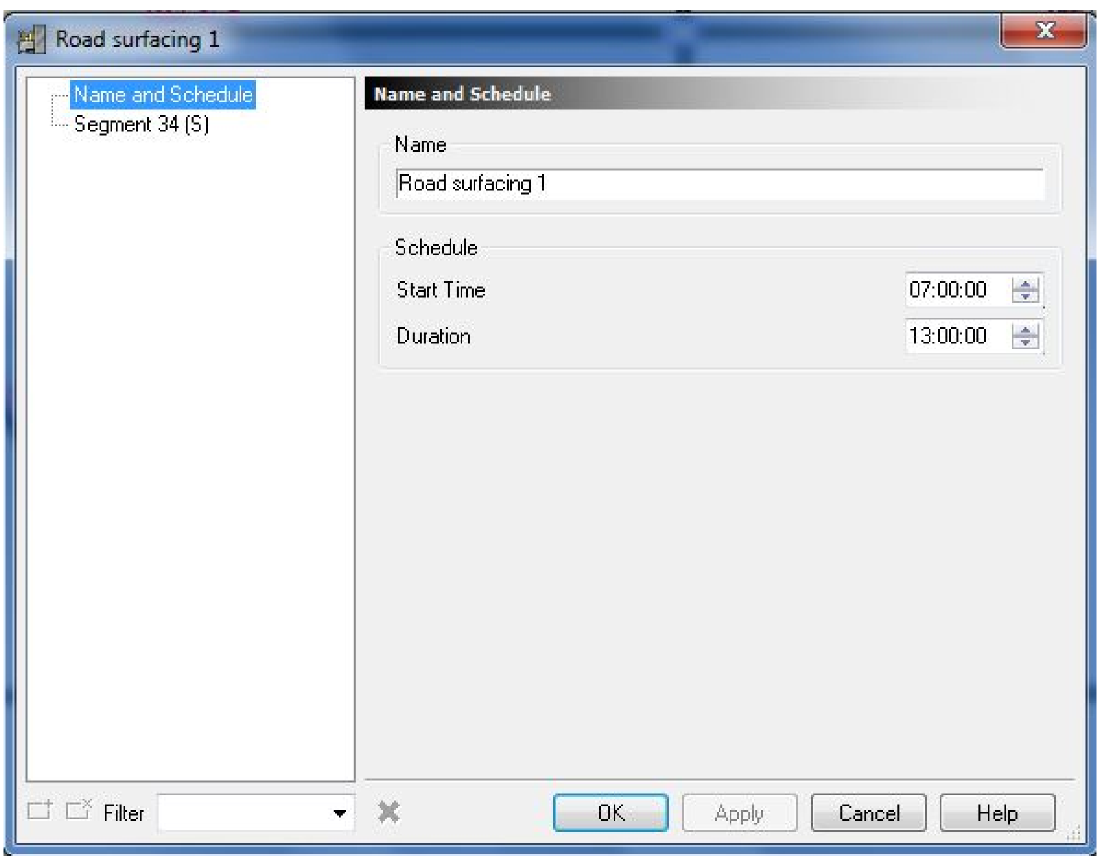


Figure 4.4 The work zone or incident toolbox

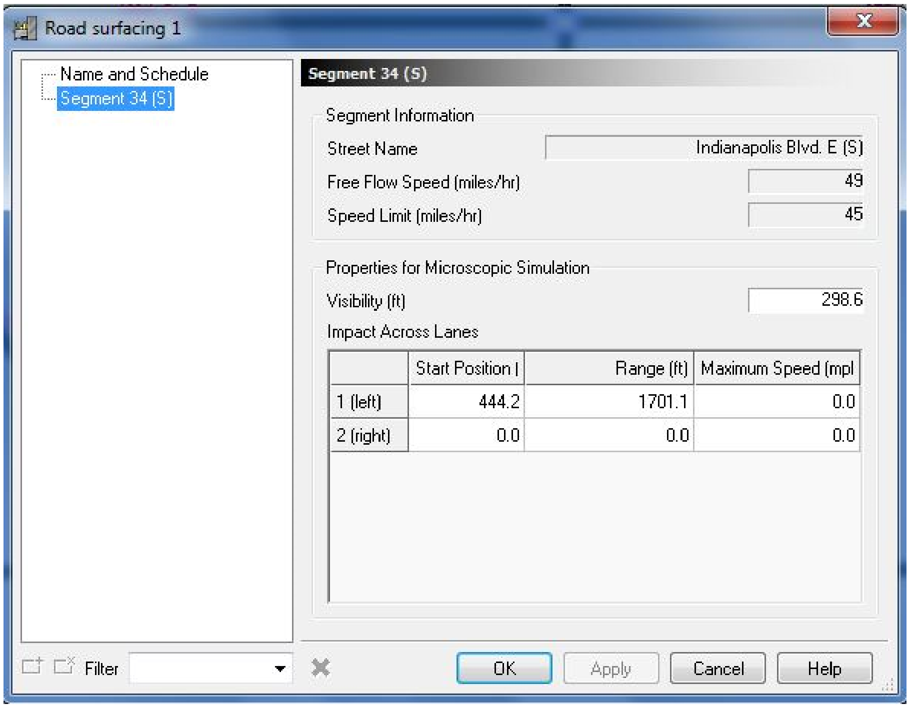


Figure 4.5 Creating a work zone from the work zone toolbox

Figure 4.6 A layout of the road with the work zones

4.3.2.5 Checking simulation database for errors and selecting simulation output

After creating the database for simulation, the error checking toolbox is used to check the road network for errors such as signalized intersections without signal phases, missing lane connectors etc. This allows one to make sure the simulation is ready to run without any warnings. The output settings in the project settings toolbox also provides the user with a list of necessary outputs from the simulation to choose from. A user can choose from measured quantities such as delay, travel times, traffic volumes, average speeds etc.

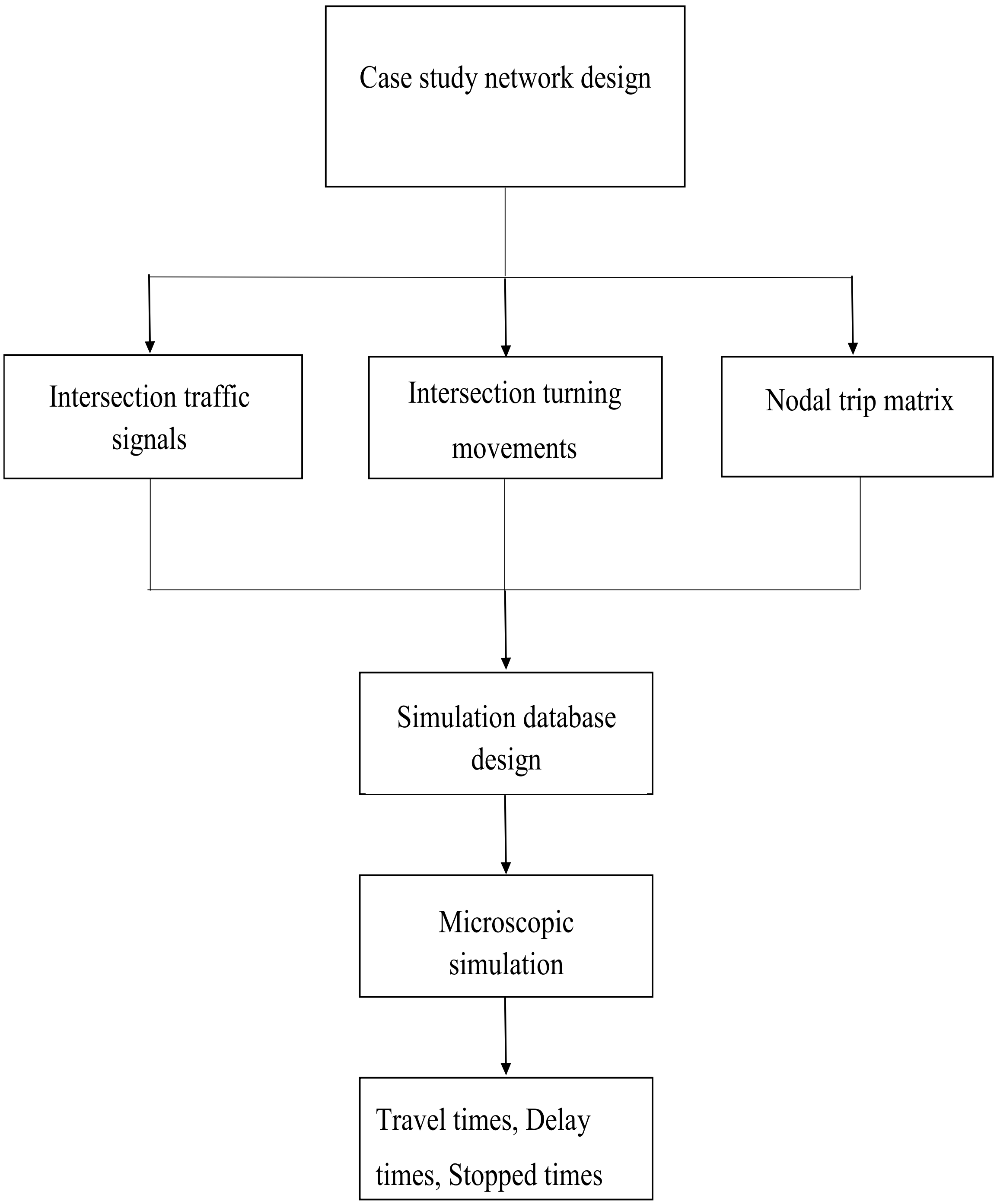


Figure 4.7 Traffic Simulation Methodology

4.4 Chapter Summary

In this chapter, the design of the road network using a traffic simulation package called TransModeler was presented. The transportation simulation database was developed using data collected on traffic signals and turning movements at intersections. Three cases were simulated. Case 1 was a road network with no work zones, case 2 was a road network with permanent work zones and case 3 was a road network with both temporary and permanent work zones. The next chapter, will discuss about the statistical model development for estimating the change in travel behavior.

5. STATISTICAL MODELLING

5.1 Overview

Different statistical models have been employed over the years in the study of road users travel behavior. A model may be chosen over the other based on the nature of the data collected and how best to fit the collected data to a given model. Whilst the motivation for picking a model over the other may also be due the data processing time and power available to the researcher. Whilst some models are easier to use, others can be very cumbersome and require a lot of processing power and time. Another factor may be the level of accuracy a research needs to be able to draw the needed conclusions. Typically, the more accurate a model is to be the more its complexity and thus requiring a lot of data, calibration and processing time.
As noticed, due to these different factors and how a factor is of importance to a given research, a particular model may be preferred over the other.

5.2 Logit and Probit Model

The concept of Logit and Probit models can be traced back to the early 1930's by Charles Ittner Bliss an entomologist at Ohio State University and John Henry Gaddum, a British statistician and a pharmacologist. The Logit Model was also introduced in 1944 by Joseph Berkson a physicist and statistician, with the named coin after the probit model. A look at history shows the introduction of the logit model was not well received at the time of its introduction but later due to its simplicity and applicability in a wide range of area it become a very popular model. By the 1960's the logit had then gained some popularity which was further enhance by statistician David Cox as he explore the usage of the Logit model is several statistical avenues.

The logit and probit model are both binary outcome models, i.e. they produce outcomes between 0 and 1.Unlike the tradition linear regression model, where the predicted probabilities can be above 1 and below zero as there are no restrictions in the functional form of the Ordinary Least Square (OLS) equation, the predicted probabilities in the Probit and Logit models are restricted between 0 and 1. This makes the Probit and Logit models best suited for predictions of situations that involves two alternatives. For example, whether or not a worker at a company participates in a work training workshop, whether or not some individual purchases a particular item etc. The alternatives are normally coded as 0 and 1. With 0 being the case that it did not happen and 1 being the case that it happens.

The Probit and Logit model yields very similar results and the main difference between the two models can be found in the theoretical form. The Probit model uses the cumulative distribution function of the standard normal distribution whilst the Logit model uses a cumulative distribution function of the logistic distribution.

The logit and probit models have been used extensively in several areas in transportation. (F. Ye and Lord, 2014; Garrido et al. 2014; Sam et al. 2018; Fountas and Anastasopoulos, 2018; Abdelmohsen and El-Rayes, 2018), used probit and logit models to predict road accidents and also assess the severity of accidents in the road network. Savolainen (2016) examined the behavior of drivers on the onset of amber light at a traffic signal. Gokasar and Bakioglu, (2018) uses the multinomial logit model to assess how driver behavior changes in response to real time traffic information. Weng et al. (2018) and Li et al. (2018) also used logit models to assess travel behavior of drivers at work zones merging areas and the travel behavior of tourists respectively. Y. Zhang et al. (2017) and Can (2013) used multinomial probit models to model passengers mode and route choices. A lot of other applications of the logit and probit models in other areas such as psychology, behavioral science, among others can also be found in literature. The Probit Model is given by the equation:

$$\Pr(Y = 1|X) = \Phi(X'\beta) \tag{1}$$

Where;

Pr is the probability of Y (dependent variable) occurring between 0 and 1

β is the coefficient of the independent variable

Φ is the cumulative standard normal distribution.

The Logit model is given by;

$$\Pr(Y = 1|X) = \frac{\exp(x'\beta)}{1+\exp(x'\beta)} \tag{2}$$

Pr is the probability of Y (dependent variable) occurring between 0 and 1

β is the coefficient of the independent variable

5.3 Ordered Logit and Probit Models

The ordered logit and probit models are extensions of the logit and probit models and are used for predicting the outcome of categorical data that are properly classified. For example, data from an opinion surveys (unlikely, somewhat unlikely, neutral, somewhat likely, likely), Ranking (1st, 2nd, 3rd etc.), Grading (A, B, C, D, E etc.) and many others. The ordered logit was first considered by an Irish statistician and distinguished professor at the University of Chicago called Peter McCullagh. The ordered probit and logit models are given by the equation

$$y_{i^*} = x'_i\beta + \varepsilon_i \tag{3}$$

Where;

y_{i^*} is the latent dependent variable i

$x_{i'}$ is the of independent variable i

β is the independent variable coefficient we wish to estimate

ε_i is the error term

The probability that an observation i will select alternative j is given by

$$p_{ij} = p(y_i = j) = F\left(\alpha_j - x'_i\beta\right) - F(\alpha_{j-1} - x'_i\beta) \tag{4}$$

Where;

α is the threshold

F is a logistic cumulative density function (cdf) in the ordered logit model and the standard normal cdf in the probit model.

5.3.1 Marginal Effects

The marginal effects reflect the change in the probability of a dependent variable y given a 1unit change in an independent or regressor variable x. The marginal effects help us determine how the independent variable affects the dependent variable. In the ordered logit and probit models the marginal effects of each variable on the different alternatives sum up to zero. The marginal effect of an increase in the regressor x_r on the probabilities given in equation 4 is given by:

$$\partial p_{ij} \Big/ \partial x_{ri} = \{F'(\alpha_{j-1} - x'_i\beta) - F'(\alpha_j - x'_i\beta)\}\beta_r \qquad (5)$$

Where;

β_r is the coefficient of the function that explains the effect of the unit increase in the independent variable on the probability of selecting alternative j.

5.4 Road User Survey

A survey was conducted among road users of the Hammond area network. The survey for road users was conducted by face-to-face interviews. A total of about120 road users were surveyed. In developing a questionnaire for road users to collect information on changes in travel behavior, several factors were taken into consideration. These factors included:

- Collecting information on the socio-economic characteristics of road users
- Collecting information on the driving experience of the road users
- Collecting information on behavioral changes when road users faces work zones
- Collecting information on which factors affects the road user's decision to change their routes the most when faced with a route with a work zone on it

This survey helped to provide a very good insight into the road user's perspective on how their travelling behavior changes with respect to the presence of road work zones on their routes.

5.4.1 Variables

In this study, the statistical model was created to assess the impacts of five different variables on an individual's decision to change his or her route with a work zone on it. The five (5) independent variables used were;

- Gender
- Age
- Driving experience
- Average annual mileage
- Percentage of non-work trips

These variables were used to predict the probabilities of three dependent variables. The dependent variables included;

- Decision to avoid a route with a work zone on a work trip

- Decision to avoid a route with a work zone on a non-work trip

Work trips are defined in this study as all work and educational related trips and non-work trips as any other trip aside the trips defined above.

Figure 5.1 shows the complete methodology applied in this research. Information from the road user survey is used on the dependent and independent variables are used to formulate the ordered probit and logit models as described above. The predicted probabilities and its corresponding marginal effects can be generated from the model.

