# STATED PREFERENCE STUDY OF LONG-HAUL COMMERCIAL VEHICLE ROUTE CHOICE BEHAVIOR

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# Abstract

Highway ON-401 is among the most congested roadways in North America with a substantial mix of both passenger and commercial traffic. This trend is expected to worsen as e-commerce continues growing alongside population and economic development. Alternatively, tolled corridors such as Highway ON-407ETR have the potential to minimize congestion by re-distributing system-wide traffic and lowering negative environmental and economic impacts.

Research on commercial vehicle route choice is needed to inform planners in developing strategies that balance mobility and sustainability. Potential factors developed from an exhaustive literature review are incorporated into a stated preference survey on routing decisions. The results of this survey are used to calibrate mixed multinomial logit models estimating the probability of route selection for trucks. Findings indicate heterogeneity in truck route choice where on average, they are willing to pay up to $81 (2020 CAD) to save one hour of their travel time.

# Dedication

To my beloved family; To Maman, to Baba.

# Acknowledgments

First and foremost, I wanted to thank my parents who supported me through ups and downs although from a long distance.

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# List of Abbreviations and Terms

| Terms | Explanation |
|---|---|
| AADT | Average Annual Daily Traffic |
| AADTT | Average Annual Daily Truck Traffic |
| AIC | Akaike Information Criterion |
| Alternative | Options containing specified levels of attributes |
| API | Application Programming Interface |
| ASC | Alternative Specific Constant |
| Attribute | Features corresponding to each alternative |
| AVC | Asymptotic Variance Covariance |
| CATI | Computer-Assisted Telephone Interview |
| CBD | Central Business District |
| DCE | Discrete Choice Experiment |
| DIST | Distance |
| ec | Error Component |
| FHWA | Federal Highway Administration |
| GDP | Gross Domestic Product |
| GTA | Greater Toronto Area |
| HIT | Human Intelligence Task |
| HOS | Hours of Service |
| IIA | Independence of Irrelevant Alternatives |
| IID | Independent and Identically Distributed |
| LCM | Latent Class Model |
| Level | A specific value taken by an attribute |
| LL | Log-likelihood |
| LTL | Less-than-truckload |
| MNL | Multinomial Logit |
| MXL | Mixed Multinomial Logit |
| ON-401 | Ontario 401 Macdonald–Cartier Freeway |
| ON-407 ETR | Ontario Highway 407 Electronic Toll Route |

| | |
|---|---|
| OTA | Ontario Truck Association |
| PMC | Pseudo-random Monte Carlo |
| PTI | Planning Time Index |
| RP | Revealed Preference |
| rp | Random Parameter |
| RSC | Relabeling, Swapping, Cycling |
| SADT | Summer Average Daily Traffic |
| SC | Stated Choice |
| SP | Stated Preference |
| TC | Toll Cost |
| TL | Truckload |
| TT | Travel Time |
| TTI | Travel Time Index |
| TTV | Travel Time Variability |
| VOR | Value of Reliability |
| VOT | Value of Time |
| VTTS | Value of Travel Time Saving |
| WADT | Winter Average Daily Traffic |
| WTP | Willingness to Pay |

# Chapter One: Introduction

## 1.1. Research Motivation

Commercial Transportation is a crucial sector in Canada as it has a huge impact on both the economy and the environment. Economically, it accounts for 4.5% of country's gross domestic product (GDP) (Transport Canada, 2019). From year 2014 to 2019, the transportation industry has been growing approximately two times faster than the broader economy. Environmentally, transportation is one of the largest sources of emissions in Canada, second only to oil and gas industries by a very small margin (2%), and responsible for approximately 24% of produced emissions (Plumptre *et al*., 2017). Moreover, the commercial transportation sector represents about 5% of total employment in the country (Transport Canada, 2019).

As the second largest country in the world by land area, Canada maintains a reliable transportation system to support the movement of passengers and goods both nationally and internationally. Trucking is the largest mode within the freight sector based on the volume of goods. In the provinces of Quebec and Ontario, more than half of the total exported goods by value, excluding pipelines, have been shipped by road (Transport Canada, 2019). Ontario is a heavily trade-oriented province with approximately one-third of its GDP represented by imports and exports, placing it between the well-known trading countries of Germany and China (Anderson, 2012). The US is the biggest trade partner for Ontario representing approximately 80% of Ontario's total exports which nearly three quarter of this trade is being shipped by truck (Anderson, 2012).

## 1.2. Research Problem

Nevertheless, there are several challenges that transportation industry and particularly road-freight is facing. Given its immense demand it is no surprise to see Ontario hosting the busiest road corridor, i.e. Highway ON-401, in North America (Business Insider, 2012) and the busiest truck corridor in the world (Sun Media, 2008). This acknowledges the tremendous effect on environment where at the provincial level, transportation is the largest source of emissions within all economic sectors. On-road heavy-duty vehicles, defined as vehicles with gross weight rating of more than 8500 lbs (Canadian Environmental Protection Act, 1999), account for 9% of the total national emissions, yet they are projected to surpass passenger-transport emissions by 2030 according to their current fastest-ever rate of growth (Plumptre *et al*., 2017).

Commercial vehicles have always been a major contributor to on-road emissions. Their fuel consumption varies depending on the driving circumstances which directly affects the emissions they produce. The rate of emissions produced per mile decreases as vehicle speed increases to a certain optimal level (ICF, 2006). This relationship will also hold true for the other way around meaning that their emission production level will increase if their speed decreases when facing congestion. A 10% increase in traffic delays will result in an average of around 5% increase in $CO_2$ emissions (Kellner, 2016). This issue is not limited to trucks only as it also affects other vehicles in a real-world mixed traffic situation. A vehicle that would travel a more congested route with roughly 50% more travel time would ultimately produce around 50% more $CO_2$ emissions compared to traveling a route with smooth traffic (Bharadwaj *et al*., 2017). For example if the vehicle’s speed falls below 30 mph, it would emit almost double the amount of emissions for each mile traveled since their engine would operate more inefficiently (Frey *et al*., 2008). Therefore, congestion and the constant stop-and-go maneuvers will significantly alter the fuel consumption level resulting in substantial rise in emissions. This clearly states the extent of this environmental impact as it not only pollutes the air but also results in substantial consumption of energy resources.

Considering the pace at which Toronto is developing which is shown as the fastest growing central city in North America for several years (Petramala and Smyth, 2020), the AADT is expected to frequently hit 500,000 vehicles by year 2030. Furthermore, the recent Covid-19 pandemic and switching to remote formats has given rise to a stronger e-commerce advancement which results in an increase in commercial vehicle traffic. Having more trucks down the road would ultimately translates into a more severe congestion situation that will impact the region in a variety of ways. Traffic congestion will negatively affect the environment as it increases the vehicle emissions. Unquestionably, any disruption in the roadway corridor will directly impact the economy. Additionally, this will influence the attractiveness of the truck driving industry as it is already dealing with driver shortage issue. This reflects the criticality of this condition since it serves as a crucial local and regional pathway for both passengers and goods.

The constantly changing nature of transportation patterns requires comprehensive planning to mitigate disruptions on the road network and subsequent impact on the economy and environment. It has been understood that increasing capacity by adding more lanes or providing new highway infrastructures would not help the situation in the long term according to “induced demand" theory. This economic phenomenon states that the extra capacity will quickly attract more users resulting in congestion once again hence not a viable solution. Meanwhile there exists a tolled corridor (i.e. Highway ON-407 ETR) alternative to the Highway ON-401 major segment which was primarily built to relieve traffic along other arteries. However, offering one of the most expensive toll rates in the world attests to its underutilization. There is little information on appropriate toll pricing schemes as there is only a single toll route within the entire province. Therefore, what should be considered instead is the possibility to redistribute the vehicles in a way that maintains smooth travel conditions along various corridors. This can be achieved by gaining knowledge about future traffic patterns through accurate forecasts of travel behavior. This has been widely done for passenger transport (Gupta *et al.*, 2006; Nakamura and Kockelman, 2002) while comparatively, freight transportation lacks sufficient research despite its great impact on both the economy and the environment.

### 1.3. Research Goal

Forecasts of future travel patterns need to be estimated as part of the long-term planning process to ensure that adequate infrastructure is available where it is needed most. Travel forecasting models are used to project future mobility trends and to provide the basis for the determination of new policies. These models involve a series of mathematical steps that attempt to simulate the behavioral choices that humans make while traveling. One of the key stages within the travel demand modelling framework is the so-called route choice or trip assignment. The goal at this stage is to determine the proportion and frequency of vehicles expected to use each segment of the roadway. One of the most powerful tools that are commonly applicable in this area are discrete choice models. Their function is to predict choices made by decision makers that can maximize their utility which is dependent on a variety of factors. For freight activities, the modelling will need to simulate truck drivers' choice of route based on the route characteristics and their preferences to accommodate their needs to arrive at their destination on time.

Despite information available on truck volumes, there is limited available information on the extent of the impact of important factors on route choice. For example, the overall travel cost has been known to influence route decision (Hunt and Abraham, 2004; Wang and Goodchild, 2014). General costs such as fuel usage can be tied to the vehicle speed profile, weight, and distance travelled. However, the influence of toll costs in Ontario is hampered by limited observations from only one tolled route along Highway ON-407 ETR. Models built using revealed preference (RP) data from observed truck trips are often negatively associated with biases such as high correlations between variables and a lack of situational variety. Stated preference (SP) on the other hand collects behavioral information through a survey representing hypothetical choice situations to the decision-maker. This thesis evaluates both approaches in Section 2.1 and selects the SP method to better understand the interactions between several important route choice factors, including travel time, delay, distance, and toll cost.

## 1.4. Research Objectives

Developing a reliable forecast of future truck patterns on Ontario roads and mitigating negative impacts requires an accurate prediction of the future mobility patterns. In other words, this demand forecasting is concerned with the behavior of consumers of transportation services. This thesis will focus on the creation of a stated preference survey to investigate the factors that are difficult to obtain from observed data and performing forecasts of truck driver behavior using econometric modeling tools. For example, what are the important factors in truck routing decision relevant to the Ontario context? How important are these factors to the truck driver? How can we improve the transportation system using this information?

The following objectives are established to achieve this research goal:

> Objective 1. Perform an exhaustive literature review identifying the most influential factors for truck route choice.
>
> Objective 2. Design a stated choice experiment that includes hypothetical routing scenarios to elicit behavioral preferences.
>
> Objective 3. Integrate the experimental design into an online survey tool for distribution to a sample of Ontario trucking carriers.
>
> Objective 4. Estimate the impact of influential factors on truck route choice in Ontario using discrete choice models.

In this process, Ngene software will be used to design the SP experiment in Objective 2. The Qualtrics platform will be employed for survey implementation in Objective 3. The Amazon Mechanical Turk crowdsourcing platform will be used to collect contact information on the target population. In Objective 4, NLogit software will be applied to estimate different logistic models and calculate route choice probabilities. After completing these objectives, better forecasting of future truck trends will be possible to ensure that transportation infrastructure remains sufficient. The findings of this study will help transportation engineers to make informed decisions to improve freight planning by reducing congestion and emissions for trucks and improve the transportation system for all road users.

## 1.5. Scope of work

The route characteristics for this research are based on the experience of truck drivers travelling through the City of Toronto, located in Ontario, Canada. A stated preference survey was designed based on trip characteristics relevant to the area in which the study is being conducted. The survey was administered online yet distributed to truck carriers in Ontario with an emphasis on route characteristics pertinent to the Greater Toronto Area (GTA).

The scope of the thesis will focus on inter-regional truck trips. Therefore, urban freight are not explicitly tested in the model. The final survey was conducted in January 2021. This survey solicited responses from both truck drivers and any other employees responsible for truck routing activities.

## 1.6. Thesis Structure

The remainder of the thesis is organized as follows. A literature review on stated preference data, route choice factors, and experimental designs will be given in Chapter 2. Chapter 3 will familiarize the reader with the Greater Toronto Area (GTA) as the study area used to generate base-line attributes for the stated preference survey. The next section in Chapter 4 will explain the survey design methodology employed for this thesis, including a detailed investigation on different design specifications and considerations. A preliminary stated choice design will be discussed in Chapter 5 as the pilot version. The pilot study will not only attempt to obtain prior parameter information to educate the final model, but it will also reveal the performance of the design. Chapter 6 will focus on revising the design procedure after reviewing the initial lessons learned and to train final design. Once the design has been generated, research proceeds to data collection where in Chapter 7 the actual survey format given to respondents will be discussed using Qualtrics software. Chapter 8 will analyze the results of the survey by performing a descriptive analysis of the results and estimating a discrete choice model. Finally, Chapter 9 will summarize the model outcomes and provide the final conclusions.

# Chapter Two: Literature Review

## 2.1. Stated Preference and Revealed Preference

An accurate forecast of choice behavior requires data records that are comprehensive, ample, and correct (Cai and Zhu, 2015). The collected data should be exhaustive to capture the complete attributes for the intended context. Data should also be large enough to provide sufficient statistical confidence on its accuracy. And finally, data should be precisely collected and refined with no major biases to be considered valid. In the context of choice modeling, the most prevalent data sources are either revealed preference (RP) or stated preference (SP).

RP data approaches such as GPS observations are the recorded behavior of decision-makers in the past which have been utilized in an abundance of studies such as Knorring *et al*., (2005); Uchida *et al*., (1994); Wang and Goodchild (2014). Although they are real events, limitations arise from a lack of choices that are not yet prevalent (Louviere *et al*., 2000) and the difficulties in separating the influence of each variable. On the other hand, SP data deals with hypothetical decision-making scenarios which users declare to behave in a real-world situation and can be used to overcome the RP limitations. A few examples of SP studies include Sun *et al*., (2013), Arentze *et al*., (2012), and Hunt and Abraham (2004). The basis of the SP approach are hypothetical scenarios with combinations of attributes as alternatives to be chosen by respondents. It therefore represents the plausible behavior stated by the respondent.

Some studies have attempted to offset the downside of each approach by combining them together. In situations where RP is available for SP survey respondents, a hybrid combination or joint RP-SP model can be estimated (Ben-Akiva *et al*., 2016). The key point in this type of study is to track the respondents before and after the decision-making to capture the consistency between the stated and the actual behavior. For example Ben-Akiva *et al.,* (2016) were able to redress the lack of actuality in SP data with the implementation of GPS loggers by collecting location, speed and timestamps. On the other hand, by providing a dedicated personal webpage for respondents which was exclusively designed based on their past revealed behavior, they were able to rectify the deficiency of RP data in terms of trip attributes and freight related characteristics. This approach has also enabled them to better capture the complexity and heterogeneity in behavior between different truck drivers.

### 2.1.1. Survey Advantages and Disadvantages

SP surveys have two barriers to achieve high-quality data (Knorring *et al*., 2005). First, respondents should be completely honest while answering hypothetical questions. And secondly, the survey might be answered imperfectly if the respondent is unable to recollect past events or understand the context of the questions.

Therefore, researchers tend to shift to RP methods such as GPS data collection to incorporate an actual route choice scenario, such as toll vs. non-toll in Ben-Akiva *et al*., (2016) and Wang and Goodchild, (2014), or downtown vs. bypass route in Knorring *et al*., (2005). Even though RP data carry valuable information about the real trips in the past, they also suffer from several limitations. For example, raw GPS data does not typically give the analyst explicit information on route characteristics and factors associated with the decision. To tackle this issue, the modeler must subsequently infer this information based on limiting assumptions and the availability of supplemental data. Alternatively, the modeler could design an RP survey to ask drivers to provide such details, but this is a costly and labor-intensive process.

RP data are fairly restricted in three major avenues (Tierney *et al*., 1996) that SP counterparts can overcome. Firstly, they are extremely constrained in providing adequate richness in variability and correlation structure of each potential factor to be incorporated without confoundment. On the other hand, data from stated choice experiments can capture the independent contribution of each source of variability in the evaluating utility function if the experimental design is properly created. Secondly, SP studies may offer insights into new alternatives which either does not currently exist or is very different from commonly used alternatives, while RP data is unable to reflect such benefit. Lastly, the other major limitation of RP approach that can be controlled with a SP survey is the inability of the former to appropriately account for the alternatives that were not chosen. For example, the analyst only has access to the information on the attributes of the chosen route, such as travel time, while relying on inferences to estimate the attributes of the other alternatives. The SP however provides information on all choices.

Given the above-mentioned factors, the analyst must choose one of these options depending on their applicability to the research question. Generally, in transportation related studies SP surveys are very useful since the effect of a new policy or measure can be estimated before it is implemented. Additionally, RP studies are often costly to conduct since they require recording devices and post-processing to clean the data. SP data enable the researcher to collect many observations from the same user and require much less processing. This issue was particularly important for the thesis study area because of the scarcity of toll routes in the Greater Toronto Area (only Highway ON-407 ETR) which made SP a more favorable approach.

### 2.1.2. Data Collection

RP approaches for route choice rely primarily on GPS loggers to trace observed vehicle paths. GPS-based data are straightforward with basic details such as the latitude and longitude of a vehicle at a specified date and time. This data has also become widely available due to their prevalence in both freight trucks and modern passenger cars. While GPS data is often given to a modeler after completion for post-processing with no design element beforehand. By contrast, SP survey methods require careful and accurate survey design and administration. This includes prior qualitative research, consideration of realistic attribute values in the design, and significant data collection efforts which add to its complexity.

There are several different delivery methods to administer a survey experiment. These range from traditional face-to-face paper-based interviews to computer-assisted telephone interviewing (CATI), to modern web surveys that may be customized for each individual respondent. The customization is a creative way to make sure that the attribute values assigned to the respondents are not too inconsistent with their experience and expectations by either asking them a question in advance (Hunt and Abraham, 2004) or extracting it from their actual behavior (Ben-Akiva *et al*., 2016). Although internet-based surveys are easier and cheaper to run, the biggest challenge associated with this type of survey is the lack of interaction between survey team and respondents, which may lead to inaccurate results due to the complexity of the survey.

According to Ben-Akiva *et al*., (2016), it was proven that in-person interviews and generally the physical presence of research team have the most response rate since contact is easily maintained. This finding is consistent with the 30 percent response rate of face-to-face interviews by Kawamura, (2000) as compared to 10 percent rate for mail survey by Zhou *et al*., (2009). To improve response rates, Ben-Akiva *et al*., (2016) have utilized incentivization tools, both monetary and non-monetary, as an encouragement for respondents to remain engaged until the last step of the survey completion. They gave drivers a complementary analysis of their behavioral pattern as non-monetary compensation in addition to monetary incentives which was observed to be a useful strategy. Generally, in community-based SP surveys, it has been proven that monetary incentives would significantly increase response rate, with high lottery incentives found to be the most cost-effective followed by prepaid cash and low lottery (Gajic *et al*., 2012). However, the author notes that these results should be cautiously incorporated into target-specific research as it might compromise data accuracy.

#### 2.1.3. Size and Participants

A famous proverb says that "You may know by a handful the whole sack" yet there are important scientific caveats due to potential bias. Bias can be mitigated if the sample fulfills three conditions including randomness, representativeness, and appropriateness in size (Martínez-Mesa *et al*., 2016). The nature of this research is on route decision making, but truck drivers are not the only ones in charge of making decisions. This applies to both pre-trip planning and en-route decisions. Sun *et al*., (2013) have identified a degree-of-freedom indicator for decision making in their analysis and have found that approximately 35 percent and 15 percent of the drivers have at least some sort of constraints in their pre-trip planning and en-route choices, respectively. In addition, Zhou *et al*., (2009), Hunt and Abraham, (2004), and Arentze *et al*., (2012) have also considered other parties such as logistic managers, truck dispatchers, and trip planners in their data collection. This has enabled them to incorporate numerous external factors into their experiment.

The literature review table in *Appendix A* demonstrates the inconsistency between the survey participants of different researches. Zhou *et al*., (2009); Arentze *et al*., (2012); Sun *et al*., (2013) all found that drivers oversee route decision making at least 80% of the time. As a result, this category of decision makers would ideally be drawn proportionally in route choice surveys. For example, a survey with 1,000 randomly drawn survey participants should be stratified to include 800 drivers. Knowing that the decision makers' characteristics would affect the choice process, one might choose the survey participants precisely to preserve randomness and representativeness of the sample. Regarding the sample size, generally there would be two situations, either running a survey or collecting digital GPS data. For the latter, one needs to be careful to gather sufficiently dense data in terms of duration and intervals to be able to extract patterns out of it. For instance, Knorring *et al*., (2005) have used 250,000 unique truck GPS data over a 13-day period which consists of more than 60,000,000 observations of truck time and location. In survey-type data we can generally assume that the larger the dataset the better, but, an optimum trade-off between data collection cost and data processing time must be strictly followed.

In most SP studies, the number of observations has always been more than a thousand. However, this does not mean that a thousand respondents were employed, instead, the number of respondents multiplied by the number of choice situations have almost always exceeded a thousand. All in all, as was stated earlier, a dataset will be identified as high quality as long as it could satisfy the above-mentioned criterion. Practically, in the case where one will conduct an in-person interview, she needs to pick the locations and the corresponding respondents in those locations in a manner that represents a good picture of the whole industry.

### 2.2. Route Choice Factors

This section reviews the most prevalent factors affecting truck route choice. In a typical choice environment, there are numerous factors that can affect the outcome. These factors can broadly be categorized into choice characteristics and respondent characteristics. In a route preference study, these two groups correspond to the attributes of the routes and the characteristics of the decision maker, respectively. In the context of routing decisions, people put a substantial value on the time and cost associated with their trip when determining their preferred route. This can be supported by the findings that time-related attributes and travel cost are the most influential factors (Arentze *et al*., 2012; Hunt and Abraham, 2004; Wang and Goodchild, 2014). The following review will focus on these two categories, followed by a discussion of other relevant factors.

#### 2.2.1. Time-related Factors

Time is a fundamental determinant when deciding between different routes. Knorring *et al*., (2005) stated that truck drivers value distance and time at different levels yet are all considered time minimizers above all. Different researchers have used different forms of time-related attributes in their route choice model. Some have only considered trip travel time (Kawamura, 2000) while others have also taken reliability of this attribute into account (Kong *et al*., 2018; Wang *et al*., 2016). Travel time reliability considers the associated uncertainty of travel time and can be a key performance measure for shippers and freight carriers to remain competitive in their businesses. This factor may capture various sources of delay such as traffic incidents, weather, and special events (Hunt and Abraham, 2004). FHWA, (2005) have suggested different measures to calculate travel time variability including the 95$^{th}$ percentile travel times, buffer time, buffer time index, and planning time index.

The travel time reliability indicates the degree to which a route is reliable, or equivalently, the extent that might be added to the travel time under potential circumstances. For example, Hunt and Abraham, (2004) have included this reliability feature as probability of delay in their route choice utility function where they have observed a greater concern for uncertainties in travel time when compared to the actual magnitude of travel time. In a conjoint experiment conducted by Arentze *et al*., (2012), a delay variable was used with three different congestion levels including low, medium, and high for their proposed routes. Sun *et al*., (2013) have used predictability of travel time as a relevant consideration for time and its reliability with results showing that 84% of drivers consider this factor in at least half of all situations. In another study, the travel time reliability metric was defined as the standard deviation of travel time and was included along with observed travel time (Wang and Goodchild, 2014). However, the authors observed that these two measures should not be used together due to high levels of correlation. On the other hand, Hunt and Abraham, (2004) concluded that the most appropriate utility function should include travel time, delay time, and the probability of delay as individual factors.

Hunt and Abraham, (2004) applied four different logit models with different inputs to measure the significance of different route attributes and their relative importance on route choice behavior of commercial movement in Montreal, Canada. Their analysis showed a higher level of significance for probability of delay over toll cost and road type. The single factor of drive time yielded poorer results in the absence of delay probability. Arentze *et al*., (2012) concluded that for drivers, road type and probability of delay positively correlate to a great extent. They then interpreted this result such that higher probability of delay might be utilized as a measure to define truck-friendly routes which allow for wider delivery timeframes.

This probability of delay attribute requires a high level of detail, which makes it impractical in many cases. This complexity arises from the stochastic nature of traffic events. However, research has suggested that indirect approaches can roughly approximate the true variability. For example, the delay probability can be segmented into terms which are easier to capture, such as the historical rate of accidents (Hunt and Abraham, 2004). Toledo *et al*., (2020) calculated reliability based on the difference between the minimum and maximum of observed travel time along a specific corridor. Kong *et al*., (2018) utilized two distinct, yet partially correlated, attributes to measure the impact of reliability on truck routing decisions. This included the travel time index (TTI) ratio as a metric for congestion intensity, and planning time index (PTI) ratio as a measure for travel time reliability. The former calculates the mean of all observed travel time during one hour along a selected route and divides it by the corresponding free flow travel time while the latter takes the 95$^{th}$ percentile of all travel times during one hour and divides it by free flow value.

### 2.2.2. Travel Cost and VOT

Substantial research in the past has focused on travel cost and toll facilities considering its importance on making revenues and reducing congestions. The concept of value of time (VOT) can be derived from models containing variables of travel time and travel cost. VOT in transport economics is the opportunity cost of time that the decision maker is planning to spend on his trip (Small, 2012). Both the positive and the negative form of the travel cost concept was utilized in the literature. Kawamura, (2000) and Holguín-Veras *et al*., (2006) had used the negative road pricing scenario to examine when the switch between tolled and non-tolled facilities occurs. Zhou *et al*., (2009) have gone through the positive scenario as a road bonus incentivization tool for using toll routes.

Holguín-Veras *et al*., (2006) looked at the effect of toll price differentiation during different traffic congestion situations in toll facilities. The novel study analyzed how freight companies react to time-of-day road pricing in the US. The authors started by studying the behavior change of truck drivers before and after the implementation of road pricing policy to see how effective it was to move freight traffic to the off-peak periods. The study observed multi-dimensional behavioral strategies. The change in facility usage was found to be the last resort alternative while productivity increases (i.e. increasing the efficiency by carrier) account for the most optimal strategy. However, the facility usage was found to be the most likely strategy when combined with cost transfers. Two reasons were identified for justifying this behavior. First, toll costs are proportionally small compared to marginal off-peak costs such as overtime pay. Second, it was understood that delivery schedule constraints imposed by customers prevent the shifting to happen which was relatively more popular among for-hire carriers. This is, however, in complete contrast with another similar study which have found higher levels of VOT for trucks during off-peak periods (Wang and Goodchild, 2014). They interpreted this finding in a way that most commercial trips with strict delivery timeframes obligated by customers do not necessarily happen during the peak period. They stated that there must be a distinct definition for truck-specific peak period which calls for a broader research in this area.

Zhou *et al*., (2009) investigated different segments of the trucking industry and their use toll roads and incentivization. This behavior was analyzed using an SP survey containing four choice sets of toll/non-toll and with/without incentives among more than 2000 participants consisting of truck drivers, logistic managers, and related businesses in Austin, Texas. The study used 20 different incentives rated by respondents to create a random parameter logit model (mixed logit). Their study revealed that the most preferred and most effective incentives were both monetary, including reduced fuel prices and off-peak discounts respectively. As a result, they have estimated a value of $USD 44.2/h for travel time savings. This indicates that a truck driver is willing to pay $44.2 to reduce his travel time by one hour.

Arentze *et al*., (2012) studied whether financial incentives or pricing instruments are more efficient and the driver's sensitivity to these pricing policies. They developed a conjoint experiment of both attributes and context variables with three different varied levels from 15 diverse transport companies focusing on short distance freight in The Netherlands. The respondents were randomly assigned either an environmental bonus or congestion charge scenario with different levels for each factor [Low, Medium, High] as the hypothetical situation in their SP choice task. Finally, by employing a mixed logit model, it was observed that high level of road pricing is the most deterring variable when compared to other variables such as high congestion, while road-bonus strategies, such as tax deduction, appeared to have no significant effect on truck route choice behavior. This means that route users are more sensitive to road pricing than road bonuses in the context of pricing policies.

Wang and Goodchild, (2014) have used toll/non-toll scenarios for their RP model collected for trucks before and after the implementation of a toll facility in Seattle, Washington. Their results on the effect of toll on truck speed and routing indicated that toll cost which were varied by time-of-day, truck type, and payment method was more significant than both travel time and its reliability. however, Hunt and Abraham, (2004) found that the probability of delay was more influential than travel cost and time. To complicate matters, Arentze *et al*., (2012) estimated a complete reversed order for the attributes' significance where they concluded travel time as the most significant factor followed by road pricing and congestion.

In the context of time-of-day congestion pricing, Holguín-Veras *et al*., (2006) did not find a considerable significance for reduced toll costs during off-peak due to the inflexibility of delivery schedules and the marginal cost associated with overtime pay. On a similar topic, Kawamura, (2000) and Hunt and Abraham, (2004) both observed greater sensitivity to time-related coefficients when compared to cost-coefficients. The former concluded that travel time has greater variation than out-of-pocket cost and the latter suggested that presenting a toll facility should place more emphasis on the potential delay avoidance. These, however, does not match with what Zhou *et al*., (2009) have found which states that in an incentivization context for using toll routes, reduction in cost of use by any means works better than improvement in time savings. This indicates that time-related attributes are better explanatory variables in predicting route choice behavior than cost-related attributes which is in complete contract to what was said before.

The inconsistencies between these findings shed light on the context-dependent nature of this type of studies meaning that depending on different circumstances of a study area such as geography, culture etc. certain attributes might be significant while they are not at some other places. Nevertheless, one important conclusion can be drawn from all these different studies which testifies the theory which says humans tend to be more strongly deterred from losses than attracted by gains of a same amount. This was concretized by Hunt and Abraham, (2004) and

Arentze *et al*., (2012) where they concluded that tolled alternatives should stress travel time savings to the extent that it does not overshadow reductions on probability of delay.

The VOT concept had been studied for more than 60 years, with Haning and McFarland, (1963) being early researchers to introduce this concept into freight transportation. A modeler can extract the ratio between different marginal utilities (i.e. parameter coefficients) in a utility function. The VOT can be calculated by taking the marginal utility of travel time divided by the marginal utility of cost to result in a dollar per hour metric which can be seen in equation below.

$$VOT\ (\$/hr) = \frac{\beta_{TT}}{\beta_{TC}} \qquad \text{Equation 1}$$

Where $\beta_{TT} = \frac{\partial U}{\partial TT}$ and $\beta_{TC} = \frac{\partial U}{\partial TC}$

A summary of VOT results are given in Table 2.1. The monetary values have been inflated and exchanged to an equivalent 2020 Canadian dollar using www.inflationtool.com and www.morningstar.com for comparison purposes.

Table 2.1 – Literature Summary of Value of Time for Commercial Vehicles (2020 $CAD/hour)

| Authors | SP or RP | VOT ($CAD/hr) | Study Area | Remarks |
|---|---|---|---|---|
| Zhou *et al*., (2009) | SP | $53.87 | Texas | |
| Kawamura, (2000) | SP | $47.15 | California | |
| Wang and Goodchild, (2014) | RP | $36.51 | Washington | The reported value corresponds to off-peak period which was 40% higher. |
| Tsirimpa *et al*., (2019) | RP-SP | $79.98 | Portugal | |
| Hyodo *et al*., (2007) | N/A | $57.01 | Tokyo, Japan | |
| Toledo *et al*., (2020) | RP | $64.64 | Texas, Chicago, Ontario | Reported median VOT for non for-hire drivers. |
| Mei *et al*., (2013) | N/A | $74.45 | Ohio, Illinois, Indiana, Kansas, Michigan, Iowa | The reported VOT corresponds to dairy commodities which was the highest. |
| Smalkoski and Levinson, (2005) | SP | $88.96 | Minnesota | |
| Ismail *et al*., (2009) | SP | $121.87 | British Columbia | VOT based on border crossing costs. |
| De Jong *et al*., (2014) | SP | $69.76 | The Netherlands | All truck sizes included (2-40t). |
| Wynter, (1995) | SP | $104.17 | France | Mean VOT for different ranges of trip distance. |
| **Average VOT = CAD$74.78/hr** | | | | |

As can be seen in the table above, there is substantial variability in the calculated VOT from different studies, ranging from $36 to $128 in Canadian 2020 currency. There are a handful of reasons that can explain this variability. One of the most important indicators is the location of the study in terms of how drivers culturally behave in their route choice. A region's geographic location and corresponding economic situation are also influential on the routing behavior of truck drivers. According to a microeconomic theory, VOT correlates with income which has a lognormal distribution (Aitchison and Brown, 1957). For example, higher hourly wages may result in a higher VOT since time spent delayed will become more costly for the business. Additionally, there are some internal factors that are influential in estimation of this value as well. For example, a larger truck with a significant amount of highly valuable goods will intuitively have a higher VOT when compared to a relatively smaller truck carrying low-value cargo (De Jong *et al*., 2014). Moreover, depending on the time-of-day, which changes travel time due to congestion, truck drivers have different attitudes towards their route choice and subsequent VOT. VOT results will unavoidably vary due to the variables, context, and model design techniques (Shams *et al*., 2017).

In addition to VOT, some studies have also investigated the Value of Reliability (VOR). De Jong *et al*.,(2014) explained this concept as "the monetary value of a change of an hour in the standard deviation of travel time", while Toledo *et al*., (2020) describes the variability as the square of the different between the minimum and maximum measured travel time during a day and its trade-off with toll cost. De Jong *et al*., (2014) have produced different values for different entities within a freight context and Toledo *et al*., (2020) have extracted a probability density distribution of this value for different driver types to capture heterogeneity. The table below reports these values along with some contextual information. For further information we refer to this paper where they have compared different methods of calculation reliability (Wang *et al*., 2016).

Table 2.2 – Value of Reliability for Commercial Vehicles (2020 $CAD/hour)

| **Author** | **Method** | **VOR** | **Study Area** | **Remarks** |
|---|---|---|---|---|
| (De Jong *et al*., 2014) | SP | $25.69 | The Netherlands | All truck sizes (2-40t). |
| (Miao *et al*., 2014) | SP | $128.34 | Texas and Wisconsin | Long-haul trucks only. Value of Delay (VOD) listed instead of VOR. |
| (Toledo *et al*., 2020) | RP | $42.33 | Texas, Chicago, Ontario | Reported Median VOR for non for-hire drivers. |

### 2.2.3. Other Factors

An investigation of the literature suggests that there are other factors affecting route choice decisions beyond time and cost. These factors can also be grouped into two categories including route characteristics such as roadway type (Arentze *et al*., 2012; Hunt and Abraham, 2004; Rowell *et al*., 2014) and decision makers' characteristics (carrier, shipment, and driver) such as contract type (Holguín-Veras *et al*., 2006; Kawamura, 2000; Zhou *et al*., 2009). In this section, the most relevant attributes that have been discussed multiple times in the literature will be elaborated.

Truck drivers may make several stops along their routes while delivering goods to their final destinations. Ben-Akiva *et al.*, (2016) studied a group of truck drivers over an extended period of time and have found that rest-, fuel-, meal-, and maintenance-purpose stops nearly account for half of all stops made during this period.

Sun *et al.*, (2013) studied the considerations that truck drivers would involve in the context of choice process between a tolled and a free route. The authors found that the availability of fuel stations is a factor that most drivers are concerned with. Their result showed that 88% of the drivers consider availability of refueling locations at least half of the time, followed in importance by travel time predictability (84%) and availability of parking locations (81%). Rowell *et al.,* (2014) similarly found that long-haul carriers are very likely to rate availability of fuel stations and parking areas as considerable factors when making route decisions. Conversely, Arentze *et al.*, (2012) did not find significance for the availability of rest areas. The availability of rest areas along the routes was proposed as an incentive by Tsirimpa *et al.,* (2019) where it was found to have a positive impact on route choice yet was less attractive than other incentives such as discount on fuel price and toll rates. In a similar context, Zhou *et al.*, (2009) have also found dining facilities with better parking lots for trucks was among the most preferred incentives to use toll routes and was ranked higher than off-peak toll discounts by a very small margin.