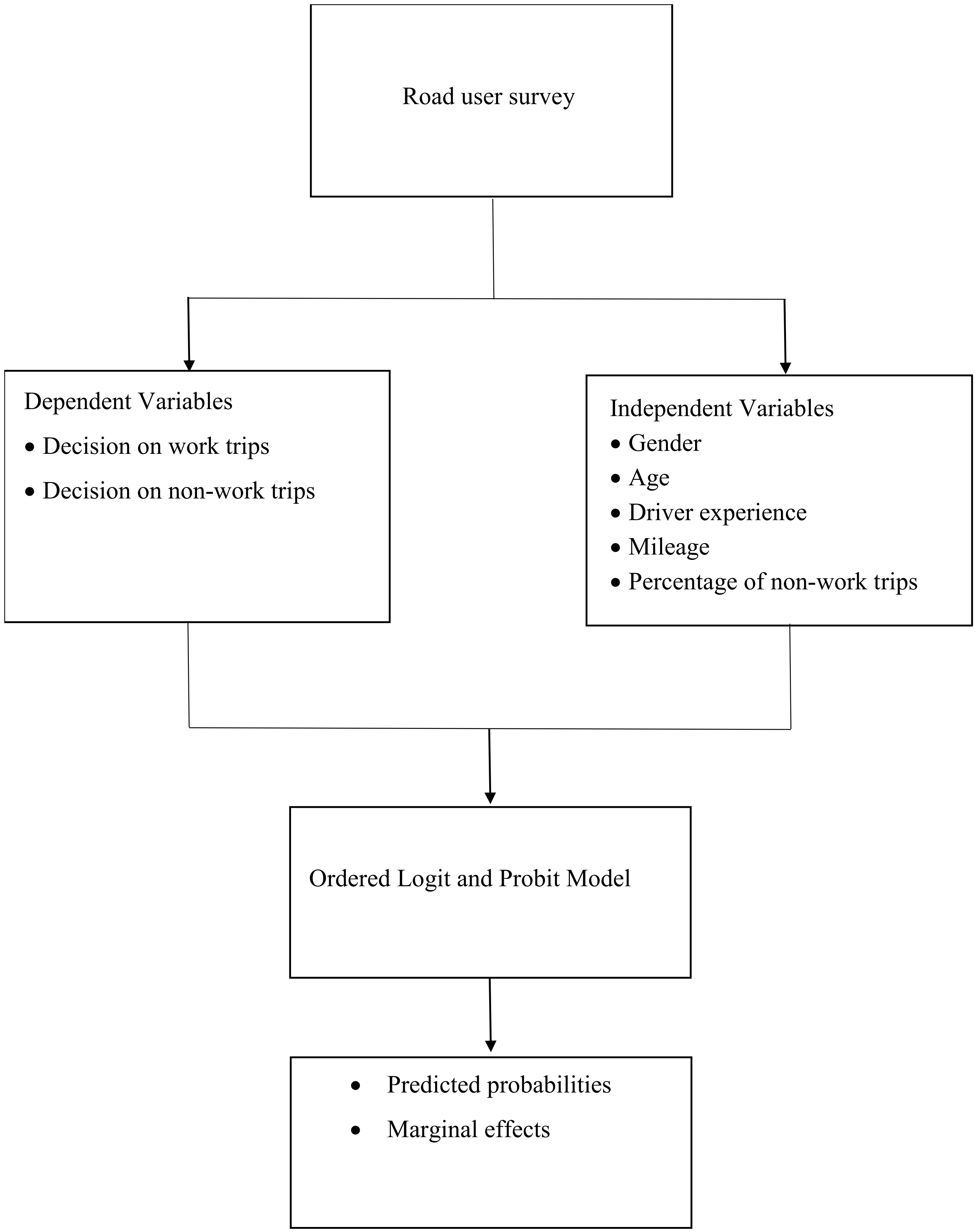


Figure 5.1 Statistical Model Methodology

5.5 Chapter Summary

In this chapter, a statistical modeling framework was presented. Specifically, an ordered probit and logit models were described that were used to estimate the change in travel behavior of road users from the presence of work zones. The importance of the marginal effects in this study was described. Road user survey administration was also presented. Finally, variables that were used to analyze the change in travel behavior on both a work and non-work trip were presented. The next chapter, discusses a framework developed for the analysis of the impact of road construction work zones on businesses.

6. BUSINESS IMPACT METHODOLOGY

For the analysis of the effect of road construction work zones on neighboring businesses, a business area located around the intersection of 169th Street and Kennedy Avenue was used. At this business area there were three fast food places, one grocery store, one liquor store and a pharmacy. The business impacts were measured as a change in revenue that may arise from change in number of customers due to the road construction and may vary depending on the business type in the construction area. The magnitude of change in revenue also depends on the construction duration in the influence area. The average expenditures and frequency of visits to these stores were estimated using information provided from a survey in the road construction influence area.

The average change in revenue for business type *i* for a given construction season is presented in Equation (6).

$$\Delta R_i = EXP_i * \Delta C_i * D * N \tag{6}$$

where

ΔR_i = Average change in revenue for business type *i* during the construction season

EXP_i = Average expenditure per household for business type *i* in the area influenced by the project (per month)

ΔC_i =Average change in number of customers for business type *i* in the area influenced by the project (per month)

D = Construction duration in months

N = Number of businesses in category *i*

The change in number of customers for a business type i during a given construction season is given in Equation (7)

$$\Delta C_i = H * HAP * F_i \tag{7}$$

H = Number of households affected by the project

HAP = Percentage of affected households that avoid commercial activities in the influence area

F_i = Average number of visits made by affected households to business type *i* before construction (per month)

The total change in revenue that occurs due to a construction workzone on the all business types is presented in Equation (8)

$$R = \sum_{i=1}^{n} \Delta R_i \tag{8}$$

where

$R =$ Total change in revenue for all business types in the project area

n = Number of business categories given in Table 6.1

Table 6.1 Business Categories for the research

• Grocery stores
• Fast Foods
• Pharmacy
• Liquor stores

6.1 Business Survey

A questionnaire for businesses was also developed for businesses in the study area. The survey for businesses was conducted by face-to-face interviews. A total of 6 businesses were surveyed. The questionnaire for business in the case study area sought to collect information in these key areas:

- Change in number of customers due to road construction
- Change in revenue due to road constructions

This survey helped to provide information on how business have been affected by road constructions in the past. A copy of the questionnaire developed can be found in Appendix A.

6.2 Chapter Summary

This chapter develops a framework for analyzing the impacts on businesses due to the presence of the road constructions in the network. The framework shows how the total change in revenue for each business type is to be analyzed and the total change in revenue from all business categories in the influence area is to be calculated. The next chapter, Chapter 7, presents the results from the traffic simulation, statistical model and business impact analyses.

7. RESULTS AND DISCUSSIONS

7.1 Traffic Simulation Results

The traffic simulation in TransCAD was conducted using a batch simulation technique. This is where a series of simulation are conducted for the same scenario and the average results from the batch are used for analysis. The batch method is used as it provides more accurate values after averaging several simulations. In this research, five (5) simulation runs are conducted for each of the three scenarios making a total of 15 simulation runs. The scenarios were

- A road network free of work zones (Case 1)
- A road network with permanent work zones – three full closures and three partial closures (Case 2)
- A road network with both permanent work zones and temporary work zones – full closures (Case 3)

Permanent work zones as defined in this research are work zones that last the whole period of the simulation while temporary work zones are the work zones that start and terminate within the simulation period. After successfully running the micro simulation of the network the following results were obtained.

7.1.1 System level impact from work zones

Figures 7.1 and 7.2 show the impacts of the work zones on the overall system speed and delay time. The system travel speed decreases with the introduction of the work zones into the system in the second case. The further addition of temporary work zones in the third case does not appear to have a major impact on the travel speed. The trend in all three cases also decreases over time due to the increase in travel volumes in the road network over time. The travel delay time in the system also increases over time and over all the three cases simulated. The average delay is highest in the third case followed by the second case and least in the first case where there were no work zones in the road network

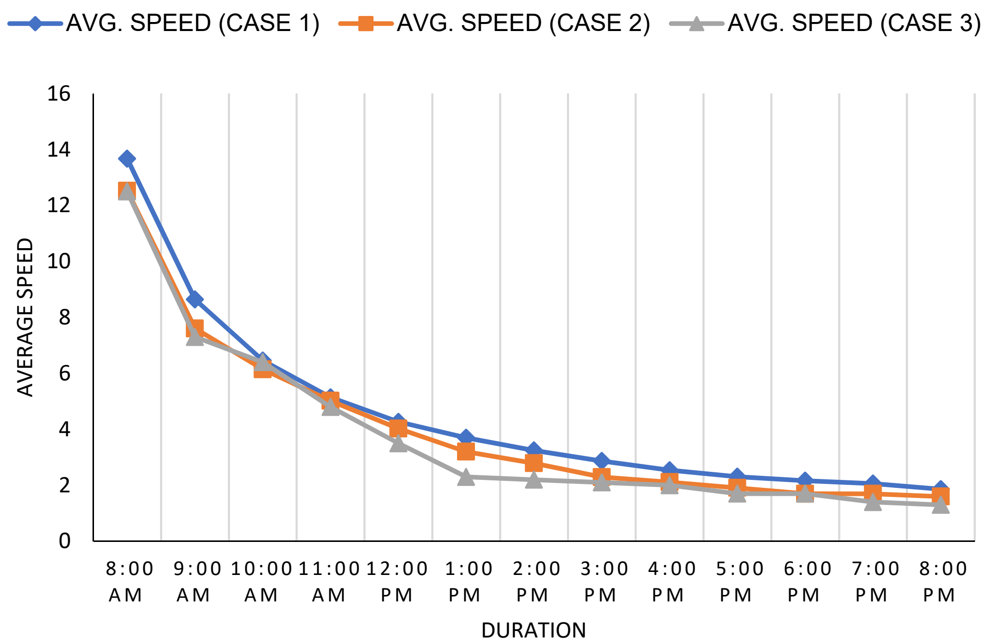


Figure 7.1 Average speed (in miles per hour) in overall road network within simulation period

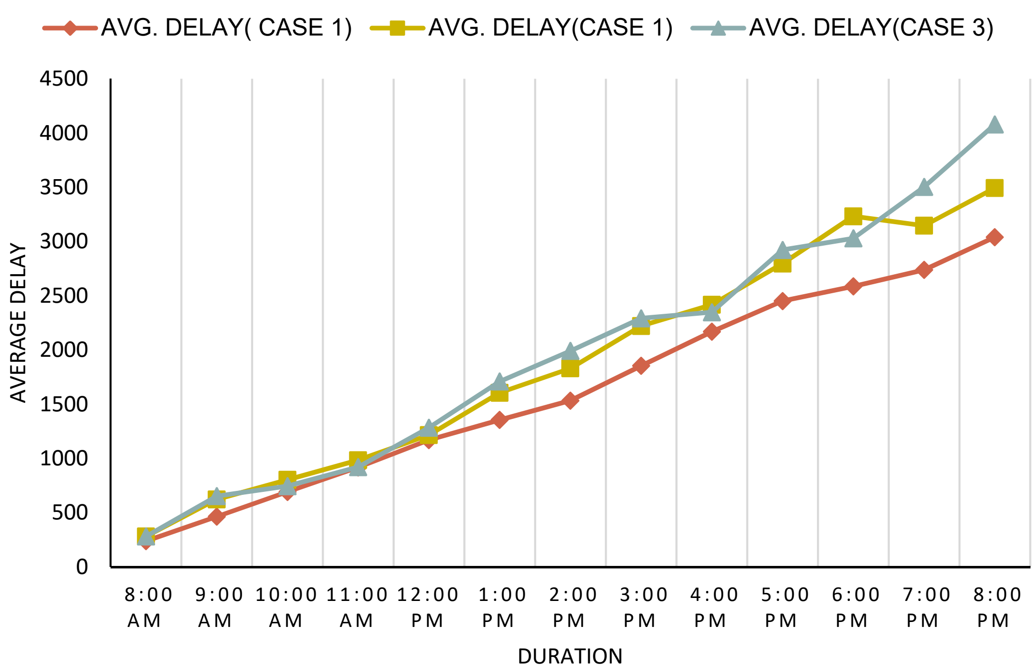
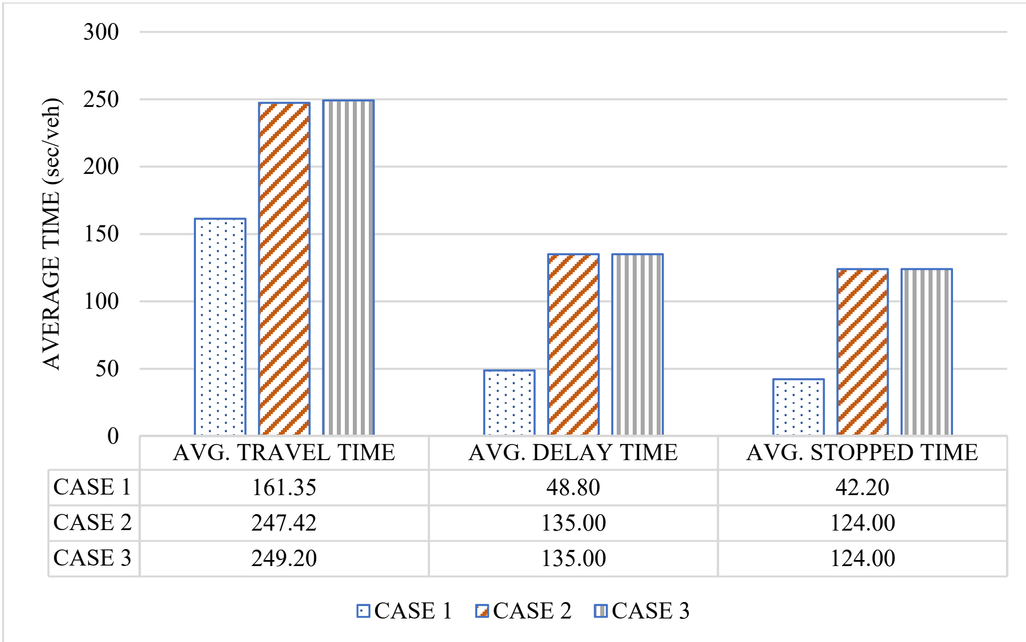


Figure 7.2 Average delay time (in sec/vehicle) in the overall network within simulation period

7.1.2 Impact on traffic performance parameters during morning peak periods

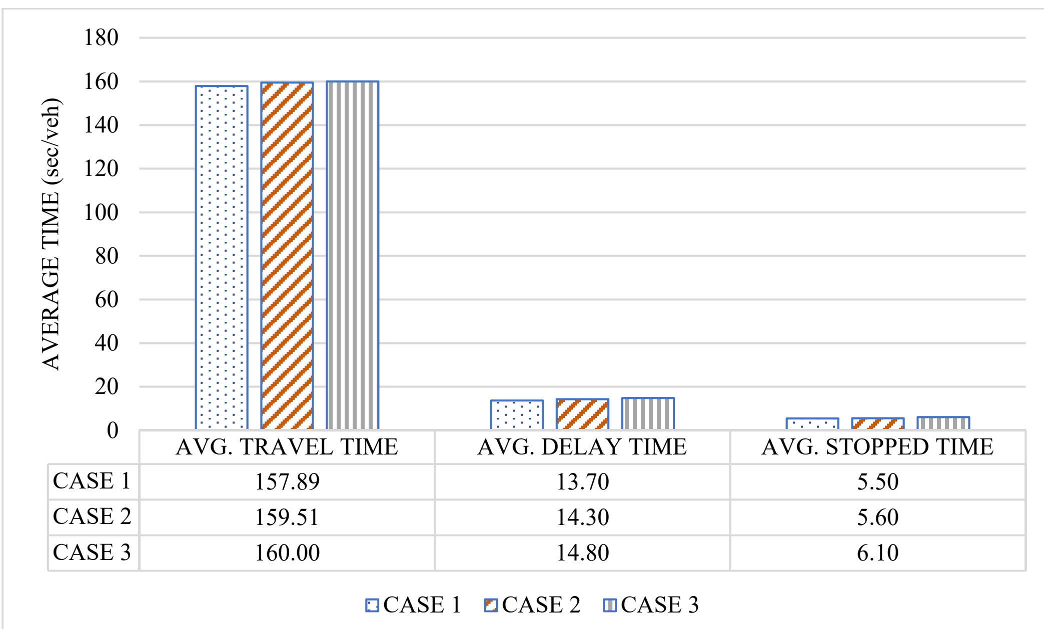
The average travel times, average delay times and average stopped times on links with permanent partial closures from work zones in the second case and the further addition of temporary work zones in the third case are presented in the figures below. Figures 7.3, 7.4, 7.5, 7.6 and 7.7 show how the network characteristics change in cases 1, 2 and 3 for the selected links with partial closures during the morning peak periods. The links exhibited different changes in travel times, delay times and average stopped times, with "165th St. D Eastbound" showing the most variability with the addition of the work zones to the link followed by "169th St. F Westbound". The least variabilities in the measured characteristics were shown by Hohman Ave. B Northbound, Kennedy Ave. B Southbound and Calumet Ave. D Southbound, respectively. The different levels of variabilities observed in the figures presented below can be attributed to the difference in the existing volumes of traffic on these road segments. Whilst some road segments are operating near capacity and thus would show a huge difference in the measured traffic parameters with the introduction of workzones, other segments operating way below roadway capacity would experience little to no change in the measured traffic parameters.

Figure 7.3 Changes in traffic performance parameters for 165th St. D during morning peak period



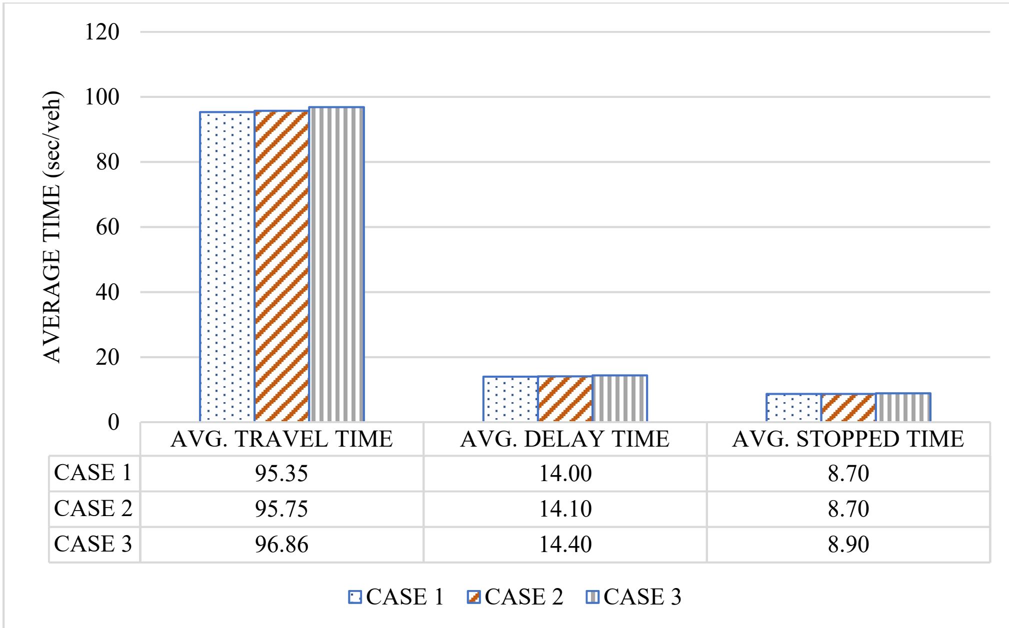
	AVG. TRAVEL TIME	AVG. DELAY TIME	AVG. STOPPED TIME
CASE 1	161.35	48.80	42.20
CASE 2	247.42	135.00	124.00
CASE 3	249.20	135.00	124.00

Figure 7.4 Changes in traffic performance parameters for 169th St. F during morning peak period



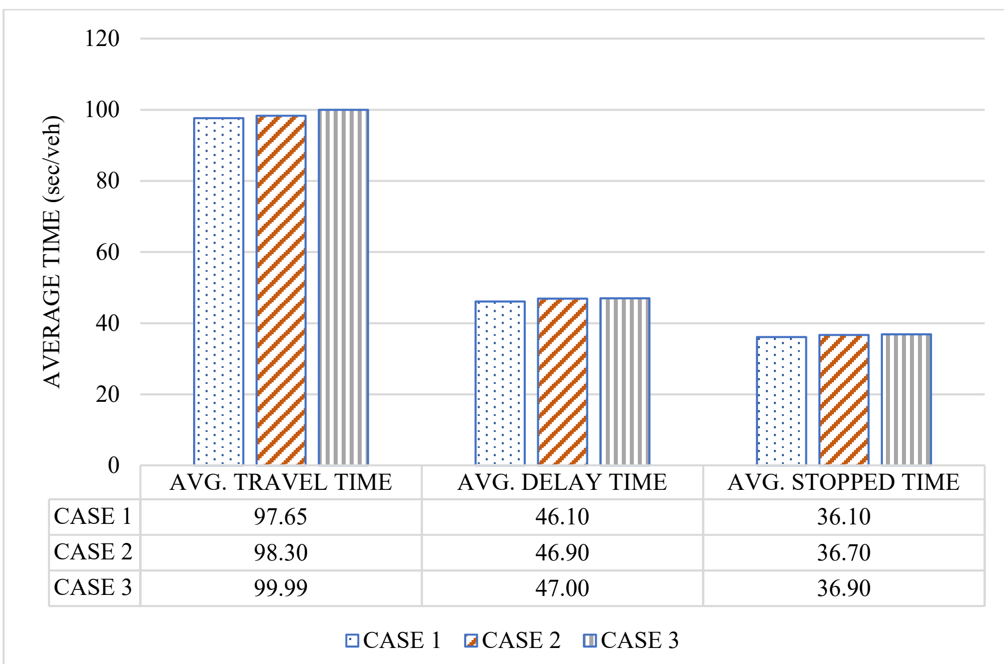
	AVG. TRAVEL TIME	AVG. DELAY TIME	AVG. STOPPED TIME
CASE 1	157.89	13.70	5.50
CASE 2	159.51	14.30	5.60
CASE 3	160.00	14.80	6.10

Figure 7.5 Changes in traffic performance parameters for Hohman Ave. B during morning peak period



	AVG. TRAVEL TIME	AVG. DELAY TIME	AVG. STOPPED TIME
CASE 1	95.35	14.00	8.70
CASE 2	95.75	14.10	8.70
CASE 3	96.86	14.40	8.90

Figure 7.6 Changes in traffic performance parameters for Kennedy Ave. B during morning peak period

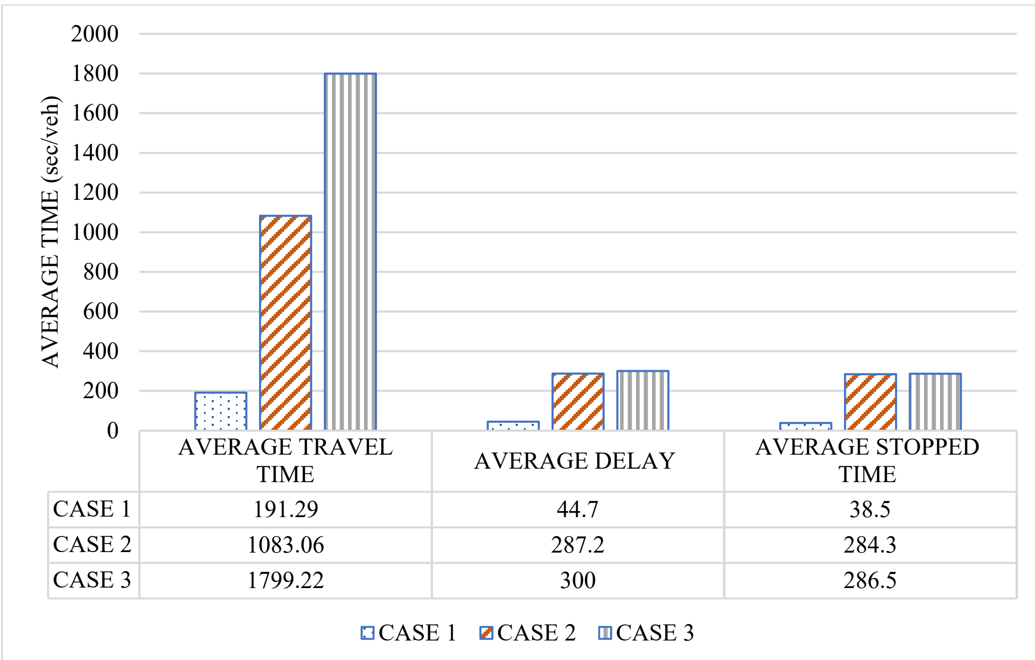


	AVG. TRAVEL TIME	AVG. DELAY TIME	AVG. STOPPED TIME
CASE 1	97.65	46.10	36.10
CASE 2	98.30	46.90	36.70
CASE 3	99.99	47.00	36.90

Figure 7.7 Changes in traffic performance parameters for Calumet Ave. D during morning peak period.

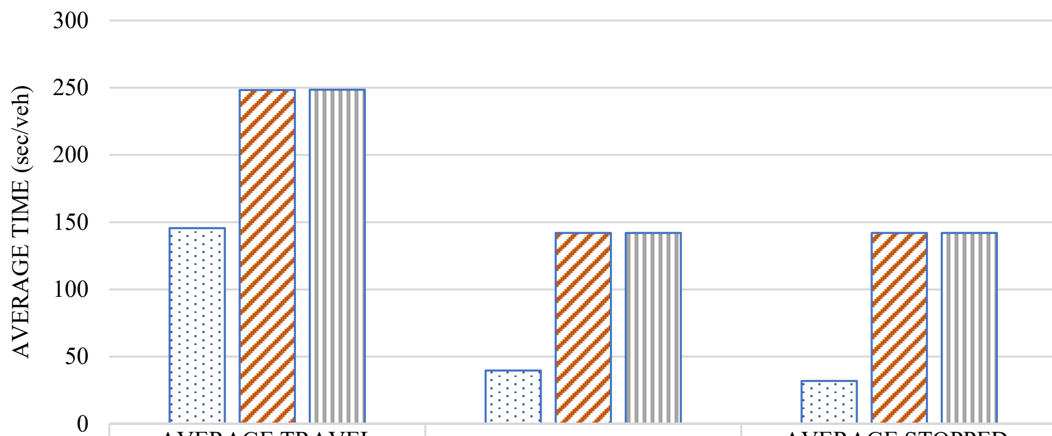
7.1.3 Impacts on traffic performance parameters during afternoon peak periods.

The network characteristics (average travel time, average delay time and average stopped time) on the links with partial closures were measured at afternoon peak periods. 165th St. D showed the highest change in travel time followed by Kennedy Ave. B, Calumet Ave D, 169th St. F and finally Hohman Ave. B. The corresponding changes in delay times and stopped times are also shown in Figures 7.8, 7.9, 7.10, 7.11 and 7.12.



	AVERAGE TRAVEL TIME	AVERAGE DELAY	AVERAGE STOPPED TIME
CASE 1	191.29	44.7	38.5
CASE 2	1083.06	287.2	284.3
CASE 3	1799.22	300	286.5

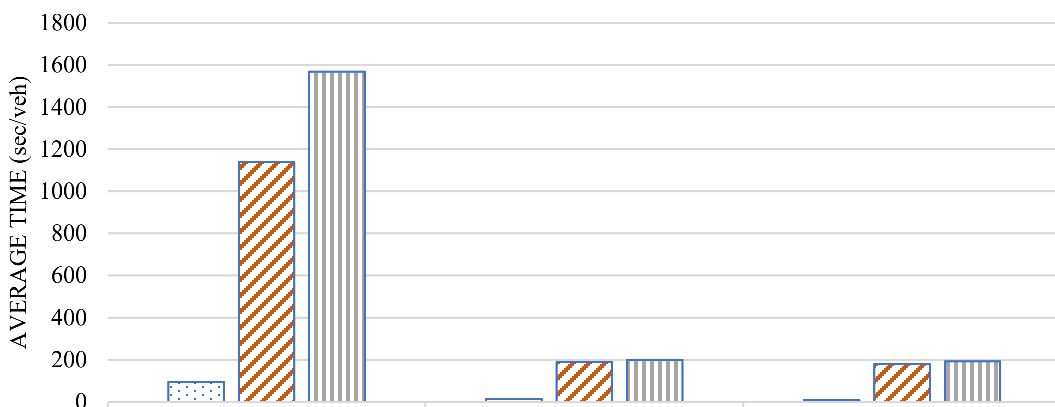
Figure 7.8 Changes in traffic performance parameters for 165th St. D during the afternoon peak period



	AVERAGE TRAVEL TIME	AVERAGE DELAY	AVERAGE STOPPED TIME
CASE 1	145.62	39.7	31.9
CASE 2	248.20	142	142
CASE 3	248.49	142	142

CASE 1 CASE 2 CASE 3

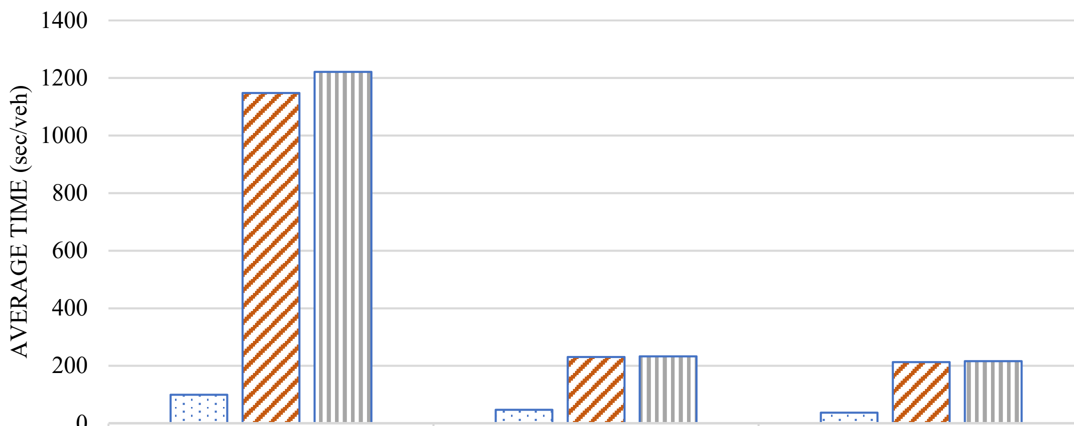
Figure 7.9 Changes in traffic performance parameters for 169th St. F during the afternoon peak period



	AVERAGE TRAVEL TIME	AVERAGE DELAY	AVERAGE STOPPED TIME
CASE 1	94.77	13.9	8.6
CASE 2	1138.72	188.3	179.9
CASE 3	1568.76	200	192.6

CASE 1 CASE 2 CASE 3

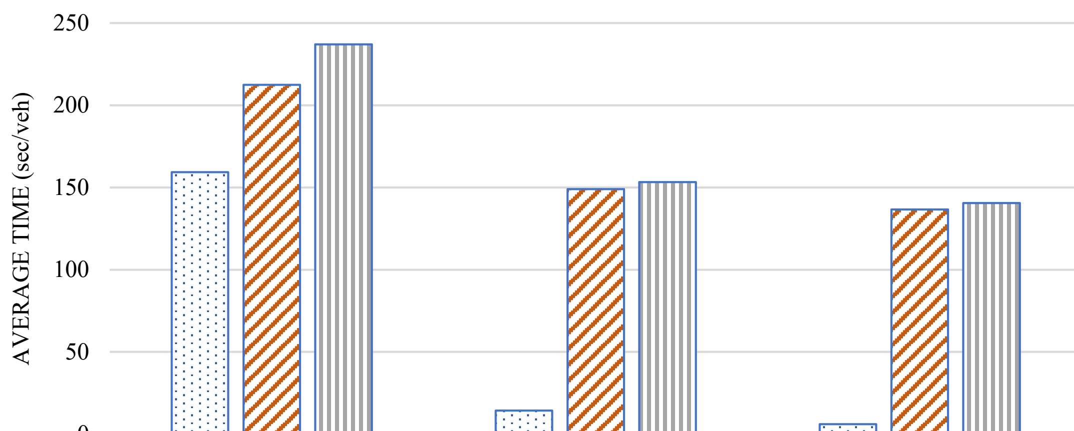
Figure 7.10 Changes in traffic performance parameters for Kennedy Ave. B during the morning peak period



	AVERAGE TRAVEL TIME	AVERAGE DELAY	AVERAGE STOPPED TIME
CASE 1	99.64	47.6	37.2
CASE 2	1147.99	230.7	213
CASE 3	1221.40	232.9	216.1

CASE 1 CASE 2 CASE 3

Figure 7.11 Changes in traffic performance parameters for Calumet Ave. D during afternoon peak period.



	AVERAGE TRAVEL TIME	AVERAGE DELAY	AVERAGE STOPPED TIME
CASE 1	159.30	14.3	6
CASE 2	212.44	149	136.6
CASE 3	237.12	153.3	140.5

CASE 1 CASE 2 CASE 3

Figure 7.12 Changes in traffic performance parameters for Hohman Ave. B during afternoon peak period

7.2 Statistical Modeling Results

The statistical model was developed utilizing input from questionnaire. The ordered logit and probit model developed is used to help us predict the decision a road user is likely to make when faced with a route with a work zone on it.

7.2.1 Statistical modeling of decision of road user on a work trip

Below the results from the ordered logit and probit model on the predicted probabilities for a road user on a work trip are presented. The selections were coded from zero through five for the six different alternatives of "Never" to "For sure" respectively. The frequencies and cumulative frequencies of the alternative are presented in Table 7.1.

Table 7.1 Summary of data on the decisions made when a work trip.

Decision on Work trip	Code for Alternatives	Percent Frequency	Cumulative Frequency
Never	0	1.67%	1.67%
Unlikely	1	5.83%	7.50%
Somewhat unlikely	2	18.33%	25.83%
Somewhat likely	3	31.67%	57.50%
Likely	4	28.33%	85.83%
For Sure	5	14.17%	100.00%

Table 7.2 presents the model coefficients from the ordered logit and probit models. Both models show an increase in the decision to switch from a route with a work zone with an increase in driving experience, annual mileage, and percentage of non-work trips. Also, females are more likely to change their route when on a route with a work zone on it than male are. Finally, an increase in age shows a decrease in the likelihood to change one's route when faced with a work zone on it.

Table 7.2 Ordered Logit and Probit Model Coefficients

Decision on Work trip	Ordered Logit Coefficients	Ordered Probit Coefficients
Gender	0.121	0.048
Age	-0.141	-0.114
Driving experience	0.086	0.054
Annul mileage	0.027	0.014
Percent non-work trips	0.149	0.093

In Table 7.3 the predicted probabilities from the both models are presented. Both models predicted the same probabilities for all alternatives in the decision made on a work trip. From the table, about 1.67% of individuals would never change their work trip routes when on a route with a work zone on it, about 5.89% of individuals are unlikely to change their work trip routes when on a route with a work zone on it , 18.65% of individuals are somewhat unlikely to change their work trip routes when on a route with a work zone on it, 31.82% are somewhat likely to change their work trip routes when on a route with a work zone on it, 27.92% are likely to change their work trip routes when on a route with a work zone on it and 14.05% are certain to change their work trip routes when faced with a route with a work zone on it.

Table 7.3 Predicted probabilities of decision made on work trip

Decision on Work trip	Ordered Probit Predicted Probabilities	Ordered Logit Predicted Probabilities
Never	0.0166742	0.0166742
Unlikely	0.0589343	0.0589343
Somewhat unlikely	0.1864526	0.1864526
Somewhat likely	0.3181628	0.3181628
Likely	0.2792268	0.2792268
For Sure	0.1405492	0.1405492

Table 7.4 presents the marginal effects of the independent variables on the dependent variable in the ordered logit model. For example, from Table 7.4, a unit increase in age is associated with 0.21% more likely to be in the never decision category, 0.7% more likely to be in the unlikely decision category, 1.75% more likely to be in the somewhat unlikely decision category, 0.76% more likely to be in the “somewhat likely” decision category, 1.81% less likely

to be in the “likely” decision category and 1.61% less likely to be in the “For sure” decision category.