Segmenting truck trips by industry has been used in some studies (Arentze *et al*., 2012; Kawamura, 2000; Sun *et al*., 2013; Zhou *et al*., 2009). There is also evidence of heterogenous behavior between drivers. Sun *et al.*, (2013) found that owner-operator drivers often pay out of pocket for expenses such as toll and fuel charges. These drivers tend to select routes that minimize these additional costs. Both Kawamura, (2000) and Zhou *et al.*, (2009) found that owner-operators are less willing to pay for these expenses. Conversely, company owned shipping and for-hire carriers are more likely to select toll routes due to the flexibility on transferring costs (Holguín-Veras *et al*., 2006). Zhou *et al.*, (2009) have also investigated how different segments of the trucking industry use toll roads and how incentivization would impact their use. They segmented the truck industry into five classifications based on their characteristics as 1. owner-operator, 2. for-hire, 3. private carriers, 4. less-than-truckload (LTL), and 5. combination of the first two categories. Their study revealed that the least and the most likely truck industries to use toll roads were owner-operator and company-owned shipping, respectively.

Kawamura, (2000) studied toll road usage in California to estimate the point of diversion where the switch from non-toll to toll road occurs. He pivoted his SP data based on three VOT grouping variables including business type, shipment size, and compensation method. The data was segmented by truckload (TL) or less-than-truckload LTL, private or for-hire, and hourly or other payment structures (fixed salary, commission by mile/load, etc.). By applying a logit model and assuming a lognormal distribution for VOT, he concluded that VOT usually varies with business type and compensation method but not with the shipment size. Within each category, for-hire and hourly pay scale types have higher VOT compared to private and other pay scales.

Rowell *et al.,* (2014) conducted an analysis where they identified service type (long-haul trucking, regional trucking, city delivery, and parcel delivery) as the covariates for group segmentation. Under this categorization, they found minimizing costs and meeting customer requirements as items that have significance regardless of industry size and type. They have also introduced two scenarios for truck trip length as more than 300 miles for semi-long trips and more than 500 miles for long-haul trips and found different significant factors for each. For example, road-related attributes such as size and weight limits, were shown to be more important for semi-long trips, while truck parking and Hours of Service (HOS) limits for long-haul trips.

Road category is a contributor to the final routing decision of truck drivers. Quattrone and Vitetta, (2011) found that a higher the level of service of a road will make it more likely it will be chosen by truck drivers. Generally, drivers have a stronger preference towards highways as compared to local roads, keeping all else equal (Arentze *et al*., 2012). This factor was introduced as an individual parameter in different route choice models and had a significant positive value for freeways (Hunt and Abraham, 2004) and a negative value for local roads (Arentze *et al*., 2012). Rowell *et al.,* (2014) have also investigated the impact of this attribute on the route choice and observed it to be the second most discriminating factor between companies. This means that road category was an important priority to one subgroup of companies and not at all for others. This factor was also used as an indicator of perceived speed by Knorring *et al.,* (2005).

Knorring *et al.,* (2005) modelled the observed choice behavior between a route passing through the downtown of a metropolitan area and a bypass route for ten individual origin-destination pairs in the US. Using a logit model, they analyzed driver preferences for the bypass route as a function of perceived speed. They observed a rather large change in the percentage of drivers using downtown route (10%) in exchange of only a 4 mph increase in perceived speed. Although their results indicated that drivers value distance and time at quite different levels, they have a fairly similar attitude in their willingness to take risk. That is, they tend to always opt out for using a route with lower perceived speed profile to reduce the risk of confronting congestion, hence primarily risk averse.

Sun *et al.,* (2013) concluded that fuel consumption is rarely considered as relevant factor. In their study, drivers were found to be least concerned with this factor as almost half of their sample (%46) never considered this attribute in their route choice. Although their sample size for this factor was not reliably large, they have observed that none of the respondents consider this factor usually or always. Driver experience and familiarity with the route was also investigated in a few studies (Knorring *et al*., 2005; Kong *et al*., 2018). Knorring *et al*., (2005) have concluded that truck drivers decide based on their perception instead of making a blind guess about route alternatives. They stated that this perception is possibly coming from their past experiences as well as their knowledge on the route.

All in all, it is now understood that different factors have different effects on the final truck routing decisions. Comparing the results of the above-mentioned studies, it can be argued that the choice of route choice is subject to the context. The extensive variability in different truck routing studies was seen and testified the fact that there is no one-size-fits-all approach for this specific behavior. Hence, this research attempts to investigate the most influential factors relevant to the study area's context. It will try to fill the gaps by studying the attributes that either have not been considered or have been ill-considered in the literature.

## 2.3. Stated Choice Experiments

### 2.3.1. Introduction

Stated choice methods are a branch of discrete choice experiments (DCE) which were proposed by Louviere during 80s (Louviere and Woodworth, 1983). The terms stated preference survey and stated choice experiment have been used interchangeably in the literature, however, one distinct difference should be noted. Essentially stated choice experiments are the tools used to collect stated preference data. They have been developing ever since with a wide range of applications in preference-elicitation studies. This spans from health studies to transportation economics. This approach belongs to a bigger, more inclusive umbrella of consumer behavior marketing and its fundamental purpose is to investigate the independent impact of various variables on the outcome of recorded decisions made by individual respondents in a hypothetical environment (ChoiceMetrics, 2018).

The procedure consists of a hypothetical decision-making scenario for the sampled respondents in a survey set-up. These experiments contain several questions that are referred to as choice situations, each of which comprises of a few alternatives to compare. Each alternative is characterized by its corresponding features (also known as factors or attributes). Each of these attributes should then differ in value (i.e. level) across alternatives and choice tasks. Ultimately, respondents will face these distinguishable alternatives and select one that is most realistic for them based on the context of the question. The underlying procedure of defining and setting all these steps is referred to as “experimental design”.

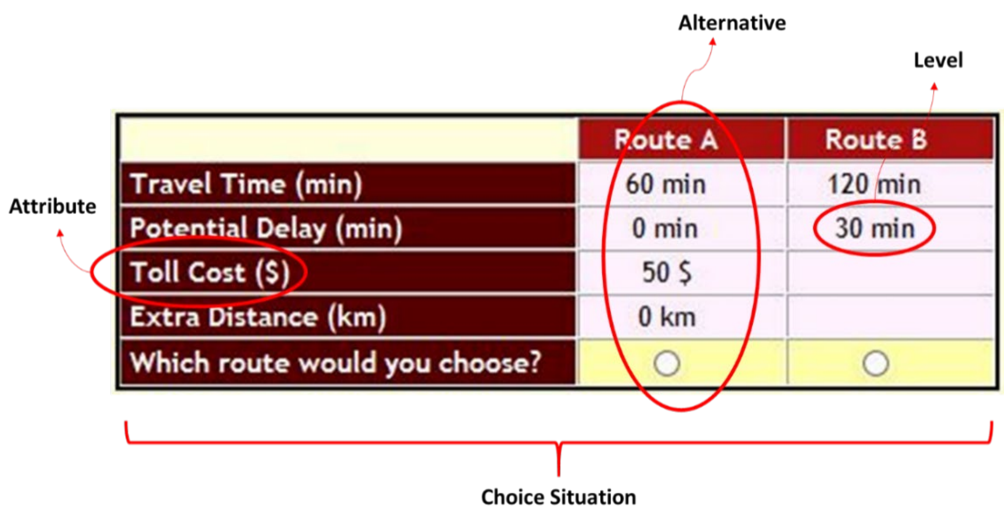



Figure 2.1 – A Typical Stated Preference Choice Scenario

Discrete choice experiment techniques trace back to 1960s when Lancaster, (1966) first suggested his novel criterion in consumer theory. He argued that it is not objects such as goods, products, or services that generally hold utility for consumers, but instead it is the characteristics and features of these objects (Lancaster, 1966). Practically, stated choice (SC) designs recreate market scenarios by means of offering different alternatives as weighted combination of different attributes. They ultimately target to capture how individuals consider these combinations of different information in the process of decision making.

As indicated above, this process requires carefully constructed hypothetical situations in which different choice scenarios are offered. The final product typically contains several choice situations, each of which has two or more alternatives forming a choice set for the respondent. The respondents are therefore supposed to choose between *alternatives* that are differentiated by their *attributes*. Different attributes for each route can be included such as a travel cost and travel time. These attributes usually differ in their dimensions which are called *levels*. It is the attribute levels in each alternative that are compared to the other choice alternatives. Therefore, experimental design is the process of systematically populating a design matrix with appropriate attribute levels in order to generate a meaningful, accurate, and efficient survey (ChoiceMetrics, 2018).

There are various methods of creating the design matrix for an SP survey depending on different design criteria. The most suitable approach should correspond to the main research objectives and tailored limitations corresponding to that specific area of research (Johnson *et al*., 2013). The survey procedure guideline below in Figure 2.2 demonstrates the fundamental stages of an SC design.

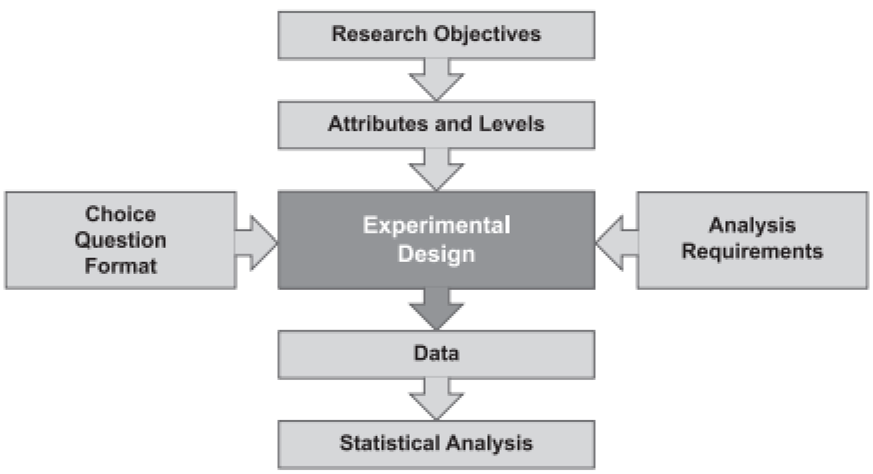



Figure 2.2 – Developing a Discrete Choice Experiment (Johnson *et al*., 2013)

In the sub-sections below, a brief introduction and background on SC designs will be provided to help determine an appropriate design methodology for this thesis.

### 2.3.2. Design Methods

Once the attributes and their levels have been identified, they will be used as inputs for designing an experiment. Historically, different methods for constructing experimental designs have been proposed. Historically, researchers have employed standard linear regression to manually produce pre-made coded tables due to a lack of computer-aided programs (Hahn and Shapiro, 1967; Zwerina *et al*., 1996). With technology advances, automated software has replaced these manual methods. Additionally, the advent of more powerful software has given rise to newer and more efficient approaches for design generation.

Researchers have traditionally used an approach called orthogonal design to deal with the correlation structure between attributes. In the context of freight transportation choice modeling, an abundance of studies have implemented this technique (Beuthe *et al*., 2008; De Jong *et al*., 2014; Small, 1999). However, the orthogonality principle which is an important property for linear models, has been suggested as a less than desirable criterion for discrete choice models since they are not linear (Train, 2009). In fact, the correlation structure between the differences of the attributes is more important. This gave rise to a more recent approach called efficient design. This type of design attempts to minimize correlation structures and also produce statistically significant results, or equivalently minimized standard errors. This approach is relatively newer and was used in a smaller number of freight-related choice modeling studies (Brooks *et al*., 2012; Tsirimpa *et al*., 2019), however, it has drawn significant attention from researchers recently. Given below is a brief overview of the two existing approaches.

### 2.3.3. Orthogonal Designs

The most basic orthogonal design is a full factorial design which considers every possible combination of attribute levels. For example, consider a situation where there are three bi-level attributes (A, B, and C). A full factorial design for such condition would result in producing 8 unique choice situations (S). In total there are eight choice situations that contain every possible combination of these attributes. The table below exhibits the idea, with -1 representing one level of each attribute and 1 representing the other level.

Table 2.3 – Full factorial design example Adapted from (ChoiceMetrics, 2018)

| **Choice Situations (S)** | **Attributes** | | |
|---|---|---|---|
| | **A** | **B** | **C** |
| 1 | -1 | -1 | -1 |
| 2 | -1 | 1 | -1 |
| 3 | -1 | -1 | 1 |
| 4 | -1 | 1 | 1 |
| 5 | 1 | -1 | -1 |
| 6 | 1 | 1 | -1 |
| 7 | 1 | -1 | 1 |
| 8 | 1 | 1 | 1 |

Now consider a situation where there are more than 3 attributes each with more than two levels. This results in exponentially growing number of choice situations. If there are J alternatives, each with $K_j$ attributes, where each attribute has $l_{jk}$ levels, then the total number of possible choice situations in a full factorial design will be (ChoiceMetrics, 2018):

$$S^{\text{full factorial}} = \prod_{j=1}^{J} \prod_{k=1}^{K_j} l_{jk} \qquad \text{Equation 2}$$

This approach is only effective when there are only a few attribute levels and alternatives. This approach is conversely not suitable for large, complex designs due to the impracticality of having a single respondent face all questions.

To reduce the burden on each respondent, a subset of total choice situations can be provided to them, which is known as fractional factorial design. The choice situations are split between respondents in blocks. For example, one respondent may be given block A, while the other respondent is given block B. This can be done using two approaches, namely 1. random blocking, and 2. orthogonal blocking. The former approach randomly generates a number of subsets each containing a fixed number of choice situations. The first approach has a disadvantage due to its random nature. There is no guarantee that respondents will face a suitable mix of levels for certain attributes.

The second approach, however, does not have this disadvantage as it attempts to produce these blocks in a more organized manner. Orthogonality in this context is a statistical property that the blocks satisfy '*attribute level balance*' (i.e. attribute levels are equally presented in the choice matrix), and simultaneously ensures that all parameters are independently estimable through consideration of every interaction term between them (ChoiceMetrics, 2018). Orthogonal designs can also be generated in a couple of ways including 1. Sequentially, and 2. Simultaneously (ChoiceMetrics, 2018). These design approaches are easy to construct and have been subsequently favored in the past. Nevertheless, the fractional factorial design suffers from a handful of issues.

The blocking technique assumes that orthogonality will be preserved if all blocks are equally presented to respondents. But, in case of non-response, a missing choice situation, or not equally presenting a specific choice task, the orthogonality is lost. Moreover, the addition of contextual variables such as socio-demographics may impact orthogonality since these variables would be constant over all choice situations for a single individual (i.e. panel data). Removing such profiles from the design to preserve orthogonality is also not recommended since the extra information is typically preferred (ChoiceMetrics, 2018).

Another problem that may arise from this approach is the restriction on transforming actual attribute levels to design codes. Orthogonality will only be preserved if and only if attribute levels are spaced equally (ChoiceMetrics, 2018). For example, if the toll cost attributes are to be transformed from \$2, \$5, \$10 to -1, 0, 1, the design will no longer be orthogonal. Furthermore, the enforcement of this property might result in behaviorally implausible choice situations in different ways. It might yield dominant alternatives in choice situations, meaning that the respondent answers are always selecting the dominant alternative. It is also likely that some of the choice situations would not be possible in reality and further impact orthogonality if they are later removed.

### 2.3.4. Efficient Designs

Given the above issues related to generating an orthogonal design, a more recent alternative approach to conduct stated choice experiments is called efficient design and have been used in recent studies (Cavalcante and Roorda, 2011; Devarasetty *et al*., 2012). This method seeks to minimize standard errors in addition to maintaining a minimal correlation in the design. To this end, the concept of an asymptotic variance covariance (AVC) matrix is utilized to conduct significance tests. In this method, design estimations will be carried out over many iterations until the precision level reaches convergence and cannot be improved. This level of precision can be identified by different efficiency measures such as D-error which will thoroughly discussed in Section 4.2.1. Efficient designs however call for some prior information regarding the parameters to be able to derive the matrix beforehand (ChoiceMetrics, 2018). This presents a circular issue if no survey has yet been performed.

Nevertheless, there are still a couple of approaches that have been suggested in the literature to collect information required for prior parameters, since even a very limited amount of information, such as parameter signage, would be beneficial in terms of outperforming the counterpart approach. Rose and Bliemer, (2009) have suggested that a literature review on similar studies can be used to derive prior parameter information. Alternatively, a small pilot study can be conducted.

In this thesis, the efficient design will be utilized instead of the factorial design. The prior parameter information is developed from the literature review of variables discussed earlier in Chapter 2, an analysis of typical attribute levels for the study area in Chapter 3, and a pilot study carried out in Chapter 5.

### 2.3.5. Design Procedure

The chart below which is adapted from Louviere *et al*., (2000) demonstrates the key components of a stated preference study.

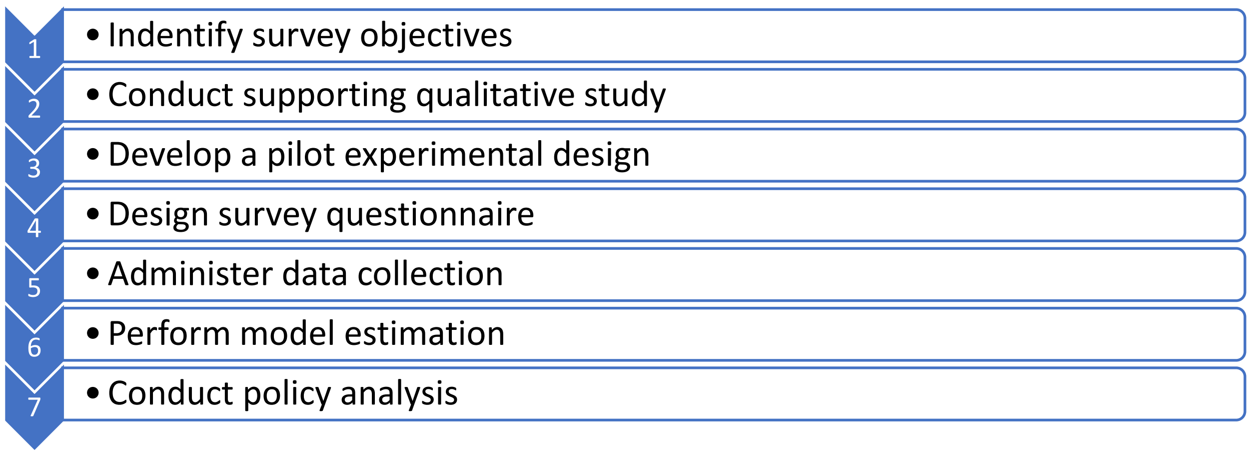



Figure 2.3 – Stated Preference Study Procedure

This thesis will follow the procedure set out in Figure 2.3. The research question was addressed previously in Chapter 1. Once the objectives of a study are identified, the foremost step in every SP study is to acquire knowledge about the state of practice in the study area. This step will give valuable insights to the analyst to conduct a study which can resemble the real-world situation as much as possible, which in this case results in guaranteeing genuine hypothetical scenarios. The output of this step will be utilized in every other step of the procedure to maintain the survey authenticity. For example, a future step would be to choose ranges for some attributes, without having a decent knowledge about their current values, we would not be able to depict the true market settings. The next chapter will comprehensively investigate the characteristics of the study area.

# Chapter Three: Study Area

As was stated earlier, Ontario is a heavily trade-oriented province within Canada. Part of the reason for this trade intensity is the geographical location of this province. Consider the so-called "Montreal-Chicago" corridor which connects the Port of Montreal with the vast intermodal rail hub in Chicago. Montreal provides the closest direct access to European and Mediterranean markets by water, while Chicago is the third most populous city in the US and represents a large hub for intermodal rail-truck activity that connects freight across the US. Additionally, the "Quebec City—Windsor" corridor on the Canadian side is the most densely populated and heavily industrialized region of Canada, representing nearly half of the country's population. Within this trade corridor, the Region of Peel accommodates $1.8 billion worth of goods moving to, from, or through its boundaries on a daily basis (Peel Region, 2017).

Highway ON-401 comprises the majority of this corridor covering around 850 kilometers and according to statistics Business Insider, (2012), is the busiest road corridor in entire North America with average annual daily traffic (AADT) above 425,000 vehicles. The situation is worst where this piece of road network passes through the City of Toronto at North York and Etobicoke regions where traffic on its busiest days during summer have already exceeded almost half a million vehicles (FHWA, 2007). Evidently, the situation is exacerbated when there is a heavy mixture of truck and passenger car traffic. For example, based on annual average daily truck traffic (AADTT) provided by MTO iCorridor, (2016) along the above-mentioned section, one out of every ten vehicles are recorded as commercial vehicles making it one of the busiest truck corridors in the world.

Hence, the study area chosen for this thesis pertains to trucks travelling within the Province of Ontario. Emphasis is placed on trips travelling through the Greater Toronto Area (GTA) due to the presence of substantial congestion and the availability of a toll route that can be used to bypass if a driver is willing to pay. The rest of this chapter will focus on the analysis of travel through the area to determine suitable characteristics as an initial input for the stated preference survey. With doing so, three important questions of the research will be answered as follows: where is the problem? What is the extent of the problem? How will be the problem in the future?

Figure 3.1 shows the average traffic count in 2016 reported by MTO, (2016a) along different sections of Highway ON-401 inside the GTA area. The locations in Figure 3.1 are shown from left to right by location, with the westernmost locations on the left. The figure demonstrates that the highway is most congested on the western side of the GTA. The connecting segment between North York and Etobicoke has recorded the largest AADT which lies around the highways ON-400 and ON-427. As noted by Higgins, (2014), the distribution of freight attractors and generators on the western side of the GTA further exacerbate the traffic because of the impact of large trucks on traffic.

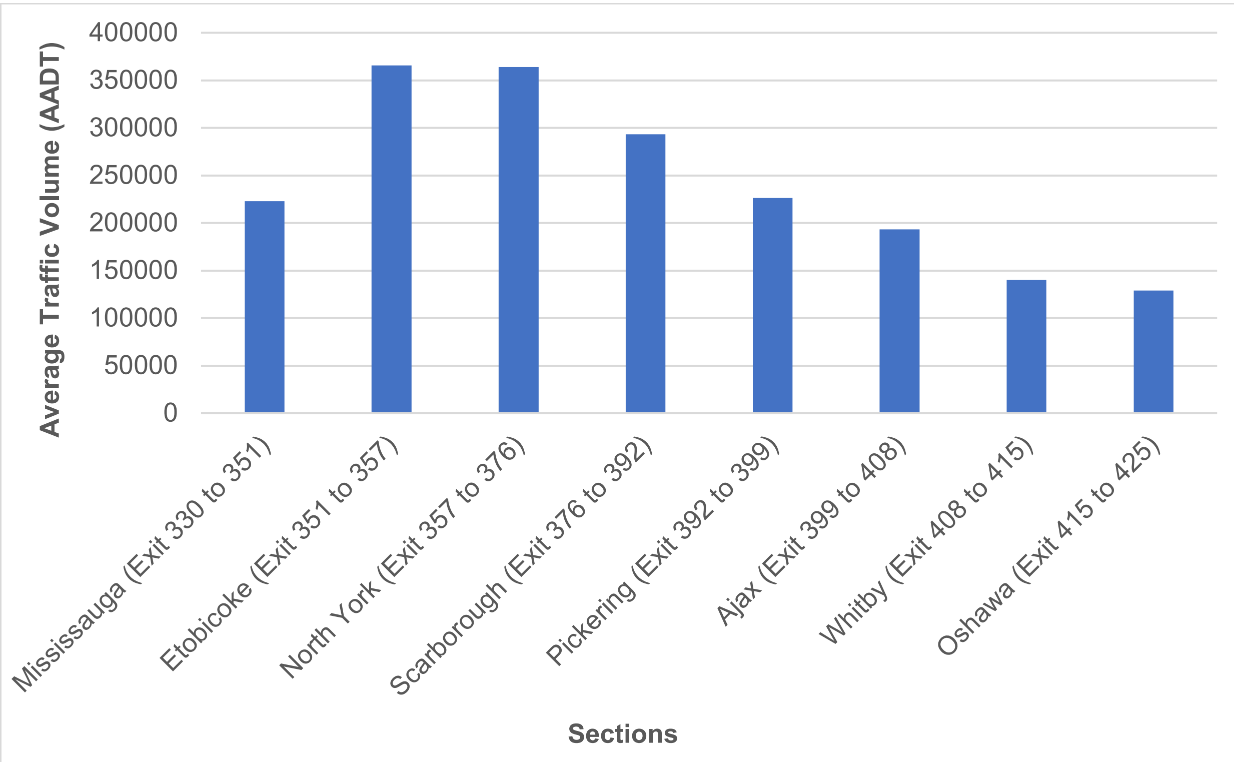



Figure 3.1 – Average AADT for Different Sections along Highway ON-401 within the GTA

Adapted from MTO, (2016a)

Congestion will continue to rise as long as traffic growth persists. MTO, (2016b) provides traffic volumes between the years of 1988 and 2016 along this section of Highway ON-401 as shown in Figure 3.2.

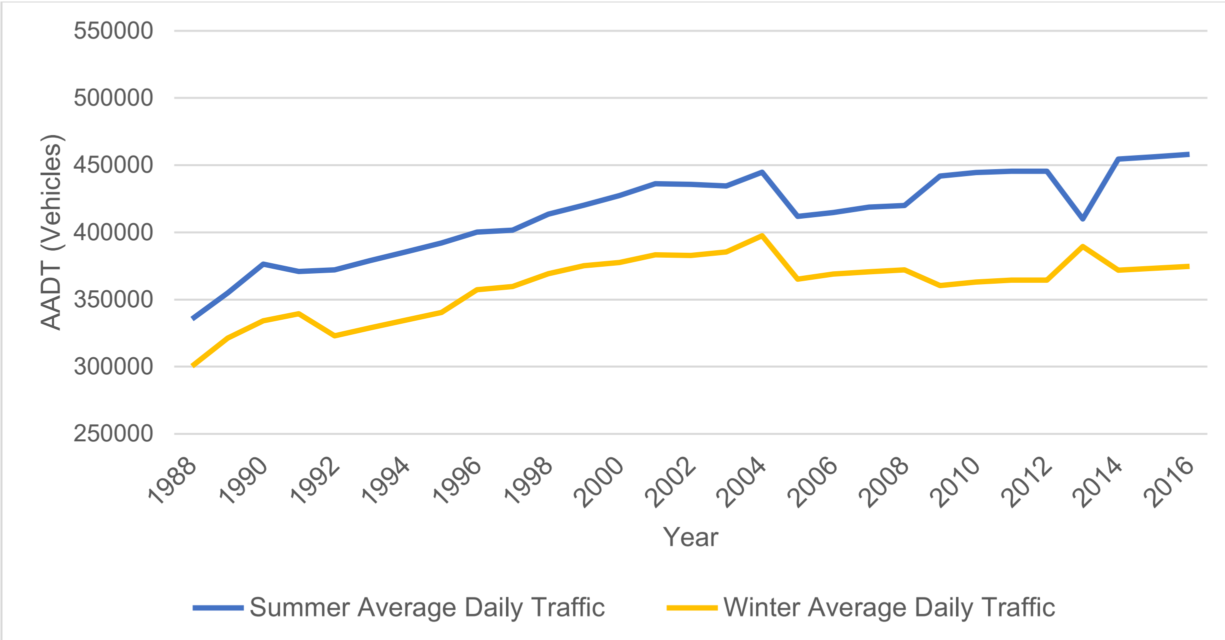



Figure 3.2 – Traffic Count on Highway ON-401 between Weston Road and Highway ON-400

Adapted from MTO, (2016b)

As seen in Figure 3.2, the traffic is more congested during the summer season as Summer Average Daily Traffic (SADT) have recorded relatively larger values compared to Winter Average Daily Traffic (WADT) which simply accounts for the lowest values. Another important point that can be interpreted from the chart above is the continuous increase in traffic. The AADT has always been on the rise during the past 30 years and considering the projected population growth and upcoming developments, the situation will only get worse.

## 3.1. Available Route Options

Several major alternatives exist for truck freight to pass through the city area. However, this analysis requires the selection of a single pair of origin and destination points. On the east-end, there is only a single highway which is Highway ON-401. The interchange at Highway ON-412 has been chosen as on the east side because it is generally known as the beginning of the congestion towards the city and has a direct connection to the other alternative with the shortest possible detour. However, for the west-end, there are several options. The interchange at ON-403/QEW was selected as the western point for several reasons. First, this location would offset the potential dominance of any of the introduced alternatives as it is the closest to where the Highway ON-407 toll route ends. Secondly, the route continues south to the Fort Erie Peace

Bridge and connects Canada-US trade with the third-busiest border crossing with over 1.2 million trucks annually (MTO, 2015).


Figure 3.3 – Three Route Alternatives Passing Through the GTA

3.1.1. Day of Week Selection

In transportation planning, peak times of travel during the weekday are typically most scrutinized since this corresponds with the worst-case recurring traffic conditions. Here, the objective is to pick a specific day for further analysis. Literature for the geographical area indicates that Thursdays tend to be the least busy weekday on the freeway systems (Sweet *et al.*, 2015). Conversely, the earlier part of the week will be busier. A traffic comparison was conducted for Highway ON-407 ETR and Highway ON-401.

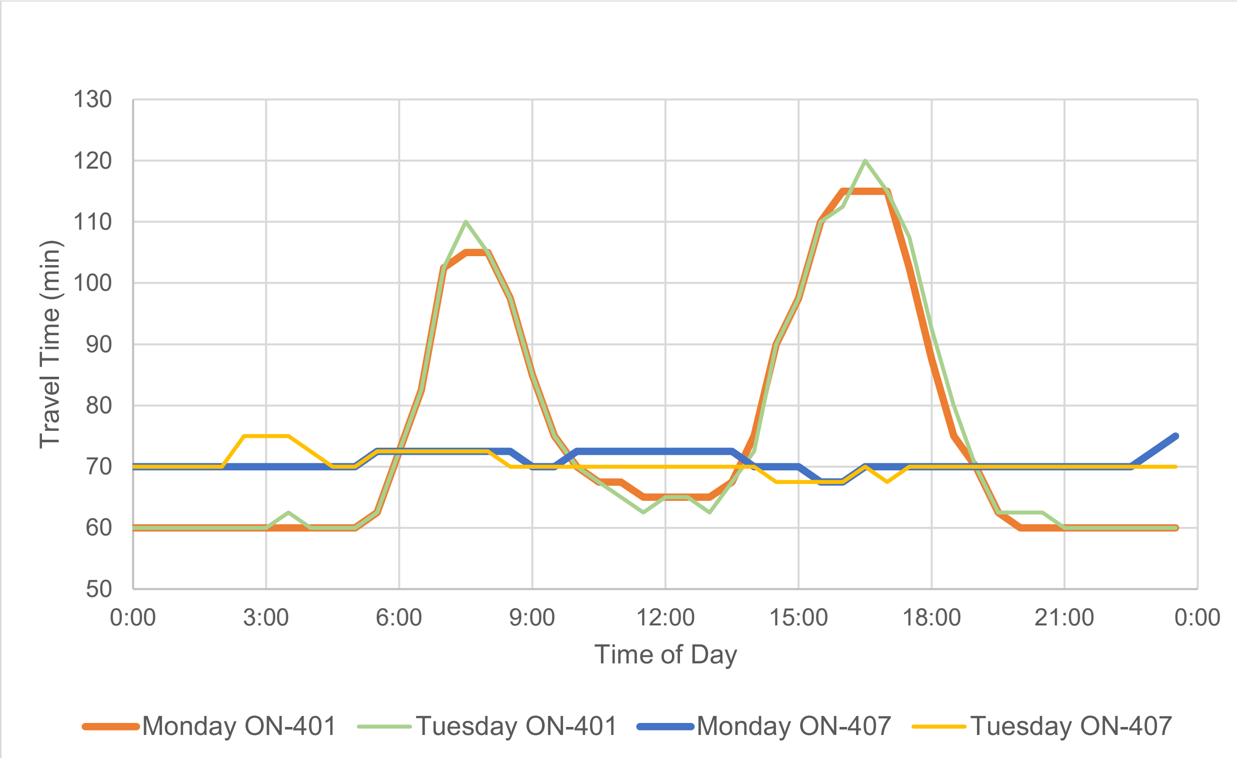



Figure 3.4 – Travel Time Comparisons for Mondays & Tuesdays along ON-401 and ON-407

After briefly reviewing travel time for all days of week, the candidates for the most congested days were narrowed down to Mondays and Tuesdays. As can be noticed from Figure 3.4, Tuesdays have shown to be slightly slower during peak hour along Highway ON-401 which is the main point of interest. Tuesday in the summer was subsequently selected for further analysis. To be more specific, the last Tuesday of a typical August was picked as the base day.

### 3.1.2. Vehicle and Direction Selection

To calculate the toll cost along Highway ON-407, a vehicle type needs to be selected since this impacts the toll rate. There were two option to select for commercial vehicles, with single unit or multiple unit categories. Due to the popularity of 5-axel truck trailers for inter-regional truck trips, the toll cost calculations are based on the latter which accounts for a more expensive toll rate. In terms of direction, the detailed toll rate for Highway ON-407 was reviewed. The influence of direction on the results was found to be negligible. The eastbound direction was subsequently selected.

## 3.2. Trip-related Characteristics

The Google Maps trip planner (Google Maps, 2020) and Highway ON-407 ETR toll calculator (407 Express Toll Route, 2020) were used to estimate the trip attributes explained in Table 3.1.

Google Maps introduced predictive travel time into its API a few years ago. It uses historical traffic data pertaining to specific time-of-day and day-of-week to forecast the travel time for a future trip (Kelareva, 2015). It provides an estimated time of arrival (ETA) as a range of times, as seen in Figure 3.3. This allowed us to consider both expected travel time and a measure for its variability along each route. An example of these attributes calculations is shown in Table 3.2. Figure 3.5 and 3.6 exhibit travel time and its variability for each of the three predefined alternatives during different times of day with 30-minutes time intervals.

Table 3.1 – List of Attributes for Study Area Routes

| **Attribute** | **Description** |
|---|---|
| *Travel Time* | Travel time in minutes, this value is taken as the mean of the lower and upper bound times given by Google Maps. |
| *Toll Cost* | Toll cost in Canadian dollars (2020), associated with taking the Highway ON-407 toll route. This is derived from the Highway ON-407 ETR toll calculator by time of day. |
| *Travel Time Variability* | The amount of time in minutes that can be added or deducted from the estimated average travel time. It is calculated as the difference between average travel time and the given upper or lower bound times provided by Google Maps. |
| *Travel Distance* | The distance for each trip in kilometers. The length is provided by Google Maps. |
| *Time of Day* | The above attributes were calculated for each 30-minute interval in a day. |

Table 3.2 – Example Trip Attributes for The Study Area at 7:30 AM on August 25, 2020

| **Route Label** | **Travel Time Range (min)** | **Travel Time (min)** | **Travel Time Variability (min)** | **Toll Cost (CAD)** | **Travel Distance (km)** |
|---|---|---|---|---|---|
| **1. ON-407** | 65’ to 80’ | 72.5’ | 7.5’ | $204.57 | 126 |
| **2. ON-401** | 80’ to 140’ | 110’ | 30’ | $0 | 104 |
| **3. DVP-Gardiner-QEW** | 90’ to 160’ | 125’ | 35’ | $0 | 106 |

As can be seen in Figure 3.5 and 3.6, the travel time and the variability are plotted by time of day for each of the three routes.