Table 7.5 presents the marginal effects of the independent variables on the dependent variable in the ordered probit model. For example, From Table 7.5, a unit increase in age is associated with 0.3% more likely to be in the” never” decision category, 1.09% more likely to be in the “unlikely” decision category, 2.17% more likely to be in the “somewhat unlikely” decision category, 0.82% more likely to be in the “somewhat likely” decision category, 2.0% less likely to be in the “likely” decision category and 1.61% less likely to be in the “For sure” decision category.

Table 7.4 Ordered Logit Model Marginal effects

Variable	Marginal Effects					
	Never	Unlikely	Somewhat unlikely	Somewhat likely	Likely	For sure
Gender	-0.0018043	-0.0060654	-0.0150889	-0.0065907	0.0156513	0.0138979
Age	0.0020872	0.0070165	0.0174551	0.0076242	-0.0181056	-0.0160773
Driving experience	-0.001281	-0.0043063	-0.0107129	-0.0046793	0.0111122	0.0098673
Annual mileage	-0.0003958	-0.0013305	-0.00331	-0.0014458	0.0034334	0.0030487
Percent non-work trips	-0.0022062	-0.0074166	-0.0184505	-0.008059	0.0191382	0.0169942

Table 7.5 Ordered Probit Model Marginal effects

Variable	Marginal Effects					
	Never	Unlikely	Somewhat unlikely	Somewhat likely	Likely	For sure
Gender	-0.0015732	-0.0045916	-0.0091301	-0.0034416	0.0084144	0.010322
Age	0.003742	0.0109218	0.0217171	0.0081862	-0.0200149	-0.0245522
Driving experience	-0.0017866	-0.0052146	-0.0103689	-0.0039085	0.0095562	0.0117225
Annual mileage	-0.0004674	-0.0013641	-0.0027124	-0.0010224	0.0024998	0.0030665
Percent non-work trips	-0.0030552	-0.0089173	-0.0177314	-0.0066838	0.0163416	0.0200461

7.2.2 Statistical modeling of decision of road user on a non-work trip

Below the results from the ordered logit and probit model on the predicted probabilities for a road user on a non-work trip are presented. The selections were coded from zero through five for the six different alternatives of "Never" to "For sure" respectively. The frequencies and cumulative frequencies of the alternative are presented in Table 7.6.

Table 7.6 Summary of data on the decisions made when a non-work trip

Decision on Non-Work trip	Code for Alternatives	Percent Frequency	Cumulative Frequency
Never	0	6.67%	6.67%
Unlikely	1	25.00%	31.67%
Somewhat unlikely	2	17.50%	49.17%
Somewhat likely	3	28.33%	77.50%
Likely	4	12.50%	90.00%
For Sure	5	10.00%	100.00%

Table 7.7 presents the model coefficients from the ordered logit and probit models. Both models show an increase in the decision to change one's non-work trip route with a work zone with an increase in age and annual mileage. Also, females are more likely to change their route when on a route with a work zone on it than male is. Finally, an increase in driving experience and percentage of non-work trips shows a decrease in the likelihood to change one's route when faced with a work zone on it.

Table 7.7 Ordered Logit and Probit Model Coefficients

Decision on Non-Work trip	Ordered Logit Coefficients	Ordered Probit Coefficients
Gender	0.2494204	0.1847871
Age	0.1798664	0.106918
Driving experience	-0.1140611	-0.060108
Annual mileage	0.0220281	0.0084053
Percent non-work trips	-0.0725912	-0.0401654

In Table 7.8 the predicted probabilities from the both models are presented. Both models predicted the same probabilities for all alternatives in the decision made on a work trip. From the table, about 6.65% of individuals would never change their non-work trip routes when on a route with a work zone on it, about 24.7% of individuals are unlikely to change their non-work trip routes when on a route with a work zone on it, 17.39% of individuals are somewhat unlikely to change their non-work trip routes when on a route with a work zone on it, 28.6% are somewhat likely to change their non-work trip routes when on a route with a work zone on it , 12.55% are likely to change their non-work trip routes when on a route with a work zone on it and 10.10% are certain to change their non-work trip routes when faced with a route with a work zone on it.

Table 7.8 Predicted probabilities of decision made on non-work trip

Decision on Non-Work trip	Ordered logit predicted probabilities	Ordered probit predicted probabilities
0	0.0665139	0.0665139
1	0.2470836	0.2470836
2	0.1739002	0.1739002
3	0.2860593	0.2860593
4	0.1254809	0.1254809
5	0.100962	0.100962

Table 7.9 presents the marginal effects of the independent variables on the dependent variable in the ordered logit model. For example, From Table 7.9, a unit increase in age is associated with 1.05% less likely to be in the never decision category, 2.78% less likely to be in the unlikely decision category, 0.66% less likely to be in the somewhat unlikely decision category, 1.42% more likely to be in the "somewhat likely" decision category, 1.52% more likely to be in the "likely" decision category and 1.55% more likely to be in the "For sure" decision category. The complete marginal effects of the independent variables can be found in Table 7.9 below.

Table 7.10 presents the marginal effects of the independent variables on the dependent variable in the ordered logit model. For example, From Table 7.10, a unit increase in age is associated with 1.33% less likely to be in the never decision category, 2.46% less likely to be in the unlikely decision category, 0.48% less likely to be in the somewhat unlikely decision category, 1.10% more likely to be in the "somewhat likely" decision category, 1.36% more likely to be in the "likely" decision category and 1.81% more likely to be in the "For sure" decision category

Table 7.9 Ordered Logit Model Marginal effects for non-work trips

Variable	Marginal Effects					
	Never	Unlikely	Somewhat unlikely	Somewhat likely	Likely	For sure
Gender	-0.0145653	-0.038538	-0.0092109	0.0196612	0.021134	0.0215189
Age	-0.0105036	-0.0277912	-0.0066423	0.0141784	0.0152405	0.0155181
Driving experience	0.0066608	0.0176236	0.0042122	-0.0089911	-0.0096647	-0.0098407
Annual mileage	-0.0012864	-0.0034036	-0.0008135	0.0017364	0.0018665	0.0019005
Percent non-work trips	0.0042391	0.0112161	0.0026807	-0.0057222	-0.0061508	-0.0062628

Table 7.10 Ordered Probit Model Marginal effects for non-work trips

Variable	Marginal Effects					
	Never	Unlikely	Somewhat unlikely	Somewhat likely	Likely	For sure
Gender	-0.0229356	-0.0425002	-0.0082606	0.0189595	0.0234401	0.0312967
Age	-0.0132705	-0.0245906	-0.0047796	0.01097	0.0135625	0.0181083
Driving experience	0.0074605	0.0138246	0.002687	-0.0061672	-0.0076247	-0.0101803
Annual mileage	-0.0010433	-0.0019332	-0.0003757	0.0008624	0.0010662	0.0014236
Percent non-work trips	0.0049853	0.0092378	0.0017955	-0.004121	-0.0050949	-0.0068027

7.3 Business Impact Calculation

Using the framework developed, a sample business impact analysis was conducted. Using a business area located the around the intersection of 169th Street and Kennedy Avenue. Table 7.11 shows the average expenditures at the four business types considered. Also, the affected households due to the work zone was estimated to be around 800 households from visual inspection from google maps. The construction duration was also assumed to be two (3) months. A spreadsheet was then created to estimate the total change in revenue due to the presence of the work zone within the two (3) month period.

Table 7.11 Average visit frequency and expenditure for different business categories

Category	Average Frequency of visits per month	Average Household expenditure per month
Grocery stores	6	310
Restaurants	6	235
Pharmacy	1	42
Liquor stores	2	110

Table 7.12 shows the loss in revenue that business in the business area stand to lose with a road construction on the link "165th St. F" leading to the business center using the predicted probability for the "For sure" category to change their route on a non-work trip. The table shows the grocery shop being impacted the most with a loss in excess of $ 450,000 over the three-month period of construction. The three restaurants follow with each restaurant losing over $340,000, followed by the liquor store with a loss of over $53000 and the least impacted being the Pharmacy with a loss just over $10,000 in terms of total revenue lost during the construction season. The total revenue lost due to the construction is estimated over $1.5 million.

Table 7.12 Revenue impacts for the different category of businesses

CATEGORY	EXP	ΔC	D	N	Total Revenue lost due to construction
Change in revenue for Grocery stores	310	484.8	3	1	$450,864.00
Change in revenue for Restaurant	235	484.8	3	3	$1,025,352.00
Change in revenue for Pharmacy	42	80.8	3	1	$10,180.80
Change in revenue for Liquor stores	110	161.6	3	1	$53,328.00
Total revenue lost					$1,539,724.80

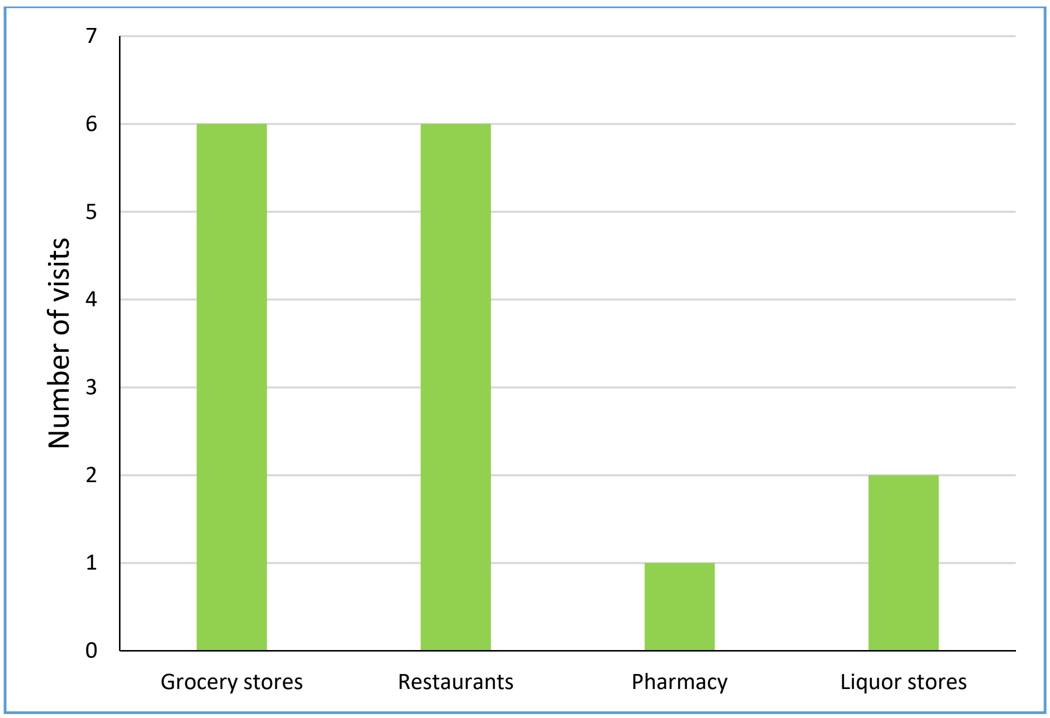


Figure 7.13 Average frequency of visits for different business categories

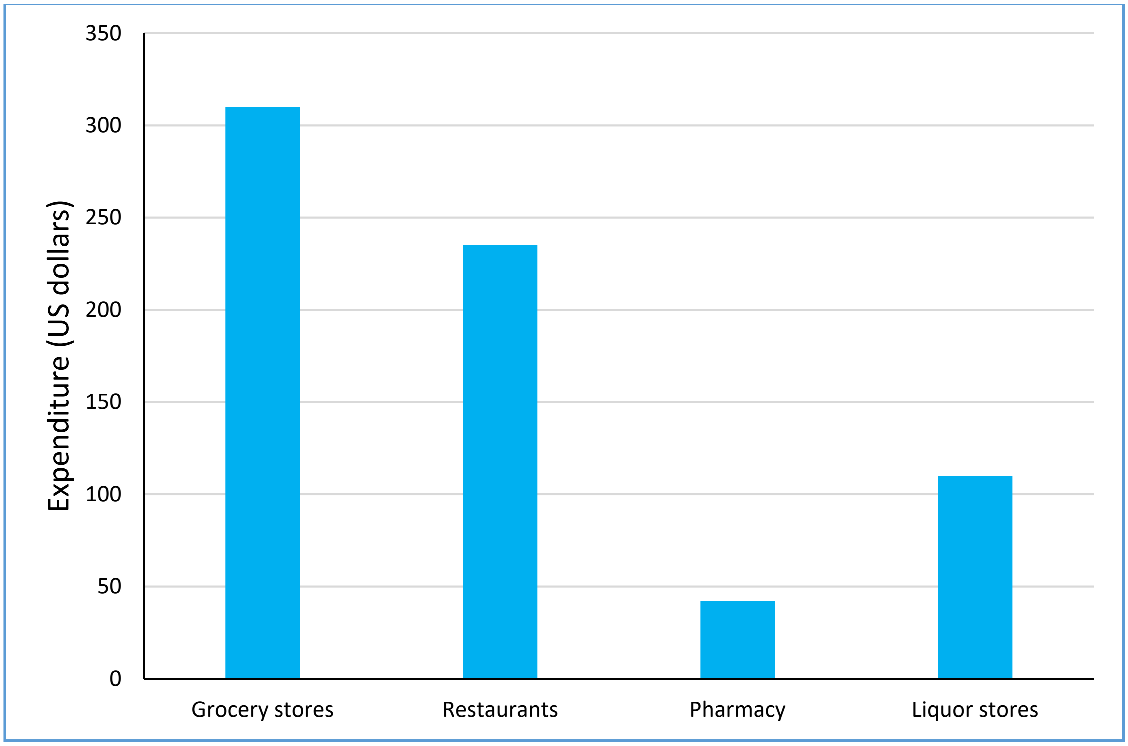


Figure 7.14 Average monthly household expenditure

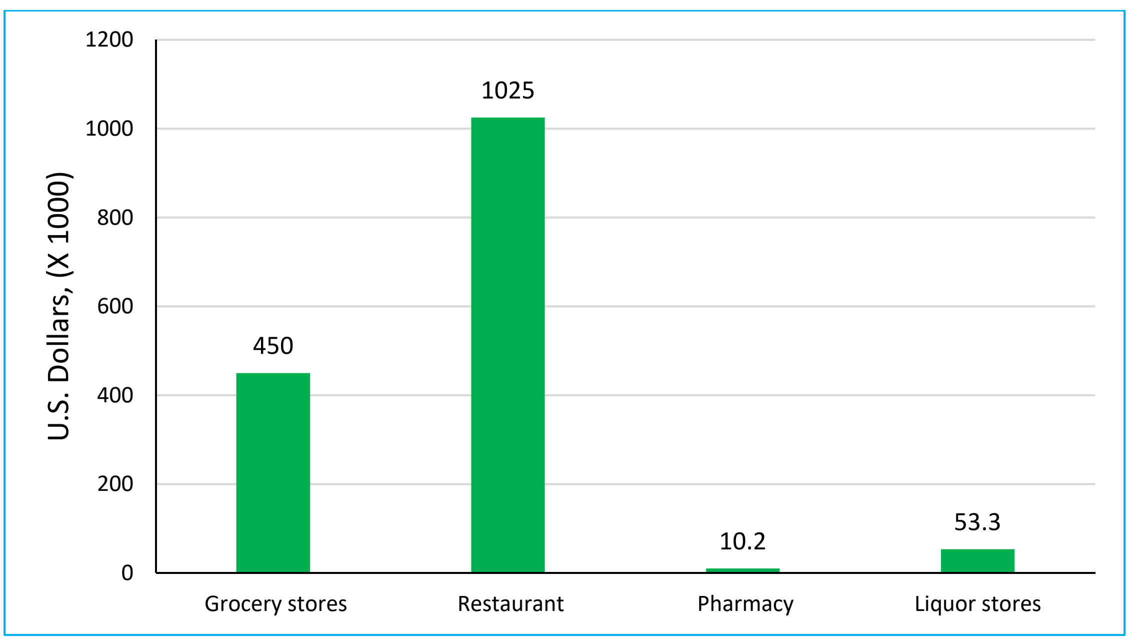


Figure 7.15 Total revenue loss for business categories

7.4 Chapter Summary

In this chapter, the results from the traffic simulation, statistical analysis and business impact analysis were presented. The results from the traffic simulation showed how travel time, delay time and vehicle stopped time increased with the introduction of workzones into the road network. The results from the traffic simulations shows how the different segments of the road network are affected differently by the road construction work zones, with the impacts on travel time, delay time and vehicle stopped times ranging from very little change to very high changes. The statistical model also provided the predicted probabilities and the marginal effects of the independent variables on the decisions of road users to change their route when faced with a work zone. The business impact assessment also provided the change in revenue for four business types found at a business area in the road network. The next chapter, Chapter 8, will present the summary and conclusions from the research

8. SUMMARY AND CONCLUSIONS

8.1 Summary

In our daily use of the transportation system, we are faced with several road construction work zones. These construction work zones found on these roads change how road users interact with the transportation system due to the changes that occur in the system ranging from increased travel times, increased delay times and vehicle stopped times in the system. The travel behavior of road users is thus impacted. This research sought to understand how the changes in a transportation system affects human travel behavior. When road users start changing and avoiding certain routes due to the changes caused in the transportation network, revenue of businesses in the area of the road construction are also impacted. The final aspect of this research developed a framework that helps estimates the changes in revenue due to the changes in travel behavior of customers.

Firstly, the traffic simulation developed of a road network in Hammond showed an increased in travel times, travel delay times and vehicle stopped times on the links with work zones. A comparison of peak period travel times, peak period travel delays and peak period vehicle stopped times on the links with work zones revealed very high increased in the measured parameters with the introduction of work zones in cases 2 and 3 within certain links whilst others showed moderate to little changes in travel times, delay times and the vehicle stopped times during the peak periods. The difference in the level of changes experienced by the links go to show how response in the transportation system differ from link to link when road constructions are being carried out in a network. Thus, we expect some links in the network to be adversely affected by the road work zones whilst others would be less affected.

Secondly, the interest in finding the changes in travel behavior of road users led to creating an ordered logit and probit model to predict the decision that road take when on a work trip or non-work trip route with a work zone on the route. The outcome of both the ordered logit and probit model for a road user on a work trip indicated that a young female with a high driving experience, annual mileage, and percentage of non-work trips is the likeliest to change the route on a work trip. Also, on a non-work trip, an older female with a low driving experience, high annual mileage and low percentage non-work trips is the likeliest to change the route.

Finally, the framework developed for the assessment of the change in revenue of businesses due to the road construction work zone was used to assess the business impact in a business area in the road network. The total loss in revenue from the four business categories were presented with the grocery store losing the most revenue of over $450,000 and the Pharmacy losing the least revenue just over $10,000.

8.2 Conclusions

From the research conducted for this thesis the following conclusions can be drawn:

- The introduction of workzones in the road network introduces an increase in delay times, vehicle stopped times, and travel times.
- The change in travel times, delay times and vehicle stopped times differs from each link to the other and this is mainly due to the existing traffic volumes that were on the link before.
- Females are more likely to change their routes when it has a work zone on it than males are.
- An increase in age makes an individual less likely to change their route on a work trip but more likely to change their route on a non-work trip.
- An increase in driving experience makes an individual more likely to change their route but less likely to change their route on a non-work trip.
- An increase in annual mileage driven makes an individual more likely to change their route on both work and non-work trips.
- An increase in the percentage of non-work trips makes an individual more likely to change their route on a work trip but less likely to change their route on a non-work trip.
- The change in revenue observed from the four business types shows grocery store losing the most revenue and the Pharmacy losing the least revenue.

8.3 Challenges and Future Scope

The major challenge experience in this survey was the deployment and collection of survey data of from businesses and road users. Most businesses are apprehensive in giving out information on information on average customer expenditures per visit or were unsure how much that amount was. In general, most businesses could have been more open to being survey to help provide more data for the business impact analysis. Acquiring a sizeable number of road users in the study area to fill out the survey also proved to be more tedious than expected.

In the future, with businesses more forthcoming, the total change in revenue between periods can be collected to assess the accuracy of the developed framework. This would help to clearly predict the changes in revenue that businesses in the influenced area of a work zone experience.

APPENDIX A. SURVEYS

A.1 Road Users Questionnaire

The main purpose of this questionnaire is to gather information on how an individual travel behavior is impacted by road construction work zones.

Thank you for participation in this survey. Your response is highly appreciated.

1. Please indicate the city you live in.
   a) Hammond
   b) Calumet
   c) Munster
   d) Highland
   e) Schererville
   f) Other (please specify) --------------------------------------

2. Please select your gender
   a) Male
   b) Female
   c) Other
   d) Prefer not to answer

3. Please indicate your age
   a) Less than 16 years
   b) 16 - 19 years
   c) 20 - 29 years
   d) 30 - 39 years
   e) 40 – 49 years
   f) 50 – 59 years
   g) 60 -69 years
   h) 70+ years
   i) Prefer not to answer

4. Please select your level of driving experience in the US
   a) < 1 year
   b) 1 – 2 years
   c) 2 – 3 years
   d) 3 – 4 years

   e) 4 - 5 years
   f) 5 – 6 years
   g) 6 – 7 years
   h) 7 – 8 years
   i) 8 – 9 years
   j) 9 – 10 years
   k) 10+ years

5. Please indicate your average miles driven per year below

   ____

6. Please indicate the percentage of your non-work related driven trips. (Non-work-related trip includes all types of trips that are made for purposes other than regular work or education-related trips.)
   a) 0%-10%
   b) 11%-20%
   c) 21%-30%
   d) 31%-40%
   e) 41%-50%
   f) 51%-60%
   g) 61%-70%
   h) 71%-80%
   i) 81%-90%
   j) 91%-100%

7. Have you ever driven through a work zone in Indiana?
   a) Yes
   b) No
   c) I do not recall

8. Would you change your regular route to work if you knew that your work commute had a work zone present?
   a) Never [SKIP QUESTION 9]
   b) Unlikely
   c) Somewhat unlikely
   d) Somewhat likely
   e) Likely
   f) For sure

9. Based on your response to question 8, if the travel time on the alternate route is higher, how much additional travel time on an alternate commute route would be acceptable to you?
   a) 1 – 10 mins
   b) 11 – 20 mins
   c) 21 – 30 mins
   d) 31 – 40 mins
   e) 41 – 50 mins
   f) 51 – 60 mins
   g) > 1 hour

10. Assume you are on a non-work trip, would you change your preferred route to your destination if there was a work zone on the route? (Non-work-related trip includes all types of trip that are made for purposes other than regular work or education-related trips.)
   a) Never [SKIP QUESTION 11]
   b) Unlikely
   c) Somewhat unlikely
   d) Somewhat likely
   e) Likely
   f) For sure

11. Based on your response to question 10, if the travel time on the alternate route is higher, how much delay would you accept on your commute to your non-work-related destination?
   a) 1 – 10 mins
   b) 11 – 20 mins
   c) 21 – 30 mins
   d) 31 – 40 mins
   e) 41 – 50 mins
   f) 51 – 60 mins
   g) > 1 hour

12. If you could choose an alternate destination with similar price and service (e.g., a different grocery store than your preferred one) to avoid driving through a work zone to your preferred destination, would you go to this alternate destination?
   a) Yes, I do not like to drive through work zones
   b) Yes, if travel time to the alternate place is within reasonable limit
   c) No, I am a loyal customer
   d) No, I do not mind driving through work zones
   e) Unsure

13. Would you change your mode of travel (e.g., public transit (if available), bicycling or walking etc.) when travelling to a destination to avoid driving through a work zone?
    a) Never
    b) Unlikely
    c) Somewhat unlikely
    d) Somewhat likely
    e) Likely
    f) For sure

14. From the table below indicate how much these work zone characteristics affect your decision to avoid roads with work zones (TICK IN THE BOX THAT APPLIES).

Characteristic	Very strong effect	Strong effect	Weak effect	No effect
Construction duration				
Time of construction (e.g., daytime or night time construction)				
Safety concerns at work zone				
High noise levels at work zone				
Speed reduction in the work zone				
Increased travel time due to detours				
Length of work zone				
Road construction on the shoulder				
Road construction on the driving lanes				

15. From the table below, please indicate the level of importance of the given factors when making the decision to make a trip from one place to the other.

Factor	Very important	Important	Less important	Unimportant
Travel time				
Vehicle operating cost (such as fuel cost, vehicle maintenance cost, etc.)				
Risk of accident				

16. From the table below, please indicate the level of importance of the given factors when making the decision to choose one route over another.

Factor	Very important	Important	Less important	Unimportant
Travel time				
Vehicle operating cost (such as fuel cost, vehicle maintenance cost, etc.)				
Risk of accident				

17. For the businesses given in the Table below, please indicate frequency of visit per month and amount of money spent per visit under normal conditions, that is, before there is any road construction on the route to these businesses?

Business Category	Frequency of Visits per Month	Amount spent per visit (U.S. dollars)
Building materials		
General merchandise		
Food stores		
Automotive		
Clothing		
Home furnishing		
Restaurants		
Drug stores		
Liquor stores		
Gas stations		
Other (Please specify)		

A.2 Businesses Questionnaire

The main purpose of this questionnaire is to gather information on how businesses are impacted by road construction work zones.

Thank you for participation in this survey. Your response is highly appreciated.

1. What is the dominant category of your business? (Please select one that applies)
    a) Hardware store
    b) General merchandise
    c) Grocery store
    d) Automotive
    e) Clothing/Home furnishing
    f) Restaurant/Coffee shop
    g) Pharmacy
    h) Liquor store
    i) Bar/Grill
    j) Gas station
    k) Other (please state) ________________________________

2. Please complete the Table below to show your level of agreement with impacts of road construction projects on your business during construction over the past 5 years.

During construction	Strongly Agree	Agree	Disagree	Strongly Disagree	No Opinion
I experienced a change in number of customers during the construction period					
I had to change the amount of investment to my business during the road construction project					
I experienced a change in revenue during the road construction activity					
I found construction zones safe to pass through					
Pedestrian access to my business was available					
Vehicle access to my business was available					
Noise levels from work zones were bearable					
Other (please state)					

3. If you experienced a change in the number of customers due to road construction, please complete the next table. Otherwise, ignore the Table below.

	Change in number of customers during road construction period (Please indicate percent gain or loss)
Percent gain	
Percent loss	

4. If you experienced a change in revenue due to road construction, please complete the next table. Otherwise, ignore the Table below.

	Change revenue during road construction period (Please indicate percent gain or loss)
Percent gain	
Percent loss	

5. What is the average expenditure per customer per visit to your business?

   $_____________________________

APPENDIX B. STATA CODES

B.1 Ordered probit and logit model for work trips

```
use "C:/Users/Augustine Marfo/Documents/logistic regression/Ordered Probit and Logit Models/survey.dta"

* Dependent variable has 6 categories denoted 0,1,2,3,4,5
global ylist decision_worktrip
global xlist gender age driving_experience mileage percent_nonworktrips

describe $ylist $xlist
summarize $ylist $xlist

tabulate $ylist

* Ordered logit model
ologit $ylist $xlist

* Ordered logit marginal effects
margins, dydx(*) atmeans predict(outcome(0))
margins, dydx(*) atmeans predict(outcome(1))
margins, dydx(*) atmeans predict(outcome(2))
margins, dydx(*) atmeans predict(outcome(3))
margins, dydx(*) atmeans predict(outcome(4))
margins, dydx(*) atmeans predict(outcome(5))

* Ordered logit predicted probabilities
predict p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit, pr
summarize p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit
tabulate $ylist
* Ordered probit model coefficients
```

```
oprobit $ylist $xlist

* Ordered probit model marginal effects
margins, dydx(*) atmeans predict(outcome(0))
margins, dydx(*) atmeans predict(outcome(1))
margins, dydx(*) atmeans predict(outcome(2))
margins, dydx(*) atmeans predict(outcome(3))
margins, dydx(*) atmeans predict(outcome(4))
margins, dydx(*) atmeans predict(outcome(5))

* Ordered probit model predicted probabilities
predict p0oprobit, pr outcome(0)
predict p1oprobit, pr outcome(1)
predict p2oprobit, pr outcome(2)
predict p3oprobit, pr outcome(3)
predict p4oprobit, pr outcome(4)
predict p5oprobit, pr outcome(5)
summarize p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit
tabulate $ylist
```

B.2 Ordered probit and logit model for non-work trips

```
use "C:/Users/Augustine Marfo/Documents/logistic regression/Ordered Probit and Logit Models/survey.dta"

* Dependent variable has 6 categories denoted 0,1,2,3,4,5
global ylist decision_nonworktrip
global xlist gender age driving_experience mileage percent_nonworktrips

describe $ylist $xlist
summarize $ylist $xlist

tabulate $ylist

* Ordered logit model
ologit $ylist $xlist

* Ordered logit marginal effects
margins, dydx(*) atmeans predict(outcome(0))
margins, dydx(*) atmeans predict(outcome(1))
margins, dydx(*) atmeans predict(outcome(2))
margins, dydx(*) atmeans predict(outcome(3))
margins, dydx(*) atmeans predict(outcome(4))
margins, dydx(*) atmeans predict(outcome(5))

* Ordered logit predicted probabilities
predict p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit, pr
summarize p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit
tabulate $ylist
```

```
* Ordered probit model coefficients
oprobit $ylist $xlist

* Ordered probit model marginal effects
margins, dydx(*) atmeans predict(outcome(0))
margins, dydx(*) atmeans predict(outcome(1))
margins, dydx(*) atmeans predict(outcome(2))
margins, dydx(*) atmeans predict(outcome(3))
margins, dydx(*) atmeans predict(outcome(4))
margins, dydx(*) atmeans predict(outcome(5))

* Ordered probit model predicted probabilities
predict p0oprobit, pr outcome(0)
predict p1oprobit, pr outcome(1)
predict p2oprobit, pr outcome(2)
predict p3oprobit, pr outcome(3)
predict p4oprobit, pr outcome(4)
predict p5oprobit, pr outcome(5)
summarize p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit
tabulate $ylist
```

APPENDIX C. TURNING MOVEMENT TABLES

Table C.1 Intersection Turning Movements at Kennedy Avenue – 173rd Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	3	114	5	31	14	0	26	107	17	5	8	27
2nd 15mins	5	138	9	35	16	0	47	113	11	5	12	15
3rd 15mins	6	114	3	32	18	5	41	101	14	11	17	20
4th 15mins	7	100	6	42	16	3	33	101	17	6	8	13

Table C.2 Intersection Turning Movements at Kennedy Avenue – 169th Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	3	55	12	36	37	10	16	70	31	8	28	13
2nd15mins	6	67	16	41	39	11	24	77	25	7	32	15
3rd 15mins	6	61	11	38	42	16	19	68	28	13	37	11
4th 15mins	5	59	14	43	40	13	14	69	32	9	28	12

Table C.3 Intersection Turning Movements at Indianapolis Blvd. – 173rd Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	7	119	4	17	22	3	36	112	13	5	16	19
2nd 15mins	9	128	6	21	23	5	42	123	18	5	25	22
3rd 15mins	11	123	7	25	17	6	44	116	15	11	24	18
4th 15mins	9	114	3	18	14	3	39	114	11	6	20	15

Table C.4 Intersection Turning Movements at Indianapolis Blvd. – 169th Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	7	60	11	22	45	13	26	75	27	8	36	5
2nd 15mins	10	57	13	27	46	16	19	87	32	7	45	22
3rd 15mins	11	70	15	31	41	17	22	83	29	13	44	9
4th 15mins	7	73	11	19	38	13	20	82	26	9	40	14

Table C.5 Intersection Turning Movements at Columbia Avenue – 169th Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	7	20	15	3	74	14	13	33	5	7	64	14
2nd 15mins	3	33	1	7	73	11	17	28	1	0	73	9
3rd 15mins	8	30	4	5	66	4	22	42	4	8	78	6
4th 15mins	7	51	5	2	88	7	10	42	3	8	116	14

Table C.6 Intersection Turning Movements at Southeastern Avenue – 173rd Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	12	28	0	4	27	14	0	17	1	0	35	5
2nd 15mins	12	26	0	8	32	12	2	18	6	0	29	5
3rd 15mins	14	27	0	7	30	17	1	12	4	0	21	7
4th 15mins	16	32	0	1	21	11	0	14	5	0	24	5

Table C.7 Intersection Turning Movements at Calumet Avenue – 173rd Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	7	141	13	13	17	4	16	130	5	16	12	25
2nd 15mins	2	171	9	15	9	5	29	158	8	13	18	30
3rd 15mins	3	181	17	11	15	8	32	176	4	12	20	20
4th 15mins	5	155	7	16	26	7	23	146	15	3	15	21

Table C.8 Intersection Turning Movements at Calumet Avenue – 169th Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	19	225	6	48	13	14	10	226	17	1	17	14
2nd 15mins	14	241	2	50	7	15	19	247	20	3	23	19
3rd 15mins	15	252	10	46	12	18	24	259	16	6	25	11
4th 15mins	17	236	3	51	18	17	21	235	26	4	20	12

Table C.9 Intersection Turning Movements at Summer Street – 165th Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	19	NA	0	NA	49	28	NA	NA	NA	2	46	NA
2nd 15mins	14	NA	0	NA	42	33	NA	NA	NA	0	44	NA
3rd 15mins	18	NA	1	NA	34	30	NA	NA	NA	1	56	NA
4th 15mins	21	NA	1	NA	33	26	NA	NA	NA	1	31	NA

Table C.10 Intersection Turning Movements at Calumet Avenue – Summer Street

Interval	Southbound			Westbound			Northbound			Eastbound		
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right
1st 15mins	11	160	NA	0	NA	10	NA	139	8	NA	NA	NA
2nd 15mins	8	185	NA	5	NA	4	NA	122	5	NA	NA	NA
3rd 15mins	7	122	NA	5	NA	4	NA	72	5	NA	NA	NA
4th 15mins	5	123	NA	2	NA	3	NA	84	6	NA	NA	NA

APPENDIX D. SIGNAL TIMINGS AT INTERSECTIONS

Table D. 1 Intersection signal times at 169^{th} – Kennedy Ave.

Signal Times in Seconds			
169th	Straight	Right Turn	Left Turn
Green	30.4	14	14.2
Red	70.8	16.9	86.8
Yellow	4.2	2.9	2.7
Kennedy	Straight	Right Turn	Left Turn
Green	66.5	14.3	14.1
Red	67	16.8	87.2
Yellow	3.5	3.3	3.4

Table D. 2 Intersection signal times at 173^{rd} – Kennedy Ave.

Signal Times in Seconds			
173rd	Straight	Right Turn	Left Turn
Green	30.4	14.6	14.3
Red	70.1	16.9	86.6
Yellow	4.4	3.1	2.5
Kennedy	Straight	Right Turn	Left Turn
Green	66	14.4	14.2
Red	70	17.3	87.4
Yellow	3.5	3.5	3.2

Table D. 3 Intersection signal times at 169^{th} – Indianapolis Blvd.