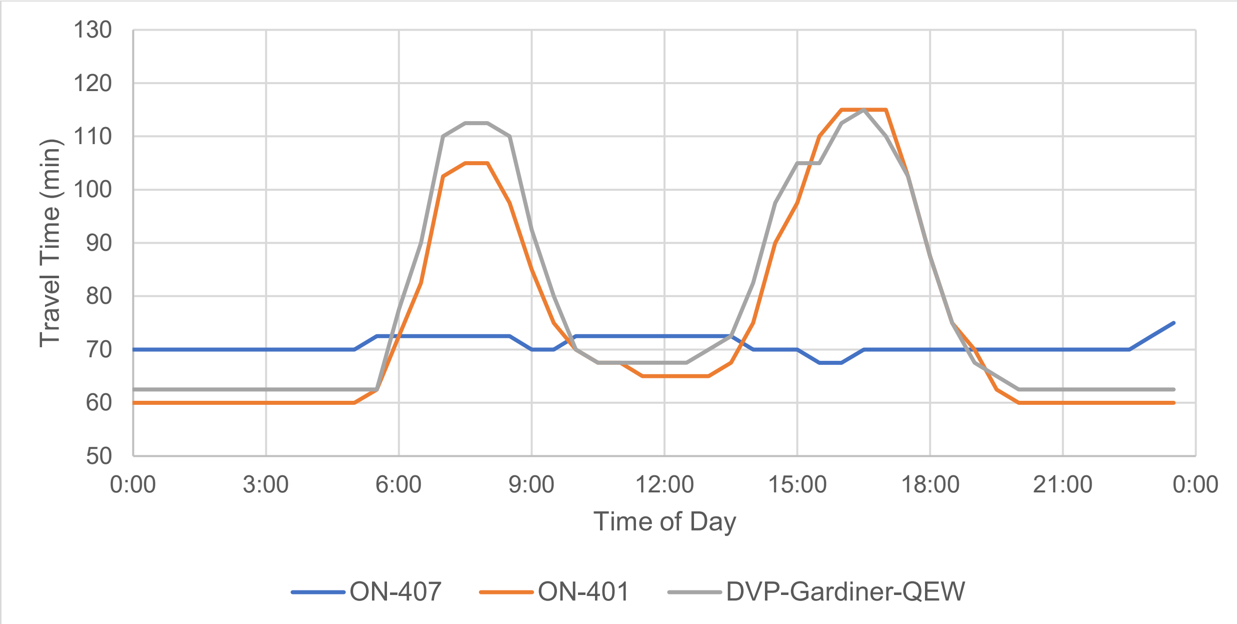



Figure 3.5 – Travel Time Along Three Routes by Time of Day

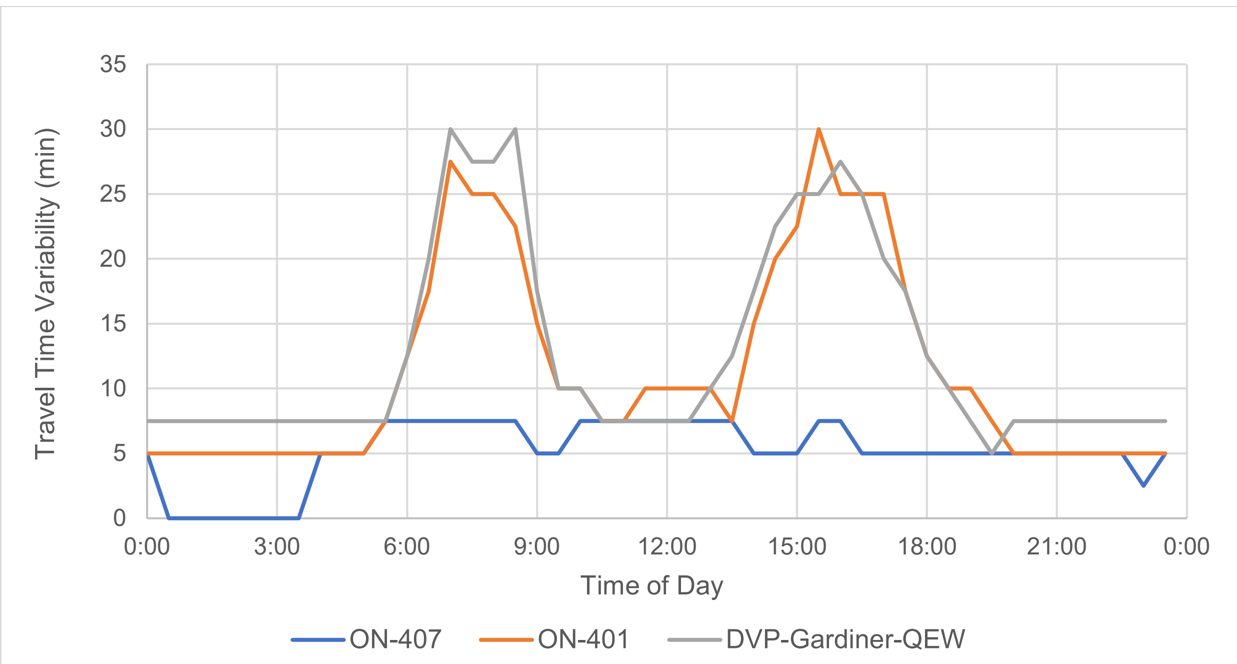



Figure 3.6 – Travel Time Variability Along Three Routes by Time of Day

By comparing Figure 3.5 and 3.6, it can be seen that these two attributes are correlated. Predictably, the two peaks in both graphs for two of the routes are reflecting the morning and afternoon peak ‘rush hour’ traffic. The downtown bypass route (i.e. DVP-Gardiner-QEW) experiences the highest congestion during the morning peak hour. This can be justified as higher number of work-trips heading to the Central Business District (CBD) of the city.

Highway ON-407 has longer travel times during off-peak which can be attributed to a longer distance. This makes the alternative less desirable during the off-peak. On the other hand, the travel time and variability for this route remain stable throughout the day. As can be seen in Figure 3.7, the toll rate surge during rush-hours discourages an increase in drivers to maintain travel times and reliability along the tolled route.

The associated toll costs for truck trips along the toll route alternative in Figure 3.3 are visualized in the figure below using the data from the Highway ON-407 ETR toll calculator (407 Express Toll Route, 2020). It should be noted that these costs were calculated for trips starting at different times of a typical Tuesday during summer season assuming a heavy commercial vehicle.

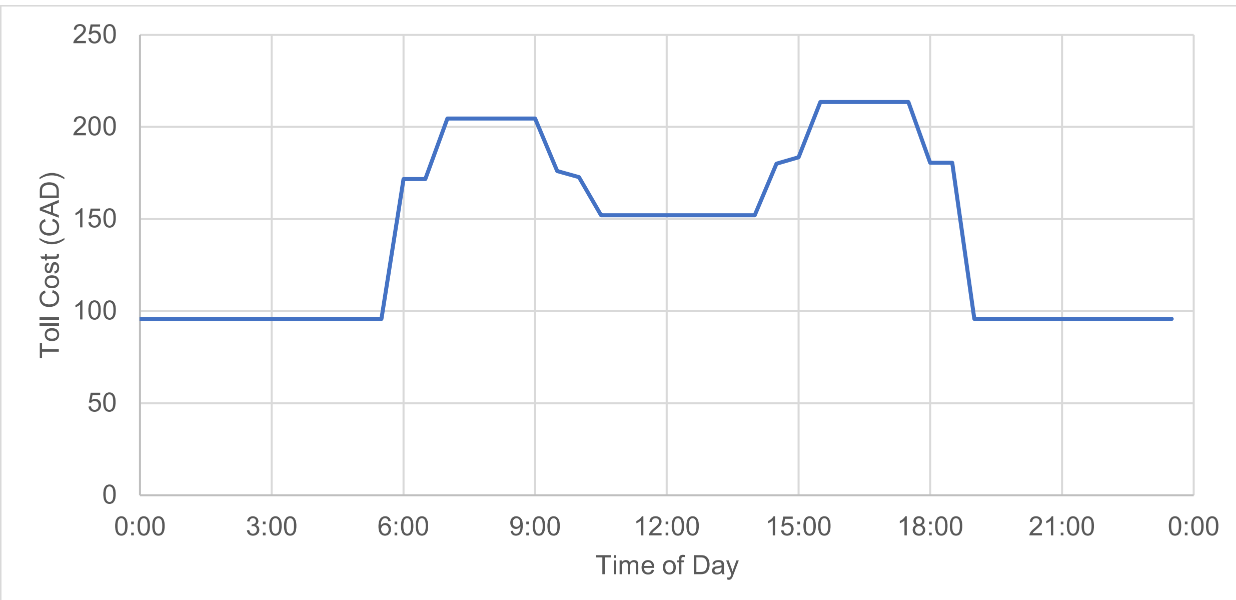



Figure 3.7 – Trip Toll Cost along Highway ON-407 for Different Times of Day

A market-based VOT pertaining to the Highway ON-407 toll route can be calculated. In transportation economics, the value of travel time savings (VTTS) is the opportunity cost of the time that a traveler spends on her journey. Fundamentally, it is the cost that a traveler would be willing to pay in order to save time (Small, 2012).

In this context, VOT is calculated by comparing the Highway ON-407 with the next best route using Highway ON-401. To calculate the minimum market VOT, an assumption regarding the route performance needed to be made. Hence, a comparison between the best-case scenario along the tolled route and the worst-performing case along the free route was implemented. For the best-case scenario along Highway ON-407, the travel time variability amount was deducted from the expected travel time whereas for the worst-case along Highway ON-401 the TTV was added to the TT. A clear calculation process is shown in Equation 3. This enabled the research to capture the potential travel time savings by subtracting the two values. The minimum market VOT for each time of day was then calculated by taking the ratio of travel time savings and toll cost and plotted in Figure 3.8 below. It is noteworthy to mention that some VOT entries were removed from the graph for a more meaningful result. These entries were either negative or infinite values for several time-of-day(s) simply because there were no travel time savings opportunity to take the Highway ON-407 route instead of Highway ON-401, though this may not be the case for other origin and destination locations.

$$Minimum\ Market\ VOT\ at\ time-of-day\ 'i'\ (\$/hr) = \frac{Toll\ Cost\ at\ i}{(TT_{407}-TTV_{407})-(TT_{401}+TTV_{401})} \qquad \text{Equation 3}$$

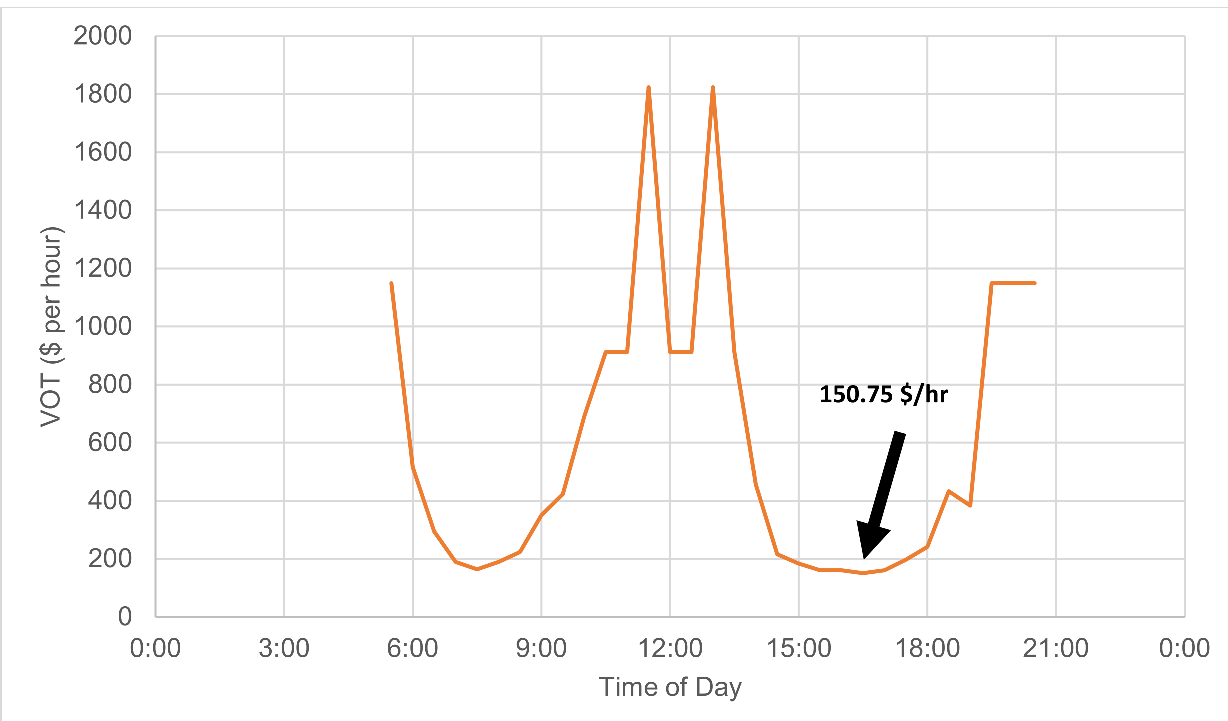



Figure 3.8 – Estimated Minimum Market VOT for Highway ON-407

The VOT plot in Figure 3.8 follows an inversed pattern when compared to the other graphs in Figures 3.5, 3.6, and 3.7. This means that the market is offering lower VOT during rush-hour and a higher VOT during off-peak. This is due to Highway ON-407 offering less travel time savings during the off-peak period, even though the off-peak toll cost is lower compared to the peak hour travel. The minimum VOT was recorded at 4:30 PM to be 150.75 $/hr. This means that for trips starting at 4:30 PM, Highway ON-407 charges $150.75 for each equivalent one hour of travel time saving. The value is higher during other parts of the day.

The market VOT calculated here for Highway ON-407 implies that individuals willing to pay more than $150.75 would be expected to choose the tolled route. This VOT is much higher than the values stated earlier in Chapter 2 Literature Review. A few causes for the high value can be noted. First, the values here are listed for Highway ON-407, which has high toll prices in comparison to most other tolled routes. Second, the VOT listed in the literature review are based on an average VOT; however, a tolled route may not be focusing on an average driver, but may rather be interested in those outliers that are willing to pay a substantial amount of money for travel time savings. The survey discussed later in this thesis will subsequently explore a distribution for VOT across decision makers to define these outliers.

The exploration of VOT for the study area of this thesis will be used to establish realistic scenarios that are faced by truck drivers travelling through the Greater Toronto Area in Ontario. More details of the survey methodology are discussed in the next chapter.

# Chapter Four: Stated Preference Survey Methodology

Having gained the required knowledge of the study area in Chapter 3, the next step is to implement a stated preference survey with realistic truck route choice scenarios. As noted in Chapter 2, the efficient design is preferred over the factorial design. The former approach has therefore been selected but requires prior parameter information. This means that a pilot study should be conducted prior to the main final survey if previous results are not available. This chapter is dedicated to the design procedure for stated preference studies.

## 4.1. Experimental Design Process

This thesis creates a SP survey since it gives the analyst the freedom to create controlled scenarios using hypothetical questions. For that, discrete choice experiments (DCE) will be employed as a tool to model consumer preferences, estimate substitution patterns between alternatives, and carry out forecasting (Louviere *et al*., 2010). These experiments determine the impact of different independent variables on observed outcomes selected by survey respondents (ChoiceMetrics, 2018). The above features have made this approach very popular for researchers in different fields including transportation, psychology, and health sciences. However, a stated choice experiment requires precise design to prevent generation of implausible choice situations, minimize correlation, and avoid biased results (Rose and Bliemer, 2009).

Stated choice methods are very popular in different fields for conducting behavioral studies, however, their design specifications are heavily dependent on the context. This means that there is basically no one-size-fits-all approach (Butkeviciute, 2017). Hence, this section provides a general overview on the essential steps of generating experimental designs. Then, a discussion on each step unique to the context of this study will be given and an example in the format of the pilot design will be introduced where necessary.

One of the most comprehensive design process fundamentals is provided by Hensher *et al.,* (2015). A general approach outlined by them is provided below in Figure 4.1 to outline steps from defining the research problem to publishing the survey questionnaire.

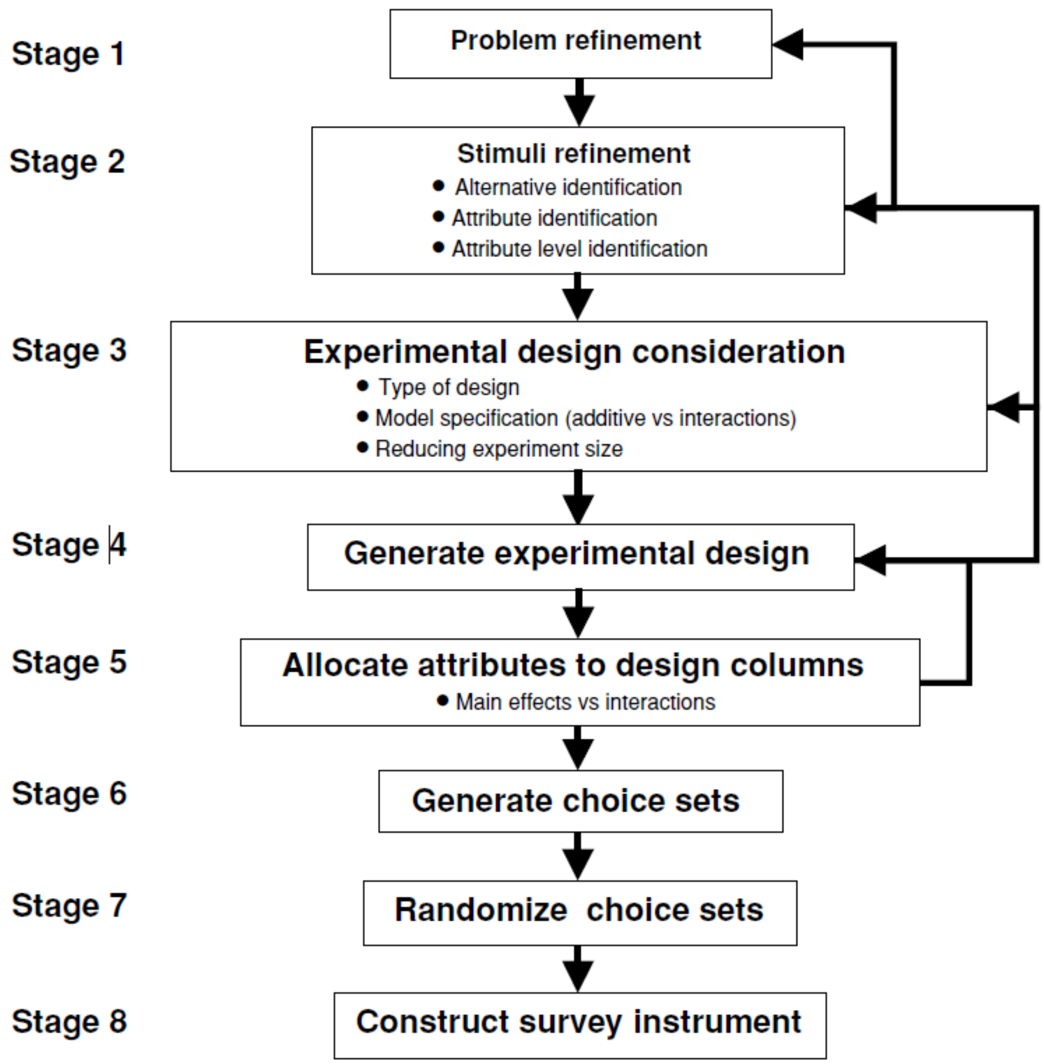



Figure 4.1 – The experimental design process (Hensher *et al*., 2015)

A condensed version of the design procedure is outlined below (Louviere *et al*., 2000):

1. Study objective definition;
2. Qualitative research (e.g.: a pilot study) to select alternatives, attributes, levels, and priors;
3. Econometric model specifications;
4. Further design considerations; and
5. Evaluate, compare, and select the most appropriate design.

Step one above was covered by Chapter 1 of this thesis. Moreover, Step 2 has been started with a discussion of realistic attributes for the Greater Toronto Area in Chapter 3. In this section, Step

2 will be further explored by discussing the design considerations regarding alternatives, attributes, and levels, along with the modeling specifications for Step 3. A pilot survey is discussed later in Chapter 5 to discuss Step 4 and Step 5.

#### 4.1.1. Design Specifications

Discrete choice experiments (DCEs) are very complex in their nature, hence a minor change in their structure might result in a completely different design. Four questions will be answered in this section: 1. How many questions should the design have? 2. How many alternatives does each question have? 3. How many features does each alternative have? 4. To what extent would these attributes vary?

A stated preference approach was chosen for this thesis because they have the ability to outperform revealed preference counterparts in policy-related studies as long as two important circumstances are met (Cherchi and Hensher, 2015). First, the realism should be maintained throughout the design by depicting real world conditions and second, they must minimize hypothetical. The former deals with the details of the survey as if it can hypothesize a true market scenario regardless of who is answering it and the latter depends on the conditional use of SP in generating questions to guarantee accurate answers. This research attempts to follow these two important guidelines in every decision of the survey structure.

##### 4.1.1.1. Alternatives, Attributes, and Levels

The number of alternatives (i.e. choices) in a question posed in a survey has a direct impact on the level of cognitive burden of the respondents (ChoiceMetrics, 2018). More importantly, this decision is contingent on the context of the study. For example, when these types of studies are being conducted in medical fields, which is quite common (Borriello *et al*., 2021; Botha *et al*., 2019), there might be multiple remedies for a single disease. While other studies may only require a pair of alternatives to be able to capture desired results. In the case of this research, a binomial choice set may be sufficient with tolled route and non-tolled route alternatives.

One option that is available for the stated preference survey is an ‘opt-out’ alternative. There are two typical forms for this type of alternative which are referred to as “no-choice” or “status quo”. The former leaves the respondents with the freedom to not select any option while the latter refers to sticking with the current option (i.e. reference point) that is currently used. In fact, this concept has been widely discussed in the literature and apparently the balance is somewhat tipped towards the inclusion of this alternative for several reasons. First, several studies recommend the consideration of no-choice alternatives (Batsell and Louviere, 1991; Louviere and Woodworth,

1983) because they believe that it contributes to the increase of realism of the choice tasks. Secondly, researchers concluded that it results in a more statistically accurate parameter estimation (Louviere *et al.*, 2000). Finally, more valid estimates have been observed when this option is included (Adamowicz and Boxall, 2001). However, this decision is dependent on the context of the study (Veldwijk *et al.*, 2014). For example, having a no-choice alternative would be reasonable when dealing with choices of buying a new product, however, in a route choice context this may not be conceived as meaningful. Although incorporating status quo alternative in route choice is viable through integrating decision makers' existing routing habit. But, it requires complex design procedures to account for dynamic experiments which is above and beyond the scope if this research project.

There are different means to collect information regarding attributes and their levels, the most common of which are literature review on similar studies, observational fieldwork, interviews with focus groups, and pilot studies (Kløjgaard *et al.*, 2012). Throughout this process, one important point is the definition of variables and their levels in a way that is consistent with the context and is realistic. In other words, for this study, the analyst must make sure that the list of attributes and their levels are aligned with Ontarian and more broadly Canadian trucking context.

Another important decision to make with regards to attributes is to choose whether an attribute should be treated as generic or alternative-specific. A generic variable shares the same parameter (β) across different alternatives. By contrast, alternative-specific attributes are applied differently to each alternative, even resulting in a value of 0 for one or another.

Once the most relevant attributes were shortlisted, the next step is to assign levels to them. In this step, in addition to the following instructions provided above, a number of practical considerations should be followed in sequence to maintain their representativeness. These considerations are highlighted below.

i. Using the minimum and maximum of observed values for each factor as the lower and upper boundaries of levels.

ii. Introduction of a few more levels within the boundaries to capture the effect of nonlinearities.

   a) The number of levels should be limited to control for yielding large designs (huge number of choice situations).

   b) For the sake of maintaining attribute level balance, the number of choice situations must be divisible by the number of all attributes' levels.

c) To preserve orthogonality, different levels within an attribute should be spaced equally along the range of that attribute.

iii. Using a wider range for attribute levels is statistically preferable and yields designs with higher efficiency (ChoiceMetrics, 2018). However, this range should be optimal to prevent the generation of dominated or indistinguishable alternatives. An example is shown in Figure 4.2.

iv. Attributes shown to the respondent must make sense.

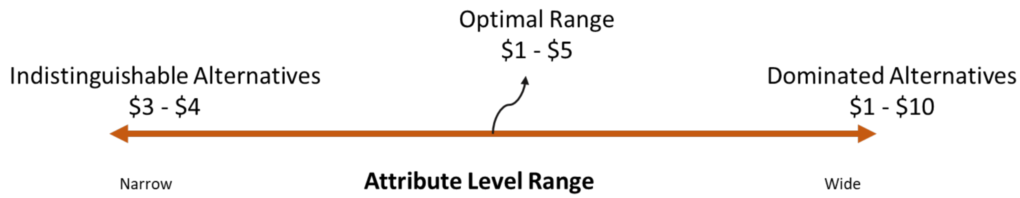



Figure 4.2 – Attribute Level Range

4.1.1.2. Choice Situations

In those studies that have human participation, one of the most critical reasons for bias is respondent fatigue and disengagement. Consequently, the decision for the number of choice questions is vital. A risk is that the researcher neither wants to have too few questions which result in a simplistic study, or too many choice tasks that is realistically implausible to handle and give rise to respondent fatigue. Therefore, an optimal number of choice questions must balance the trade-off between these two issues.

These limitations leave the analyst with an upper and lower feasible boundary. The literature strongly recommends restricting the number of choice situations to control for survey length and potential biases arising from choice set complexity (Chung *et al.*, 2011). Secondly, this number cannot be lower than design's degrees of freedom (Rose and Bliemer, 2007). In the experimental design context, each parameter equivalently represent an extra degree of freedom and the design degree of freedom is the number of parameters, excluding constants, minus one (ChoiceMetrics, 2018). Hence, the minimum number of rows (S), which represent choice situations, should be equal or greater than the degrees of freedom. That is the number of parameters (K) to be estimated divided by the number of alternatives (J) minus one, which is shown in the equation below. Additionally, if one is looking for an attribute level balance design, then he needs to make sure that the number of rows is divisible by all attribute levels specified in the utility functions of the design.

$$S = \frac{K}{J-1} \quad \text{Equation 4}$$

## 4.2. Efficient Design Type

As previously discussed, many researchers have shifted interests from factorial design to efficient experimental designs. It has been understood that these designs will outperform orthogonal designs if some prior parameter information is available. In this section, the definition of efficient designs along with their advantages over the counterpart will be discussed.

Experimental designs as a concept are a visual representation of an organized matrix populated by values that are comprised of attribute levels. Hence, the key objective in generating these designs is “how best to allocate the attribute levels to the design matrix” (ChoiceMetrics, 2018). Efficient designs propose a statistical approach in which it minimizes correlations between the attributes, and also aims to produce estimates with the smallest standard errors possible. For that, they make use of Asymptotic Variance-Covariance (AVC) matrix of parameter estimates.

These matrices are the covariance of parameter estimates over repeated sampling and can be calculated by taking the negative inverse of the Fisher information matrix. The detailed structure of these matrices is complex and beyond the scope of this research. Thus, we only discuss the elements required in this study. The diagonal elements in AVC matrix represent the variance and can be used as indices of estimation precision. The standard errors for each parameter can be derived by taking the square roots of these diagonal elements (Preacher *et al*., 2006).

The AVC matrix can be built for any given choice experiment. Assume a design with $J$, $j=1,\ldots,J$, alternatives and $K_j$ attributes. Let the number of choice situations denoted by $S$, and the number of respondents by $N$. Then, the AVC matrix depends on the experimental design choice data $X = [X_{jksn}]$ (attributes), $\tilde{\beta}$ prior parameter information (best guesses for true parameters), and $Y=[y_{jsn}]$ choice outcomes (either zero or one depending on being chosen or not). The AVC matrix can be constructed as a function of its choice probability since the Fisher information matrix is equal to the second derivatives of the log-likelihood function. Depending on the assumed error distribution, the equation can result in a closed form that can be solved either by Monte Carlo simulation or analytically (Rose and Bliemer, 2009). With the recent advancements of computer power in solving mathematical equations, the AVC matrix is generated implicitly by computer software. In this research, Ngene software has been utilized to generate this matrix.

There are multiple inputs to this matrix that can alter the final AVC matrix. The role of software is to generate different AVC matrices and look for the one that guarantees the least standard errors.

For this, hundreds of thousands of comparisons should be done to make sure that the final matrix is the most optimal. But, even for the most powerful computers, comparing the whole AVC matrix for many different possible configurations of a design can be very time consuming. Therefore, a single value named the efficiency measure is discussed in the next section as an alternative to the evaluation of a full AVC.

#### 4.2.1. Efficiency measures

Efficiency measures are used as single-value indices for design comparison. These measures refer to the expected standard errors of parameter estimates, with a lower efficiency value representing a more efficient design. They are also known as efficiency error in which the objective is to minimize the error and subsequently produce a lower inefficiency.

A popular measure of efficiency is called **D-error** and is calculated as the determinant of the AVC matrix (Ω). The design with the lowest D-error is called D-optimal. There are three potential categories of measures within the D-efficient designs which will be explained below.

In some contexts, there is absolutely no information available regarding prior parameter information, not even signage. In such a case, the $\tilde{\beta}$s are set to zero and the error measure is $D_z$error (z from 'zero'). Alternatively, there might be a situation where there is some reliable information available regarding the parameters, and the $\tilde{\beta}$s are set to the best guess which results in a $D_p$error (p from 'prior'). Finally, there might be some information available that are not quite reliable, hence instead of assuming a fixed prior, a probability distribution for the parameters will be defined to account for the uncertainty. This results in a Bayesian approach and the efficiency error is called $D_b$error (b from 'Bayesian'). The equations for these efficiency measures are provided below (ChoiceMetrics, 2018).

$$D_z error = det\big(\Omega_1(X,0)\big)^{\frac{1}{K}} \qquad \text{Equation 5}$$

$$D_p error = det\big(\Omega_1(X,\beta)\big)^{\frac{1}{K}} \qquad \text{Equation 6}$$

$$D_b error = \int det\left(\Omega_1\big(X,\tilde{\beta}\big)\right)^{\frac{1}{K}} \phi\big(\tilde{\beta}|\theta\big)\, d\tilde{\beta} \qquad \text{Equation 7}$$

*K* is the number of parameters that should be estimated. As can be seen in the third equation, the error is a function of an assumed random distribution that explains the specific parameter. For example, the $\tilde{\beta}$s could follow a normal or uniform distribution with their mean and variance identified in the probability distribution function Φ(). Any form of distribution function can be assumed, however, normal and uniform distributions are seemingly the only types that have been used in the literature so far (ChoiceMetrics, 2018).

In addition to D-error, there are other efficiency measures that have been used in the literature. Another widely used measure is called **A-error**. This measure takes the summation of all diagonal elements of the AVC matrix, and therefore only takes into account the variance of the design. Similar to D-error, a smaller value indicates a more efficient design. This measure, like D-error, can also be mathematically formulated based on the available parameter information as found in the equation below.

$$A_p error = \frac{tr\left(\Omega_N(X,\widetilde{\beta})\right)}{K} \qquad \text{Equation 8}$$

A measure has also been introduced in literature to determine the minimum required sample size (Rose *et al*., 2009), using the knowledge that t-value estimates are reliant on the required confidence interval of the model. As can be seen in the equation below, a lower bound on the sample size requirement is calculated given the required precision in the model estimation in order to obtain significant parameters. This measure is called **S-optimality** (s from ‘sample size’).

$$\frac{\beta_k}{se_{N,k}(X,\beta)} \geq t_\alpha \qquad \text{Equation 9}$$

$$N \geq \left(\frac{se_{I,k}(X,\widetilde{\beta})t_\alpha}{\widetilde{\beta}_k}\right)^2 \qquad \text{Equation 10}$$

All of the above-mentioned measures are mathematically comparing the designs, yet cannot compare the designs in terms of their realism. Consider a situation where the best-performing design with the most favorable efficiency measures (values) is producing choice situations that are unbalanced. This arises from hypothetical scenarios that are dominated by one alternative over another or are too similar with equal utility (perfectly balanced). In either case, the comparison between the alternatives is flawed since the choice outcome is either too obvious (dominated alternative) or there is no clear preference (too balanced). Neither scenario will result in reliable results. Therefore, it is strongly advised to manually evaluate the choice situations to assure the level of balance which depicts realism in terms of the attribute levels associated with each alternative and their hypothetical comparison environment.

Since going over every choice situation for every single design is very time consuming, researchers have developed an approach that can equivalently represent the level of balance by producing a single number for the entire design (Kessels *et al*., 2006). This measure calculates the balance for each individual choice situation by multiplying the probabilities of each alternative and dividing it by the number of choice situations. Next, it averages out a single value for all of the choice situations in a single design. This measure is called **B-error** and tries to maximize the value to certain degree. There is no optimal value for B reported in the literature since it is dependent on the context and the nature of the prior information, but observations have suggested that a good range for B lies between 70 to 90 percent (ChoiceMetrics, 2018). The equation for this index is provided below.

$$B_s = \prod_{j=1}^{J} \left( \frac{P_{js}}{1/_J} \right) \times 100\% \qquad \text{Equation 11}$$

$$B = \frac{1}{S} \sum_{s=1}^{S} B_s \qquad \text{Equation 12}$$

Ngene software is used in this thesis to generate the discussed efficiency measures. In this research, it is prioritized to compare D-errors at first hand, then compare best designs using the remaining efficiency measures.

4.2.1.1. Drawing for parameter distribution

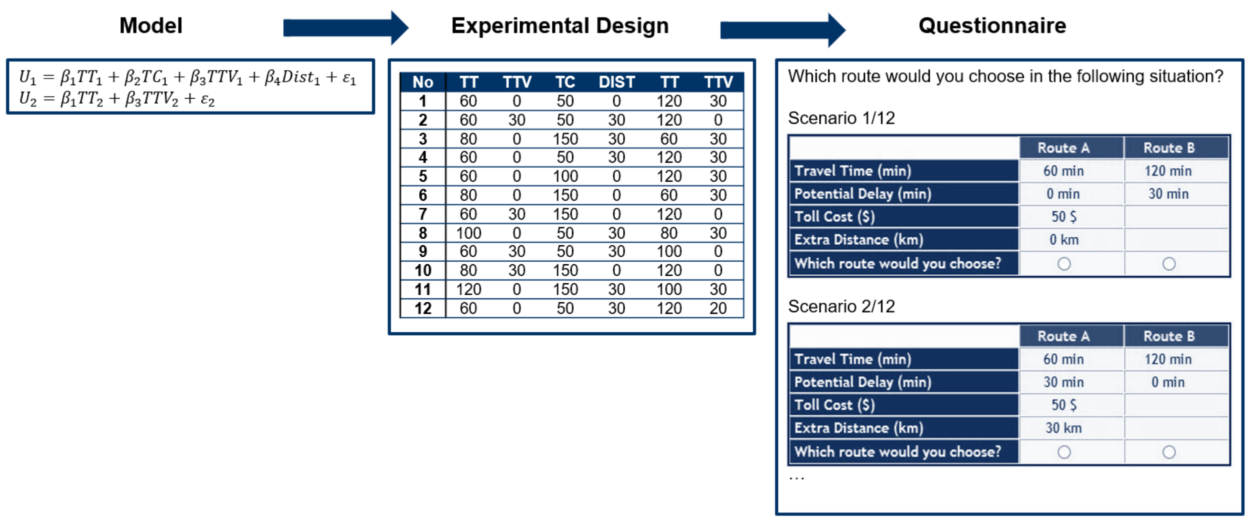
As previous stated, a researcher is likely not certain of prior parameter values. In this type of situation, a range of values (i.e. distribution) may be assumed instead of a single value. This means that the efficiency of the design will be estimated as an expected value of the parameter over the specified range of its distribution function. A Bayesian approach can be utilized with simulations to generate different draws and ultimately calculate the expected value of the parameter over a large number of iterations.

For Bayesian approaches, three mandatory features need to be identified, namely: 1. Distribution type, 2. Simulation type, and 3. Number of draws. Depending on the type of the parameter, different assumptions regarding the distribution of type can be made. Ngene software is able to account for two most popular distributions: Normal and Uniform, by providing the machine with two values: *mean* and *standard deviation.* There are several built-in simulation methods within Ngene which will be briefly explained hereunder.

There are three main categories of simulations depending on the complexity of their algorithms 1. Pseudo-random Monte Carlo (PMC), 2. Quassi-random Monte Carlo, and 3. Gaussian quadrature (Bliemer *et al.*, 2008). The first two methods are relatively simpler as they both take an unweighted average over different draws to calculate $D_b$error, however, the method of draws varies. The former takes completely random draws while the latter has an intelligent and wellstructured algorithm to do so. In contrast, the third approach assigns different weights to different prior parameters and computes a weighted average. More information on their specific capabilities can be found in this article (Bliemer *et al.*, 2008). In this thesis, the possibility to account of Bayesian design along with the most appropriate simulation method will be discussed for both pilot and final survey in their corresponding section.