Signal Times in Seconds			
169th	Straight	Right Turn	Left Turn
Green	31	14.12	14.4
Red	70	17	87.3
Yellow	4	3.11	2.5
Indianapolis	Straight	Right Turn	Left Turn
Green	66.5	14.7	14.5
Red	67	16.8	87
Yellow	3.5	3.4	3.5

Table D. 4 Intersection signal times at 173rd – Indianapolis Blvd.

Signal Times in Seconds			
173rd	Straight	Right Turn	Left Turn
Green	30.2	14.37	14.5
Red	69.6	17.2	86.8
Yellow	4.3	3.2	2.4
Indianapolis	Straight	Right Turn	Left Turn
Green	66.2	14.8	14.5
Red	66.7	17	87.1
Yellow	3.5	3.6	3.3

Table D. 5 Intersection signal times at 165th – Columbia Ave.

Signal Times in Seconds			
165th	Straight	Right Turn	Left Turn
Green	20	8.3	10.1
Red	75	89	84.3
Yellow	2.45	2.9	2.3
Columbia Ave	Straight	Right Turn	Left Turn
Green	39.15	11.03	10.15
Red	59	86	82.8
Yellow	3.2	2.96	2.4

Table D.6 Intersection signal times at Summer Street – Columbia Ave

Signal Times in Seconds			
Summer St.	Straight	Right Turn	Left Turn
Green	17.23	NA	NA
Red	45.2	NA	NA
Yellow	2.4	NA	NA
Columbia Ave.	Straight	Right Turn	Left Turn
Green	37.33	NA	NA
Red	24.3	NA	NA
Yellow	3.5	NA	NA

Table D.7 Intersection signal times at Michigan Street – Hohman Ave

Signal Times in Seconds			
Michigan St.	Straight	Right Turn	Left Turn
Green	27	NA	27.35
Red	87.2	NA	107
Yellow	3.1	NA	3
Hohman Ave	Straight	Right Turn	Left Turn
Green	107	NA	27.35
Red	27.35	NA	107
Yellow	3.5	NA	3

Table D.8 Intersection signal times at Michigan St – Indianapolis Blvd

Signal Times in Seconds			
Michigan St	Straight	Right Turn	Left Turn
Green	26.93	NA	11.83
Red	87.71	NA	72.1
Yellow	4.14	NA	2.03
Indianapolis	Straight	Right Turn	Left Turn
Green	15.43	NA	15.2
Red	66.2	NA	65.3
Yellow	3.8	NA	3.1

Table D.9 Intersection signal times at 169^{th} – Calumet Street

Signal Times in Seconds			
169th	Straight	Right Turn	Left Turn
Green	30.8	14.5	14.8
Red	69.9	16.8	86.9
Yellow	4.5	3	3.1
Calumet	Straight	Right Turn	Left Turn
Green	66.7	14.5	14.1
Red	66.2	16.6	86.8
Yellow	3.3	3.3	3.5

Table D.10 Intersection signal times at 173rd – Calumet Street

Signal Times in Seconds			
173rd	Straight	Right Turn	Left Turn
Green	31.2	14.6	14.6
Red	70	16.5	87.1
Yellow	4.4	3.3	3.2
Calumet	Straight	Right Turn	Left Turn
Green	67	14.6	14
Red	66	16.5	86.5
Yellow	3.4	3.5	3.5

Table D.11 Intersection signal times at 169th – Columbia Ave.

Signal Times in Seconds			
169th	Straight	Right Turn	Left Turn
Green	18.3	NA	9.8
Red	45.4	NA	32.1
Yellow	2.5	NA	2.3
Columbia Ave	Straight	Right Turn	Left Turn
Green	38.2	NA	10.15
Red	23.9	NA	32.8
Yellow	3.2	NA	2.4

Table D.12 Intersection signal times at 173rd – Southeastern Ave.

Signal Times in Seconds			
173rd	Straight	Right Turn	Left Turn
Green	38	14.6	10
Red	25.2	16.3	31.7
Yellow	3	2.6	2.5
Southeastern	Straight	Right Turn	Left Turn
Green	31.6	NA	NA
Red	24.1	NA	NA
Yellow	3.3	NA	NA

Table D.13 Intersection signal times at 165th – Kennedy Ave.

Signal Times in Seconds			
165th	Straight	Right Turn	Left Turn
Green	30.9	14.5	14.1
Red	71.2	17	87
Yellow	4	3	2.8
Kennedy	Straight	Right Turn	Left Turn
Green	67.1	14.7	14.3
Red	66.6	16.3	86.9
Yellow	3.4	3.4	3.5

Table D.14 Intersection signal times at Michigan Street – Kennedy Ave

Signal Times in Seconds			
Michigan St	Straight	Right Turn	Left Turn
Green	27.08	NA	12
Red	87.8	NA	72.3
Yellow	4.1	NA	2.2
Kennedy	Straight	Right Turn	Left Turn
Green	67.3	14.7	14.5
Red	66.5	16.5	86.7
Yellow	3.3	3.4	3.4

Table D.15 Intersection signal times at Summer Street – Indianapolis Blvd

Signal Times in Seconds			
Summer St	Straight	Right Turn	Left Turn
Green	17.23	NA	NA
Red	45.2	NA	NA
Yellow	2.4	NA	NA
Indianapolis	Straight	Right Turn	Left Turn
Green	66.5	14.8	14.6
Red	66.8	17.2	87.1
Yellow	3.5	3.5	3.3

Table D.16 Intersection signal times at 165th – Indianapolis Blvd.

Signal Times in Seconds			
165th	Straight	Right Turn	Left Turn
Green	31.3	14.2	14.5
Red	69.8	17.3	87
Yellow	3.7	3.2	2.6
Indianapolis	Straight	Right Turn	Left Turn
Green	66.6	14.7	14.7
Red	67	16.5	87.1
Yellow	3.3	3.4	3.4

Table D.17 Intersection signal times at 169th – Southeastern Ave.

Signal Times in Seconds			
169th	Straight	Right Turn	Left Turn
Green	37.7	14.9	10.3
Red	25.4	16.4	32
Yellow	3.2	2.8	2.6
Southeastern	Straight	Right Turn	Left Turn
Green	31.4	NA	NA
Red	24.3	NA	NA
Yellow	3.5	NA	NA

Table D.18 Intersection signal times at Michigan Street – Columbia Ave

Signal Times in Seconds			
Michigan St	Straight	Right Turn	Left Turn
Green	24.3	NA	10.2
Red	71	NA	61.6
Yellow	3.8	NA	2.5
Columbia Ave	Straight	Right Turn	Left Turn
Green	37.9	NA	10.3
Red	24	NA	33
Yellow	3.3	NA	2.6

Table D.19 Intersection signal times at 165th – Calumet Ave.

Signal Times in Seconds			
165th	Straight	Right Turn	Left Turn
Green	31	14.5	14.6
Red	70.2	17	87
Yellow	4.2	3.3	3.2
Calumet	Straight	Right Turn	Left Turn
Green	66.5	14.4	14.2
Red	66.3	16.9	86.9
Yellow	3.4	3.5	3.5

Table D.20 Intersection signal times at Summer Street – Calumet Ave

Signal Times in Seconds			
Summer St	Straight	Right Turn	Left Turn
Green	17.2	NA	NA
Red	45.1	NA	NA
Yellow	2.5	NA	NA
Calumet	Straight	Right Turn	Left Turn
Green	70.2	NA	NA
Red	33.5	NA	NA
Yellow	2.2	NA	NA

Table D.21 Intersection signal times at Michigan Street – Calumet Ave

Signal Times in Seconds			
Michigan St	Straight	Right Turn	Left Turn
Green	24.4	NA	10.4
Red	71.4	NA	62.2
Yellow	3.6	NA	2.6
Calumet Ave	Straight	Right Turn	Left Turn
Green	47.8	NA	14.7
Red	27.3	NA	38.8
Yellow	3	NA	2.4

Table D.22 Intersection signal times at 165th – Hohman Ave.

Signal Times in Seconds			
165th	Straight	Right Turn	Left Turn
Green	30.9	NA	20.2
Red	73.2	NA	86.5
Yellow	3.1	NA	3.1
Hohman Ave	Straight	Right Turn	Left Turn
Green	98.3	NA	27.6
Red	31.9	NA	88.6
Yellow	3.5	NA	3.4

Table D.23 Intersection signal times at 169th – Hohman Ave.

Signal Times in Seconds			
169th	Straight	Right Turn	Left Turn
Green	31	NA	20.7
Red	73.5	NA	87
Yellow	3.3	NA	3.3
Hohman Ave	Straight	Right Turn	Left Turn
Green	99.2	NA	28.3
Red	31.5	NA	87.7
Yellow	3.2	NA	3.1

Table D.24 Intersection signal times at 173rd – Hohman Ave.

Signal Times in Seconds			
173rd	Straight	Right Turn	Left Turn
Green	30.7	NA	20.5
Red	72.9	NA	86.8
Yellow	3	NA	3.3
Hohman Ave	Straight	Right Turn	Left Turn
Green	98.8	NA	28.1
Red	31.3	NA	88.2
Yellow	3.1	NA	3.1

APPENDIX E. MICROSCOPIC SIMULATION OUTPUT

Table E.1 Measured parameters from the microscopic simulation

		CASE 1			CASE 2			CASE 3		
Interval Ending	Run	VMT (veh-mi)	VHT (veh-hrs)	Avg. Speed (mi/hr)	VMT (veh-mi)	VHT (veh-hrs)	Avg. Speed (mi/hr)	VMT (veh-mi)	VHT (veh-hrs)	Avg. Speed (mi/hr)
8:00:00AM	1	16151.1	1173.6	13.8	12631.9	1012.6	12.5	12404.2	988.8	12.5
	2	16236	1180.5	13.8	12647.2	1006.2	12.6	12634.3	1016	12.4
	3	16044.7	1175.6	13.6	12794.8	1010.6	12.7	12641.1	1006.7	12.6
	4	16105.6	1195.2	13.5	12615.5	1025.9	12.3	12580.5	1018.4	12.4
	5	16062.1	1170.5	13.7	12468.3	988	12.6	12546.7	982.6	12.8
9:00:00AM	1	18170.8	2088.6	8.7	12921.8	1679.6	7.7	13114.7	1815.2	7.2
	2	18078.3	2019.5	9	12998.4	1698.7	7.7	13064.8	1722	7.6
	3	18286.1	2150.7	8.5	13019.1	1671.4	7.8	12926.6	1714	7.5
	4	18294.2	2118	8.6	13093.2	1751.5	7.5	12926.4	1793.5	7.2
	5	18344.3	2180.3	8.4	12972	1751.6	7.4	12972.7	1817.4	7.1
10:00:00AM	1	18031.6	2831.4	6.4	12215.4	1861.2	6.6	12074	1954	6.2
	2	18077.5	2752.4	6.6	12336.2	2008.6	6.1	12016.8	1878.8	6.4
	3	18195.8	2881.9	6.3	12120.8	2109.7	5.7	12047.6	2005.2	6
	4	18004.4	2776.4	6.5	12108.3	2059.5	5.9	12080.2	1859.3	6.5
	5	18096	2760.1	6.6	12225.8	1911.3	6.4	12258	1811.3	6.8

Table E.1 continued.

11:00:00AM	1	18231.3	3551.6	5.1	11712.6	2284.9	5.1	10404.3	2201.2	4.7
	2	18202.6	3483.4	5.2	12069.4	2466	4.9	10043.2	2072.6	4.8
	3	18056.2	3404.4	5.3	11217.3	2108.5	5.3	9871.5	2104.6	4.7
	4	18171	3520	5.2	11785.2	2648.3	4.5	10143.8	2124.2	4.8
	5	18060.6	3689	4.9	11610.4	2184.4	5.3	10040.7	1997.9	5
12:00:00PM	1	18343.8	4252	4.3	11207.1	2638.5	4.2	9715.3	2415	4
	2	18320.4	4148.9	4.4	11524.9	2832.3	4.1	9563.5	3028.9	3.2
	3	18265.7	4355	4.2	10790.8	3106.4	3.5	9077.7	2680.8	3.4
	4	18287.3	4344.8	4.2	11758.1	2832.3	4.2	9561.7	2737.5	3.5
	5	18236.3	4340.6	4.2	10787.7	2570.9	4.2	9476.4	2569.2	3.7
1:00:00PM	1	18048.3	5084.5	3.5	11087.1	3604.8	3.1	11580.7	4792	2.4
	2	17940.5	4716	3.8	11446.1	3478.8	3.3	11752.3	5278.3	2.2
	3	17931.3	4848.1	3.7	10663.5	3218.8	3.3	11308.4	5174.9	2.2
	4	17972.8	4915	3.7	11086.7	3424.4	3.2	11951.6	5262.1	2.3
	5	18347.5	4856.4	3.8	10773.7	3486.1	3.1	12150.9	5217.9	2.3
2:00:00PM	1	18177.3	5841.3	3.1	10532.4	3916.3	2.7	10388	4566.3	2.3
	2	18298.9	5587.7	3.3	10611.2	3793.9	2.8	10000.7	4315.4	2.3
	3	18395.1	5150.7	3.6	10845.5	3732.1	2.9	9504.9	5252.8	1.8
	4	18333.8	5898.7	3.1	11498.1	4149.3	2.8	10314.4	4189.7	2.5
	5	18116.2	5719.6	3.2	10322.4	3719.4	2.8	9917.1	4305.1	2.3

Table E.1 continued.

3:00:00PM	1	18198.2	6303.6	2.9	10445.8	4447.6	2.3	9925.4	4813.6	2.1
	2	18370.8	6297.9	2.9	10778.5	4357.6	2.5	9492	4519.2	2.1
	3	18239.9	6731.2	2.7	10860	4349.1	2.5	9563.6	5178.7	1.8
	4	18156.5	5982.5	3	11020.1	4709	2.3	9810.4	4132.2	2.4
	5	18375.3	6571.1	2.8	10849.5	5999.4	1.8	9880.5	4462.4	2.2
4:00:00PM	1	18124.1	6778.9	2.7	10512.3	6134.6	1.7	9882.6	5126.3	1.9
	2	18126.1	7191	2.5	10774.1	4750	2.3	9857.5	4889.8	2
	3	18142.8	6961	2.6	10681.2	5013.9	2.1	9582.7	4551.3	2.1
	4	18471.6	7735.9	2.4	10937.3	4610	2.4	9529.7	4245	2.2
	5	18140.3	7233.5	2.5	10774.3	5188.8	2.1	9476.2	5624	1.7
5:00:00PM	1	18236.2	7782.4	2.3	10546	7254.3	1.5	9986.9	5578.2	1.8
	2	18025.2	7522.3	2.4	10736.5	5478.8	2	9351.6	5108.5	1.8
	3	18184.3	8402.9	2.2	11012.7	5598.6	2	9841.1	5918.7	1.7
	4	18277.8	8002.8	2.3	11174.8	5024.1	2.2	9567.6	5105.8	1.9
	5	18125.1	7715.9	2.3	10594.4	5497.1	1.9	9515.6	6265.6	1.5
6:00:00PM	1	18439.6	8285.7	2.2	10598.4	6337.9	1.7	10496.3	6710.7	1.6
	2	18233.3	8446.1	2.2	10842.3	8250.1	1.3	9436.1	5458.9	1.7
	3	18253.1	8345	2.2	11015.8	5948.6	1.9	9490.7	5814.1	1.6
	4	18190.4	8624.7	2.1	10515.5	5044.9	2.1	9602.8	6146.7	1.6
	5	18318	8582.7	2.1	11243.3	7180	1.6	9439.5	5186.3	1.8

Table E.1 continued.

7:00:00PM	1	18159.7	8625.2	2.1	10890.7	6218.9	1.8	9563.9	6393.9	1.5
	2	18228.1	8835.7	2.1	11021.3	7993.3	1.4	9122.7	6510.9	1.4
	3	18160	8653	2.1	10717.3	6288.9	1.7	9215.3	6508.2	1.4
	4	18077.7	8947.4	2	10914	5799.6	1.9	9289.2	9556.5	1
	5	18066.3	8942.6	2	10540.4	5998.3	1.8	9432.7	6006.5	1.6
8:00:00PM	1	18097.4	9212.5	2	10732.4	6755.2	1.6	9673.2	8729.1	1.1
	2	18169.4	10563.7	1.7	10800.1	6929.9	1.6	9273.3	7481.1	1.2
	3	17856.9	9482.1	1.9	10615.6	6731.2	1.6	9344.6	7248.3	1.3
	4	18056.7	9253.5	2	10798.1	6392.7	1.7	9138.3	6803.7	1.3
	5	18122.7	10118.9	1.8	10679	6799.5	1.6	9039.4	6901.3	1.3

Table E.2. The average delay and average stopped times from batch simulation

		CASE 1		CASE 2		CASE 3	
Interval Ending	Run	Avg. Delay (sec/mi)	Avg. Stopped Time (sec/mi)	Avg. Delay (sec/mi)	Avg. Stopped Time (sec/mi)	Avg. Delay (sec/mi)	Avg. Stopped Time (sec/mi)
8:00:00AM	1	237.9	116.3	279.3	141.9	283.1	139.6
	2	236.8	115.7	274.6	131.6	289.6	136.8
	3	239.9	116.2	274.8	128.9	281.1	136.2
	4	247	118.8	294.2	138	290.4	136.5
	5	234.8	117	286.5	140.5	268.7	135
9:00:00AM	1	456.2	161.1	606.1	223.6	677.5	217.9
	2	425.3	158.4	633.8	227.7	625.3	221.6
	3	482.8	158.2	603.4	225.8	627	222.5
	4	464.9	160.4	647.5	221.7	651.6	226.3
	5	497	156	626.4	231.5	688.9	228.9
10:00:00AM	1	725.7	162.3	701.3	238.6	741.6	254.5
	2	691.5	176	781.8	250.3	725.9	265.8
	3	711.9	178.5	867.5	258.9	851.7	255.1
	4	651.9	180	864	254.3	693	262.7
	5	686	173.6	809.7	265.3	720	257.6
11:00:00AM	1	859.6	189	1016.6	309.6	975.8	335.1
	2	899.5	173.7	1073.3	291.4	837.9	336.6
	3	879	175.9	837	324	942.8	351.5
	4	934.2	182.8	1084.1	323.6	934.4	347.5
	5	1020.4	177.5	916.4	296.7	919.1	308.4
12:00:00PM	1	1177.5	189.7	1223.4	387.1	1092.2	396.2
	2	1070.7	185.3	1315.6	348.3	1398.1	419.1
	3	1207.7	174.5	1195.4	363.5	1354	449.7
	4	1224.6	182.3	1239	393	1339.8	448.3
	5	1174.3	183.4	1112.7	360.9	1238.6	420.1

Table E.2 continued.