### 4.2.2. Model Specification

This step is an important part of the study as it clearly defines what is going to be estimated in terms of influential parameters. Figure 4.3 below demonstrates the backbone of a choice experiment survey. Looking at the actual questionnaire on the right side of the figure indicate that there is two options being compared in each choice situation which means that two utility functions for each alternative needed to be identified ($U_1$ and $U_2$). Having a closer look at the experimental design matrix, it reveals that each column is representing the attribute corresponding to each alternative in the questionnaire ($TT_{1,2}$, $TTV_{1,2}$, $TC_1$, and $DIST_1$). Each row is also putting forward a hypothetical choice scenario in the questionnaire.




| No | TT | TTV | TC | DIST | TT | TTV |
|---|---|---|---|---|---|---|
| 1 | 60 | 0 | 50 | 0 | 120 | 30 |
| 2 | 60 | 30 | 50 | 30 | 120 | 0 |
| 3 | 80 | 0 | 150 | 30 | 60 | 30 |
| 4 | 60 | 0 | 50 | 30 | 120 | 30 |
| 5 | 60 | 0 | 100 | 0 | 120 | 30 |
| 6 | 80 | 0 | 150 | 0 | 60 | 30 |
| 7 | 60 | 30 | 150 | 0 | 120 | 0 |
| 8 | 100 | 0 | 50 | 30 | 80 | 30 |
| 9 | 60 | 30 | 50 | 30 | 100 | 0 |
| 10 | 80 | 30 | 150 | 0 | 120 | 0 |
| 11 | 120 | 0 | 150 | 30 | 100 | 30 |
| 12 | 60 | 0 | 50 | 30 | 120 | 20 |

Figure 4.3 – Steps in Designing a Stated Choice Experiment

Adapted from ChoiceMetrics, (2018)

Principally, three questions have to be addressed in this step. First, the number of alternatives for each question need to be identified (i.e. how many utility functions the study should have). Secondly, the attributes and attribute levels for each alternative should be determined. Lastly, the type of model must be chosen. Finalizing the three elements above will provide details of the utility functions that will be established for the model. The utility function of discrete choice models are discussed in the next section.

4.2.2.1. Model Type

Decision makers are assumed to be utility maximizers or disutility (regret) minimizers in their choice behavior. Lancaster, (1966) developed early research in the area to the consumer demand and utility. He stated that this utility is based on the characteristics of the objects, though other research has also added attributes of decision makers to this utility. The utility function can be described as a linear relationship of the attribute levels and their corresponding weights as shown in Equation 13 (Lancaster, 1966).

$$V_{in} = \beta_i X_{in} \qquad \text{Equation 13}$$

*Where V is the Observable part of a utility function as a linear relationship of attributes* $X_{in}$ *and their parameter weights* $\beta_i$

The actual utility for a choice situation includes the observable utility and a stochastic distribution of error. This is included for several reasons. First, not all variables are necessarily included in the utility function, indicating that the specification of the model is not exhaustive. There are also taste variations in β values that are simplified in many models, indicating that the different preferences of decision makers can lead to errors at the individual level. Formally, the error component is considered in basic discrete choice models by adding a new vector $\varepsilon_{in}$ to the utility function as an error term. This accounts for the uncertainty of all the parameters involved in the calculation which can be seen in Equation 14.

$$U_{in} = V_{in} + \varepsilon_{in} = \beta_i x_{in} + \varepsilon_{in} \qquad \text{Equation 14}$$

Consider a choice scenario with two alternatives *i* and *j*, and integrating and rearranging the above-mentioned utility functions of either choices, the probability of an alternative being chosen over the other will look like the Equation 15.

$$P_{in} = Prob\ (\varepsilon_{jn} - \varepsilon_{in} < V_{in} - V_{jn}\ , \forall\ j \neq i) \qquad \text{Equation 15}$$

*Where P is the Probability of choosing alternative i of alternative j*

To solve this equation, an assumption needs to be made regarding the distribution of the error terms. In 1974, Daniel McFadden was able to resolve this issue and earned the Nobel Prize for his contribution. He assumed an identically and independently extreme value type 1 (EV1) distribution, also known as Gumbel distribution, for the error component, which results in a closed-form equation for the probability of a decision maker selecting an alternative as provided below. This model is known as a multinomial logit (MNL) and is a basic but powerful model for choice problems with two or more alternatives.

$$P_{ni} = \frac{e^{V_{in}}}{\sum_j e^{V_{jn}}}$$ Equation 16

Depending on the research question, the analyst can impose other assumptions to produce a different model. In this chapter, the discussion has focused on the MNL model and its implications. The MNL model structure was used in the thesis as the foundation for the stated preference survey. A more advanced version of the model known as the mixed multinomial logit model (MXL) will be discussed later in the thesis after identifying heterogeneous preferences among several attributes in the survey results.

### 4.2.3. Further Design Considerations

#### Labeling

Choosing between labeled alternatives or leaving them without labels is an important element of the design since it can be influential on the choice outcomes. As Kløjgaard *et al.,* (2012) suggested, for the example of a mode choice study, the modality can be treated as an attribute instead of a label. This can also be applied to a route choice context. For example, alternatives could be labeled as "tolled" or "free" route, however, it might infer negative associations with the first alternative due to the costs they require, and subsequently impact respondent answers. Hence, it was decided to leave the alternatives unlabeled as Route A and Route B, with one of two routes representing a tolled option using the alternative-specific attribute of cost.

#### Design Constraints

Sometimes a combination of attributes for a given alternative is not feasible. For instance, according to the qualitative investigation of the study area, there were no situation where tolled route experiences a higher travel time reliability as compared to the free alternative. Ngene software used for the survey design enables the analyst to impose constraints on the design to prevent these unrealistic combinations. There are plenty of built-in syntaxes to use such as conditional if statements, require, and reject properties. These properties basically restrict the formation of choice situations in such a way that can satisfy the imposed constraints. For example, reject property can be implemented to prevent the generation of choice tasks where travel time variability of tolled route is higher than free route. In another case where the analyst is seeking to produce scenarios in which toll cost levels should be provided based on the travel time saving opportunities, conditional if statement can be used. In other words, the incorporation of higher toll values can be conditional to higher travel time savings.

## 4.3. Efficient Design Generation

With the knowledge of design considerations discussed in previous sections, the research question can be addressed by establishing the stated preference survey design. Given the general specifications of the design (attribute levels, alternatives, choice situations, prior parameters), a design is sought that can minimize the efficiency error in Equation 4. A factorial design was not considered practically feasible due to a large number of choice situations and recent research in favour of an efficient design. According to Equation 2, a full factorial design with moderate to semi-complex specifications will produce thousands of choice situations l*et al*one the desired complexity level of the experiment used in this thesis. Therefore, the efficient design was selected as a suitable approach.

Ngene software utilizes several possible algorithms to detect the efficient design. These algorithms can be divided into two groups: 1. Row-based algorithms and 2. Column-based algorithms. Each row represents a choice situation, while each column represents the attribute levels for each attribute. The row-based approach therefore works on the choice situation as a whole and removes lower-quality choice situations from the candidate set, while the column-based approach substitutes attribute levels within a pre-defined candidate set.

The Modified Fedorov Algorithm is a row-based algorithm which is discussed in detail by Cook and Nachtsheim, (1980). An overview of the algorithm is illustrated in Figure 4.4. First, a candidate set is created, and in each iteration, a subset is evaluated and the design with the smallest error will be stored. This iteration will run until there is no further combination to compare or it has reached the predefined number of iterations.

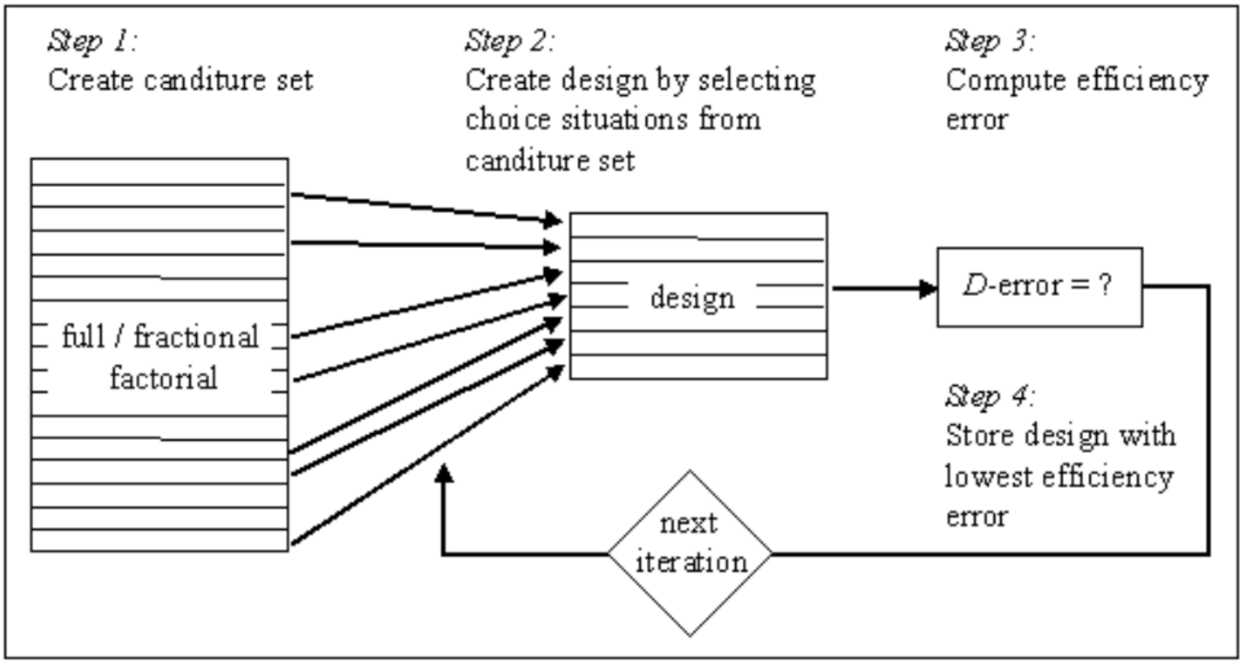



Figure 4.4 – Modified Fedorov algorithm (ChoiceMetrics, 2018)

An alternative approach is the relabelling, swapping and cycling (RSC) algorithm, which is a column-based algorithm that have been discussed by Huber and Zwerina, (1996) and Sándor and Wedel, (2001). As can be seen in the graph below, it works on the same logic, but instead of substituting different choice situations, it swaps different attribute values and evaluates the D-error for each iteration. The design with the least error will be stored and it moves on until there is no further evaluation.

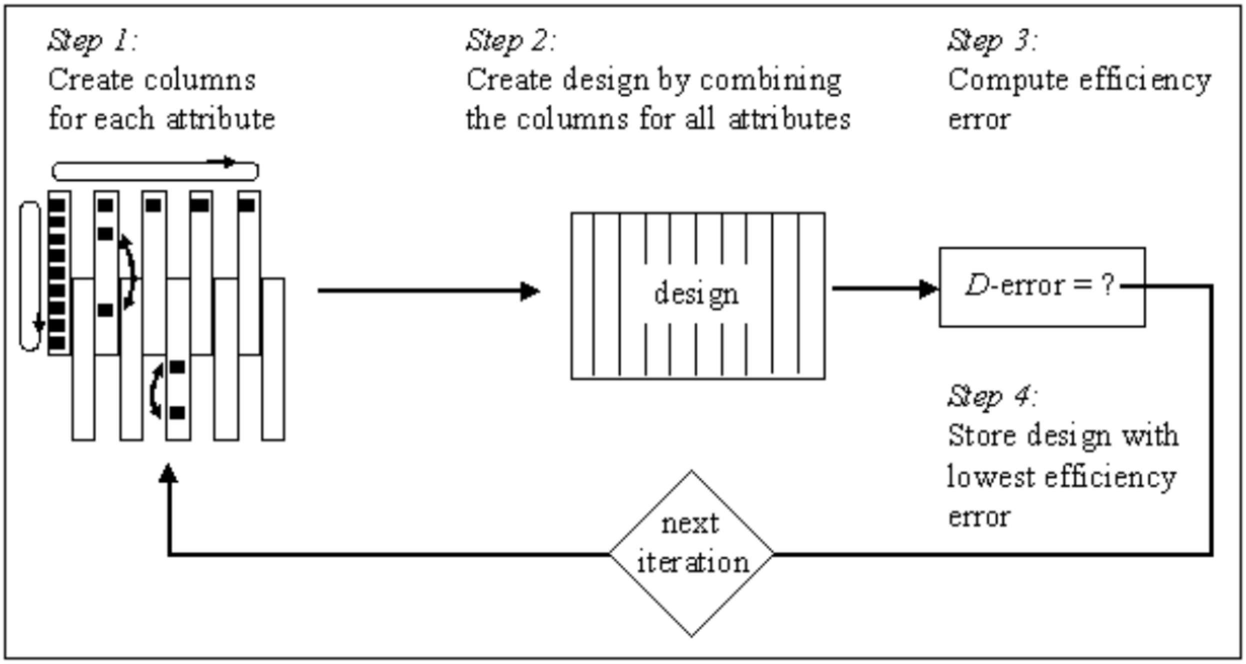



Figure 4.5 – RSC algorithm framework (ChoiceMetrics, 2018)

In general column-based algorithms are more suitable particularly when dealing with large designs, however, row-based algorithms are more flexible for special cases such as constrained or unlabelled designs (ChoiceMetrics, 2018). This thesis will utilize the Modified Fedorov row-based algorithm since imposing constraints on the design will not be possible within the column-based algorithm.

### 4.3.1. Example SP Design

This research has utilized the Ngene software to develop the experiment design for several reasons. First, this tool is designed explicitly for discrete choice models and is very powerful. The software is also heavily supported by reputable sources. Finally, the programming is easy to understand and flexible. Example code from the design process is provided in Figure 4.6. The code represents a basic example of an efficient design generation.

```
Design
;alts = Alt1, Alt2 #Number of Alternatives
;rows = 8 #Number of Choice Situations
;eff = (MNL,D) #Identification of Design Type, Model Type, and Efficiency
Measure
;model: #Identification of Utility Functions
U(Alt1) = b1[-0.1] + b2[0.4] * A[0,1] + b3[-0.6] * B[2,4] /
U(Alt2) = b2 * A + b4[0.5] #Prior Parameter * C[1,2,3,4] #Attribute Levels
$
```

Figure 4.6 – Syntax Structure of a Stated Choice Design Example

The output of the code is shown in Figure 4.7. As can be seen in the figure below, different efficiency measures along with basic statistics of the parameter and the final choice situation are reported.

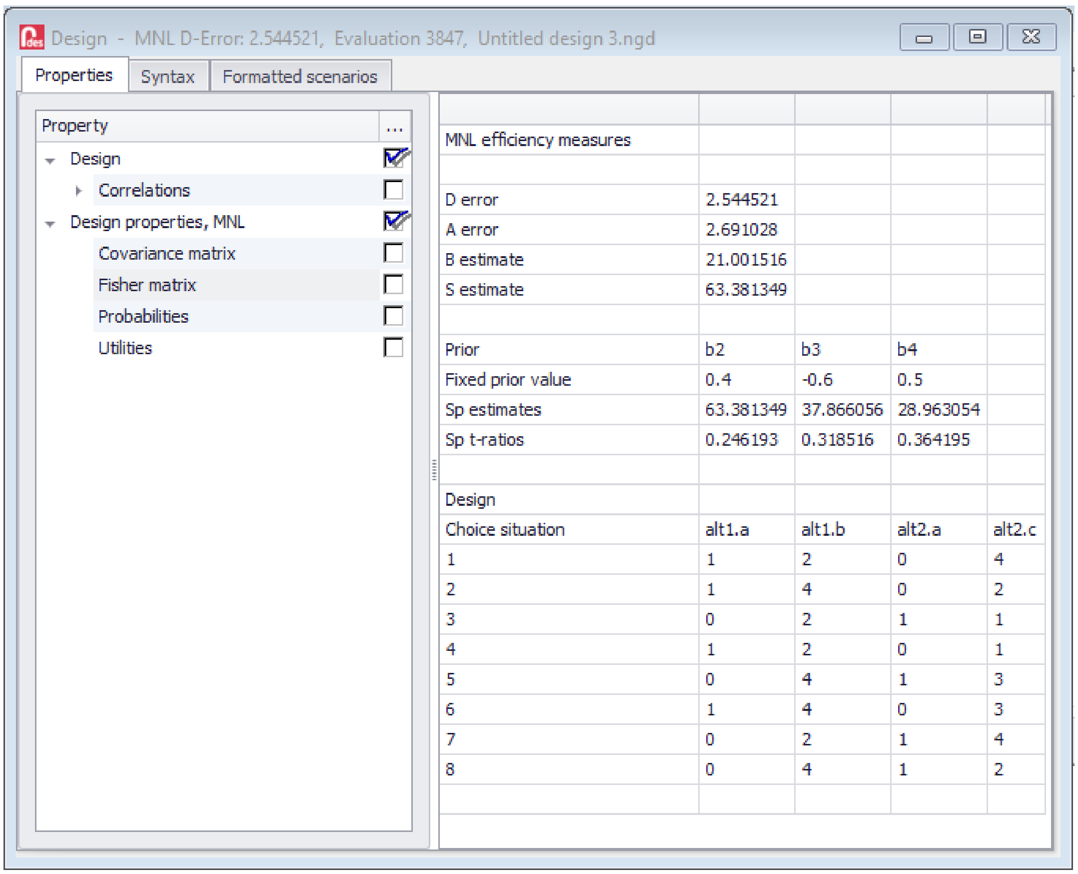



Figure 4.7 – Example Design Ngene Output

Once the best design is selected, it can be converted into actual choice scenarios that will be given to respondents. Every row of the design in Figure 4.7 represents a choice situation that can be translated into a question, also known as a game or treatment. Ngene software has a built-in tool that automatically provides the choice situations in a survey format. Consider the 8$^{th}$ choice situation in the figure above. It can be formatted into a question-form as shown in the figure below. Having a closer look at Figures 4.6, 4.7, and 4.8, it can be observed how the software assigned the predefined attribute levels to each choice situation which then finally will be translated into an understandable SP format.

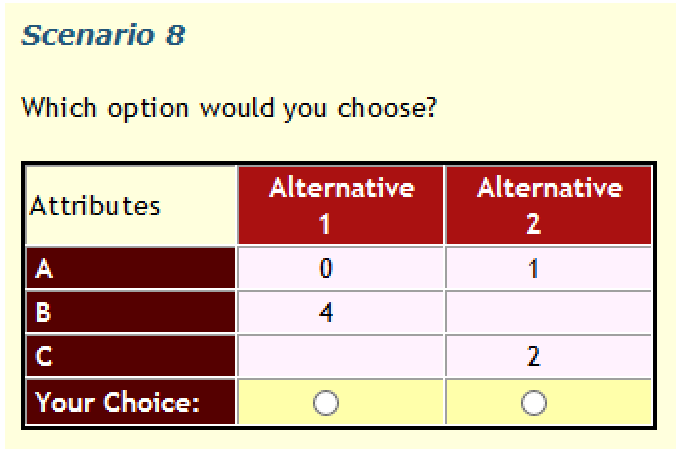



Figure 4.8 – Visual Representation of a Single Choice Situation in a SP Scenario

4.4. Data Collection

The questions derived from survey design are added to a questionnaire to distribute the choice scenarios to respondents and collect meaningful data. An online survey was selected as the appropriate method of dissemination due to a broad reach and quick implementation within the scope of this research.

It has been understood that respondent characteristics such as socio-demographics can improve model results (Quattrone and Vitetta, 2011) in a variety of topic areas including route choice. As previously discussed, Zhou *et al.*, (2009) and Arentze *et al.*, (2012) have concluded that truck company characteristics and driver identities were helpful in their data categorization. Therefore, this information can be collected along with SC questions. These factors correspond to different characteristics of respondents such as age, gender, income, to name a few.

To disseminate the results, an online survey has been selected as the appropriate method. Other methods were not considered due to the emergence of a worldwide pandemic in 2020 that has limited contact between individuals. The online format has several advantages including the ability to reach a broad audience and avoid over-sampling respondents from specific locations. An online survey also makes it possible to randomize questions and the order of appearance. A trade-off to this approach is that there is no supervision when the respondent completes the survey to ensure that the questions are fully understood. A lower successful completion rate is also typical of online surveys.

An online survey must be built on a suitable online platform before distribution is possible. Software that has been used includes basic options such as Google Forms or Survey Monkey along with more extensive platforms such as Qualtrics. This thesis utilizes the latter software due to the ability of the software to randomize the order of appearance of each SP question and each alternative therein. In addition, the software has established protocols for data security that conform to ethics requirements established for the research.

Online surveys are relatively more complex to handle since they require comprehensive sampling and distribution endeavours. If the survey was conducted in-person using an intercept approach by contacting drivers in the field, then no pre-defined distribution list was required. However, an online survey requires a contact list of potential respondents before it can be distributed. The methods used to generate this list will be discussed in Chapter 7.

The next chapter will discuss the application of the survey methodology explained in this chapter to generate and conduct the pilot survey.

# Chapter Five: Pilot Survey

Efficient designs can outperform an orthogonal counterpart when there is reliable available information regarding parameters. One of the most reliable approaches that can be utilized to collect prior information is conducting a pilot study to calibrate the design for the main survey, though there are other approaches such as previous literature and expert judgement. But conducting a pilot study is recommended since it can provide information that suitable for the given context. Pilot studies are also a smaller version of an experimental design and they might require this priori information depending on the approach the analyst would choose.

This chapter will discuss the design and implementation of a pilot study using the design procedure explained in the previous chapter. A few design candidates will be assessed before implementing the prior survey. The design will be relatively less complex at this stage to collect prior information. Once the design is finalized and the data has been collected, the remainder of the chapter will focus on the estimation of the discrete choice model.

## 5.1. General Design Specifications

This section will focus on the general specifications of the pilot design. This step will translate the graphical layout of the hypothetical scenarios into mathematical equations representing the utility of each choice. In the following sections, the number of alternatives in the pilot study is first discussed. Then, the type and number of attributes in each alternative is established. Finally, a discussion on the selected levels for each attribute along with the number of choice situations will be provided.

### 5.1.1. Alternatives, Attributes and Levels

A qualitative investigation on the study area was conducted as per the discussion provided in section 4.1.1.1. The analysis indicated showed that there are only two major route options available given the hypothetical scenario that this research has assumed. The third alternative, shown in Figure 3.5, is not favorable at any given time of day and it is mostly used for urban deliveries which is beyond the scope of this study. Therefore, the pilot survey is assigned only **2 unlabeled alternatives** for each choice situation. This aligns with general knowledge that trip makers consider very few routes when making routing decisions. This is because they are neither able nor prefer to consider many alternatives at a time (Lima *et al*., 2016).

Among the two route choices, one alternative represents a free route option similar to Highway ON-401, while the other alternative represents a tolled route similar to Highway ON-407 ETR. The two alternatives are given to respondents anonymously as Route A and Route B (i.e. unlabeled) to reduce the potential influence of their brand on the respondents' choice (Jin *et al*., 2017).

Once the alternatives were defined, the next step is to assign relevant variables to them. A brief rationale on this process was explained in section 4.1.1.1. In Chapter 3, information has been collected on a group of factors for a typical 24-hour period. These include *travel time, travel time variability, toll cost, distance,* and *time of day*. It was decided not to add any more variables into the pilot design due to a handful of reasons. Firstly, a main objective of this research is to investigate the VOT, requiring a nonlinear study of time-related and cost-related attributes. Furthermore, it was already concluded in other relevant studies that other potential trip-related attributes are comparatively not as significant as the two above-mentioned factors (Arentze *et al*., 2012; Hunt and Abraham, 2004). Additionally, it has been concluded that cognitive abilities of respondents are limited in a sense that they are not capable of comparing more than a limited group of factors, therefore introducing more variables may increase the chance of error (ChoiceMetrics, 2018). With all this considered, 4 out of 5 observed variables namely *travel time, travel time variability, toll cost,* and *distance* were included in the pilot survey. Time of day variable was eliminated from the design due to two main reasons. First, adding this variable into the design would have required imposing strong constraints for ensuring consistency between variables which would compromise the efficiency. Secondly, the two time-related attributes were able to depict the time of day in a scenario to a great extent.

*Travel time variability* attribute was renamed to *potential delay* to mirror the variability in travel time more understandably. *Distance* variable was also adjusted to *extra distance* to reflect the difference in length of the alternatives. The two time-related attributes were considered generic and the other two variables were included only in the tolled route. A summary of the attributes, their levels, and their type are reported in Table 5.1.

Table 5.1 – Pilot Survey Attributes and Levels

| Attribute | Code | Levels | Type | Remarks |
|---|---|---|---|---|
| Travel Time (min) | TT | {60, 80, 100, 120} | Generic | |
| Toll Cost ($) | TC | {50, 100, 150} | Alternative-Specific | |
| Potential Delay (min) | TTV | {0, 10, 20, 30} | Generic | Potential delay represents the variability that might be added to the travel time. |
| Extra Distance (km) | DIST | {0, 15, 30} | Alternative-Specific | This attribute mirrors the relative different in distance instead of the absolute value. |

Next, appropriate levels were allocated to each attribute. The guidelines discussed in section 4.1.1.1 have been applied to each of the attribute ranges found in Figure 3.5, 3.6, and 3.7. For example, as illustrated in Figure 3.5, the TT for either of the route options was found to be between 60 to 120 minutes. These two values were subsequently selected as the minimum and maximum boundaries, along with two additional levels in this range to capture non-linearities. The same procedure was applied on the rest of the attributes and a summary of the selected levels is provided in Table 5.1.

After reviewing the potential combinations of attribute levels, it was found that there are some implausible outcomes that are not observed in practice. Referring to the travel time and toll cost in the observed data, a situation where the tolled route travel time and potential delay exceeds the free route is not feasible. Thus, a constraint on attribute combinations was made using the "reject" property in Ngene software to remove these implausible situations in the pilot design. The formula is highlighted in the syntax section in *Appendix B*.

The next step is to set the number of games in the experimental design. The guideline provided in section 4.1.1.2 with regards to the number of levels for each attribute provides some discussion on this topic. After evaluating different possibilities, it was decided to give 12 scenarios to each respondent.

### 5.1.2. Design and Model Type

The utility functions for a basic binomial model of the pilot survey is provided in the equations below, where the first utility equation represents a tolled route, and the second utility equation represents a free route:

$$U_1 = \beta_1 TT_1 + \beta_2 TC_1 + \beta_3 TTV_1 + \beta_4 Dist_1 + \varepsilon_1 \quad \text{Equation 17}$$

$$U_2 = \beta_1 TT_2 + \beta_3 TTV_2 + \varepsilon_2 \quad \text{Equation 18}$$

A model design type needs to be selected next. For the pilot design, it was decided to use efficient designs. The efficient design outperforms the orthogonal designs counterpart if there is information available regarding prior parameters. In addition to producing large designs as was discussed in 2.3.3, another big disadvantage of using orthogonal designs is that the analyst will not be able to impose constraints on the choice outcomes. Therefore, every possible combination of the attribute levels might exist in the design matrix. Sometimes these combinations are too dominant such that the route choice is self-evident or implausible in a real-world situation. Literature suggests that that even a small amount of information such as knowledge of the parameter signage would be considered beneficial to the design (ChoiceMetrics, 2018). Hence, we reject to make use of orthogonal designs for the pilot study and will stick to the efficient design methods.

To generate the efficient design candidates, a stochastic model of the utility functions needs to be introduced, with the inclusion of an unobservable error component. For the pilot design, a basic MNL model is selected with the implementation of advanced models reserved for later in the final survey design. In the following section 17 designs with different types and different prior parameter assumptions will be generated and evaluated. The comparison criteria includes two steps. First, the statistical properties of each design will be assessed. Second, the final design matrix (i.e. choice set) for each candidate will be manually reviewed in order to make sure that the final choice tasks are neither dominated nor implausible hence realistic. The design with the best reported statistical performance in efficiency measures and most realistic choice situation will be nominated for the pilot study.

### 5.1.3. Design Candidates

As said, for generating efficient designs, availability of priori information regarding parameters is necessary. Similar existing studies and logical judgements will be used to identify the initial priors for each candidate design. Three different categories of prior parameter types namely 1. Zero prior, 2. Fixed prior, 3. Bayesian prior will be evaluated. Below a summary of the rationale used for generation of these different designs will be provided.

The parameters for the model design can be intuitively identified with a negative relationship in the utility function. For instance, toll costs will decrease the attractiveness of an alternative, meaning that the more cost that an alternative incurs, the less likely that it would be chosen by decision maker. The same logic can be applied to time, distance, and potential delay as an increase in any of these features would make that alternative less favorable. This fact can be validated in the literature as different studies have concluded that these factors have negative parameter signage (Arentze *et al*., 2012).

So far, the signage of all the parameters has been established as negative. Design guidelines suggest that comparing to assuming zero prior, even a small positive or negative value would already improve the design (ChoiceMetrics, 2018). Therefore, it can be argued that $D_p$-optimal designs are more likely to outperform the $D_z$-optimal counterpart.

Next, the variables should be investigated in the literature to identify which attribute has a greater impact on the utility function compared to the others. Simply put, the relative influence of the attributes was needed. Referring to the literature review section 2.2.1, it was concluded that travel time and toll cost are much more influential on the route choice decision comparing to distance and delay attributes. Based on these information, different combinations of prior parameters for each attribute were tested and the result are provided in Table 5.3.

Table 5.2 – List of Zero- and Fixed-Prior Candidate Designs

| Design No | Input Prior Parameters | | | | Output Efficiency Measures | | | |
|---|---|---|---|---|---|---|---|---|
| | TT | TTV | TC | DIST | D-error | S-estimate | A-error | B-estimate |
| **Zero-Prior Design** | | | | | | | | |
| **1** | 0 | 0 | 0 | 0 | 0.000212 | 0 | 0.000466 | 100.00 |
| **Fixed-, Non-Zero-Prior Designs** | | | | | | | | |
| **2** | -0.001 | 0 | 0 | 0 | 0.000212 | 824.15 | 0.000476 | 99.94 |
| **3** | 0 | -0.001 | 0 | 0 | 0.000212 | 1840.61 | 0.000466 | 99.97 |
| **4** | 0 | 0 | -0.001 | 0 | 0.000213 | 153.45 | 0.000467 | 99.59 |
| **5** | 0 | -0.001 | -0.001 | 0 | 0.000213 | 1848.17 | 0.000467 | 99.62 |
| **6** | 0 | -0.001 | -0.01 | 0 | 0.00029 | 2221.42 | 0.000537 | 78.68 |
| **7** | -0.001 | 0 | -0.001 | 0 | 0.000213 | 825.85 | 0.000467 | 99.67 |
| **8** | -0.001 | -0.001 | -0.001 | 0 | 0.000212 | 1844.45 | 0.000467 | 99.71 |
| **9** | -0.001 | -0.0001 | -0.01 | 0 | 0.000288 | 218022.08 | 0.000532 | 79.21 |
| **10** | -0.001 | -0.0001 | -0.01 | -1.00E-06 | 0.000288 | 4712418826.53 | 0.000532 | 79.21 |
| **11** | -0.001 | -0.0001 | -0.1 | 0 | 0.014989 | 7736398.91 | 0.025563 | 2.74 |

*The highlighted row represents the selected design.*

Referring to B-estimate property of design number 1, which is a fixed zero prior design, the Ngene software could hardly tell the differences between attributes resulting in generating a completely balanced design. This means that all alternatives in all choice situations have equal observed utility which brings about indistinguishability issue. Too much utility balance would make the design incomparable to the respondents where they might have no preference in choosing either of the alternatives. This tells us that using a fixed zero prior approach would not produce our desired design. So, we started giving the attributes a very low value corresponding to their intuitive signage to make them distinguishable by the software. One can argue that in this process, we are compromising some degrees of efficiency which is indeed correct, but the fact is that this lost efficiency is due to applying more constraints (i.e. signage for the parameters) which in the end will help producing more meaningful designs.

We have gone over similar truck route choice studies to find out the order of importance of the above factors. A study which tried to address the ranking order of truck route choice attributes have concluded that distance variable is relatively less influential compared to other factors

(Cullinane and Toy, 2000). Arentze *et al.*, (2012) have concluded that cost-related attributes were estimated to have more effect on the utility as compared to time-related attributes. In another research by Sun, (2013), it was concluded that toll rates are the most influential factor followed by travel time and delay. Considering this feedback from the literature the different designs with different combinations of prior parameters pertaining to their order of importance was generated. Designs with relatively better statistical properties (i.e. lower D-error and reasonable range for B-estimate) were thoroughly reviewed. Design number 10 was observed to yield the most realistic choice situations. The details of the choice situations for this design are provided in the table below.

Table 5.3 – Choice Situations for Selected Design No.10

| **Choice situation** | **Route A (Tolled)** | | | | **Route B (Free)** | |
|---|---|---|---|---|---|---|
| | **TT** | **TTV** | **TC** | **DIST** | **TT** | **TTV** |
| **1** | 60 | 0 | 50 | 0 | 120 | 30 |
| **2** | 60 | 30 | 50 | 30 | 120 | 0 |
| **3** | 80 | 0 | 150 | 30 | 60 | 30 |
| **4** | 60 | 0 | 50 | 30 | 120 | 30 |
| **5** | 60 | 0 | 100 | 0 | 120 | 30 |
| **6** | 80 | 0 | 150 | 0 | 60 | 30 |
| **7** | 60 | 30 | 150 | 0 | 120 | 0 |
| **8** | 100 | 0 | 50 | 30 | 80 | 30 |
| **9** | 60 | 30 | 50 | 30 | 100 | 0 |
| **10** | 80 | 30 | 150 | 0 | 120 | 0 |
| **11** | 120 | 0 | 150 | 30 | 100 | 30 |
| **12** | 60 | 0 | 50 | 30 | 120 | 20 |

As was previously mentioned, another approach to take the uncertainty regarding the prior parameters into account was to implement a Bayesian approach to the design. We have designed the experiment using this approach considering both uniform and normal distribution for all of the parameters. Two different simulation techniques with regards to their complexity as Halton (simpler) and Gaussian (advanced) were also tested. The statistics of each design along with the choice situations for the best-performing candidate are reported below.

Table 5.4 – List of Bayesian Candidate Designs

| Design No | Distribution Type | TT | TTV | TC | DIST | Simulation Type | D-error | S-estimate |
|---|---|---|---|---|---|---|---|---|
| **12** | Uniform | {-0.01,0} | | | | Halton | 0.00024 | 11088.98 |
| **13** | Uniform | {-0.01,0} | | | | Gaussian | 0.00024 | 4269.59 |
| **14** | Normal | (-0.01,0.01) | | | | Halton | 0.00037 | 32971.36 |
| **15** | Normal | (-0.01,0.01) | | | | Gaussian | 0.00037 | 125.23 |
| **16** | Normal | (-0.01,0.01) | (-0.001,0.001) | (-0.01,0.01) | (-0.001,0.001) | Gaussian | 0.00035 | 12510.45 |
| **17** | Normal | (-0.001,0.001) | (-0.0001,0.0001) | (-0.01,0.01) | (-0.00001,0.00001) | Gaussian | 0.00036 | 119560291 |

*Notes: *The highlighted row represents the best-performing design.*

***For uniform distribution parameters, the first and second values represent the range of the distribution.*

****For normal distribution, the first value represents the mean while the second value represents the standard deviation.*

Table 5.5 – Choice Situations for Candidate Design No.15

| Choice situation | Route A (Tolled) | | | | Route B (Free) | |
|---|---|---|---|---|---|---|
| | TT | TTV | TC | DIST | TT | TTV |
| **1** | 60 | 30 | 50 | 30 | 120 | 0 |
| **2** | 60 | 0 | 50 | 0 | 120 | 30 |
| **3** | 120 | 0 | 150 | 0 | 100 | 30 |
| **4** | 60 | 0 | 50 | 30 | 120 | 30 |
| **5** | 60 | 30 | 100 | 0 | 120 | 0 |
| **6** | 60 | 0 | 100 | 0 | 120 | 30 |
| **7** | 100 | 0 | 150 | 0 | 80 | 30 |
| **8** | 80 | 0 | 50 | 30 | 60 | 30 |
| **9** | 100 | 0 | 50 | 30 | 80 | 30 |
| **10** | 60 | 30 | 150 | 0 | 120 | 0 |
| **11** | 60 | 30 | 50 | 30 | 100 | 0 |
| **12** | 60 | 0 | 50 | 30 | 120 | 20 |

A comparison of the choice situations between the two best designs from Table 5.3 and 5.5 indicates that they are mostly similar. This implies that both approaches result in somewhat similar designs, particularly at this early stage of the pilot survey. A decision between these two designs can be made based on the level of confidence with the prior values comparing to the true parameter values. The Bayesian approach represents a degree of uncertainty with the prior values that is not considered in the fixed-prior design, but we decided to use the fixed-prior approach for the pilot experiment.

## 5.2. Data Collection and Administration

The pilot survey was conducted online using Google Forms and the link was sent to peer colleagues as sample respondents. In literature, this is referred to as "convenience sampling" (Stopher, 2012) and has proven to be useful for pilot studies. There were 15 respondents for this pilot survey with 180 × 2 observations.

## 5.3. Analysis

The pilot survey results were processed into a comma delimited format and imported to NLogit software for model estimation. Two model results are shown below, one with an alternative constant and the other without any constant. The coding syntax is provided in the Appendix. Both model results can be found in the table below.

Table 5.6 – Model Results with (MNL1) and without (MNL2) Alternative Specific Constant

| | MNL1 | | | MNL2 | | |
|---|---|---|---|---|---|---|
| **Variable** | **Coef.** | **Std. Errors** | **t-stat** | **Coef.** | **Std. Errors** | **t-stat** |
| Constant | -2.432 | 1.50038 | -1.62 | | | |
| Travel Time | -0.0543*** | 0.0133 | -4.09 | -0.0405*** | 0.0084 | -4.84 |
| Delay | -0.0341*** | 0.0094 | -3.62 | -0.0274*** | 0.0082 | -3.33 |
| Toll Cost | -0.0161 | 0.0099 | -1.63 | -0.0307*** | 0.0057 | -5.38 |
| Extra Distance | 0.0100 | 0.0232 | 0.43 | -0.0231* | 0.0129 | -1.79 |
| LL[0] | -124.8 | | | -124.8 | | |
| LL[C] | -108.21 | | | -108.21 | | |
| LL[F] | -61.588 | | | -62.94 | | |
| Naïve $\rho^2$ | 0.506 | | | 0.495 | | |
| Restricted $\rho^2$ | 0.4308 | | | 0.4183 | | |
| Adjusted $\rho^2$ | 0.4146 | | | 0.4051 | | |
| AIC | 133.2 | | | 133.9 | | |
| No. of Resp. | 15 | | | 15 | | |
| No. of Obs. | 180 | | | 180 | | |

*Notes: ***, **, *, represent statistical significance at 1%, 5%, and 10% respectively.*

As can be seen in the table above, in contrast to expectations these two models are somewhat different. The model without ASC appears to be working well since three out of four parameters are significant at above 99% confidence and the signages are intuitive. However, the model which accounted for ASC has only two parameters at a 99% confidence level and the other two parameters are not significant within a 10% confidence interval which is unfavorable. Additionally, the signage for the distance variable is counterintuitive (i.e.: the more the distance, the more desirable the route will be which contradicts intuition) although this result is not reliable due to the parameter insignificance. Moreover, the toll cost variable which was supposed to be influential in route choice appears to have no significance at all. Although, the adjusted-$\rho^2$ was slightly worsened in the second model. With all this considered, we concluded that the model without ASC works relatively better in terms of fitting the regression to the observed data and consequently predicting the chosen alternative.

A key function of these choice models is that they offer approximations on the effect of variations in independent variables on the substitution patterns between the dependent variables (i.e.: alternatives). In literature, these capabilities are referred to as "choice elasticities" and are defined as the impact on the probabilities of the choices when an attribute in a particular choice changes (Econometric Software, 2012). We have calculated the choice elasticities for each attribute within each alternative and the results are provided in Table 5.9. The values in the table below can be interpreted as follows. For example, a percentage increase in travel time attribute within the first alternative would reduce the probability that individuals would choose this alternative by 2.24 percent and an increase of 0.73 percent in the chance of the second alternative.

Table 5.7 – MNL2 Elasticities for Pilot Survey

| **Percent Changes in Alternative Attributes*** | | **Probabilities** | |
|---|---|---|---|
| | | **Route A (Tolled)** | **Route B (Free)** |
| **TT** | Route A | -2.24 | 0.73 |
| | Route B | 2.78 | -1.40 |
| **TTV** | Route A | -0.23 | 0.04 |
| | Route B | 0.34 | -0.19 |
| **DIST** | Route A | -0.29 | 0.12 |
| **TC** | Route A | -2.39 | 0.55 |

**Note: Elasticity with regards to a change of X [row choice] on Probability [column choice]*

## 5.4. Results and Discussion

Based on the modeling result provided above, the utility function for both alternatives are as follows:

$$U_{ON-407} = -\,0.04051\,TT_{407} - \,0.0274\,TTV_{407} \,-\, 0.03067\,TC \,-\, 0.02315\,Dist \qquad \text{Equation 19}$$

$$U_{ON-401} = -\,0.04051\,TT_{401} - \,0.0274\,TTV_{401} \qquad \text{Equation 20}$$

These β parameters mirror the sensitivity of utilities to changes in their associated independent variables (Wang and Goodchild, 2014). Thus, the ratio between each of those parameters cancels out the utility component and captures the trade-off between them. If one takes the ratio of travel time over the toll cost coefficient, it results in a value that is known as the value of time (VOT). According to Equation 21, the value of truck travel time is estimated to be \$79.25/hr (Canadian Dollar in 2020), indicating that our pilot survey respondents are willing to pay up to \$79.25 to save one hour of their travel time.

$$VOT = \frac{\beta_1}{\beta_3} = \frac{-\,0.04051}{-\,0.03067} * \,60 = \,79.25\ {}^{\$}/_{hr} \qquad \text{Equation 21}$$

Comparing this value to the \$150/hr market value in Chapter 3, the market is requiring very expensive travel value compared to survey respondent willingness to pay (WTP). The results from the second model MNL2 will be used as the prior parameter information for the final survey of the thesis discussed in Chapter 6.

# Chapter Six: Full Survey Design

Chapter 4 put forward a full discussion on theoretical methodologies for designing experiments. It was concluded that efficient designs will outperform traditional factorial designs only if some prior information regarding parameters are available. For that, a pilot study was conducted in Chapter 5 to obtain prior parameter values and assess the practicality of the selected design. There were several lessons learned from the pilot survey. These ranged from general design specifications such as number of attributes to more advanced model considerations like utility function components. The feedback from the pilot survey revealed that respondents were hesitant to incorporate too many factors in their decision-making process. Moreover, it was concluded that SP survey should be complemented with other demographic/socio-economic questions to reinforce the robustness of the result.

This chapter will discuss the design of the final version of the survey considering the lessons learned in the two previous chapters. Efforts are made to improve the initial design by reviewing the design specifications and applying changes based on received feedback. In addition, the usage and functionality of a few advanced model type specifications (e.g. mixed logit) will also be discussed. These changes will be applied to the design and a performance evaluation will be conducted to assess different candidate models, with the chapter concluding with a final design.

## 6.1. General Design Specifications

### 6.1.1. Alternatives

After reviewing the feedback from the pilot study, where two route choices were presented for each scenario, it was determined that survey respondents faced challenges when considering every single attribute of each alternative in their decision-making effort. This attests to respondent difficulties processing and evaluating too many alternatives and attributes at a time. The final design will also be limited to only containing two possible route choices for each scenario, including a tolled and a free route.

An opt-out alternative was also considered for the final design; however, several reasons led to a decision to not include this additional third option. First, a realistic routing decision case for freight would not give the option of choosing no path. Moreover, the two routes that are presented to the respondent are already assumed to be favourable routes in the hypothetical scenario. Other routes would be assumed as sub-optimal for the respondent. A respondent might also be tempted to select the opt-out alternative out of boredom while completing the survey. It was subsequently decided to not include an opt-out option.

### 6.1.2. Attributes and Levels

In section 4.1.1.2 several different criteria were established to define the number of attributes and their levels. The initial design attempted to abide by these different principles. However, after reviewing the pilot result, it became apparent that the level of realism, which is arguably the most important measure in this stage, needs to be revisited. It has been strongly suggested that in order to have meaningful and reliable results, hypothetical scenarios need to depict the state-of-practice (Bradley, 1988; Kløjgaard *et al*., 2012). Two adjustments will be discussed below to increase the realism of the final design.

Both alternatives shared the time-related attributes while toll cost and extra distance was specific to the tolled alternative to mimic the observed routes (i.e. Highway ON-401 is neither tolled nor lengthier). However, this decision is re-evaluated for the final survey. Contingent on the location of the origin and destination of a trip, there might be a situation where the toll route lies in the proximity of these locations which results in a shorter distance for that specific alternative. For example, considering the future Ontario GTA West corridor proposed plan in Figure 6.1, it might cut the distance for those trips going from west to north or vice versa. This clearly indicates that assuming extra distance as an alternative-specific feature to only toll routes is flawed. Consequently, the extra distance attribute was adjusted to be applicable to both alternatives.

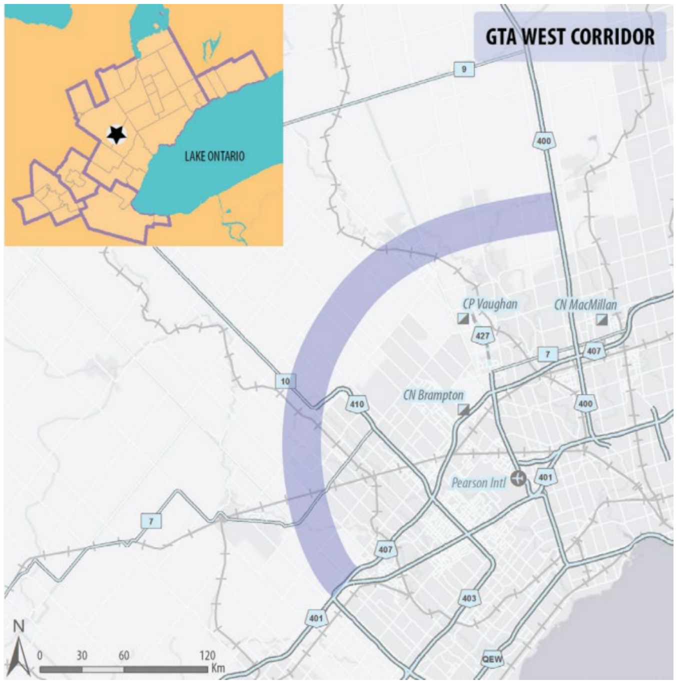



Figure 6.1 – GTA West Corridor Proposed Plan

Additionally, the potential delay attribute was originally defined as a generic feature that shares the same parameter for both alternatives. However, according to the study area characteristics in Figure 3.6, this contradicts the reality for Ontario since there is no typical situation where Highway ON-407 toll route travel time variability exceeds 10 minutes or surpasses that of the free route. Thus, a new set of levels for the toll route alternative was developed based on Figure 3.6 values. Table 6.1 below demonstrates the final adjusted values for attributes and their levels.

Table 6.1 – Final List of Attributes and Levels

| Attributes | Alternatives | |
|---|---|---|
| | **Route A (Toll Route)** | **Route B (Free Route)** |
| **Travel Time (min)** | [60, 80, 100, 120] | [60, 80, 100, 120] |
| **Potential Delay (min)** | [0, 5, 10] ~~*[0, 15, 30]*~~* | [0, 15, 30] |
| **Extra Distance (km)** | [0, 15, 30] | [0, 15, 30] ~~*[N/A]*~~* |
| **Toll Cost (CAD)** | [50, 100, 150] | [0] |

**Note: Pilot survey values are shown with a strikethrough line.*

### 6.1.3. Constraints

After adjusting the attribute levels and their ranges, the next step reviewed the possibility of implausible scenarios in choice situations in light of the new modifications to the design. Two potential inconsistencies were identified which will be elaborated below.

The extra distance attribute was previously adjusted and is no longer an alternative-specific attribute. This value should not be non-zero for both alternatives at the same time since the variable is measured with one alternative in relation to the second alternative. A constraint has been added to tell the Ngene software not to allocate zero values to both alternatives at the same time.

A condition was previously implemented on the design such that the sum of time-based attributes (*travel time* and *travel time variability*) of the free route should always be equal or greater than that of toll route. After reviewing the final choice situations of the pilot design, we were quite skeptical on the performance of this property in eliminating implausible situations. For this, the expected trip time has been adjusted for different situations based on the probability of the potential delay. For example, different scenarios were considered for chance of delay (0%, 50%, 100%) along the free route, and calculated the added travel time due to this congestion for the free route while assuming a 100% chance of delay for the toll route. The Figure 6.2 below demonstrates these different situations. During the peak times there is a significant difference between the expected trip time of the two routes. This is the main point of interest as the most congested period in the day. In summary, a conditional statement was added by enforcing no situation where the total travel time along the toll route could be equal or greater than the free route. A summary of these constraints is provided in the table below and the syntax code can be found in the *Appendix B*.

Table 6.2 – Summary of Imposed Constraints on Design Candidate Set

| No. | Constraints | Property | Conditional Statement | Remarks |
|---|---|---|---|---|
| 1 | Expected Trip Time | Reject | $TT_A + TTV_A > TT_B + TTV_B$ | Does not allow the design to produce situations where expected trip time (sum of travel time and its variability) along the toll route exceed that of free route. |
| 2 | Relative Difference in Distance | Reject | $DIST_A > 0 \ AND \ DIST_B > 0$ | Does not allow the design to produce situations where both alternatives have a non-zero distance attribute. |

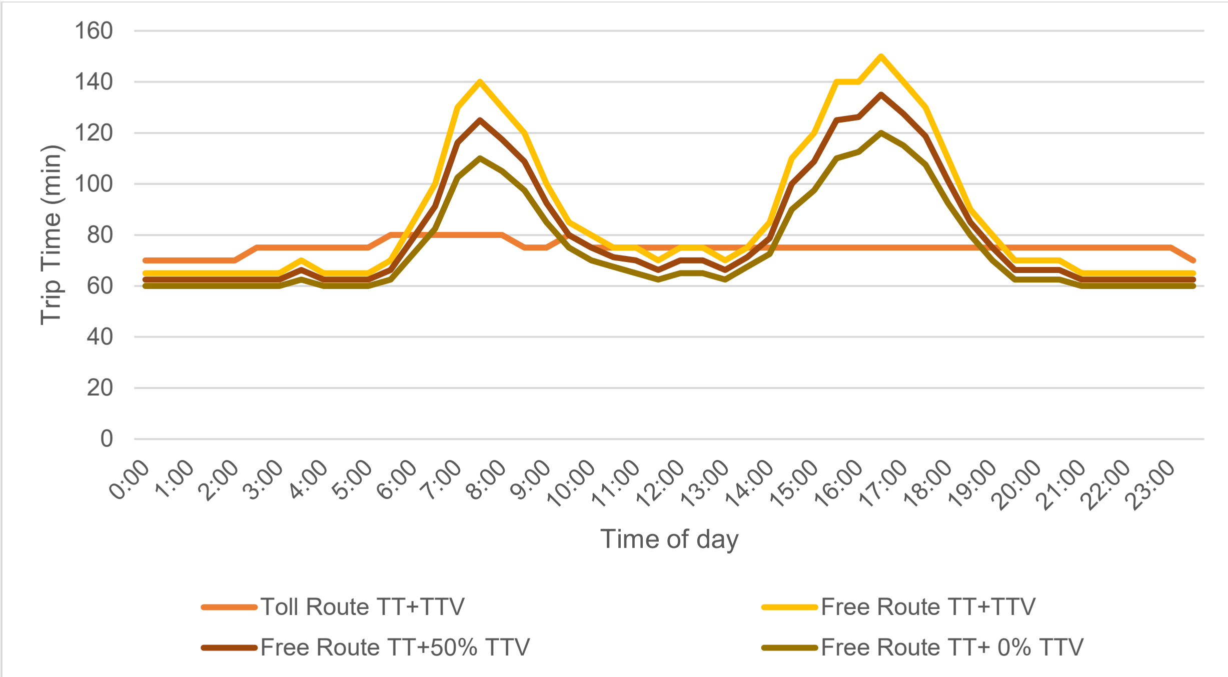



Figure 6.2 – Different Scenarios for Expected Trip Time Along Both Route Alternatives

### 6.1.4. Choice Situations

The pilot survey originally utilized a single set of 12 choice situations as seen in section 5.1.1. However, discussions with experts in this field (Bliemer, 2020) has led to a reconsideration of this strategy in favour of increasing number of scenarios. Ngene software tries to capture the variation between attribute levels in each choice situation to be able to estimate parameters for each attribute.

Since the survey design has 4 attributes and the software needs to estimate two coefficients (i.e. mean and standard deviation) for each of them, 12 choice situations would not generate adequate variations and result in a poor model performance and estimation quality. A total of 24 choice situations will be introduced to the final survey to provide greater variation. To keep the survey manageable for respondents, these scenarios are blocked into two groups with each respondent receiving only a group of 12 questions. As a result, a greater variation in attribute levels will be included while holding the original number of choice tasks presented to each respondent constant.

## 6.2. Model Type

For the pilot study, a multinomial logit (MNL) model was selected due to its simplicity and frequent use in discrete choice modelling. The strong assumptions identified by McFadden, (1972) result in a closed-form equation for the aforementioned model, however, these assumptions inevitably give rise to a few limitations on the performance of the model. In the following section, these limitations along with alternative approaches that were suggested in literature and considerations for the final design will be discussed.

The MNL model assumes a single value for each parameter in the estimation process, which ignores the preference heterogeneity expected for individuals. In other words, this assumption is not able to take the taste variation into the account (Train, 2009). In a typical stated preference survey, different respondents with varied preference behaviors are employed to answer the survey. For instance, different truck routing decision-makers have different sensitivities towards tolled routes based on their characteristics. This results in a significant variability in their stated VOT. As a case in point, referring to Table 2.1, researchers have reported different VOTs for different commodity types (Mei *et al*., 2013), truck sizes (De Jong *et al*., 2014), and or contract types (Toledo *et al*., 2020).

In addition, considering that each respondent will face numerous preference questions in an SP experiment, another downside of this method is that it cannot reflect the correlations that occur for repeated choice tasks completed by a single respondent (Bliemer and Rose, 2010). This limitation results from the MNL model assumption that says the unobserved part of the utilities is independently and identically distributed (IID).

And finally, the MNL model suffers from a restricted substitution pattern because of the assumption of Independence from Irrelevant Alternatives (IIA). This property restricts the model such that the ratio between different choice probabilities of different alternatives is independent from any other alternative available in the choice set. It compels the model to assume that if decision makers want to change their mind, they switch between alternatives proportionately (Beville and Kerr, 2008). For example, if a route travel time is increased because of road constructions, it will result in an increase of chances of other alternatives in a proportional manner regardless of their individual favorability (e.g. their accessibility). However, it should be noted that this last limitation is not a concern in this survey since the hypothetical routes are designed to be independent.

The limitations of the MNL model has been known for quite a while and many researchers have been investigating different methods to accommodate these drawbacks. For instance, some have proposed using another category of logit models known as Nested Logit (NL) (Bliemer *et al*., 2009) and some other have implemented Latent Class Models (LCM) (Kim *et al*., 2017). Still, these alternative approaches can only partially relax some of these limitations. Both models can preserve preference heterogeneity within groups of sample population by introducing some from nests or classes, however, they still assume a homogenous nature for behavior within these groups (Beville and Kerr, 2008). This has given rise to the Mixed Multinomial Logit (MXL) models which are far more flexible and can overcome the MNL limitations quite substantially.

### 6.2.1. Mixed Multinomial Logit

The Mixed Multinomial Logit (MXL) model was first introduced in 1980 (Boyd and Mellman, 1980; Cardell and Dunbar, 1980). The name is derived from the property of this model to include a mixture of possible parameter values for each given decision maker. It works based on an important principle that a random parameter value is drawn for each sample respondent and based on a predefined coefficient distribution. In other words, it is the weighted average of numerous standard logit probabilities over different parametric distribution function (Train, 2009). MXL utility function and choice probability are explained in equations below.

$$P_{in} = \int \left( \frac{e^{\beta\prime x_{in}}}{\sum_j e^{\beta\prime x_{jn}}} \right) f(\beta)\, d\beta \qquad \text{Equation 22}$$

As can be seen in equation 8, by assuming fixed parameters for β, f(β) becomes 1 and the choice probability reduces to the multinomial logit model. By assuming different values for β using a density function f(β), it obviates the most important limitation of standard logit and allows for random taste variation and relaxes the IID assumption to a great extent. Additionally, by adding error components that can create correlations among different alternative through the unobserved part of their utility, they can accommodate IIA assumption and allow for unrestricted substitution patterns. Hence, MXL models can be categorized into two subgroups: 1. Random Parameter (rp) models, 2. Error Component (ec) models depending on how the utility functions were defined which can be seen in Equations 23 and 24. Contingent to the research objectives and the importance of each limitation to the study, either one or a combination of these two modules can be utilized (Train, 2009).

$$U_{in} = \beta'_n\, x_{in} + \varepsilon_{in} \qquad \text{Equation 25}$$

$$U_{in} = \alpha'\, x_{in} + \mu'_n \zeta_{in} + \varepsilon_{in} \qquad \text{Equation 26}$$

These models have become popularized after computer capacities improved to accommodate simulation methods with many draws. By utilizing these model types, the analysis can account for variations in parameter estimation. The following section will focus on the feasibility study of employing a MXL model type for this thesis. The required steps for generating a survey design based on the mixed logit model will be introduced and the final design performances will be evaluated and compared.

6.2.1.1. Design Generation and Performance

Ngene software can accommodate random parameter (rp) and error component (ec) properties within the mixed logit modeling framework. The decision on choosing the components of the utility function is inspired by the objectives of the research. As was mentioned earlier, the IIA property (3rd limitation) is not an issue since there is only a pair of alternatives in this study per question. However, the ability of the model to consider taste heterogeneity between respondent (1st limitation) and to account for observation dependency within respondent (2nd limitation) is more crucial. Therefore, a panel version of random parameter mixed logit model is designed and evaluated.

In the random parameter approach, the β coefficients need to be defined as a distribution. Different forms of distribution can be implemented; however, Ngene software is only able to account for normal and uniform distributions (ChoiceMetrics, 2018). The acquired parameter information in Table 5.6 with a normal distribution will be used as the distributional assumption for the final design. For generating these random draws, different simulation techniques such as Pseudo-random Monte Carlo (PMC), Quassi-random Monte Carlo, and Gaussian quadrature which were discussed in section 4.2.1.1 will also be appraised. The above-listed properties for the model have been used to generate the design and the output is provided in Figure 6.3. Design syntax can also be found in *Appendix B.*

Based on the literature review, a panel mixed logit design necessitates substantial computational effort due to their relative complexities (Bliemer and Rose, 2010). A panel mixed logit design requires approximately 400 times more computation time compared to a similar MNL model (Bliemer and Rose, 2010). With the above-listed specifications being far too complex for the software given the limited prior parameter information, our model experienced a very slow design generation process with too many invalid designs being produced. As can be seen in the graph below, one of candidate models was run for more than 24 hours and still could not converge to its final D-error value.

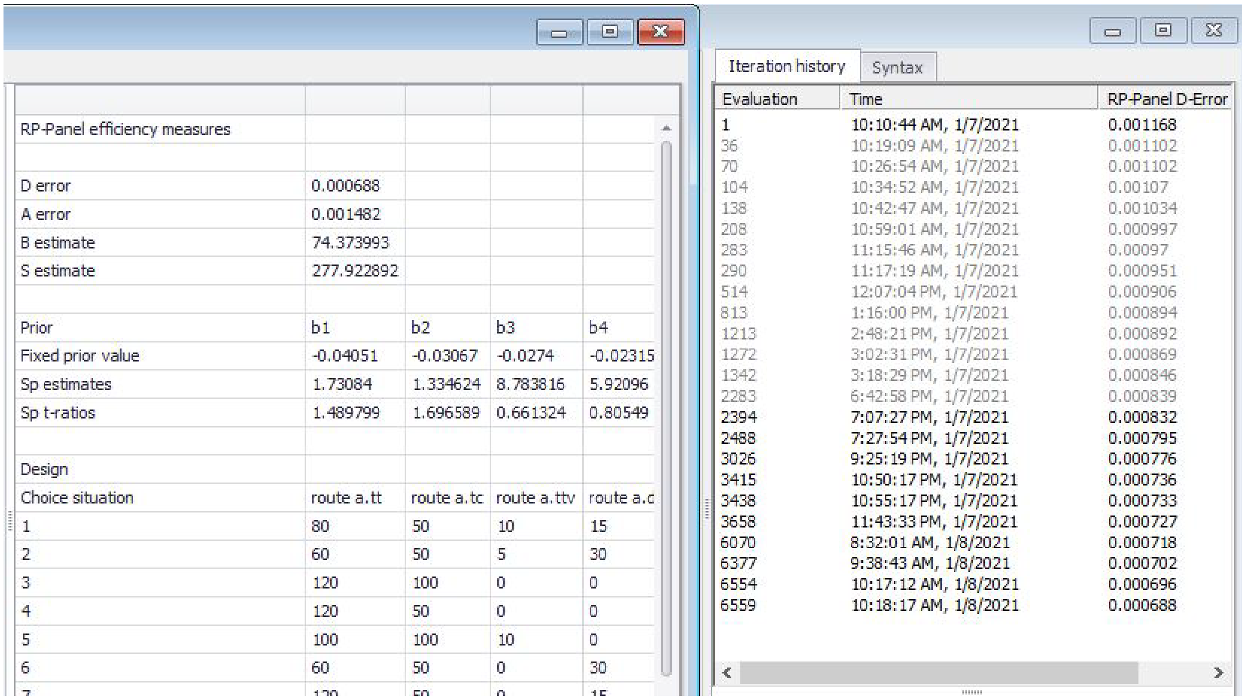



Figure 6.3 – Screenshot of RPPanel Design Result for 24hr Run-time

The generation of these many invalid designs made us suspect the process and started to look for an alternative solution. One potential solution was to reduce the complexity of the design. For example, we could have got rid of the panel version and opted-in for a cross-sectional MXL design that could help reducing the computation time. However, this was more of a passive solution and the statistical efficiency of the design would not be verified yet. Additionally, letting go of panel property in stated choice panel surveys for the sake of improving design performance is not a logical decision.

After discussing with the experts in the field (Bliemer, 2020), we concluded that optimizing experimental designs using mixed logit models can be problematic given the unreliability of prior parameters. This was also done quite rarely in the literature. Considering the uncertainty regarding the obtained prior values from a very small pilot sample size, one can question the reliability of the mixed logit design parameters. Additionally, research has suggested that estimating for a panel mixed logit model over a design originally modelled on a MNL specification can still be efficient (Bliemer and Rose, 2010). As a result, the mixed logit design was rejected for the survey phase and postponed until the estimation phase of model results. Instead, a Bayesian MNL design was chosen as a viable alternative which will be elaborated in the following section.

### 6.2.2. Bayesian MNL Design

As discussed in section 4.2, there are different ways to define prior parameters. They can either be identified as zero or a fixed non-zero value where the analyst is assuming that she knows the prior values. However, there is always uncertainty regarding the true parameter values. This has given rise to the development of a third useful approach called Bayesian efficient designs. In this method, the analyst can assume a range of values instead of a fixed or zero prior to account for this uncertainty. These ranges can be defined using different forms of distributions that can be employed depending on the nature of the attribute.

After generating a few sample design and consulting with experts, we have finally decided to opt-in for using a Bayesian efficient design. A normal distribution is assumed for each parameter and the obtained results from the pilot study are be considered as the mean and the standard deviation of the corresponding distribution.

## 6.3. Further Considerations

After generating multiple designs with the new specifications, the best-performing design in terms of D-error does not include some levels of the scenario attributes. This means that the software was able to generate a more efficient design by not considering some levels in the final choice situations. However, the improved efficiency comes at the cost of compromising some attribute levels that capture the nonlinear relationships within attributes. Therefore, an additional constraint was imposed on the design to assure each attribute level is included in the design. This resulted in a lower efficient design; however, the lost efficiency was quite negligible. A minimum and a maximum value has been introduced for each level. As an example, the design was constrained to guarantee that the choice tasks will contain each toll cost attribute level at least 4 times and at most 12 times. The same logic was applied to the rest of the attributes which can be found in the design syntax in the appendix.

Moreover, a decision was made for the simulation type and the number of draws that performs best when using Bayesian approach. Even though this decision is dependent on the level of complexity of the design, research has shown that the Gaussian quadrature method will generally outperform other techniques, particularly when standard deviation values are relatively large (Bliemer *et al*., 2008). Using this technique leads to a faster convergence to the true value of D-error via a smaller number of draws. Hence, for generating Bayesian draws in the final design Gaussian quadrature simulation with 5 abscissas for each attribute was selected.

## 6.4. Final Design Output

With the required design specifications identified, the final version of the SC experiment can be completed. The Modified Fedorov row-based algorithm was selected due to incompatibility of column-based approach with the design constraints. The design syntax along with its instructional comments are provided in the appendix. The model was run overnight to generate the survey design, taking approximately 4 hours to converge to the final values in Ngene using a computer with an Intel® Core™ i7-7700 processor @ 3.6 GHz and 8.0 GB memory. In Table 6.3, the design statistics are reported, and the final design output can be found in Table 6.4. The incorporation of this design into survey software to distribute to respondents will be discussed in the next chapter.

Table 6.3 – Final Design Statistics

| **Distribution** | **TT** | **TTV** | **TC** | **DIST** | **Simulation** | **D-error** | **A-error** | **B-estimate** | **S-estimate** |
|---|---|---|---|---|---|---|---|---|---|
| Normal (μ,σ) | (-0.04051,0.00837) | (-0.02740,0.00823) | (-0.03067,0.00570) | (-0.02315,0.01293) | Gaussian | 0.000302 | 0.00056 | 57.45 | 20.53 |

Table 6.4 – Final Design Choice Situations Matrix

| Choice Task | Block | Route A (Tolled) | | | | Route B (Free) | | | | VOT ($/hr) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | TT | TTV | DIST | TC | TT | TTV | DIST | TC | |
| 1 | 1 | 120 | 0 | 0 | 50 | 100 | 30 | 30 | 0 | 150 |
| 2 | | 80 | 10 | 0 | 100 | 120 | 0 | 30 | 0 | -150 |
| 3 | | 80 | 5 | 0 | 150 | 60 | 30 | 30 | 0 | 450 |
| 4 | | 100 | 5 | 0 | 50 | 100 | 30 | 30 | 0 | N/A |
| 5 | | 60 | 0 | 30 | 50 | 100 | 30 | 0 | 0 | -75 |
| 6 | | 60 | 10 | 0 | 100 | 120 | 0 | 15 | 0 | -100 |
| 7 | | 60 | 10 | 30 | 50 | 100 | 0 | 0 | 0 | -75 |
| 8 | | 60 | 0 | 30 | 50 | 120 | 30 | 0 | 0 | -50 |
| 9 | | 80 | 0 | 30 | 50 | 60 | 30 | 0 | 0 | 150 |
| 10 | | 100 | 0 | 15 | 150 | 120 | 15 | 0 | 0 | -450 |
| 11 | | 100 | 0 | 0 | 100 | 100 | 0 | 15 | 0 | N/A |
| 12 | | 80 | 5 | 15 | 100 | 80 | 15 | 0 | 0 | N/A |
| 13 | 2 | 60 | 0 | 0 | 100 | 120 | 30 | 30 | 0 | -100 |
| 14 | | 80 | 5 | 0 | 50 | 60 | 30 | 30 | 0 | 150 |
| 15 | | 60 | 10 | 30 | 50 | 120 | 0 | 0 | 0 | -50 |
| 16 | | 120 | 0 | 30 | 50 | 120 | 30 | 0 | 0 | N/A |
| 17 | | 60 | 0 | 30 | 50 | 60 | 30 | 0 | 0 | N/A |
| 18 | | 100 | 5 | 15 | 50 | 80 | 30 | 0 | 0 | 150 |
| 19 | | 60 | 10 | 0 | 100 | 120 | 0 | 30 | 0 | -100 |
| 20 | | 80 | 5 | 0 | 150 | 80 | 15 | 15 | 0 | N/A |
| 21 | | 120 | 0 | 0 | 150 | 120 | 15 | 15 | 0 | N/A |
| 22 | | 60 | 10 | 0 | 100 | 100 | 0 | 30 | 0 | -150 |
| 23 | | 60 | 0 | 30 | 50 | 80 | 30 | 0 | 0 | -150 |
| 24 | | 120 | 0 | 15 | 100 | 120 | 15 | 0 | 0 | N/A |

# Chapter Seven: Data Collection

As part of the data collection process, a final survey consisting of the stated preference design in Chapter 6 is included along with complementary questions pertaining to the respondent and associated shipping activities. Apart from trip-related attributes, there are some other factors that might be influential in route choice decisions (Zhou *et al*., 2009). For example, the route choice behavior of different truck sizes with different commodities may be heterogeneous. This chapter will discuss the survey questionnaire design and format. Data collection and distribution methods will also be addressed.

## 7.1. Survey Questionnaire Design

In discrete choice models, apart from the alternative-based choice attributes, there are other potential factors that affect the choice decision (Hensher and Greene, 2003). These factors are unique to the context of the study and can be categorized in a group called respondent-related characteristics. This research targets respondents who oversee routing decisions for commercial vehicles (i.e. drivers, route planners, manages etc.). Thus, a questionnaire has been designed for these respondents to record the above-mentioned characteristics. After a comprehensive study on the relevant literature, the most important questions were accumulated. This batch of questions have undergone a few rounds of assessment during focus group meetings with experts. This was particularly done to ensure compliance of our survey to other commercial vehicle travel surveys conducted in Ontario in order to pick the most relevant questions. The survey was grouped into four different parts as shown below.

1. Stated Preference Survey
   - Route Choice Hypothetical Scenarios
2. Respondent Characteristics Questions
   - Age, Experience, Role, Vehicle Size
3. Company Characteristics Questions
   - Contracts, Role, Commodities, Behavior, Trips, HOS
4. Descriptive Questions
   - Technology, Navigation, e-Commerce

Figure 7.1 – Survey Questionnaire Structure

## 7.2. Online Survey Platform

The two most common approaches that have been utilized in the literature for survey platforms included paper-based and electronic-based surveys. The former traditional approach conducts the study using a hard-copy format while the latter does the same in a digital fashion and may store data in a cloud-based software. Research has suggested that the digital version would result in significant time and cost savings (Leisher, 2014). It was concluded that a digital version of a survey would decrease interview time by 75% hence faster, and it approximately contributes to almost 50% reduction in expenditures mostly because of the cleaner data that it can generate. To this end, this research will implement the survey using an online digital platform. In this section, the transformation of the survey to a digital version will be elaborated in detail.

A variety of web-based platforms have been used to conduct stated preference studies. They can be as simple as Google Forms, as used for the pilot survey of this thesis, or more sophisticated software such as *Qualtrics* (Yan *et al*., 2019), *SurveyMonkey* (Abrizah *et al*., 2015), and *Unipark* (Twaddle, 2011). The Qualtrics platform was selected for the survey since a site license was available and maintains secure storage of the survey results within Canada.

The Qualtrics software has numerous built-in functions to create different types of questions, however, there was no specific module to import the choice experiment. A necessary task was to convert the matrix of choice situations from Chapter 6 into a format that can be read by the software. The software alone was not capable of this input automatically, hence a step-by-step approach for transforming choice experiments into Qualtrics (Weber, 2019) was utilized. Weber took advantage of software capability to read advanced text files by re-producing a HTML-coded version of the matrix through STATA. This process has been followed in this thesis, resulting in the transformation of our choice matrix into suitable hypothetical examples visualized in Qualtrics.