1:00:00PM	1	1437.6	180.3	1818.5	427.3	1515	729.8
	2	1289.1	200	1594	452.6	1854	771.3
	3	1357.5	191.8	1526.8	453.2	1798.2	776.4
	4	1342.5	179.1	1456.7	482.3	1762.9	745.6
	5	1355.9	199.6	1637.1	422.1	1622.9	762.7
2:00:00PM	1	1795.4	177.4	1970.7	498.6	1930.9	581.8
	2	1385.7	193	1840.6	489.1	2036	589.9
	3	1379	200.4	1750.1	512.3	2053.1	571.8
	4	1727.9	200.2	1778.8	519	1858.5	563.2
	5	1382.2	196	1819.8	484.1	2083.4	565.2
3:00:00PM	1	1835.5	174.5	2321.8	482.4	2285.2	650.3
	2	1896.2	186.3	2091.6	494.5	2351.7	639.1
	3	1804.7	196.1	2139.9	619.8	2780	666.6
	4	1709	198.6	2217.9	574.4	1962.2	594.2
	5	2029.4	183.6	2337.4	462.7	2084	593.5
4:00:00PM	1	2029.2	175.4	2679	458.5	2622	551.3
	2	2224.8	177.1	2364.1	468.1	2337.7	523
	3	2086.2	184.9	2462.6	680.3	2057.1	597
	4	2207.2	189.9	2008.5	574.4	2185.2	532.4
	5	2299.8	178.1	2571.7	516.4	2540.7	482.7
5:00:00PM	1	2252.9	181	3317	450.5	2829.8	558.5
	2	2293.3	174.4	2790.2	475.5	2579.8	615.8
	3	2758.6	178.7	2678	602.6	3243.1	635
	4	2563.1	187.5	2273.1	577.8	2809	557.7
	5	2394.3	172.6	2931	605.5	3153.1	469.1
6:00:00PM	1	2421.5	198.3	3477.6	463.2	3039.4	588.2
	2	2694.9	174.7	3593.8	468.9	2903.7	643.1
	3	2458.5	175.4	2915.5	605.1	2907.3	593.2
	4	2725.8	182.4	2409.2	512.3	3419.4	513.4
	5	2636.2	174.2	3766.5	613	2880.8	662.2

Table E.2 continued.

7:00:00PM	1	2595.7	195.7	3283.5	459.9	3407.2	576.9
	2	2800.7	175.4	3635.7	443.8	3804.5	685.2
	3	2576.1	177.3	3109.5	579.4	3537.4	674
	4	2851.5	177.2	2681.2	523.1	3511.2	490.7
	5	2872.9	176.6	3021.3	556.3	3258.9	615.9
8:00:00PM	1	2627.2	199.2	3660.6	454.7	4079.9	614.7
	2	3409.8	177.8	3718.5	582.2	4542.4	723
	3	3072.3	175.8	3670.2	620	4072.5	708.4
	4	2777.9	176.1	3084.2	527.2	3555.5	615.8
	5	3315	178.9	3334.1	635.8	4149	639.9

APPENDIX F. RESULTS FROM STATISTICAL MODEL

F.1 Results on decision on non-work trip from Stata

```
.  doedit "C:\Users\Augustine Marfo\Documents\logistic regression\Ordered Probit and Logit Models\s

.  do "C:\Users\AUGUST~1\AppData\Local\Temp\STD48f0_000000.tmp"

.  * Ordered Probit and Logit Models in Stata
.
.
.  clear all

. set more off

.
. use "C:/Users/Augustine Marfo/Documents/logistic regression/Ordered Probit and Logit Models/surv

.
.  * Dependent variable has 6 categories denoted 0,1,2,3,4,5
.  global ylist decision_nonworktrip

. global xlist gender age driving_experience mileage percent_nonworktrips

.
.
. tabulate $ylist
```

decision_no nworktrip	Freq.	Percent	Cum.
0	8	6.67	6.67
1	30	25.00	31.67
2	21	17.50	49.17
3	34	28.33	77.50
4	15	12.50	90.00
5	12	10.00	100.00
Total	120	100.00	

```
.  * Ordered logit model
.  ologit $ylist $xlist

Iteration 0:    log likelihood = -201.55669
Iteration 1:    log likelihood = -199.06059
Iteration 2:    log likelihood = -199.04906
Iteration 3:    log likelihood = -199.04906

Ordered logistic regression                     Number of obs   =        120
                                                LR chi2(5)      =       5.02
                                                Prob > chi2     =     0.4140
Log likelihood   = -199.04906                   Pseudo R2       =     0.0124
```

decision_nonworktrip	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
gender	.2494204	.362612	0.69	0.492	-.4612861	.9601269
age	.1798664	.1943222	0.93	0.355	-.2009982	.560731
driving_experience	-.1140611	.073843	-1.54	0.122	-.2587908	.0306686
mileage	.0220281	.0170085	1.30	0.195	-.0113079	.0553641
percent_nonworktrips	-.0725912	.071352	-1.02	0.309	-.2124386	.0672562
/cut1	-2.714969	.6039336			-3.898657	-1.531281
/cut2	-.8153524	.5141992			-1.823164	.1924596
/cut3	-.0543747	.510173			-1.054295	.9455459
/cut4	1.26876	.5263225			.2371869	2.300333
/cut5	2.246683	.5662836			1.136787	3.356578

```
.
. * Ordered logit marginal effects
. margins, dydx(*) atmeans predict(outcome(0))

Conditional marginal effects                    Number of obs   =        120
Model VCE      : OIM

Expression     : Pr(decision_nonworktrip==0), predict(outcome(0))
dy/dx w.r.t. : gender age driving_experience  mileage percent_nonworktrips
at             : gender          =    .3083333 (mean)
                 age             =    2.241667 (mean)
                 driving_ex~e    =    4.841667 (mean)
                 mileage         =    13.84583 (mean)
                 percent_no~s    =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
gender	-.0145653	.021503	-0.68	0.498	-.0567104	.0275799
age	-.0105036	.0117186	-0.90	0.370	-.0334715	.0124644
driving_experience	.0066608	.0046427	1.43	0.151	-.0024388	.0157604
mileage	-.0012864	.0010356	-1.24	0.214	-.003316	.0007433
percent_nonworktrips	.0042391	.004332	0.98	0.328	-.0042514	.0127295

```
. margins, dydx(*) atmeans predict(outcome(1))

Conditional marginal effects                    Number of obs     =        120
Model VCE      : OIM

Expression     : Pr(decision_nonworktrip==1), predict(outcome(1))
dy/dx w.r.t. : gender age driving_experience        mileage percent_nonworktrips
at             : gender            =    .3083333 (mean)
                 age               =    2.241667 (mean)
                 driving_ex~e      =    4.841667 (mean)
                 mileage           =    13.84583 (mean)
                 percent_no~s      =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.038538	.0562964	-0.68	0.494	-.1488768	.0718009
age	-.0277912	.0302405	-0.92	0.358	-.0870615	.0314791
driving_experience	.0176236	.0116958	1.51	0.132	-.0052997	.0405469
mileage	-.0034036	.0026675	-1.28	0.202	-.0086317	.0018246
percent_nonworktrips	.0112161	.011124	1.01	0.313	-.0105866	.0330188

```
. margins, dydx(*) atmeans predict(outcome(2))

Conditional marginal effects                    Number of obs     =        120
Model VCE      : OIM

Expression     : Pr(decision_nonworktrip==2), predict(outcome(2))
dy/dx w.r.t. : gender age driving_experience        mileage percent_nonworktrips
at             : gender            =    .3083333 (mean)
                 age               =    2.241667 (mean)
                 driving_ex~e      =    4.841667 (mean)
                 mileage           =    13.84583 (mean)
                 percent_no~s      =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.0092109	.0140704	-0.65	0.513	-.0367883	.0183666
age	-.0066423	.0078225	-0.85	0.396	-.0219741	.0086895
driving_experience	.0042122	.0033621	1.25	0.210	-.0023774	.0108017
mileage	-.0008135	.0007497	-1.09	0.278	-.0022828	.0006558
percent_nonworktrips	.0026807	.002914	0.92	0.358	-.0030307	.0083921

```
. margins, dydx(*) atmeans predict(outcome(3))

Conditional marginal effects                    Number of obs     =        120
Model VCE      : OIM

Expression     : Pr(decision_nonworktrip==3), predict(outcome(3))
dy/dx w.r.t. : gender age driving_experience        mileage percent_nonworktrips
at             : gender            =    .3083333 (mean)
                 age               =    2.241667 (mean)
                 driving_ex~e      =    4.841667 (mean)
                 mileage           =    13.84583 (mean)
                 percent_no~s      =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
gender	.0196612	.0290637	0.68	0.499	-.0373027	.076625
age	.0141784	.0159985	0.89	0.375	-.0171782	.045535
driving_experience	-.0089911	.0064896	-1.39	0.166	-.0217105	.0037282
mileage	.0017364	.0014473	1.20	0.230	-.0011002	.0045731
percent_nonworktrips	-.0057222	.0059285	-0.97	0.334	-.0173418	.0058974

. margins, dydx(*) atmeans predict(outcome(4))

Conditional marginal effects Number of obs = 120
Model VCE : OIM

Expression : Pr(decision_nonworktrip==4), predict(outcome(4))
dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at : gender = .3083333 (mean)
age = 2.241667 (mean)
driving_ex~e = 4.841667 (mean)
mileage = 13.84583 (mean)
percent_no~s = 3.25 (mean)

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
gender	.021134	.0311768	0.68	0.498	-.0399714	.0822394
age	.0152405	.0167719	0.91	0.364	-.0176317	.0481128
driving_experience	-.0096647	.0066164	-1.46	0.144	-.0226325	.0033031
mileage	.0018665	.0015027	1.24	0.214	-.0010787	.0048117
percent_nonworktrips	-.0061508	.0062018	-0.99	0.321	-.0183061	.0060044

. margins, dydx(*) atmeans predict(outcome(5))

Conditional marginal effects Number of obs = 120
Model VCE : OIM

Expression : Pr(decision_nonworktrip==5), predict(outcome(5))
dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at : gender = .3083333 (mean)
age = 2.241667 (mean)
driving_ex~e = 4.841667 (mean)
mileage = 13.84583 (mean)
percent_no~s = 3.25 (mean)

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
gender	.0215189	.0316677	0.68	0.497	-.0405487	.0835865
age	.0155181	.0170536	0.91	0.363	-.0179063	.0489425
driving_experience	-.0098407	.0066582	-1.48	0.139	-.0228905	.0032091
mileage	.0019005	.001514	1.26	0.209	-.0010669	.0048679
percent_nonworktrips	-.0062628	.0062592	-1.00	0.317	-.0185306	.0060049

. * Ordered logit predicted probabilities
. predict p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit, pr

. summarize p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit

Variable	Obs	Mean	Std. Dev.	Min	Max
p0ologit	120	.0665139	.025984	.0228756	.1689394
p1ologit	120	.2470836	.0598073	.1124197	.40708
p2ologit	120	.1739002	.0146009	.1155798	.187982
p3ologit	120	.2860593	.0313234	.171997	.3192187
p4ologit	120	.1254809	.0326775	.0506	.2127401
p5ologit	120	.100962	.0362109	.0332949	.2302134

. tabulate $ylist

decision_no nworktrip	Freq.	Percent	Cum.
0	8	6.67	6.67
1	30	25.00	31.67
2	21	17.50	49.17
3	34	28.33	77.50
4	15	12.50	90.00
5	12	10.00	100.00
Total	120	100.00	

.
.
. * Ordered probit model coefficients
. oprobit $ylist $xlist

Iteration 0: log likelihood = -201.55669
Iteration 1: log likelihood = -199.2992
Iteration 2: log likelihood = -199.29898
Iteration 3: log likelihood = -199.29898

Ordered probit regression		Number of obs	= 120
		LR chi2(5)	= 4.52
		Prob > chi2	= 0.4778
Log likelihood = -199.29898		Pseudo R2	= 0.0112

decision_nonworktrip	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	.1847871	.2075069	0.89	0.373	-.2219188	.5914931
age	.106918	.1121001	0.95	0.340	-.1127943	.3266302
driving_experience	-.060108	.0411024	-1.46	0.144	-.1406671	.0204511
mileage	.0084053	.0089612	0.94	0.348	-.0091583	.025969
percent_nonworktrips	-.0401654	.0424054	-0.95	0.344	-.1232783	.0429476
/cut1	-1.536653	.3331099			-2.189536	-.8837693
/cut2	-.4967884	.3052077			-1.094984	.1014077
/cut3	-.0335239	.3035244			-.6284207	.5613729
/cut4	.763128	.3086611			.1581633	1.368093
/cut5	1.300478	.3210831			.6711664	1.929789

```
. * Ordered probit model marginal effects
. margins, dydx(*) atmeans predict(outcome(0))

Conditional marginal effects                      Number of obs   =        120
Model VCE         : OIM

Expression        : Pr(decision_nonworktrip==0), predict(outcome(0))
dy/dx w.r.t. : gender age driving_experience       mileage percent_nonworktrips
at                : gender              =     .3083333 (mean)
                    age                 =     2.241667 (mean)
                    driving_ex~e        =     4.841667 (mean)
                    mileage             =     13.84583 (mean)
                    percent_no~s        =         3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.0229356	.0262877	-0.87	0.383	-.0744585	.0285874
age	-.0132705	.0142498	-0.93	0.352	-.0411997	.0146586
driving_experience	.0074605	.0053869	1.38	0.166	-.0030976	.0180186
mileage	-.0010433	.00114	-0.92	0.360	-.0032776	.0011911
percent_nonworktrips	.0049853	.0053962	0.92	0.356	-.005591	.0155616

```
. margins, dydx(*) atmeans predict(outcome(1))

Conditional marginal effects                      Number of obs   =        120
Model VCE         : OIM

Expression        : Pr(decision_nonworktrip==1), predict(outcome(1))
dy/dx w.r.t. : gender age driving_experience       mileage percent_nonworktrips
at                : gender              =     .3083333 (mean)
                    age                 =     2.241667 (mean)
                    driving_ex~e        =     4.841667 (mean)
                    mileage             =     13.84583 (mean)
                    percent_no~s        =         3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.0425002	.0483291	-0.88	0.379	-.1372235	.0522232
age	-.0245906	.0260992	-0.94	0.346	-.0757441	.0265628
driving_experience	.0138246	.0097334	1.42	0.156	-.0052525	.0329016
mileage	-.0019332	.0020818	-0.93	0.353	-.0060133	.002147
percent_nonworktrips	.0092378	.0098582	0.94	0.349	-.0100839	.0285595

```
. margins, dydx(*) atmeans predict(outcome(2))

Conditional marginal effects                      Number of obs   =        120
Model VCE         : OIM

Expression        : Pr(decision_nonworktrip==2), predict(outcome(2))
dy/dx w.r.t. : gender age driving_experience       mileage percent_nonworktrips
at                : gender              =     .3083333 (mean)
                    age                 =     2.241667 (mean)
                    driving_ex~e        =     4.841667 (mean)
                    mileage             =     13.84583 (mean)
                    percent_no~s        =         3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
gender	-.0082606	.0099737	-0.83	0.408	-.0278088	.0112875
age	-.0047796	.0054888	-0.87	0.384	-.0155374	.0059782
driving_experience	.002687	.0022194	1.21	0.226	-.001663	.007037
mileage	-.0003757	.0004394	-0.86	0.392	-.0012369	.0004854
percent_nonworktrips	.0017955	.0020785	0.86	0.388	-.0022782	.0058693

. margins, dydx(*) atmeans predict(outcome(3))

Conditional marginal effects Number of obs = 120
Model VCE : OIM

Expression : Pr(decision_nonworktrip==3), predict(outcome(3))
dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at : gender = .3083333 (mean)
age = 2.241667 (mean)
driving_ex~e = 4.841667 (mean)
mileage = 13.84583 (mean)
percent_no~s = 3.25 (mean)

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
gender	.0189595	.0220797	0.86	0.391	-.0243159	.0622349
age	.01097	.0120126	0.91	0.361	-.0125743	.0345143
driving_experience	-.0061672	.0046465	-1.33	0.184	-.0152741	.0029397
mileage	.0008624	.0009625	0.90	0.370	-.0010241	.0027489
percent_nonworktrips	-.004121	.0045537	-0.90	0.365	-.0130462	.0048041

. margins, dydx(*) atmeans predict(outcome(4))

Conditional marginal effects Number of obs = 120
Model VCE : OIM

Expression : Pr(decision_nonworktrip==4), predict(outcome(4))
dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at : gender = .3083333 (mean)
age = 2.241667 (mean)
driving_ex~e = 4.841667 (mean)
mileage = 13.84583 (mean)
percent_no~s = 3.25 (mean)

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
gender	.0234401	.0270344	0.87	0.386	-.0295464	.0764266
age	.0135625	.0145668	0.93	0.352	-.014988	.042113
driving_experience	-.0076247	.0055328	-1.38	0.168	-.0184687	.0032194
mileage	.0010662	.0011646	0.92	0.360	-.0012164	.0033488
percent_nonworktrips	-.0050949	.0055265	-0.92	0.357	-.0159266	.0057367