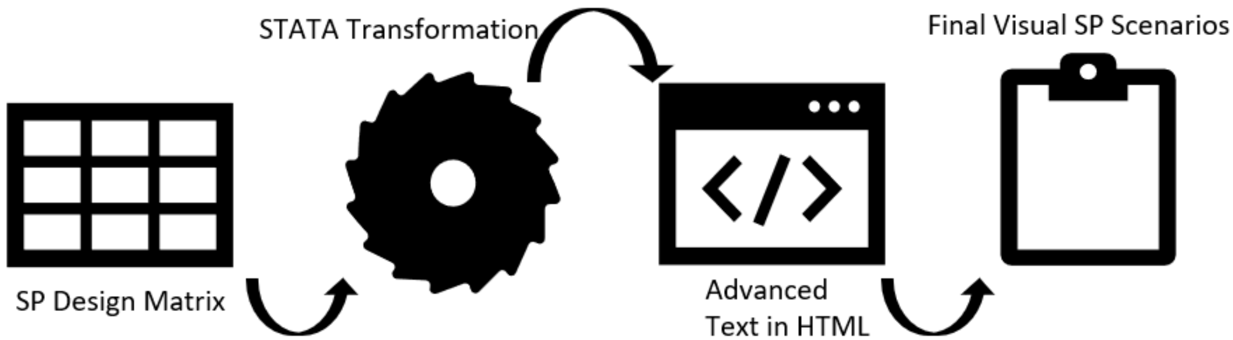



Figure 7.2 – Illustration of Choice Experiment Transformation

The first step of this process was to code attribute levels to an integer format. The matrix of choice situations needed to be recoded to substitute different attribute levels with their corresponding integer order. For example, for the TT attribute, the levels (60, 80, 100, 120) were substituted by (0, 1, 2, 3). After using the coding structure, which can be found in Table 7.1, a new matrix consisting of newly coded attributes was generated as an input to STATA software.

Table 7.1 – Attribute Levels Re-Coded Values

| **Attribute** | **Labels** | **Route A (Tolled)** | | **Route B (Free)** | |
|---|---|---|---|---|---|
| | | **Coded value** | **Actual level** | **Coded value** | **Actual level** |
| A1 | Travel Time | 0 | 60 | 0 | 60 |
| | | 1 | 80 | 1 | 80 |
| | | 2 | 100 | 2 | 100 |
| | | 3 | 120 | 3 | 120 |
| A2 | Toll Cost | 0 | 0 | 0 | 0 |
| | | 1 | 50 | | |
| | | 2 | 100 | | |
| | | 3 | 150 | | |
| A3 | Potential Delay | 0 | 0 | 0 | 0 |
| | | 1 | 5 | 3 | 15 |
| | | 2 | 10 | 4 | 30 |
| A4 | Extra Distance | 0 | 0 | 0 | 0 |
| | | 1 | 15 | 1 | 15 |
| | | 2 | 30 | 2 | 30 |

The initial STATA syntax code which was written by Weber, (2019) and available for public use. Adjustments made to this code to match the context of this survey, such as attribute names, values, colors, etc., can be found in the appendix. Having imported the re-coded matrix into

STATA and run the procedure, an output was created that consisted of an advance text file with predominantly HTML codes. The text file was then imported into Qualtrics and the result is shown in figure below the question design (top) converted into the visual table (bottom).

| Choice Task | Block | Org Choice situation | route a.tt | route a.ttv | route a.dist | route a.tc | route b.tt | route b.ttv | route b.dist | route b.tc |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 4 | 120 | 0 | 0 | 50 | 100 | 30 | 30 | 0 |

| choice task | block | A1_1 | A1_2 | A1_3 | A1_4 | A2_1 | A2_2 | A2_3 | A2_4 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 3 | 0 | 0 | 1 | 2 | 4 | 2 | 0 |

| | Route A | Route B |
|---|---|---|
| Travel Time | 120 min | 100 min |
| Potential Delay | 0 min | 30 min |
| Extra Distance | 0 KM | 30 KM |
| Toll Cost | $50 | $0 |

Figure 7.3 – Matrix Transformation to Qualtrics Choice Scenarios

Once the choice experiment was imported into the Qualtrics platform, several issues were identified. These issues were mostly related to the user experience and sampling biases. We have managed to address most of these concerns by making use of different modules of the software which will be explained below.

As was stated earlier, one of these concerns was related to removing potential biases through appropriate randomizations at different levels of the survey. First, the two potential blocks of questions need to be randomly assigned to survey respondents with an even distribution. In addition, a randomization of the order of the questions and alternatives posed to the respondent is desired. These questionnaire biases can be found in the literature as so-called response-order issues (Israel and Taylor, 1990; Mccoll *et al*., 2001; Perreault, 1975). The randomization of question blocks and questions within the blocks were resolved by using Qualtrics built-in randomizers with minor modifications. However, randomizing the order of appearance for alternatives within each question was more difficult. After trying different methods, this problem was resolved by duplicating each choice task and swapping the order of the alternatives. Therefore, an option exists for each question to have the free route shown first as Route A, while another option exists for the toll route to be shown first as Route A. A randomizer was created for each question to randomly select one option.

It was found that the repeated SP questions look very similar with only some changes in attribute values and may appear identical to some respondents. Thus, it is a good practice to make each SP question stand out and such that the respondent is aware of each scenario as a unique question. This can be achieved by introducing different colors as a theme for each question or numbering them. The latter method was chosen, but Qualtrics does not have a built-in tool that can be used for dynamically numbering questions due to the shuffling process that has been imposed. The most suitable approach was found to be a counter, originally intended to track quiz results, and add it as a dynamic label the SP questions. For example, after SP Question #1 is completed, the counter goes up by one to label the next scenario appropriately as the second question. This process unfortunately resulted in the loss of the back button during the SP part of the survey, but no better alternative was presented by Qualtrics customer support.

Finally, after preparing the first version of the survey, a few focus group meetings with academic experts were scheduled to eliminate the potential drawbacks of the survey. We have collaborated with researchers from University of Toronto to review our survey to confirm its compatibility with their future shipper-based survey. During these meetings, we have also reviewed the flow of the survey and the understandability of the questions in respondents' eye. A complete version of the survey can be found in the appendix.

### 7.3. Survey Mode

Historically, a survey of this type would be performed in a face-to-face format, where an interviewer asks questions from the respondent in person. Although some surveys are still conducted this way, but sampling concerns and costs associated with in-person interviews have shifted this trend toward a more remote format such as telephone and mail-in surveys. Recently, with the rapid growth and accessibility of internet, researchers have shown interest in executing surveys through an online format. Different factors are influential in the decision for survey modes, the most common of which are cost and response rate. For example internet surveys are amongst the cheapest yet fastest approaches for data collection (Fricker and Schonlau, 2002), however, they suffer from a relatively lower response rate (Sinclair *et al.*, 2012). Nevertheless, the two most important factors regarding this decision are sample composition and measurement effects (Lindhjem, 2011).

Arguably, the most important measurement effect arises from social desirability bias which was first introduced by DeMaio *et al.,* (1984). This bias is the tendency of the respondent to provide untruthful answers to cover their socially disapproved behavior (Lindhjem, 2011). For this survey, we are most concerned with issues pertaining to the value of time and impact of costs on individuals. This issue is more common when an interviewer (either in person or over the phone) are involved mainly because anonymity is compromised. Internet surveys, due to their isolated environment of the respondent. On the other hand, an online survey may suffer from poor representative sample compositions if some respondents are not typically online. This issue was discussed in the literature due to the inaccessibility of elderly, lower income, and or uneducated households to internet specifically when a community-based survey is taking place (Sinclair *et al*., 2012).

The final decision on survey mode is contingent on the limitations and the objectives of the research and trade-offs for each format type. This study is a form of willingness-to-pay where we want to capture how likely are the truck drivers to pay for using toll routes. Thus, it is obvious that the truthfulness and the reliability of the responses supersede other factors which can be maintained through anonymity. Additionally, due to the emergence of Covid-19 global pandemic and restrictions on moving research endeavors to remote formats, an internet-based approach was selected for this research.

## 7.4. Survey Distribution

Prior to this stage, the survey has been fully implemented online and was accessible through a link via Qualtrics platform. Next, a target population was needed to provide them with access to the survey. In the context of internet surveys, there are a couple of direct and indirect approaches to reach out to the potential respondents. Examples include contacting a relevant organization to announce the survey, and a direct so-called 'cold calling' approach to every individual trucking company that can be identified. Both methods were conducted in this survey, although the latter was far more successful.

The former method this case utilized contact with the Ontario Truck Association (OTA), which has been used in previous research such as Ismail *et al.,* (2009). After contacting the OTA, they have posted a link to the survey on their website and newsletter. An image of this posting is provided in Figure 7.4 below.


Figure 7.4 – Survey Posting on OTA Website

The second approach led to emails sent to many relevant trucking carriers that could be identified using a rich directory of companies' contact list (i.e. email addresses). A basic website could be used for this purpose such as [www.canadatransportation.com](http://www.canadatransportation.com). However, the sample size that it could produce was relatively small. As an alternative, an initial database of trucking carriers originally derived from Yellow Pages was used as a starting point. The initial directory contained information on the name and physical address of approximately three thousand trucking companies. After removing duplicate entries, the list came to 2,389 individual companies. Unfortunately, no consistent email contact was provided in this dataset. Manually identifying emails for each data record was estimated to take around 37 hours of monotonous constant work. To complete this work quickly, crowdsourcing was employed via Amazon Mechanical Turk (MTurk).

MTurk is an online crowdsourcing platform that enables individuals such as businesses or researchers to hire a distributed workforce network to perform their on-demand tasks virtually (Amazon Mechanical Turk, 2018). These individuals which are also known as requesters can define a job, that are referred to as Human Intelligence Task (HIT), for any allotted price. On the other side, workers will browse among the existing jobs and decide to complete them in exchange for the rate already set by the requester. The process is expressed in Figure 7.5 below. Research has shown that the data obtained from MTurk is at least as reliable as other traditional data collection methods (Buhrmester *et al*., 2016). Employing Amazon Mechanical Turk subsequently provides a relatively inexpensive solution during a very short period of time.

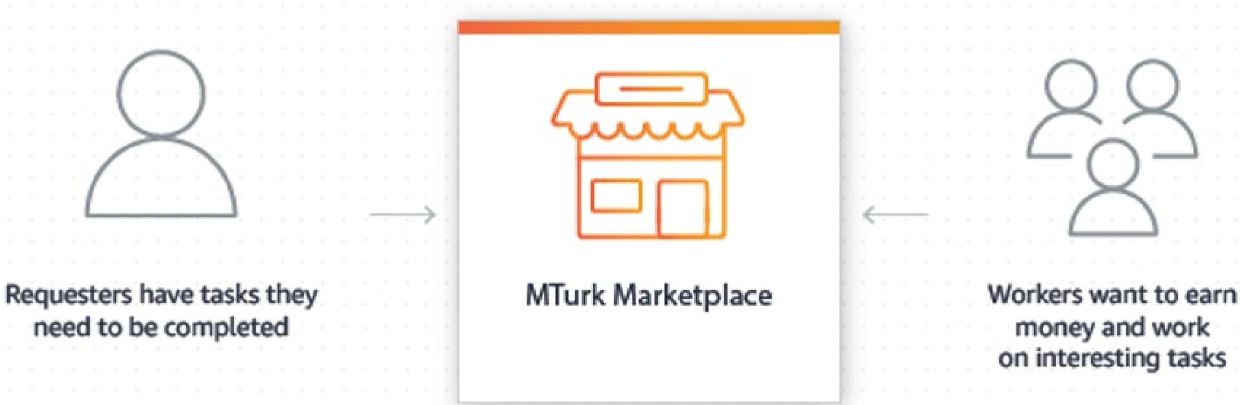
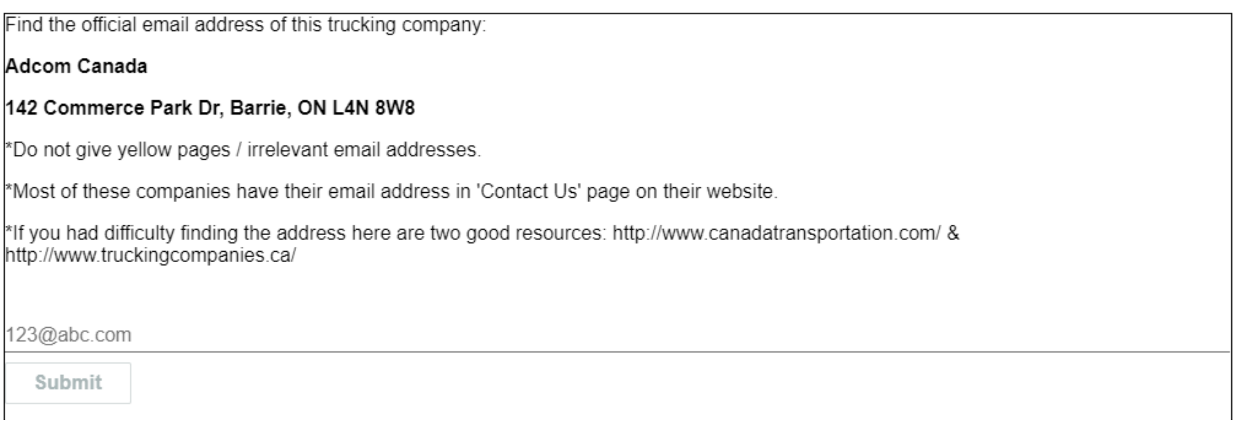



Figure 7.5 – Amazon Mechanical Turk Crowdsourcing Process

Adapted from (“Amazon Mechanical Turk,” 2018)

The list of companies was exported to MTurk, with a request for workers to find the official email address associated with each company given their name and location. Thanks to the MTurk built-in tool, a batch list of companies was created by uploading a *.csv* file that automatically generates the same task for each entry of the initial directory. A monetary reward as an incentive and a task duration of 5 minutes was allotted to each task. The entire directory was assigned contact emails with the help of 432 individual workers in approximately three days with an average time per assignment of 57 seconds per entry. A preview of the task can be seen in Figure 7.6.



Find the official email address of this trucking company:

**Adcom Canada**

**142 Commerce Park Dr, Barrie, ON L4N 8W8**

*Do not give yellow pages / irrelevant email addresses.

*Most of these companies have their email address in 'Contact Us' page on their website.

*If you had difficulty finding the address here are two good resources: http://www.canadatransportation.com/ & http://www.truckingcompanies.ca/

123@abc.com

Submit

Figure 7.6 – MTurk Assignment Preview

Once the full assignment batch was completed, another comprehensive refinement needed to be done to make sure that the sample has a certain accuracy level. This was implemented mainly because some companies either did not provide email address on their website or they no longer exist hence invalid email addresses. Numerous validation criteria were employed with around 700 responses removed, leading to a final list of 1,640 entries. The criteria included:

- Removing generic (i.e. *.org*, *.gov etc.*) or non-Canadian email domains
- Removing entries for businesses that are no longer operating
- Randomly validating entries to identify the accuracy of MTurk workers
- Removing generically patterned responses from MTurk workers

To send an email to the resulting contacts, an email template was written with a customized unique link sent out to each of the 1,640 trucking companies. A sample of 50 companies were first sent this email, but no issues were raised and the remaining companies were later contacted.

# Chapter Eight: Modelling and Estimation

## 8.1. Introduction

In this chapter, a general overview of the data statistics from the survey are presented and followed by before providing modelling results. A basic MNL model is implemented as a reference point, while more complex models are extended from the initial model. The final model includes a random parameter estimation, accounting for stated choice panel data, with further analysis on parameter elasticity and willingness-to-pay (WTP). The chapter concludes by providing a distribution for truck VOT and VOR.

## 8.2. General Statistics

The survey was sent out in two batches, with a small test group and final distribution on December 29, 2020 and January 5, 2021 respectively. It was online and accessible on the Qualtrics platform for a duration of 45 days. Three email reminders were sent to improve the response rate. From the 1,697 contacts that were emailed, 14% failed or bounced back to the sender, 56% were delivered but never opened, and 25.6% percent of the emails were opened but did not complete the survey. A total of 69 respondents initiated the survey; however, not all questions were answered in each case with an average completion rate of 65.6%. A total of 39 responses were collected for the SP part where 32 of them also answered to the second part of the survey. The final SP part response rate was calculated at 2.3%.

The raw collected data was processed to guarantee data quality and ensure the representativeness of the Ontario trucking industry. These checks included removal of responses with survey duration less than 5 minutes (10%), excluding responses from outside of Ontario (4%), and removing responses which were observed to follow a static pattern in their answers (4%). The latter issue was indicative of answering the survey without comprehending the full details of each question. As seen in Figure 8.1 illustrating the general location of the respondents, the highest concentration can be found in the GTA and Ottawa.

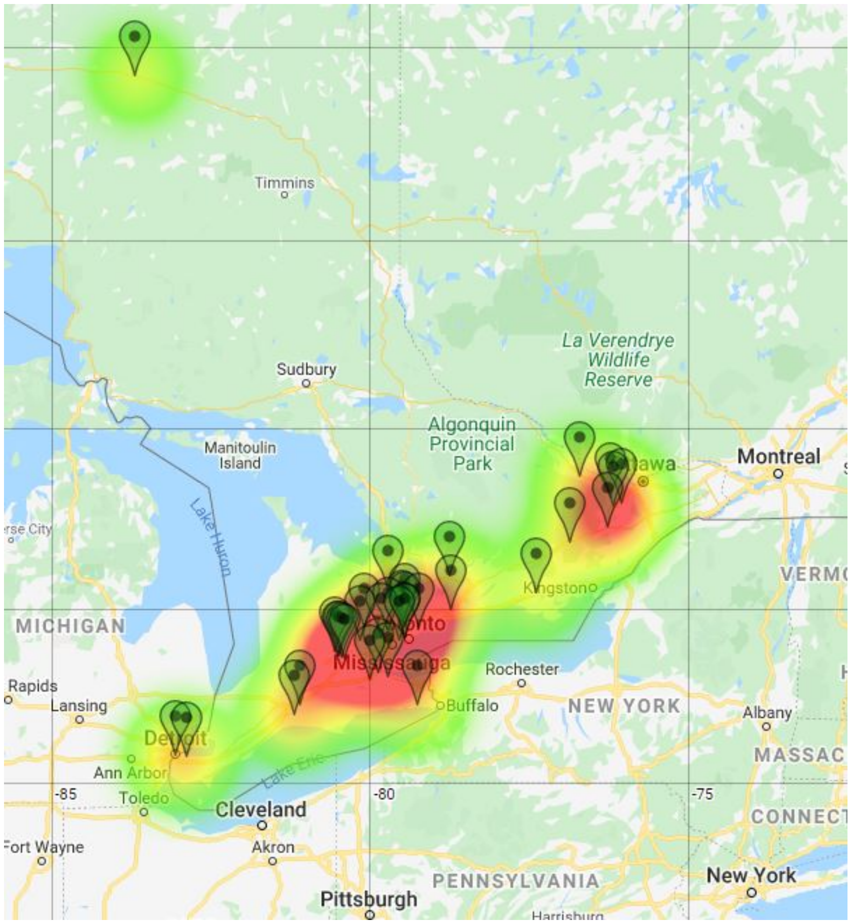



Figure 8.1 – Survey Respondents Map

Table 8.1 contains respondent characteristics. The statistics were compared to the Ontario freight trucking population where possible for comparison, using multiple sources including TruckingHR Canada, (2020), Toronto Workforce Innovation Group, (2020), Statistics Canada, (2021), and IBI Group, (2013). A few of the industry statistics were manually adjusted based on logical assumptions to match the surveyed data classes for consistency. For instance, the employment size categories reported by Statistics Canada, (2021) have used another grouping criteria for each establishment size. They have identified the categories based on number of employees of 1-4 people as *Micro*, 5-99 as *Small*, 100-499 as *Medium*, and 500+ as *Large*. In order to cut the effect of inconsistent category sizes, a new criterion based on average number of employees (i.e. midpoint for each category such as *Large:* $299.5 = \frac{100+499}{2}$) for each category was imposed and the industry percentages were adjusted based off of this new criterion.

The results indicate that the survey oversampled respondents belonging to small-sized businesses. A comparison of respondent age and gender reveals that the survey reasonably aligns with industry proportions.

For respondent experience in the trucking industry, one can notice the concentration towards more experienced respondents with 78% having 16 or more years of experience. While this indicates that the respondents are likely very knowledgeable on the subject matter, it is also likely a reflection of the aged labor force market for the trucking industry.

The trip-related characteristics of the survey sample indicates that almost half (44.12%) of the truck trips have only a single destination per tour. Additionally, two thirds of respondents exceed 8 hours of daily driving.

The average trip distance shows a wide variety between respondents but appears reasonable when compared to the average trip distance for the industry identified as 670 km (IBI Group, 2013). The statistics for cargo value are similarly reasonable.

Table 8.1 – Sample Characteristics; General Demographics

| Demographic Variable | Description | Respondents (%) | Industry (%) |
|---|---|---|---|
| **Age** | 18 - 25 | 2.80 | 3 |
| | 26 - 35 | 8.30 | 14 |
| | 36 - 45 | 19.40 | 23 |
| | 46 - 55 | 33.30 | 29 |
| | 55+ | 36.20 | 31 |
| **Gender** | Male | 77.80 | 73 |
| | Female | 22.20 | 27 |
| **Employment Size Category** | Micro (1-9 employees) | 25.00 | 37 |
| | Small (10-49) | 38.90 | 12 |
| | Medium (50-249) | 27.80 | 43 |
| | Large (250+) | 8.30 | 8 |
| **Company Age** | 0 - 5 | 5.60 | N/A |
| | 6 - 10 | 2.80 | |
| | 11 - 20 | 27.80 | |
| | 20+ | 63.90 | |
| **Trucking Experience** | 0 - 5 | 0.00 | N/A |
| | 6 - 10 | 11.11 | |
| | 11 - 15 | 11.11 | |
| | 16+ | 77.78 | |
| **Consignees per trip** | 1 | 44.12 | N/A |
| | 2 | 23.53 | |
| | 3 | 17.65 | |
| | 4+ | 14.71 | |
| **Hours daily driving** | 0 - 4 | 14.71 | N/A |
| | 4 - 8 | 17.65 | |
| | 8+ | 67.65 | |
| **Trip Distance** | 0 - 200km | 20.59 | Industry Average: 670km |
| | 200 - 600km | 44.12 | |
| | 600 - 1000 km | 14.71 | |
| | 1000+ km | 20.59 | |
| **Cargo worth (2020 CAD)** | 25000 or less | 32.14 | Industry Average: $23,000 |
| | 25000 - 50000 | 21.43 | |
| | 50000 - 75000 | 10.71 | |
| | 75000 - 10000 | 14.29 | |
| | 100k + | 21.43 | |

*Note: *Figures may not add up to 100 due to rounding or multiple answer by same respondent.*
***Due to inconsistent classifications, some industry representation might show a significant difference.*

Figures 8.2 to 8.5 demonstrate the vehicle and cargo characteristics of the survey respondents. As can be seen, the most prevalent types of vehicles are shown to be classes 9 and 10, which refer to single-trailer trucks with five or more axles (FHWA, 2014). The data also indicates that multi-trailer trucks are relatively less common.

According to Figure 8.3, the sample was not completely successful in terms of explaining the overall distribution of commodity types, however, it should be noted that part of these variations resulted from inconsistencies between the classifications used in the survey and the references. For instance, one particular discrepancy was the consideration of *empty* cargo within the reference commodity classification which in fact was not included in our survey. Nevertheless, an interesting finding in the data reveals that delivering petroleum products is at least far less common between private motor carrier companies. The reason might be the fact that these special types of commodities are being handled directly by their shippers due to the special vehicle types that they require. Figure 8.4 indicates that over-sized cargos are the most common special service type within freight followed by expedited and refrigerated goods. The survey data also reveals that approximately one out of every four carriers never deal with special types of services/goods.

Figure 8.5 and 8.6 show that delivery pattern of Ontario trucking companies covers local, national, and international deliveries almost evenly. There is also a mix of truckload (TL) and less-than-truckload (LTL) deliveries, with very few respondents indicating that they deliver parcels. This was expected since parcel carriers tend to be focus on urban intercity trips which are not a focus of this thesis. Another important finding is that the most common form of driver compensation is recorded to be time-based while the industry distribution is heavily focused on actual distance travelled.

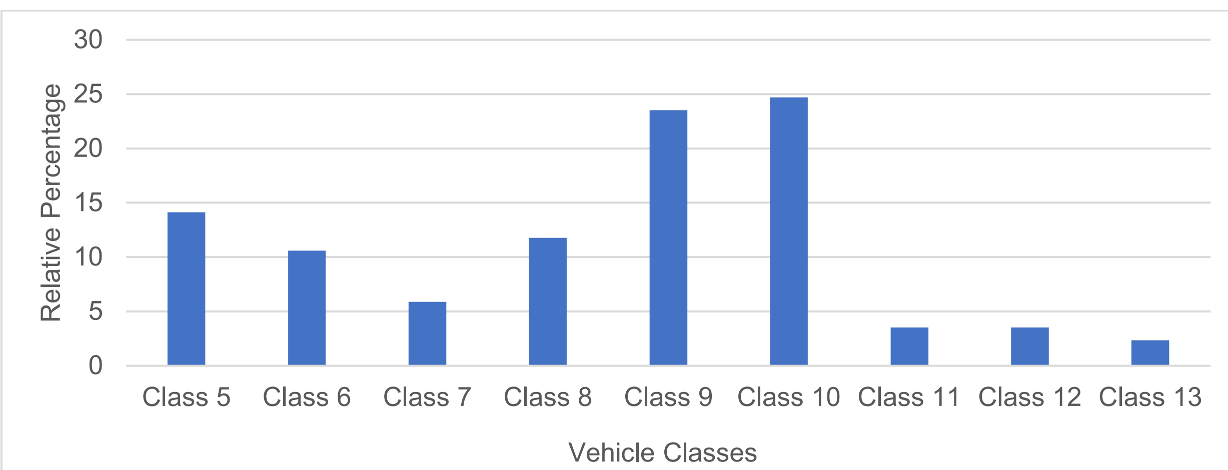



Figure 8.2 – Distribution for FHWA Vehicle Classification

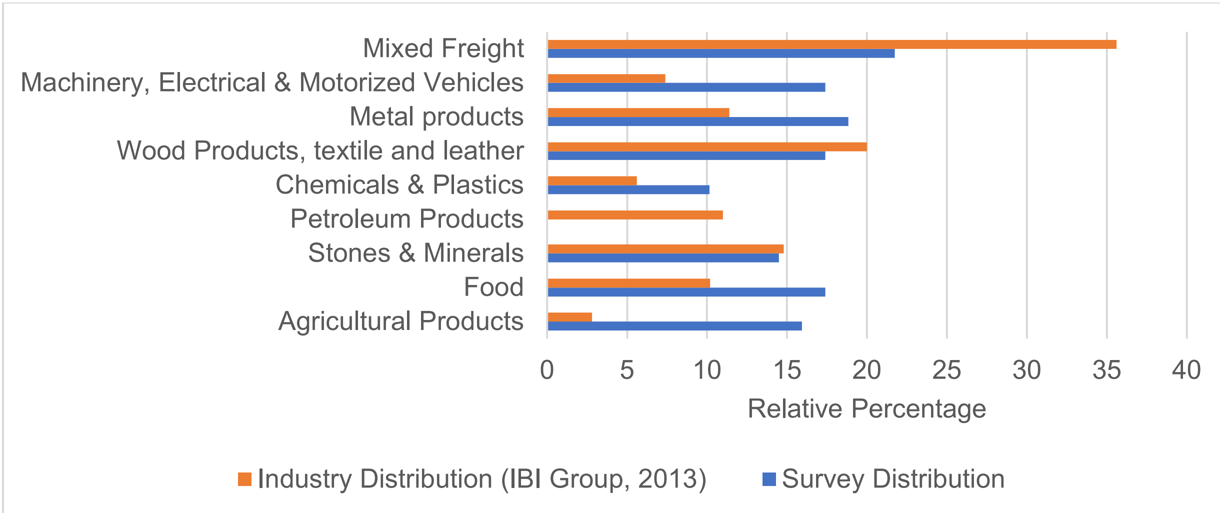



Figure 8.3 – Commodity Type Distribution

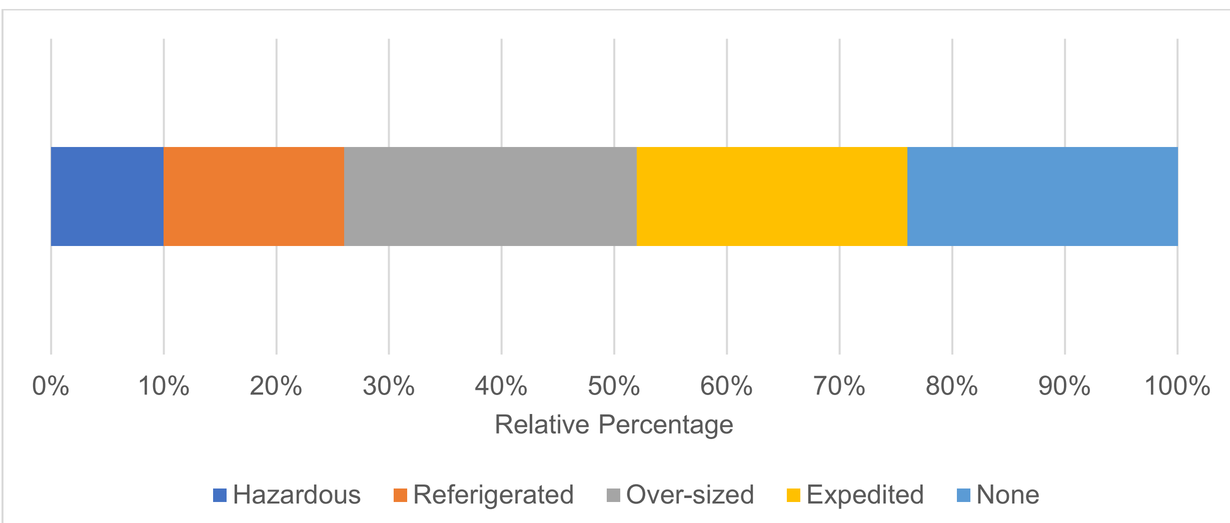



Figure 8.4 – Distribution for Special Goods / Services Categories

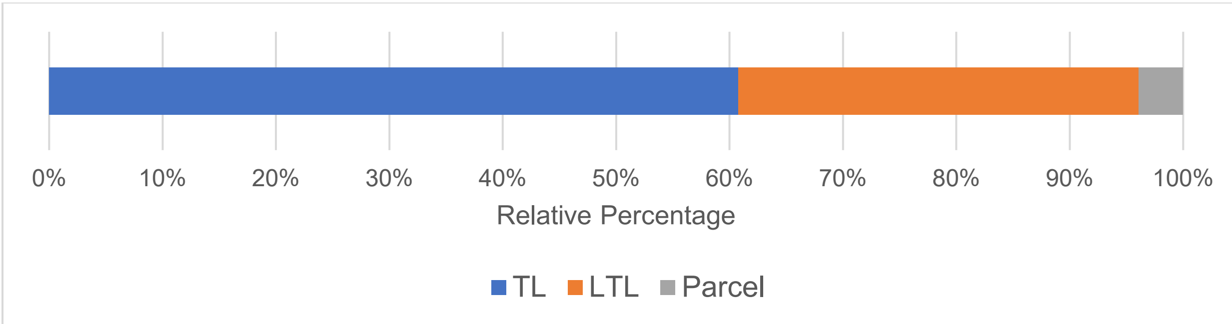



Figure 8.5 – Shipment Size Distribution

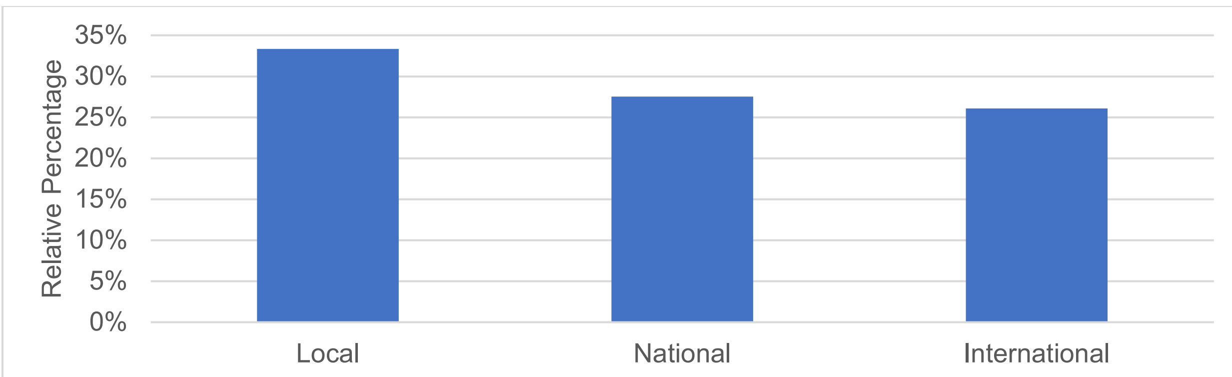



Figure 8.6 – Delivery Coverage

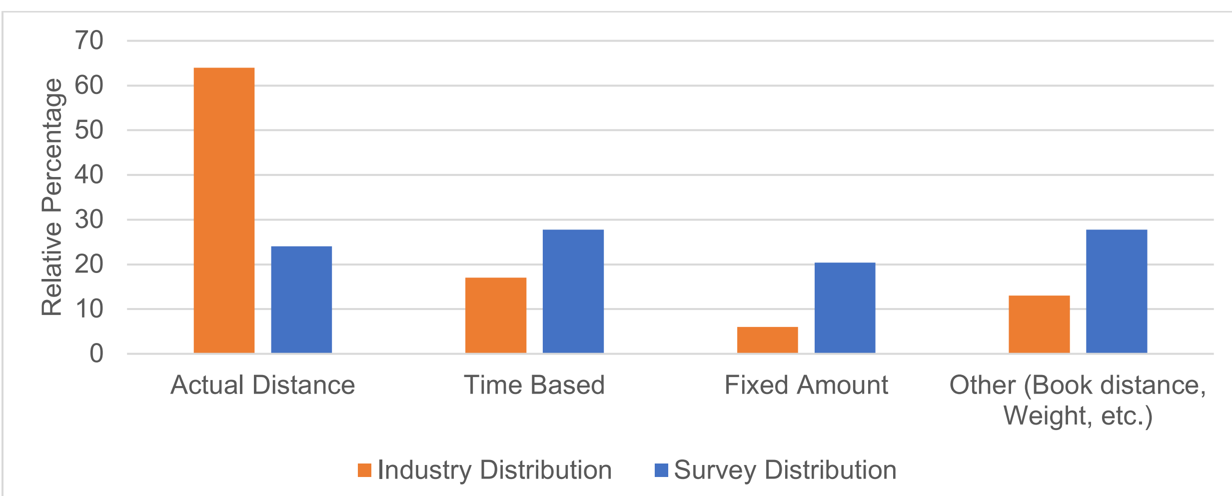



Figure 8.7 – Distribution for Contract Type

A general breakdown of respondents' route choice in shown in Figure 8.8 below. As can be seen, in a total of $39 * 12 = 468$ choice situations, toll route was selected 25% of the times. This means that on average, within each respondent toll route was preferred over free route 3 out of 12 times. A more detailed breakdown is provided in Figure 8.9. The figure illustrates the number of respondents with respect to the frequency of choosing toll routes.

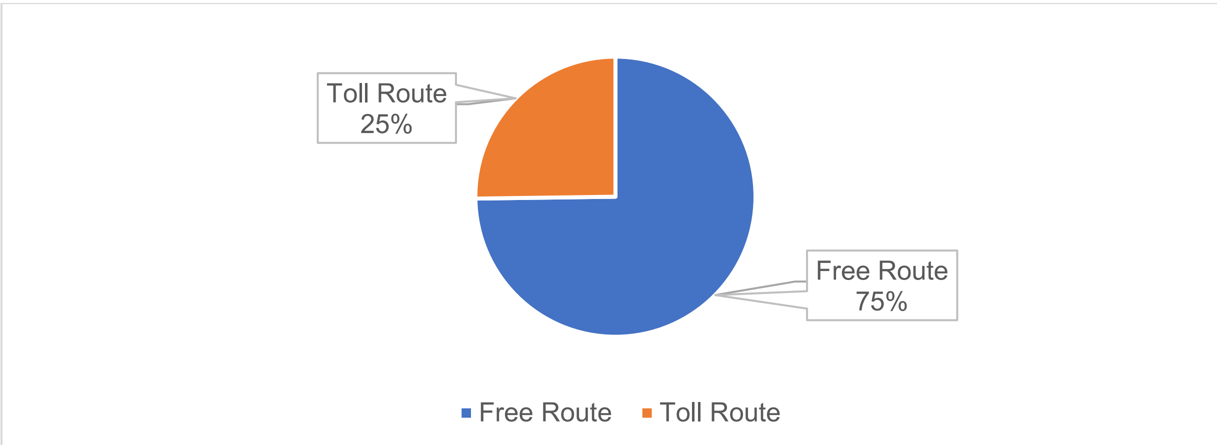



Figure 8.8 – Distribution of Toll Vs Free Route Choice

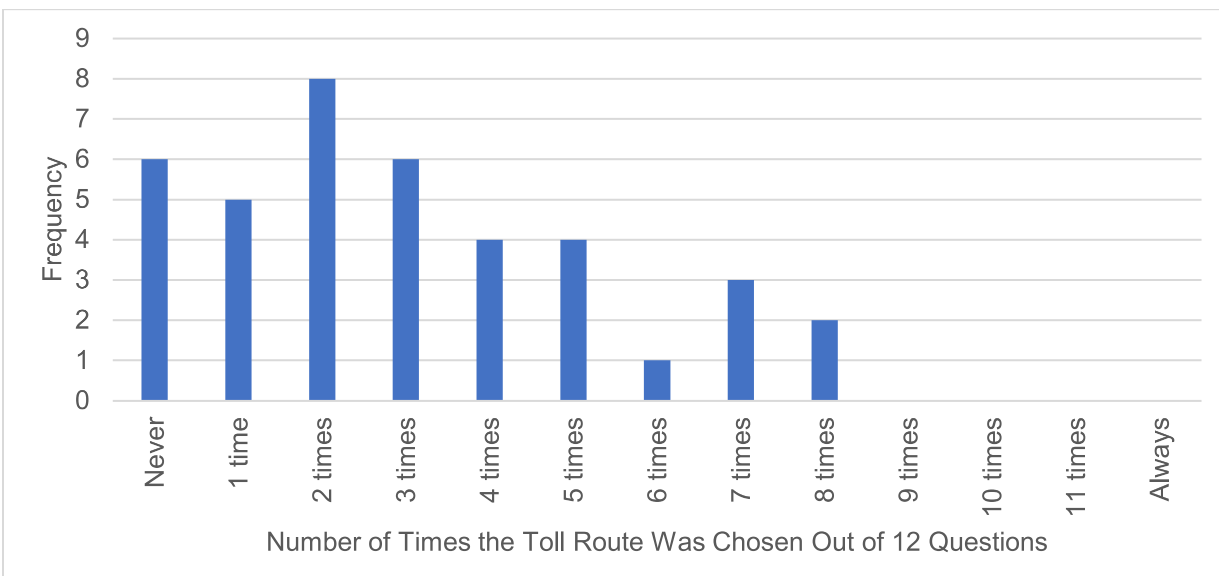



Figure 8.9 – Toll Route Frequency

## 8.3. Modelling Analysis

After processing the raw survey data, NLogit software was used to calibrate several discrete choice models. The refined data included a total of 39 individual responses, 7 of which only filled out the SP part and ignored the non-SP questions. The data was fitted to a number of logistic models outlined previously in section 6.2. First, the core SP attributes without considering any external variable were tested. These include estimation of a cross-sectional MNL model, analyzing a few different combinations of random parameters for comparison purposes, and an estimation of a panel version for the MXL models. Next, we expanded the model by incorporating numerous external socio-economic / demographic variables. These variables were tested using a dummy formatting and the results are reported in its corresponding section. After examining the individual performance of dummy variables, those who performed better in explaining the choices were included in a final model. An analysis of parameter elasticity is conducted afterwards to determine the most impactful variables for route choice. A willingness-to-pay model is finally estimated to derive VOT and VOR distributions of the sampled respondents.

### 8.3.1. Models with Core SP Variables

The core SP variables represent those included in the hypothetical scenarios presented in the SP survey. The four variables that were part of each scenario include travel time (minutes), delay (minutes), toll cost (CAD), and extra distance compared to the alternative route (km).

A basic multinomial logit (MNL) model is shown below in Table 8.2 with the core SP variables included. Additional variables were added to later models. The constant value was less significant compared to the rest of the variables, which were significant with 99% confidence. This indicates that a larger portion of the data is being explained by the main variables. However, the difference between the *Naïve* and *Restricted* $\rho^2$ indicates that a constant alone is able to represent a portion of the choice outcome.

All of the SP variables have negative signage, indicating that an increase in value results in a decrease of the probability of their corresponding alternative. This is in line with expectations, such that higher travel time, toll cost, delay, and distance are unfavorable.

Table 8.2 – Cross-sectional MNL Model Results

| **Model Name** | | **MNL3** | |
|---|---|---|---|
| **Variable** | **Coef.** | **Std. Errors** | **t-stat** |
| Constant | 0.776* | 0.453 | 1.71 |
| Travel Time | -0.037*** | 0.005 | -7.71 |
| Delay | -0.031*** | 0.008 | -3.67 |
| Toll Cost | -0.020*** | 0.005 | -3.86 |
| Extra Distance | -0.023*** | 0.005 | -4.50 |
| | | | |
| LL[0] | 324.4 | | |
| LL[C] | -264.3 | | |
| LL[F] | -216.6 | | |
| Naïve $\rho^2$ | 0.332 | | |
| Restricted $\rho^2$ | 0.180 | | |
| Adjusted $\rho^2$ | 0.168 | | |
| AIC | 443.3 | | |
| No. of Resp. | 39 | | |
| No. of Obs. | 468 | | |

*Notes: ***, **, *, represent statistical significance at 1%, 5%, and 10% respectively.*

LL*[0]=log likelihood with no constants or variables,* LL*[C]=log-likelihood with constant only,* LL*[F]=log-likelihood for the full model.*

Next, the core variables were tested with different assumptions regarding distributions of the parameters using the framework of a mixed multinomial logit (MXL) model, with the results provided in Table 8.3. The standard deviation values are given for parameters that have been allowed to follow a normal distribution instead of a single parameter value.

As can be noticed in the first three models, the performance is not desirable for a variety of reasons. MXL1 observes a significant alternative specific constant which indicates that the other parameters are not able to sufficiently explain the data. The MXL2 and MXL3, have parameter distributions with non-significant parameters, indicating that they are no better than single values of each associated parameter. However, incorporating the panel function in MXL4 was beneficial as it solved both previously mentioned issues by accounting for within respondent potential biases. The MXL4 model also has all variables showing at 99% with a non-significant constant. Additionally, the significance of the standard deviation of both random parameters indicates that there exists some form of taste heterogeneity in the data which is now being explained by the two random parameters.

Table 8.3 – Cross-sectional and Panel Random Parameter Mixed Logit Models

| Model Name | MXL1 | | | MXL2 | | |
|---|---|---|---|---|---|---|
| **Variable** | **Coef.** | **t-stat** | **St. Dev.** | **Coef.** | **t-stat** | **St. Dev.** |
| Constant | 3.144*** | 2.78 | | -0.698 | -0.54 | |
| Travel Time | -0.058*** | -4.29 | 0.085*** | -0.078** | -2.23 | |
| Delay | -0.095*** | -3.03 | | -0.058** | -2.07 | |
| Toll Cost | -0.012* | -1.89 | | -0.073* | -1.68 | 0.036 |
| Extra Distance | -0.039*** | -4.12 | | -0.056** | -2.05 | |
| | | | | | | |
| LL[0] | -324.4 | | | -324.4 | | |
| LL[C] | -264.3 | | | -264.3 | | |
| LL[F] | -212.9 | | | -212.7 | | |
| Naïve $\rho^2$ | 0.344 | | | 0.344 | | |
| Restricted $\rho^2$ | 0.194 | | | 0.195 | | |
| Adjusted $\rho^2$ | 0.184 | | | 0.185 | | |
| AIC | 437.8 | | | 437.5 | | |
| No. of Resp. | 39 | | | 39 | | |
| Panel Groups | N/A | | | N/A | | |
| No. of Obs. | 468 | | | 468 | | |
| **Models Name** | **MXL3** | | | **MXL4 (Panel)** | | |
| **Variable** | **Coef.** | **t-stat** | **St. Dev.** | **Coef.** | **t-stat** | **St. Dev.** |
| Constant | 2.859 | 0.71 | | 0.281 | 0.50 | |
| Travel Time | -0.150 | -0.66 | 0.196 | -0.060*** | -6.67 | 0.025*** |
| Delay | -0.204 | -0.65 | | -0.039*** | -4.40 | |
| Toll Cost | -0.101 | -0.57 | 0.060 | -0.045*** | -4.78 | 0.022*** |
| Extra Distance | -0.096 | -0.69 | | -0.039*** | -5.48 | |
| | | | | | | |
| LL[0] | -324.4 | | | -324.4 | | |
| LL[C] | -264.3 | | | -264.3 | | |
| LL[F] | -211.5 | | | -190.5 | | |
| Naïve $\rho^2$ | 0.348 | | | 0.412 | | |
| Restricted $\rho^2$ | 0.200 | | | 0.279 | | |
| Adjusted $\rho^2$ | 0.187 | | | 0.268 | | |
| AIC | 437.0 | | | 395.1 | | |
| No. of Resp. | 39 | | | 39 | | |
| Panel Groups | N/A | | | 12 | | |
| No. of Obs. | 468 | | | 468 | | |

*Notes: ***, **, *, represent statistical significance at 1%, 5%, and 10% respectively.*

LL*[0]=log likelihood with no constants or variables,* LL*[C]=log-likelihood with constant only,* LL*[F]=log-likelihood for the full model*

### 8.3.2. Models with Expanded Variables

Apart from the SP portion of the survey, there are other questions pertaining to the demographics and general characteristics of the respondents. To investigate the potential impact of these variables on the choice outcome, they were categorized into different groups and coded as dummy variables, with the number of true observations denoted in the table. These variables were introduced in the toll route alternative for both models to capture their individual influence on the choice outcome. Table 8.4 summarizes the best performing dummy variables in each different category for both MNL and MXL(Panel) models. Note that the values are listed together in the table but were estimated individually with the core variables. The sample size for estimating these variables was reduced from 39 to 32 respondents due to incomplete responses. There were a few other variables that were tested but are not reported in the table below either because they were not significant, or their number of observations were not sufficiently conclusive.

Table 8.4 – Dummy Variable Performance

| **Model Name** | | | **MNL4** | | **MXL5(Panel)** | |
|---|---|---|---|---|---|---|
| **Category** | **Variable** | **Obs.** | **Coef.** | **t-stat** | **Coef.** | **t-stat** |
| Compensation | Actual Distance | 12 | -0.426 | -1.49 | -1.147* | -1.90 |
| Method | Time-based | 15 | 0.884*** | 3.25 | 1.061** | 2.17 |
| | Fixed Amount | 11 | -0.368 | -1.26 | -1.156* | -1.84 |
| Establishment | 20 years or younger | 10 | -1.073*** | -3.22 | -1.250** | -2.10 |
| Characteristics | More than 21 years old | 21 | 0.807*** | 2.84 | 0.954* | 1.95 |
| | Micro/Small Enterprise | 22 | -1.075*** | -3.78 | -1.038** | -2.11 |
| | Medium/Large Enterprise | 10 | 0.988*** | 3.42 | 1.171** | 2.19 |
| Shipment | Truckload | 28 | -0.800** | -2.38 | -0.843 | -1.58 |
| Characteristics | Less-Than-Truckload | 17 | 0.523** | 1.96 | 0.192 | 0.38 |
| Vehicle | Single Unit | 22 | 0.638** | 2.33 | 1.197** | 2.23 |
| Characteristics | Single Trailer | 42 | -0.934** | -2.37 | -0.769 | -1.37 |
| | Multi Trailer | 5 | 1.200** | 2.29 | 2.649** | 2.36 |

*Notes: ***, **, *, represent statistical significance at 1%, 5%, and 10% respectively.*

*All of the dummy variables were introduced only to the toll route utility function.*

According to the table above, most of the variables were more significant in the MNL model compared to the mixed logit model with panel information for two main reasons. First, the random parameters in the mixed logit are capturing more heterogeneity and there is subsequently less need for the dummy variables. Secondly, the panel function appears to be performing well to remove bias errors for repetitive questions from individual respondents. The signages for different variables are generally intuitive, however, there are a few variables that are occasionally reporting counterintuitive signage. For example, the single truck trailer parameter is negative, indicating that truck drivers of this specific vehicle type are against using toll routes while single unit and multi trailer vehicles are in favor of using toll routes. This might arise from the fact that heavier multi-trailer trucks encounter relatively cheaper toll rates as compared to single unit lighter trucks.

Next, the notable significant variables were added together to create expanded models for both the MNL model type and MXL model type. The performance of a combination of these variables to explore their significance in a more sophisticated model. Different combinations of these attributes were tested and the best-performing results for both MNL and MXL models are provided in the table below. We note that the external independent dummy variables were included in the toll alternative.

Table 8.5 – Best Performing MNL and RPPanel Models for Combination of Dummies

| **Model Name** | **MNL5** | | **MXL6(Panel)** | | |
|---|---|---|---|---|---|
| **Variable** | **Coef.** | **t-stat** | **Coef.** | **t-stat** | **St. Dev.** |
| Constant | 0.586 | 0.91 | 0.347 | 0.39 | |
| Travel Time | -0.048*** | -7.65 | -0.068*** | -6.16 | 0.028*** |
| Delay | -0.040*** | -3.99 | -0.064*** | -4.39 | |
| Toll Cost | -0.030*** | -3.98 | -0.049*** | -4.18 | 0.019*** |
| Extra Distance | -0.031*** | -4.73 | -0.044*** | -5.02 | |
| d_TimeBased | 0.818*** | 2.67 | 0.925 | 1.55 | |
| d_MicroSmall | -0.785** | -2.49 | -1.158* | -1.83 | |
| d_MultiTrailer | 1.097** | 2.01 | 2.187** | 1.97 | |
| | | | | | |
| LL[0] | -266.2 | | -266.2 | | |
| LL[C] | -212.6 | | -212.6 | | |
| LL[F] | -150.3 | | -136.0 | | |
| Naïve $\rho^2$ | 0.435 | | 0.489 | | |
| Restricted $\rho^2$ | 0.293 | | 0.36 | | |
| Adjusted $\rho^2$ | 0.274 | | 0.343 | | |
| AIC | 316.5 | | 291.9 | | |
| No. of Resp. | 32 | | 32 | | |
| Groups | N/A | | 12 | | |
| No. of Obs. | 384 | | 384 | | |

*Notes: ***, **, *, represent statistical significance at 1%, 5%, and 10% respectively.*

LL*[0]=log likelihood with no constants or variables,* LL*[C]=log-likelihood with constant only,* LL*[F]=log-likelihood for the full model*

*All of the dummy variables were introduced only to the toll route utility function.*

As can be seen in the table above, some of these variables which were performing well when implemented individually, are not as significant when included with each other. This fact was more severe in the mixed logit model. However, the main variables in both models are still strongly significant. The overall parameter signage for all variables also makes sense. For instance, the dummy variable for micro/small enterprises is negative implying that smaller-size companies are generally against using toll routes in their routing behavior presumably because of lower budgets. On the other hand, companies/drivers with large vehicles such as multi-trailer trucks are more likely to use toll routes.

Comparing the indices with regards to the overall performance of the model in MXL6 and previous mixed logit versions, it can be noticed how the adjusted-ρ2 was enhanced. This improvement indicates that the current model is doing a better job in explaining the choice outcomes. Therefore, this model will be exploited to derive parameter elasticities and generate the contingency table in the following section.

### 8.3.3. Elasticities and Cross-tabulation

As discussed in Chapter 5, a major function of choice models is to estimate the effect of changes in every variable on the choice outcome. Table below summarizes the elasticities with respect to a unit change in a given variable to show the associated percentage change on the probability of choosing alternatives. The variable with elasticities exceeding a value of 1 or -1 have the most impact on the model. These travel time has the highest elasticity values, followed by the toll cost.

Elasticities for the dummy variables were not included since a 1% change in the variable is not feasible. However, the lower significance in the model results for these variables when compared to the core variables is an indicator that they have less impact on the model. The values in the table below can be interpreted as follows. For example, a percentage increase in toll cost attribute within the second alternative would reduce the probability that individuals would choose this toll route by 1.45% and an increase of 0.52% in the chance of the free route alternative.

Table 8.6 – MXL6 (Panel) Model Elasticities

| **Alternatives** | **Variables** | **Change in Probability** | |
|---|---|---|---|
| | | **Free Route** | **Toll Route** |
| **Free Route** | Travel Time | -1.134 | 3.788 |
| | Delay | -0.225 | 0.714 |
| | Toll Cost | N/A | N/A |
| | Extra Distance | -0.110 | 0.268 |
| **Toll Route** | Travel Time | 0.815 | -3.400 |
| | Delay | 0.040 | -0.125 |
| | Toll Cost | 0.524 | -1.449 |
| | Extra Distance | 0.101 | -0.352 |

A commonly-used approach in determining model performance is by generating *contingency table* which lets the analyst assess the model-produced choice outcomes compared to actual observed data (Hensher *et al*., 2015). This can be done through NLogit software by utilising *;Crosstab* function. This was done for the MXL6 model and the results are provided in the table below. This table for a binary choice reads as the diagonal elements exhibit the times the model predicted the actual observed choice correctly whereas the off-diagonal elements represent the incorrectly predicted choices. For example, referring to the values in the first column, the model was successful in accurately predicting the free route 244 times out of 291 questions where free route was actually selected, hence an almost 84% accuracy. Whereas the toll route was only predicted with a 50% accuracy. This reveals that the model prediction is struggling when the toll route alternative will be chosen by the respondents.

Table 8.7 – Cross Tabulation of Actual Vs. Predicted Choices in MXL6

| | | **Predicted Choice** | | |
|---|---|---|---|---|
| | | Free Route | Toll Route | Total |
| **Actual Choice** | Free Route | 244 | 47 | 291 |
| | Toll Route | 47 | 46 | 93 |
| | Total | 291 | 93 | 384 |

### 8.3.4. Willingness to Pay and VOT

As was outlined in Chapter 5, a common practical usage of discrete choice models is to derive monetary measures that are intended to determine the amount of money individuals are willing to spend in exchange for some benefits by opting in to specific alternatives. Such measures are referred to as willingness to pay (WTP) (Hensher *et al*., 2015). The application of these measures in transportation studies is often calculated as a value of travel time savings (VTTS), or simply value of time (VOT). This measure will indicate the monetary cost the truck driver/route planner is willing to pay to save a certain amount of time, which can be measured as a dollar per hour unit. For fixed parameter models such as the MNL, WTP measures are calculated by taking the ratio of time parameter to cost parameter estimates, holding all else constant. The original MNL3 model is first used here to derive an initial VOT measure with only the core variables included in the model. The equations below report VOTs for two MNL models with and without alternative specific constants (ASC).

$$VOT = \frac{\beta_{TT}}{\beta_{TC}} = \frac{-0.03566}{-0.02842} * 60 = 75.28 \ {}^{\$}/_{hr} \qquad \text{Equation 27}$$

*MNL3 Value of Time (without constant)*

$$VOT = \frac{\beta_{TT}}{\beta_{TC}} = \frac{-\ 0.03733}{-\ 0.02033} * \ 60 = \ 110.17 \ {}^{\$}/_{hr}$$ Equation 28

*MNL3 Value of Time (with constant)*

While the constant in MNL3 shows limited significance slightly above the 90% confidence level, the impact on VOT is substantial with a value of $75.28 without the constant and $110.17 with the constant. The large change in value was primarily caused by adjustment in toll cost parameter used in the denominator of the equation. The sensitivity of the VOT value is worth highlighting here, and further indicates the need for a distribution of values.

In models where at least one of the parameters is estimated with a distribution, a more complex function for VOT can be utilized by including both the mean value and the distribution into account. This can be done in NLogit using specific “wtp” function. However, the analyst should be cautious in constructing such measures due to the possibility of obtaining behaviorally implausible results such as negative or extremely high VOT (Hensher *et al*., 2015). Hensher and Greene, (2003) suggest imposing constraints on the distributions from which the random parameters are drawn to avoid such conditions. Limited information is reported in the literature as to the best constraint to use since context can severely impact this decision. In this thesis, the model outputs were tested several times using different constraints. The objective was to find the most appropriate standard deviation for the assumed distribution in such a way that is not prohibiting the model natural skewness as well as producing close to average values of time. A value of 0.25 was used as the final standard deviation constraint which was the point where mean VOT converged to the VOT calculated from MNL model.

The VOT distributions are presented in Figure 8.10 below. These figures were calculated from the cross-sectional (i.e. non-panel) model without ASC, since the panel feature in Nlogit was unfortunately leading to erroneous VOT distributions. A similar process was also used to calculate value of reliability, with the travel time parameter replaced with the delay parameter.

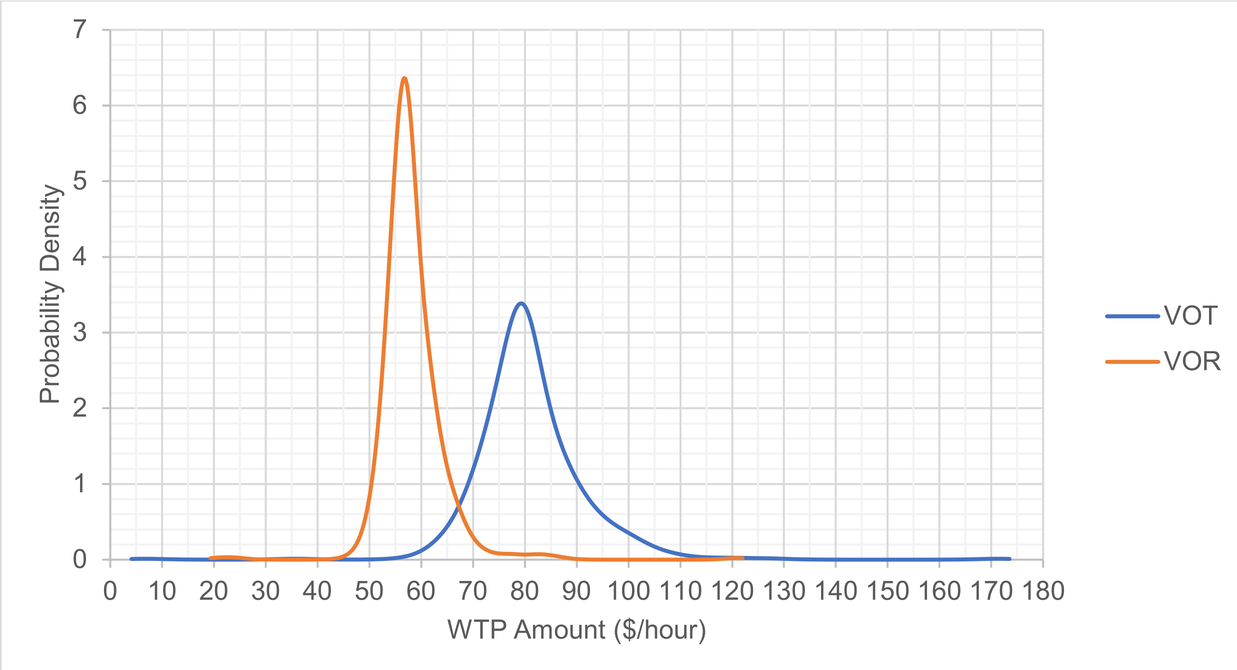



Figure 8.10 – VOT and VOR Distribution

The mean VOT for the distribution was calculated as 81.01 $/hr, with a standard deviation of $10.09. Expectedly, VOR was recorded to be valued less than VOT with the mean of $58.18 and the standard deviation of $5.84. Similar to the literature values which were reported in Section 2.2.2, drivers/route planners usually value the travel time savings higher than reliability savings.

As can be seen in Table 8.7, there is a substantial range between the minimum and maximum for VOT and VOR, which is represented by the tails of the distribution. This reveals that route decision-makers are heterogenous in their willingness to pay, which could not be captured in the basic MNL model. It should also be reiterated that there is sensitivity of VOT to the attribute level ranges selected for the SP scenarios (Hensher *et al.*, 2015). Therefore, the context of the survey questions and assumed study area for this research can impact the range of attribute values in a SP survey.

Table 8.8 – Distribution Statistics for VOT and VOR

| **Statistic** | **VOT ($/hr)** | **VOR ($/hr)** |
|---:|:---:|:---:|
| Mean | 81.01 | 58.18 |
| St. dev. | 10.09 | 5.84 |
| Maximum | 171.23 | 120.69 |
| Minimum | 6.74 | 20.87 |

The survey presented to respondents included a question directly asking what they believe to be their typical VOT value. The results are aggregated and presented in Figure 8.11 below. Very few respondents list a VOT above $50/hr which is considerably lower than values obtained from the distribution derived from the model results. This however is not an unexpected result since people will not necessarily have a decent understanding of their VOT due to its abstract concept. Additionally, another reason for this might be the poor perception of people regarding the Highway ON-407 which is reflected in their artificially lower stated VOT.

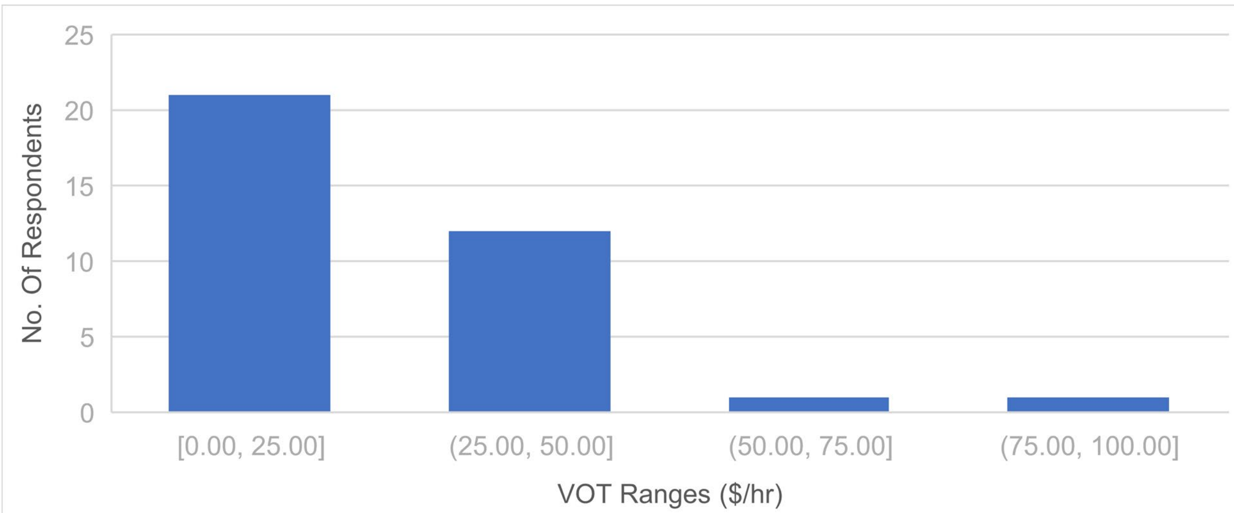



Figure 8.11 – Stated VOT by Survey Respondents

The market VOT offered by Highway ON-407 ETR was discussed earlier in Chapter 3 with a calculated minimum value of $150 during a typical peak period. This value is outside the range directly stated by respondents, providing further indications that the respondents are likely under-stating their VOT values. However, the market VOT is captured in the right-tail of the calculated VOT distribution from the SP models, indicating that some decision makers are willing to pay the market price. Only a 0.15% of the sample distribution are willing to pay the calculated market VOT of Highway ON-407 ETR.

# Chapter Nine: Conclusion

## 9.1. Summary and Discussion

The research in this study was motivated by congestion on Highway ON-401 as the most congested artery in North America with an AADT close to half a million vehicles. This situation is exacerbated when this roadway passes through the City of Toronto where there is also a high volume of truck traffic. Yet, there is a tolled route alternative that can be used if a driver or company is willing to pay the required costs. Tolled routes inherently present an added layer of complexity to route choice decisions as a driver must consider travel time, delay, and distance, with the trade-off presented by explicit financial costs. Therefore, the goal of this research was to evaluate the route choice decision-making of commercial vehicles to better understand their behavior in choosing tolled routes. The objectives of this thesis to achieve the goal are summarized below.

*Objective 1. Perform an exhaustive literature review identifying the known factors for truck route choice.*

The review on preference elicitation literature included an assessment on the most practical approaches in collecting behavioral data, identification of the most influential factors in truck route choice, and an evaluation of the most suitable methods for designing survey experiments. The commonly used data sources were investigated to be stated preference and revealed preference. The former refers to a survey-based technique where the respondent is asked to state his behavior in a hypothetical choice environment while the latter deals with the actual choice that has happened in the past. An examination on the performance of these data sources were conducted and this research focused on utilizing a SP approach due to the scarcity of RP data for tolled routes and the flexibility of SP experiments to incorporate additional factors.

The core attributes which were shortlisted from the literature include travel time, potential delay, toll cost, and trip distance. In addition, demographic and firmographic variables pertaining to the decision makers were identified since they may elicit heterogenous behavior in route choice.

*Objective 2. Design a stated choice experiment that includes hypothetical routing scenarios to elicit behavioral preferences.*

To investigate the independent impact of various variables on the outcome of recorded decisions made by individual respondents, a careful generation of choice experiment was required. The experiment was designed to contain a realistic number of questions (twelve), each comprising of two alternatives to compare including a tolled route and non-tolled route. Each alternative is characterized by its corresponding attributes which differ in values across the questions given to a respondent. To develop the choice experiment matrix, an efficient design method was preferred over the older method of orthogonal design. Efficient designs can outperform orthogonal counterparts by limiting the number of choice tasks and improving the statistical efficiency. Since the efficient design benefits from limited prior information on variable parameters, a two-stage design was introduced with a pilot survey distributed to peers and a final survey distributed to members of the trucking industry that work as drivers or planners involved in route choice for trucks.

A qualitative study over the study area was conducted to provide a reasonable range for each of the core route choice factors, followed by the pilot survey to calibrate prior parameters. Ngene software was employed to systematically populate the choice matrix with different values of the attributes and develop a design for the final survey.

*Objective 3. Integrate the experimental design into an online survey tool for distribution to a sample of Ontario trucking carriers.*

After preparing the final choice experiment, a survey questionnaire was generated to complement the study by collecting socio-demographic characteristics of the respondents. Prior to the implementation of the final survey, an examination on the potential survey modes was conducted. The result informed the decision as to administer the survey online considering its time- and cost-efficiency. The covid-19 pandemic currently limiting physical contact also influenced the decision to select an online method of survey distribution. The survey was imported into Qualtrics software and was sent out to the target population. However, the communication required an exhaustive list of motor carrier company email addresses. An existing list of Ontario trucking companies originally sourced from public Yellow Pages was imported into Amazon Mechanical Turk to gather industry email addresses. The email collection procedure was successfully established through this crowd-sourcing platform and resulted in more than 1,500 contact addresses. An initial contact email was followed by several reminders to the trucking companies during the data collection period.

The survey was accessible online for 45 days and a total of 69 individuals took part in the experiment. A total of 39 people completed the SP portion of the survey which contained 12 choice tasks each representing two alternatives.

*Objective 4. Estimate the impact of influential factors on truck route choice in Ontario using discrete choice models.*

A series of data quality assessments were undertaken prior to modelling the survey results. The refined observations were then processed and imported into a discrete choice modelling software called NLogit to measure the relative importance of truck route choice attributes. A comprehensive list of dummy variables based on the socio-demographics and firmographics of the respondents were also generated and inputted into the model where appropriate. Several multinomial and mixed logit models with different specifications were tested and the outputs were presented. The results indicate that all four core variables were significant at a 99% confidence level. The estimated random parameter model showed that taste heterogeneity exists for travel time and toll cost variables. The mean and standard deviation of VOT in the final mixed logit model was 81.01 $/hr and 10.01 $/hr respectively.

## 9.2. Limitations and Future Research

This section discusses some of the limitations associated with different steps of the research and will provide recommendations and insights.

Although one of the main objectives of this research was to estimate willingness to pay measure for truck routing decisions, the initial choice experiment was not optimized for producing precise WTP estimates for all contexts. This task would have required a careful consideration of price levels in the design to incorporate different ranges of value sufficient variation (Butkeviciute, 2017). As such, the VOT distribution should be interpreted cautiously. Additionally, integrating for a customized pivot design based on an existing reference alternative for the respondent has shown explanatory strength in economic behavior (Starmer, 2000). However, optimizing such designs where the choice experiment is dynamically designed on the fly requires substantial programming and intensive computational effort with a risk of producing non-optimal designs (ChoiceMetrics, 2018). These efforts were subsequently outside the scope of this thesis.

An interesting area for future research is the investigation of values of travel time saving for different times of day. It is strongly suggested to design the SP experiment in a way that choice tasks represent a specific time of day and ultimately estimate for time-of-day-dependent WTP. This, however, requires a rich dataset for every single choice task to be able to accurately measure VOT for a subgroup of choice situations. A future survey with more funding resources to produce larger panels of respondents will be better suited for this task. Given a sufficiently big sample size, one can also increase the number of blocks and subsequently more attribute levels to capture nonlinearities and parameter distributions more precisely.

The smaller-sized trucking enterprises such as owner-operators are unfortunately underrepresented in the sample population of this research, even though they comprise a large portion of the freight trucking industry. This issue generally arises from the limitation of the sampling strategy where a directory of Ontario motor carriers was utilized and owner-operators may not widely publicize their services. For future endeavors, it is good practice to contact different driver types as well as a wide range of company sizes proportionately. Alternatively, the model results in this thesis could be adjusted to better align with the proportional representations of establishment size and industry type.

Theoretical evaluations of different modelling techniques were also outside of the scope of this research. Nevertheless, the author suggests further investigation for model specifications. For example, observing the modeling performance under different distributional assumptions. Extra research is needed to investigate the use of constrained distributions in calculating WTP as there is little empirical evidence in the literature.

## 9.3. Concluding Remarks and Research Implications

One of the most important objectives of toll road infrastructures is to serve communities by relieving traffic congestion from other transportation arteries. This was not an exception for Highway ON-407 ETR at the time of privatization (Mendoza *et al.*, 1999). However, according to the statistics which were reported in this research, Highway ON-401 has become the busiest corridor in North America (FHWA, 2007) while Highway ON-407 ETR has been identified as one of the most expensive toll corridors comparing to other similar routes in the US. The congestion situation will not improve unless an appropriate redistribution of traffic occurs. That is when the monetary value for an equivalent amount of travel time savings along the toll alternative makes sense for more route decision makers.

This study has calculated a VOT of $81.01 per one hour of travel time saving for Ontario trucking companies which is in line with the average value reported in other toll-related studies (74.78 $/hr). Yet Highway ON-407 is requiring a minimum of $150.75 for the opportunity of saving one hour of travel time which is almost double the amount of consumer-driven value. Moreover, the market is offering substantially higher VTTS during off-peak where the consumer VOT is in fact lower.