```
. margins, dydx(*) atmeans predict(outcome(5))

Conditional marginal effects                    Number of obs   =        120
Model VCE       : OIM

Expression      : Pr(decision_nonworktrip==5), predict(outcome(5))
dy/dx w.r.t. : gender age driving_experience          mileage percent_nonworktrips
at              : gender            =     .3083333 (mean)
                  age               =     2.241667 (mean)
                  driving_ex~e      =     4.841667 (mean)
                  mileage           =     13.84583 (mean)
                  percent_no~s      =         3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	.0312967	.035473	0.88	0.378	-.038229	.1008225
age	.0181083	.0192613	0.94	0.347	-.0196432	.0558598
driving_experience	-.0101803	.0071704	-1.42	0.156	-.0242341	.0038735
mileage	.0014236	.0015342	0.93	0.353	-.0015834	.0044305
percent_nonworktrips	-.0068027	.0072536	-0.94	0.348	-.0210194	.0074141

```
.
.  * Ordered probit model predicted probabilities
.  predict p0oprobit, pr outcome(0)

.  predict p1oprobit, pr outcome(1)

.  predict p2oprobit, pr outcome(2)

.  predict p3oprobit, pr outcome(3)

.  predict p4oprobit, pr outcome(4)

.  predict p5oprobit, pr outcome(5)

.  summarize p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit
```

Variable	Obs	Mean	Std. Dev.	Min	Max
p0ologit	120	.0665139	.025984	.0228756	.1689394
p1ologit	120	.2470836	.0598073	.1124197	.40708
p2ologit	120	.1739002	.0146009	.1155798	.187982
p3ologit	120	.2860593	.0313234	.171997	.3192187
p4ologit	120	.1254809	.0326775	.0506	.2127401
p5ologit	120	.100962	.0362109	.0332949	.2302134

```
. tabulate $ylist
```

decision_nonworktrip	Freq.	Percent	Cum.
0	8	6.67	6.67
1	30	25.00	31.67
2	21	17.50	49.17
3	34	28.33	77.50
4	15	12.50	90.00
5	12	10.00	100.00
Total	120	100.00	

F.2 Results on decision on work trip from Stata

```
. doedit "C:\Users\Augustine Marfo\Documents\logistic regression\Ordered Probit and Logit Models\s

. do "C:\Users\AUGUST~1\AppData\Local\Temp\STD48f0_000000.tmp"

. * Ordered Probit and Logit Models in Stata
.
.
. clear all

. set more off

. * Dependent variable has 6 categories denoted 0,1,2,3,4,5
. global ylist decision_worktrip

. global xlist gender age driving_experience mileage percent_nonworktrips

.

.
. tabulate $ylist
```

decision_worktrip	Freq.	Percent	Cum.
0	2	1.67	1.67
1	7	5.83	7.50
2	22	18.33	25.83
3	38	31.67	57.50
4	34	28.33	85.83
5	17	14.17	100.00
Total	120	100.00	

```
. * Ordered logit model
. ologit $ylist $xlist

Iteration 0:   log likelihood = -185.19925
Iteration 1:   log likelihood = -181.27238
Iteration 2:   log likelihood = -181.25366
Iteration 3:   log likelihood = -181.25365

Ordered logistic regression
                                                  Number of obs     =        120
                                                  LR chi2(5)        =       7.89
                                                  Prob > chi2       =     0.1623
Log likelihood = -181.25365                       Pseudo R2         =     0.0213

------------------------------------------------------------------------------------
    decision_worktrip |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------+-------------------------------------------------------------
               gender |   .1216503   .3546086     0.34   0.732    -.5733697    .8166703
                  age |  -.1407265   .1857478    -0.76   0.449    -.5047854    .2233324
   driving_experience |   .0863695    .069804     1.24   0.216    -.0504438    .2231827
              mileage |   .0266859   .0157573     1.69   0.090    -.0041979    .0575697
percent_nonworktrips |   .1487518   .0751254     1.98   0.048     .0015087    .2959948
----------------------+-------------------------------------------------------------
                /cut1 |  -3.187497   .8475328                     -4.848631   -1.526364
                /cut2 |   -1.60087   .5790954                     -2.735876   -.4658635
                /cut3 |  -.0923618   .5277763                     -1.126784    .9420607
                /cut4 |    1.33336   .5466775                      .2618922    2.404828
                /cut5 |   2.880469   .5943912                      1.715484    4.045454
------------------------------------------------------------------------------------

.
. * Ordered logit marginal effects
. margins, dydx(*) atmeans predict(outcome(0))

Conditional marginal effects                      Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==0), predict(outcome(0))
dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at           : gender          =    .3083333 (mean)
               age             =    2.241667 (mean)
               driving_ex~e    =    4.841667 (mean)
               mileage         =    13.84583 (mean)
               percent_no~s    =        3.25 (mean)

------------------------------------------------------------------------------------
                      |            Delta-method
                      |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------+-------------------------------------------------------------
               gender |  -.0018043   .0054095    -0.33   0.739    -.0124067    .0087981
                  age |   .0020872   .0031075     0.67   0.502    -.0040034    .0081778
   driving_experience |   -.001281   .0013456    -0.95   0.341    -.0039183    .0013563
              mileage |  -.0003958   .0003533    -1.12   0.263    -.0010883    .0002967
percent_nonworktrips |  -.0022062   .0018382    -1.20   0.230    -.0058091    .0013966
------------------------------------------------------------------------------------
```

```
. margins, dydx(*) atmeans predict(outcome(1))

Conditional marginal effects                    Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==1), predict(outcome(1))

dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at                                    :  gender
               =    .3083333 (mean) age            =
               2.241667 (mean) driving_ex~e     =
               4.841667 (mean) mileage          =
               13.84583 (mean) percent_no~s     =
               3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.0060654	.0177735	-0.34	0.733	-.0409008	.0287701
age	.0070165	.0095842	0.73	0.464	-.0117682	.0258012
driving_experience	-.0043063	.0037545	-1.15	0.251	-.011665	.0030524
mileage	-.0013305	.0008864	-1.50	0.133	-.0030679	.0004068
percent_nonworktrips	-.0074166	.0044077	-1.68	0.092	-.0160555	.0012223

```
. margins, dydx(*) atmeans predict(outcome(2))

Conditional marginal effects                    Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==2), predict(outcome(2))

dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at           : gender          =    .3083333 (mean)
               age             =    2.241667 (mean)
               driving_ex~e    =    4.841667 (mean)
               mileage         =    13.84583 (mean)
               percent_no~s    =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.0150889	.0440278	-0.34	0.732	-.1013818	.0712039
age	.0174551	.023229	0.75	0.452	-.028073	.0629831
driving_experience	-.0107129	.0088789	-1.21	0.228	-.0281152	.0066895
mileage	-.00331	.0020212	-1.64	0.101	-.0072714	.0006514
percent_nonworktrips	-.0184505	.0099111	-1.86	0.063	-.0378759	.000975

```
. margins, dydx(*) atmeans predict(outcome(3))

Conditional marginal effects                    Number of obs     =       120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==3), predict(outcome(3))

dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at                                    :  gender
               =    .3083333 (mean) age            =
               2.241667 (mean) driving_ex~e     =
               4.841667 (mean) mileage          =
               13.84583 (mean) percent_no~s     =
               3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.0065907	.0194731	-0.34	0.735	-.0447573	.0315759
age	.0076242	.0106019	0.72	0.472	-.0131551	.0284035
driving_experience	-.0046793	.004313	-1.08	0.278	-.0131327	.0037741
mileage	-.0014458	.0011137	-1.30	0.194	-.0036287	.0007371
percent_nonworktrips	-.008059	.005532	-1.46	0.145	-.0189014	.0027834

```
. margins, dydx(*) atmeans predict(outcome(4))

Conditional marginal effects                      Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==4), predict(outcome(4))
dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at           : gender          =    .3083333 (mean)
               age             =    2.241667 (mean)
               driving_ex~e    =    4.841667 (mean)
               mileage         =    13.84583 (mean)
               percent_no~s    =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	.0156513	.045752	0.34	0.732	-.074021	.1053237
age	-.0181056	.0241676	-0.75	0.454	-.0654732	.029262
driving_experience	.0111122	.0092612	1.20	0.230	-.0070396	.0292639
mileage	.0034334	.0021496	1.60	0.110	-.0007798	.0076465
percent_nonworktrips	.0191382	.0103441	1.85	0.064	-.0011359	.0394122

```
Conditional marginal effects                      Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==5), predict(outcome(5))
dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at           : gender          =    .3083333 (mean)
               age             =    2.241667 (mean)
               driving_ex~e    =    4.841667 (mean)
               mileage         =    13.84583 (mean)
               percent_no~s    =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	.0138979	.0405157	0.34	0.732	-.0655113	.0933072
age	-.0160773	.0213231	-0.75	0.451	-.0578699	.0257153
driving_experience	.0098673	.0080476	1.23	0.220	-.0059056	.0256402
mileage	.0030487	.0018436	1.65	0.098	-.0005646	.0066621
percent_nonworktrips	.0169942	.0089239	1.90	0.057	-.0004964	.0344847

```
. * Ordered logit predicted probabilities
. predict p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit, pr

. summarize p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit
```

Variable	Obs	Mean	Std. Dev.	Min	Max
p0ologit	120	.0166742	.007791	.0050688	.043895
p1ologit	120	.0589343	.0249286	.019225	.1393614
p2ologit	120	.1864526	.0552342	.0768633	.3202608
p3ologit	120	.3181628	.0280291	.2177691	.3420619
p4ologit	120	.2792268	.0544869	.1435565	.3685609
p5ologit	120	.1405492	.0564327	.0480212	.3125128

```
. tabulate $ylist
```

decision_wo rktrip	Freq.	Percent	Cum.
0	2	1.67	1.67
1	7	5.83	7.50
2	22	18.33	25.83
3	38	31.67	57.50
4	34	28.33	85.83
5	17	14.17	100.00
Total	120	100.00	

```
.
.
. * Ordered probit model coefficients
. oprobit $ylist $xlist

Iteration 0:   log likelihood = -185.19925
Iteration 1:   log likelihood = -181.01156
Iteration 2:   log likelihood = -181.01064
Iteration 3:   log likelihood = -181.01064

Ordered probit regression                         Number of obs   =        120
                                                  LR chi2(5)      =       8.38
                                                  Prob > chi2     =     0.1366
Log likelihood = -181.01064                       Pseudo R2       =     0.0226
```

decision_worktrip	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	.0479483	.2080504	0.23	0.818	-.3598231	.4557197
age	-.1140515	.1119169	-1.02	0.308	-.3334045	.1053015
driving_experience	.0544543	.0411959	1.32	0.186	-.0262882	.1351968
mileage	.0142447	.0091419	1.56	0.119	-.003673	.0321624
percent_nonworktrips	.0931199	.043193	2.16	0.031	.0084632	.1777765
/cut1	-1.712582	.3936974			-2.484214	-.9409491
/cut2	-.9822448	.3209942			-1.611382	-.3531078
/cut3	-.1461983	.3051361			-.744254	.4518574
/cut4	.7261914	.3116697			.1153301	1.337053
/cut5	1.633413	.3268439			.9928112	2.274016

```
. * Ordered probit model marginal effects
. margins, dydx(*) atmeans predict(outcome(0))

Conditional marginal effects                    Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==0), predict(outcome(0))

dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at                                : gender
               =    .3083333 (mean) age             =
               2.241667 (mean) driving_ex~e     =
               4.841667 (mean) mileage          =
               13.84583 (mean) percent_no~s     =
               3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.0015732	.0069281	-0.23	0.820	-.0151519	.0120056
age	.003742	.0043355	0.86	0.388	-.0047555	.0122395
driving_experience	-.0017866	.0017282	-1.03	0.301	-.0051737	.0016005
mileage	-.0004674	.0004246	-1.10	0.271	-.0012996	.0003649
percent_nonworktrips	-.0030552	.0023244	-1.31	0.189	-.007611	.0015005

```
. margins, dydx(*) atmeans predict(outcome(1))

Conditional marginal effects                    Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==1), predict(outcome(1))
dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at           : gender          =    .3083333 (mean)
               age             =    2.241667 (mean)
               driving_ex~e    =    4.841667 (mean)
               mileage         =    13.84583 (mean)
               percent_no~s    =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.0045916	.0199217	-0.23	0.818	-.0436374	.0344542
age	.0109218	.0112033	0.97	0.330	-.0110364	.0328799
driving_experience	-.0052146	.0042456	-1.23	0.219	-.0135359	.0031066
mileage	-.0013641	.0009655	-1.41	0.158	-.0032564	.0005283
percent_nonworktrips	-.0089173	.0049706	-1.79	0.073	-.0186596	.0008249

```
. margins, dydx(*) atmeans predict(outcome(2))

Conditional marginal effects                    Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==2), predict(outcome(2))

dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at           : gender          =    .3083333 (mean)
               age             =    2.241667 (mean)
               driving_ex~e    =    4.841667 (mean)
               mileage         =    13.84583 (mean)
               percent_no~s    =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.0091301	.0396345	-0.23	0.818	-.0868122	.0685521
age	.0217171	.0217632	1.00	0.318	-.0209381	.0643722
driving_experience	-.0103689	.0081384	-1.27	0.203	-.0263198	.005582
mileage	-.0027124	.0018042	-1.50	0.133	-.0062486	.0008238
percent_nonworktrips	-.0177314	.0090071	-1.97	0.049	-.035385	-.0000778

```
. margins, dydx(*) atmeans predict(outcome(3))

Conditional marginal effects                    Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==3), predict(outcome(3))
dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at           : gender          =    .3083333 (mean)
               age             =    2.241667 (mean)
               driving_ex~e    =    4.841667 (mean)
               mileage         =    13.84583 (mean)
               percent_no~s    =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	-.0034416	.0150507	-0.23	0.819	-.0329404	.0260572
age	.0081862	.0088915	0.92	0.357	-.0092409	.0256133
driving_experience	-.0039085	.0034619	-1.13	0.259	-.0106937	.0028767
mileage	-.0010224	.0008203	-1.25	0.213	-.0026301	.0005853
percent_nonworktrips	-.0066838	.0043569	-1.53	0.125	-.0152231	.0018555

```
Conditional marginal effects                    Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(decision_worktrip==4), predict(outcome(4))
dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at           : gender          =    .3083333 (mean)
               age             =    2.241667 (mean)
               driving_ex~e    =    4.841667 (mean)
               mileage         =    13.84583 (mean)
               percent_no~s    =        3.25 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	.0084144	.0365644	0.23	0.818	-.0632505	.0800794
age	-.0200149	.0200946	-1.00	0.319	-.0593995	.0193698
driving_experience	.0095562	.0074954	1.27	0.202	-.0051346	.024247
mileage	.0024998	.0016948	1.47	0.140	-.000822	.0058215
percent_nonworktrips	.0163416	.0082752	1.97	0.048	.0001226	.0325606

```
. margins, dydx(*) atmeans predict(outcome(5))

Conditional marginal effects                      Number of obs     =        120
Model VCE    : OIM

 Expression   : Pr(decision_worktrip==5), predict(outcome(5))
 dy/dx w.r.t. : gender age driving_experience mileage percent_nonworktrips
at           : gender          =    .3083333 (mean)
               age             =    2.241667 (mean)
               drivin~_ex~e    =    4.841667 (mean)
               mileag~         =    13.84583 (mean)
               percent_no~s    =        3.25 (mean)

------------------------------------------------------------------------------
                     |            Delta-method
                     |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------
              gender |    .010322   .0447865     0.23   0.818    -.0774579    .0981018
                 age |  -.0245522   .0242666    -1.01   0.312    -.0721139    .0230095
  driving_experience |   .0117225    .008979     1.31   0.192     -.005876     .029321
             mileage |   .0030665   .0019972     1.54   0.125     -.000848     .006981
percent_nonworktrips |   .0200461   .0096467     2.08   0.038     .0011389    .0389534
------------------------------------------------------------------------------

. 
. * Ordered probit model predicted probabilities
. predict p0oprobit, pr outcome(0)

. predict p1oprobit, pr outcome(1)

. predict p2oprobit, pr outcome(2)

. predict p3oprobit, pr outcome(3)

. predict p4oprobit, pr outcome(4)

. predict p5oprobit, pr outcome(5)

. summarize p0ologit p1ologit p2ologit p3ologit p4ologit p5ologit

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
    p0ologit |        120    .0166742     .007791   .0050688    .043895
    p1ologit |        120    .0589343    .0249286    .019225   .1393614
    p2ologit |        120    .1864526    .0552342   .0768633   .3202608
    p3ologit |        120    .3181628    .0280291   .2177691   .3420619
    p4ologit |        120    .2792268    .0544869   .1435565   .3685609
-------------+---------------------------------------------------------
    p5ologit |        120    .1405492    .0564327   .0480212   .3125128

. tabulate $ylist

decision_wo |
     rktrip |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |          2        1.67        1.67
          1 |          7        5.83        7.50
          2 |         22       18.33       25.83
          3 |         38       31.67       57.50
          4 |         34       28.33       85.83
          5 |         17       14.17      100.00
------------+-----------------------------------
```

Total	120	100.00

```
-
end of do-fi
```

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