The results of this study can be incorporated into calculations of dynamic smart pricing schemes for toll route authorities to offer toll tariffs that accommodate optimal traffic re-distributions. The data in this research revealed that approximately 78% of the respondents use toll routes at least sometimes, while 81% of them consider buying a toll subscription package (e.g.: monthly pass) at a discounted rate. Realistic rates would result in incentivizing motor carrier companies to utilize the toll infrastructure which could then lead to smoother traffic flow and alleviate congestion. This consequently contributes to producing less emissions by reducing fuel consumption levels and ultimately a significant positive impact on the economy, hence a sustainable solution.

Highway ON-401 has historically undergone numerous multi-million-dollar expansion projects to accommodate additional traffic and relieve congestion. The added highway capacity induces additional traffic demand and potentially negates the original intention of the expansion. An interesting application for transportation planners would be the difference in optimal toll cost for public operators of tolled facilities compared to private operators. The latter are profit-maximizers that are not concerned with the system-wide impacts of their toll policies. However, a public authority may want to subsidize toll costs to optimally re-distribute commercial traffic to benefit the entire transportation system.

The findings of this thesis can additionally contribute to long-term transportation masterplans and development of sustainable policies. The obtained behavioral preferences and characteristics of commercial vehicles can be used to calibrate macroscopic transportation planning models. The captured variation in toll rates for different users can be integrated into an intelligent toll friction factor to simulate network equilibrium for new or existing road corridors. This friction factor could be adaptive to different variables such as time-of-day, real-time congestion, and vehicle characteristics.

Finally, the developed methodology in this research along with the thorough discussion on the utilized step-by-step systematic approach can be instrumented in any sort of consumer behavior studies. The comprehensive design of the discrete choice experiment, online survey administration and data collection, and the implemented modelling techniques may be used to help future research develop robust route choice model designs.

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# Appendix A: Literature Review Tables

| **Citation:** | (Sun *et al.,* 2013) |
|---|---|
| **Method** | SP |
| **Model** | Mixed Logit |
| **Administration** | Computerized Intercept interviews at 3 rest areas in Texas, Indiana, Ontario |
| **Sample** | 252 Drivers, 1121 observations |
| **Topic** | Understanding of trucks' route choices when faced with toll route |
| **Research Question** | Finding Additional key factors on truck routing beyond time and cost |
| **Analysis Priority** | • Carrier, Shipment, Drivers Characteristics, • Employment terms<br>, • Ability to change route, • Route Sources of information |
| **Significant Factors & Remarks** | • Fuel Stations, • Travel time predictability, • Availability of parking locations<br>Effect on fuel consumption is rarely considered as relevant factor<br>Sources of information are limited |

| **Citation:** | (Arentze *et al.,* 2012) |
|---|---|
| **Method** | Conjoint experiment |
| **Model** | Mixed Logit |
| **Administration** | Web application on internet |
| **Sample** | 15 diverse freight companies (100 drivers and 1 planner per company) |
| **Topic** | Truck drivers' (Route planners') preferences to define truck-friendly routes and sensitivity to pricing policies in short distance freight |
| **Research Question** | 1. Relative Importance of Road accessibility<br>2. Personal & Situational effective variables<br>3. Drivers' sensitivity to pricing policies<br>4. Financial incentives Vs. pricing instrument |
| **Analysis Priority** | •Decision maker identities, •Route-related attributes, •Road-pricing Vs. road-bonus scenario, •Congestion<br>Different levels for each factor [Low, Medium, High] |
| **Significant Factors & Remarks** | •Travel time, •Pricing [High], •Congestion [Low], •Road Category [Hwy]<br>Road price negatively correlates with vehicle size<br>Road pricing is as effective as congestion in shifting traffic<br>Road category correlates with the probability of a delay<br>Preference for avoiding urban area correlates with time-of-day<br>Availability of rest areas, effect of role, and road bonus appears to have no significant effect |

| | |
|---|---|
| **Citation:** | (Hunt and Abraham, 2004) |
| **Method** | SP |
| **Model** | Logit Model |
| **Administration** | 1. Intercept at roadside, 2. Face-to-face at office |
| **Sample** | 242 interviews, 1885 observation |
| **Topic** | Influence of route attributes on Commercial movement in Montreal, Canada |
| **Research Question** | 1. How respondents trade-off among conditions regarding the attributes<br>2. Making inferences about relative & absolute importance of attributes<br>3. Guiding the specifications of travel demand modeling of CVs |
| **Analysis Priority** | •Delay, •Expected TT, •Toll cost & collection, •Roadway type<br>Bundles of values for each route attribute<br>4 models with different combinations of surveys and specific route attributes |
| **Significant Factors & Remarks** | •Probability of delay, •Toll cost, •Freeway rather than arterial, •Expected driving time<br>Best utility function includes delay time and its probability<br>A practical approach to tackle level of information is to segment probability of delay into separate terms such as rate of accidents in historical data<br>Presentation of toll facilities should stress TT savings<br>Toll collection method was not significant<br>Greater sensitivity to delay time than drive time |

| | |
|---|---|
| **Citation:** | (Knorring *et al.,* 2005) |
| **Method** | RP |
| **Model** | Logit Model |
| **Administration** | GPS data |
| **Sample** | 250,000 unique trucks (13-day period) |
| **Topic** | Trade-off between time and distance for US long-haul truck drivers when faced with multiple routes |
| **Research Question** | 1. Usage of bypass route as a function of perceived speed on downtown route<br>2. To accurately capture drivers' preferences on willingness to take risk<br>3. Are truck drivers rational decision makers? |
| **Analysis Priority** | Downtown Vs. Bypass Scenario<br>Stop determination based on minimum average speed and the length between two consecutive stops<br>Using percentage difference of distance and time to remove units and keep the generalizability |
| **Significant Factors & Remarks** | •Past experience on the route, •Time of day, •Current traffic conditions, •Knowledge of the route<br>The flat slope at the point of indifference in perceived speed curve signifies a high level of risk aversion<br>Truck drivers are primarily time minimizers<br>RP is better than SP because it can replicate the actual behavior |

| **Citation:** | (Rowell *et al.,* 2014) |
|---|---|
| **Method** | Survey Questionnaire |
| **Model** | LCA & IRT |
| **Administration** | Telephone |
| **Sample** | 850 Companies (413 valid responses) |
| **Topic** | How different priorities vary between shippers, carriers, and receivers in Washington? |
| **Research Question** | What are truck routing priorities for different subgroups of trucking industry and how these priorities can be implemented in truck routing models? |
| **Analysis Priority** | •Transportation activity, •Route choice priorities, •Business demographic<br>IRT is used to identify routing items that discriminate between companies<br>LCA is used to form classes of respondents that have differences in response patterns |
| **Significant Factors & Remarks** | •Minimizing cost, •Meeting customer requirements, •Road grade, •Hours of service limits, •Driver availability<br>Travel distance, time, total cost, meeting customer requirements, and congestion were highly correlated<br>Long-haul carriers are more likely to rate refueling locations, parking availability, size and weight limits, and hours of service limits higher than parcel delivery |

| **Citation:** | (Zhou *et al*., 2009) |
|---|---|
| **Method** | SP |
| **Model** | LCA & IRT |
| **Administration** | 1929 web-based and 233 paper-based surveys |
| **Sample** | 2023 valid and refined observation from truckers, logistic managers, & related businesses |
| **Topic** | Incentives on truck toll road use in Austin, Texas and its impact on performance of the toll road in both revenue and congestion reduction |
| **Research Question** | 1. How segments of truck industry use toll roads?<br>2. How incentives would impact this use?<br>3. What are the variations of these results?<br>4. VOT elasticity |
| **Analysis Priority** | Five truck industry segmentation<br>1. OOs, 2. For-hire, 3. Private carriers, 4. LTL, 5. Combination of 1&2<br>20 Incentives for tolls to rate between 1 to 3<br>Percentage of trucks chose toll was broken into Value of Travel Time Savings |
| **Significant Factors & Remarks** | Most preferred incentives:<br>•Reduced fuel prices, •No congestion, •Dining facilities with better parking, •Off-peak toll discounts, •Wide shoulders for emergencies<br>Most effective incentives will be those that reduce the cost of use such as:<br>•Off-peak discounts, •Free trip after several paid trips<br>OOs and company-owned shipping were the least and the most likely to use toll roads<br>Toll facility must improve time savings<br>Resulting value of travel time saving is $44.2/h |

| Citation: | (Ben-Akiva *et al.,* 2016) |
|---|---|
| **Method** | Hybrid SP and RP |
| **Model** | N/A |
| **Administration** | GPS data complemented by web-based prompted recall SP questionnaires via telephone and or in person at rest areas |
| **Sample** | 107 Drivers in 2255 validated days |
| **Topic** | Application of experimental designs capabilities on intercity truck route choice in North America with a focus on choice between tolled & free roads |
| **Research Question** | Implementation of next-generation freight data collection |
| **Analysis Priority** | GPS Logger: 1. Location, 2. Instantaneous speed, 3. Timestamp<br>Web survey: 1. Delivery schedules, 2. Tolls & payment method, 3. Stop activities, 4. Sociodemographic characteristics, 5. Employment terms<br>6. Freight related characteristics |
| **Significant Factors & Remarks** | The largest share of stops was at rest areas<br>In most cases, the carrier or shipper was responsible for the toll cost<br>Several distinct driver patterns:<br>i) Series of regular, long tours spanning several days, ii) Shorter tours within a smaller region, iii) Combination of short and long tours, iv) No exhibited distinctive tour pattern<br>Capture of complexity and heterogeneity as compared to average<br>Presenting SP survey, soon after the activity is made, can provide higher-quality data |

| Citation: | (Kawamura, 2000) |
|---|---|
| **Method** | SP |
| **Model** | Mixed Logit Model (RPL) |
| **Administration** | Telephone (Selection), Face-to-face interviews (survey), Mail (follow-up) |
| **Sample** | 70 freight Companies |
| **Topic** | Toll facility Vs free road in route choice for different combinations of travel time and cost in California |
| **Research Question** | 1. Estimation of the point where switch from free road to toll facility occur<br>2. Variation of VOT associated with characteristics of truck operators |
| **Analysis Priority** | VOT grouping variable: •Business type, •Shipment size, •Compensation<br>Data segmentation: •TL Vs LTL, •Private Vs For-hire, •Hourly Vs Pay scale<br>Lognormal distribution was assumed for VOT |
| **Significant Factors & Remarks** | The mean VOT was found to be $23.4/ h<br>Sensitivity to TT has greater variation than out-of-pocket cost<br>TL is more sensitive to cost<br>VOT varies with business type & pay scale but apparently not shipment size<br>VOT: For-hire > Private and Hourly > Pay scale<br>For-hire group has the highest value of time while the “other pay scale” group recorded the lowest<br>For evaluating 1. Demand prediction and 2. Project cost-benefit, the attributes of truck operators and physical characteristics of vehicles must be taken into account |

| Citation: | (Wang and Goodchild, 2014) |
|---|---|
| **Method** | RP |
| **Model** | Logit Model |
| **Administration** | GPS data before and after toll |
| **Sample** | Every 2-15 min including (ID, Location, Direction, Spot Speed, Date, Time) |
| **Topic** | Observing the Effect of a toll route on truck speed & routing in Seattle using GPS data |
| **Research Question** | Impact of set of cost & time attribute resulted by using toll/non-toll route on route choice and speed |
| **Analysis Priority** | •Travel Time (TT), •Travel Time Reliability, •Toll Rates<br>Travel time reliability defined as the SD of TT<br>Toll rates vary depending on:<br>•Time of day, •Truck type, •Payment method |
| **Significant Factors & Remarks** | Toll Rates was the most significant in route choice followed by TT<br>Travel Time Reliability shouldn't be used with TT due to correlation<br>Travel speed on toll road improved significantly and travel time was more stable with reduced fluctuations<br>Passenger car traffic reduced more than commercial truck trips<br>VOT(peak): $18.26/hr and VOT(off-peak): $25.69/hr |

| Citation: | (Holguín-Veras *et al.*, 2006) |
|---|---|
| **Method** | SP |
| **Model** | N/A |
| **Administration** | Telephone interview |
| **Sample** | 200 companies (current & former regular users defined as all carriers that have used toll facilities at least once per week and selected from two groups: Private & For-hire) |
| **Topic** | How freight carriers would react to road pricing |
| **Research Question** | Is time of day road pricing effective in moving freight traffic to the off-peak periods? |
| **Analysis Priority** | Behavioral strategies: 1. Changes in facility usage, 2. Productivity increases, 3. Cost Transfers<br>Differentiation of toll prices among its facilities, to charge higher tolls at the most congested facilities |
| **Significant Factors & Remarks** | Carriers respond to the policy by using multi-dimensional responses<br>Utilizing only productivity increases was found to be the most optimal strategy, change in facility usage is the last resort alternative<br>Private carriers have more flexibility to adjust their operation schedule<br>Low awareness of discounts diminishes effectiveness<br>Switch to E-ZPass > switch off-peak period<br>For-hire was more likely to transfer costs<br>Constraints imposed by customers prevent shifting to off-peak<br>Toll cost are small as compared to marginal off-peak staff cost<br>Greater sensitivity found in through trips compared to local |

| Citation: | (Quattrone and Vitetta, 2011) |
|---|---|
| **Method** | Hybrid SP and RP |
| **Model** | RUM Vs Fuzzy Utility Model |
| **Administration** | 280 Road-side interviews, 52 GPS monitoring |
| **Sample** | Freight drivers |
| **Topic** | Italy-wide freight road network |
| **Research Question** | Identification of a sub-set of few routes between and OD pair that both best satisfies individual's criteria and less commonality |
| **Analysis Priority** | N/A |
| **Significant Factors & Remarks** | •Topological factors, •LOS, •Socio-economic factors<br>Low amount of feasible perceived routes |

| Citation: | (Uchida *et al.*, 1994) |
|---|---|
| **Method** | Hybrid SP and RP |
| **Model** | Probit Model |
| **Administration** | Mail |
| **Sample** | 5817 responses from 72 participants |
| **Topic** | Longitudinal survey examination on drivers' route choice behavior under travel time information |
| **Research Question** | How dynamic traffic information should be provided by observing drivers' response to travel time information?<br>Predicting changes of traffic flow caused by providing travel time information |
| **Analysis Priority** | Aspects considered: 1. Tactical reaction: Immediate reaction<br>2. Strategic choice: Gradual change of route tendency<br>One free arterial and two tolled alternatives all equipped with variable message sign |
| **Significant Factors & Remarks** | Providing travel time information is influential in route choice |

| Citation: | (Wynter, 1995) |
|---|---|
| **Method** | SP |
| **Model** | Logit Model |
| **Administration** | Telephone interview (low rate of mail-back) |
| **Sample** | 408 fleet managers or drivers with 20 percent response rate |
| **Topic** | Calculating values of time of road freight transport in France |
| **Research Question** | The critical point of value of time in which the respondent is indifferent in choosing either alternatives |
| **Analysis Priority** | Questionnaire includes freight-related characteristics and choice experiment<br>A percentage increase in travel time and toll cost was implemented in scenarios |
| **Significant Factors & Remarks** | VOT for French transporters could be described by a log-normal distribution<br>Calculating for a range in user VOT instead of mean value is necessary for effectively testing different toll pricing schemes<br>VOT was shown to vary with trip distance in a linear pattern |

| | |
|---|---|
| **Citation:** | (Tsirimpa *et al.*, 2019) |
| **Method** | SP |
| **Model** | Binomial Logit |
| **Administration** | Paper and Internet |
| **Sample** | 50 Freight operator and 25 drivers |
| **Topic** | VOT calculation for Portuguese freight forwarders and truck drivers |
| **Research Question** | Estimating the probability of using two alternative routes (toll road vs. national road), based on route attributes and user characteristics |
| **Analysis Priority** | TC, Total TT, Fuel Cost, Incentives<br>Most effective incentives: Fuel Price Discount, off-peak discount, Rest Area<br>3 different models were defined and tested |
| **Significant Factors & Remarks** | Most effective incentive: Dedicated truck lane<br>Drivers were very limited to change routes<br>VOT= 49.4 euro/hr<br>Elasticity to change to toll routes with change in toll cost<br>Booked distance compensation positively affects choice of toll route |

| | |
|---|---|
| **Citation:** | (Toledo *et al.,* 2020) |
| **Method** | RP |
| **Model** | Binomial Logit |
| **Administration** | Employ drivers at roadside or by telephone to add GPS loggers |
| **Sample** | 107 drivers (1021 trips) |
| **Topic** | Intercity truck drivers route choice decisions |
| **Research Question** | Address the existence of heterogeneity in decision-making between truck drivers |
| **Analysis Priority** | Assumed lognormal distribution with negative signage for TT and TTV<br>TTV captured by the square of the difference between the Min and Max TT over the day<br>solicit information on socio-demographic characteristic of the drivers |
| **Significant Factors & Remarks** | 9.7 average routes per trip<br>chosen routes are more likely to involve tolls compared to other routes<br>Contract Type and Level of experience were considered in the model<br>Distribution of VOT and VOR were reported (Simulation with Halton Draws) |

| | |
|---|---|
| **Citation:** | (Kong *et al*., 2018) |
| **Method** | RP |
| **Model** | Binomial Logit |
| **Administration** | GPS data |
| **Sample** | 15,000 GPS devices (50 million trips) |
| **Topic** | Impact of congestion and TT reliability on non-frequent and frequent drivers |
| **Research Question** | N/A |
| **Analysis Priority** | Used ratios of TTI and PTI in the model |
| **Significant Factors & Remarks** | TTR is a major concern for familiar drivers and not for first-time users and the opposite applies to congestion level |

# Appendix B: Software Coding Syntax

### Ngene Pilot Design Syntax:

```
Design
;alts = Route A, Route B
;alg = mfederov
;rows = 12
;eff = (mnl,d)
;reject:
Route A.TT + Route A.TTV >= Route B.TT + Route B.TTV
;model:
U(Route A)= b1 [-0.001]*TT[60,80,100,120] + b2[-0.0001]* TTV[0,10,20,30] +
b3[-0.01] * TC[50,100,150] +
b4[-0.000001]* Dist[0,15,30] /
U(Route B) = b1*TT + b2 * TTV $

NLogit Model Syntax
NLOGIT
;lhs = CHOICE
;choices = 1,2
;Effects: Dist(*)/TTV(*)/TT(*)/TC(*)
;Model:
U(1) = TT * TT + TTV * TTV + TC * TC + Dist * Dist /
U(2) = TT * TT + TTV * TTV $
NLOGIT
;lhs = CHOICE
;choices = 1,2
;Effects: Dist(*)/TTV(*)/TT(*)/TC(*)
;Model:
U(1) = Alt1Constant + TT * TT + TTV * TTV + TC * TC + Dist * Dist /
U(2) = TT * TT + TTV * TTV $
```

### Ngene MXL Design Syntax

```
Design
;alts = Route A, Route B
;alg = mfederov
;rows = 12
;eff = (rppanel, d)
;rep = 1000
;rdraws = Halton (500)
;reject:
Route A.TT + Route A.TTV > Route B.TT + Route B.TTV, #The study area shows that the
toll route's travel time and its potential delay is always lower than the free route's
Route A.Dist > 0 and Route B.Dist > 0  #Since the situation where both routes have
"extra" distance does not make sense, I always have to keep one of them zero
;model:
U(Route A) = b1[(n,-0.04051,0.00837)] * TT[60,80,100,120](4-10,4-10,4-10,4-10)
           + b2[(n,-0.03067,0.00570)] * TC[50,100,150](4-12,4-12,4-12)
           + b3[(n,-0.02740,0.00823)] * TTV[0,5,10](4-12,4-12,4-12)
           + b4[(n,-0.02315,0.01293)] * Dist[0,15,30](4-12,4-12,4-12) /
U(Route B) = b1 * TT + b3 * TTV1[0,15,30](4-12,4-12,4-12)   + b4 * Dist $
```

**Ngene Final Bayesian MNL Design Syntax**

```
Design
;alts = Route A*, Route B*
;alg = mfederov
;rows = 24
;block = 2
;eff = (mnl, d, mean)
;bdraws = gauss(5)
;reject:
Route A.TT + Route A.TTV > Route B.TT + Route B.TTV1,
Route A.Dist > 0 and Route B.Dist > 0
;model:
U(Route A) = b1[(n,-0.04051,0.00837)] * TT[60,80,100,120](4-10,4-10,4-10,4-10)
           + b2[(n,-0.03067,0.00570)] * TC[50,100,150](4-12,4-12,4-12)
           + b3[(n,-0.02740,0.00823)] * TTV[0,5,10](4-12,4-12,4-12)
           + b4[(n,-0.02315,0.01293)] * Dist[0,15,30](4-12,4-12,4-12) /
U(Route B) = b1 * TT + b3 * TTV1[0,15,30](4-12,4-12,4-12)   + b4 * Dist $
```

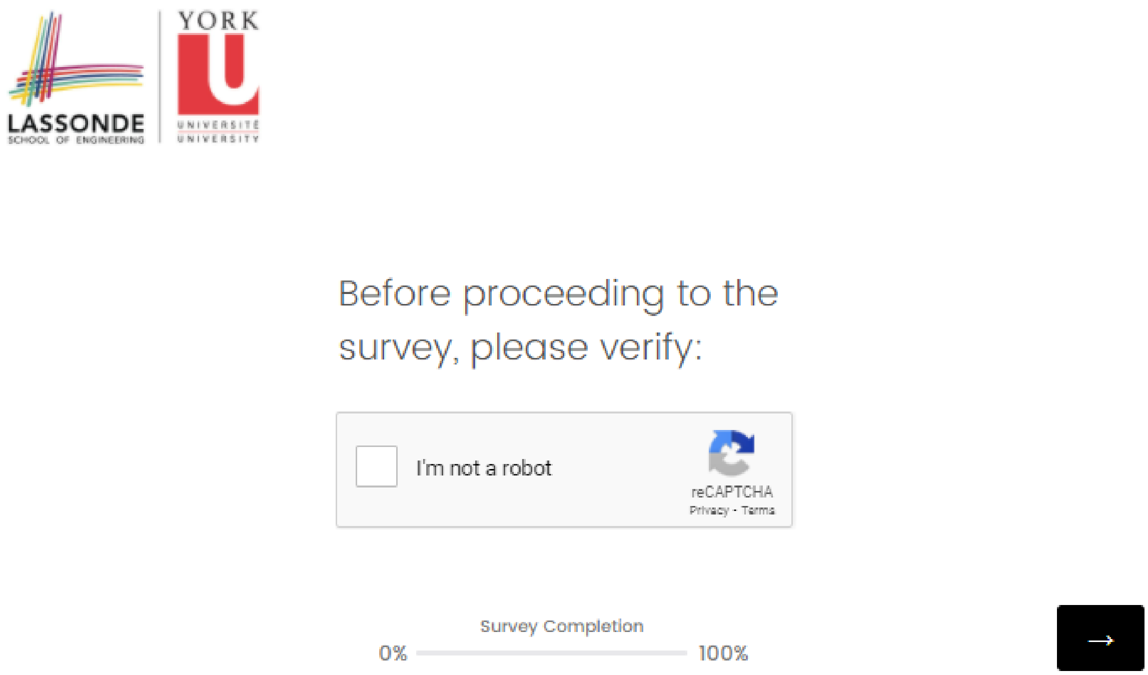
**STATA Code:**

```
Input: ExpDesign.xlsx (experimental design coded in a spreadsheet)
Output: DCE_English.txt (advanced format txt file to be imported into Qualtrics)
version 15
clear all
set more off
*** 1. Import experimental design ***
*Import experimental design from spreadsheet
#d ;
import excel using ExpDesign.xlsx, clear
	sheet(ExperimentalDesign)
	cellrange(A1:J25)
	first
;
#d cr
*** 2. Label attributes and levels ***
*Note: where necessary, labels must be translated
*Attribute 1
forv i = 1/2 {
	la var A`i'_1 "Travel Time"
	recode A`i'_1 (0=60) (1=80) (2=100) (3=120)
}
forv l = 60(20)120 {
	la def farelab `l' "`l' min", modify
}
la val A?_1 farelab

*Attribute 2
forv i = 1/2 {
	la var A`i'_2 "Potential Delay"
	recode A`i'_2 (0=0) (1=5) (2=10) (3=15) (4=30)
}
forv l = 0(5)30 {
	la def timelab `l' "`l' min", modify
}
la val A?_2 timelab

*Attribute 3
forv i = 1/2 {
	la var A`i'_3 "Extra Distance"
	recode A`i'_3 (0=0) (1=15) (2=30)
}
forv l = 0(15)30 {
	la def foodlab `l' "`l' KM", modify
}
la val A?_3 foodlab

*Attribute 4
forv i = 1/1 {
	la var A`i'_4 "Toll Cost"
	recode A`i'_4 (0=0) (1=50) (2=100) (3=150)
}
forv l = 0(50)150 {
	la def audiolab `l' "\$`l'", modify
}
la val A?_4 audiolab
*Transform all variables from numeric to string.
*Makes it easier to include the elements in HTML
*table to be constructed below.
forv i = 1/2 {
	forv j = 1/4 {
		decode A`i'_`j', gen(tmp)
		drop A`i'_`j'
		ren tmp A`i'_`j'
```

### Nlogit Cross-sectional Multinomial (MNL1) and Mixed Multinomial Logit (MXL1) Models Syntax

```
RPLOGIT
;lhs = CHOICE
;choices = 1,2
;rpl
       ;fcn = TC(n),TT(n)
       ;halton
       ;pts=500
       ;Model:
U(1) = constant + TT * TT + TTV * TTV + TC * TC + Dist * Dist /
U(2) = TT * TT + TTV * TTV + TC * TC + Dist * Dist  $
```

# Appendix C: Online Survey Demo



## Commercial Vehicle Route Choice Survey

Dear valued respondent,

This survey is being conducted by researchers from **York University** to analyze the factors that impact route choice decisions for inter-regional truck trips.

This survey is expected to take **10 - 15 minutes** to complete. Thank you in advance for your time and participation.

**Contact information:**
Dr. Kevin Gingerich: kging@yorku.ca
Yashar Zarrin Zadeh: yasharzz@yorku.ca

← Survey Completion 0% 100% →

## Acknowledgment

This research will be used for academic (non-profit) purposes only. Results published from this survey will be aggregated to ensure that individual responses remain confidential. The full informed consent form is available here.

I have understood the nature of this project and wish to participate. I am not waiving any of my legal rights by providing my consent. Selecting 'I agree' below indicates my consent.

← Survey Completion 0% 100% →

What best describes your role in the logistics chain within your organization?

- ◯ Driver
- ◯ Non-driver (fleet manager, route planner, dispatcher, etc.), please specify:

- ◯ No authority in routing decisions

←

Survey Completion

0% 100%

→

## Part 1 of 2. Stated Preference (SP)

You will be faced with **12 route choice questions** each containing **two route alternatives.** For each question, you will need to select your preferred route. The attributes of these routes include the following:

**Travel Time:** The expected time (in minutes) that it takes to travel from the trip origin to the destination.
**Potential Delay:** There is a reasonable chance to have some additional delay (in minutes) added to your travel time.
**Extra Distance:** The given route has an extra distance (in km) when compared to the other route.
**Toll costs:** The amount of money (in CAD currency) required to use the given route.

Survey Completion

0% 100%

→

**SP Question 1 of 12**

## Among the following hypothetical route choice options, which one do you prefer?

*Travel Time: The expected time (in minutes) that it takes to travel from the origin of your trip to the destination.*
*Potential Delay: There is a reasonable chance to have some additional delay time (in minutes) added to your travel time.*
*Extra Distance: The given route has an extra distance (in km) when compared to the other route.*
*Toll costs: The amount of money (in CAD currency) required to use the given route.*

| | Route A | Route B |
|---|---|---|
| **Travel Time** | 100 min | 120 min |
| **Potential Delay** | 0 min | 15 min |
| **Extra Distance** | 15 KM | 0 KM |
| **Toll Cost** | $150 | $0 |

| | Route A | Route B |
|---|---|---|
| Your choice: | ○ | ○ |

Survey Completion

0% 100%

→

**SP Question 12 of 12**

Among the following hypothetical route choice options, which one do you prefer?

*Travel Time: The expected time (in minutes) that it takes to travel from the origin of your trip to the destination.*
*Potential Delay: There is a reasonable chance to have some additional delay time (in minutes) added to your travel time.*
*Extra Distance: The given route has an extra distance (in km) when compared to the other route.*
*Toll costs: The amount of money (in CAD currency) required to use the given route.*

| | Route A | Route B |
|---|---|---|
| **Travel Time** | 100 min | 60 min |
| **Potential Delay** | 30 min | 0 min |
| **Extra Distance** | 0 KM | 30 KM |
| **Toll Cost** | $0 | $50 |

| | Route A | Route B |
|---|---|---|
| Your choice: | ○ | ○ |

Survey Completion

0% 100%

→

## Part 2 of 2. Descriptive Questions

This is the second part of the survey, in which you will be asked to complete a set of questions about yourself and your typical routing activities.

Survey Completion
0% 100%

→

### Respondent Characteristics

Who makes routing decisions in your organization? (select all that apply)

- ☐ Driver
- ☐ Manager/dispatcher
- ☐ Software
- ☐ Other (please specify):

Please indicate your age:

| | |
|---|---|
| ◯ 18 to 25 | ◯ 56 to 65 |
| ◯ 26 to 35 | ◯ 66+ |
| ◯ 36 to 45 | ◯ Prefer not to say |
| ◯ 46 to 55 | |

Please indicate your gender:

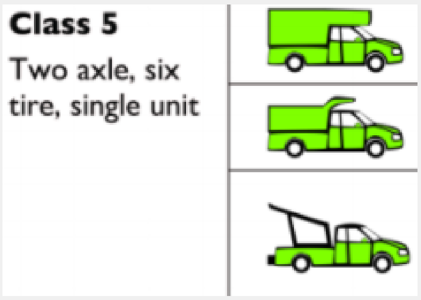
- ◯ Female
- ◯ Male
- ◯ Other
- ◯ Prefer not to say

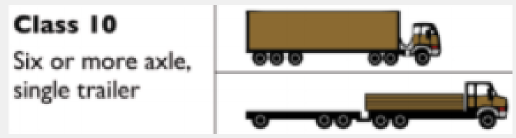
How much commercial driving experience do you have?

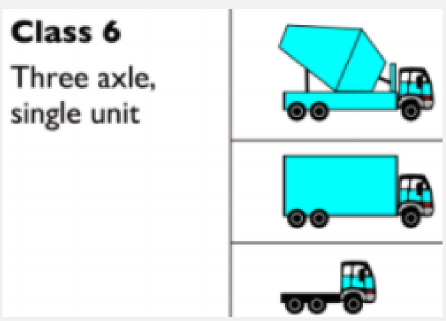
- ◯ 0 to 5 years
- ◯ 5 to 10 years
- ◯ 10 to 15 years
- ◯ 16+ years
- ◯ Prefer not to say

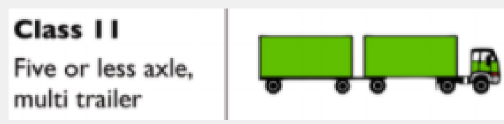
What size of vehicle do you or your organization typically operate? (Select all that apply)

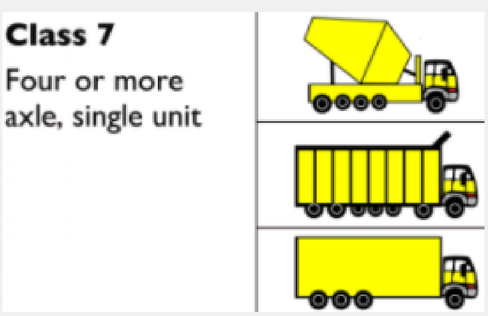
*Images are retrieved from the US Federal Highway Administration

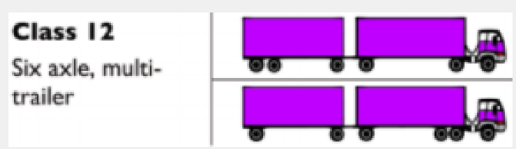
☐ 


☐ 

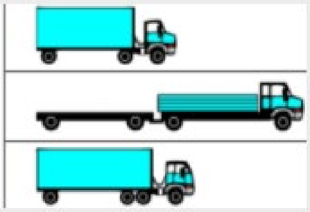

☐ 


☐ 

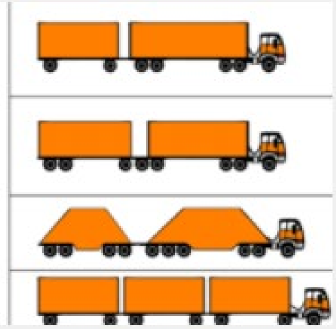

☐ 


☐ 

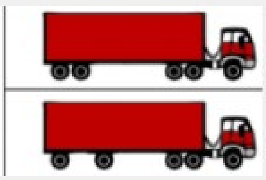
☐ **Class 8**
Four or less axle, single trailer



☐ **Class 13**
Seven or more axle, multi-trailer



☐ **Class 9**
5-Axle tractor semitrailer



←

Survey Completion
0% 100%

→

## Contract Characteristics

What best describes your contracts? (Select all that apply)

- ☐ Owner-operator
- ☐ For-hire
- ☐ Private Carrier
- ☐ Trip Lease
- ☐ Other (Please specify):

How are 'you' or 'drivers in your organization' paid? (Select all that apply)

- ☐ Book Distance
- ☐ Actual Distance
- ☐ Time based
- ☐ Load Weight
- ☐ Fixed amount
- ☐ Prefer not to say

Which of the following applies to your organization? (Select all that apply)

- [ ] Full Truckload (TL)
- [ ] Less-than-truckload (LTL)
- [ ] Parcel delivery
- [ ] Other (please specify):

← Survey Completion 0% 100% →

## Company Characteristics

How long has the trucking company you are associated with been established?

- ◯ 0 to 5 years
- ◯ 6 to 10 years
- ◯ 11 to 20 years
- ◯ 21+ years

Which employment category size does your business belong to?

- ◯ Micro-enterprise: 1 to 9 employees.
- ◯ Small enterprise: 10 to 49 employees.
- ◯ Medium-sized enterprise: 50 to 249 employees.
- ◯ Large enterprise: 250 employees or more.
- ◯ Prefer not to say.

Which answer best describes your delivery patterns? (Select all that apply)

- ☐ Local
- ☐ National
- ☐ International

What type of commodities do you / your organization typically ship? (select all that apply)

- ☐ **Agricultural Products:** Live animals, unprocessed grains, fresh vegetables, and animal feed
- ☐ **Food:** Processed or partially processed products and prepared foodstuffs consumed by human such as: Meat, Poultry, Seafood, Grains, Beverages, and Tobacco.
- ☐ **Stones & Minerals:** Non-metallic mineral products, plastering materials, stone, sand, lime and cement, ores, coal, slag, and ash.
- ☐ **Petroleum Products:** Fuel oils, gasoline, and crude petroleum.
- ☐ **Chemicals & Plastics:** Basic chemicals, pharmaceutical products, fertilizers, plastics, and rubber.

☐ **Wood Products, textile and leather:** Cellulose material, wood, pulp, logs, paper, textiles, and leather.

☐ **Metal products:** Primary, semi-finished, and or finished base metals.

☐ **Machinery, Electrical & Motorized Vehicles:** Engines, appliances, construction vehicles, electronic and
other electrical equipment and components, computers and office equipment.

☐ **Mixed Freight:** Furniture, miscellaneous manufactured products.

☐ Other (Please specify):

Do you or your company typically ship the following special types of goods? (select all that apply)

☐ Hazardous

☐ Refrigerated

☐ Over-sized

☐ Expedited

☐ None of the above

## Route Characteristics

Does seasonality (Fall, Winter, Summer) affect your route choice decisions?

- ○ Never
- ○ Sometimes
- ○ About half the time
- ○ Most of the time
- ○ Always

How often do 'you' or 'drivers in your organization' use tolled routes?

- Never
- Sometimes
- About half the time
- Most of the time
- Always

Have 'you' or 'drivers in your organization' ever used Ontario Highway 407 ETR?

- Yes
- No

Who pays for tolls? (Select all that apply)

- [ ] Driver
- [ ] Shipper
- [ ] Carrier
- [ ] Receiver
- [ ] Not applicable

← Survey Completion 0% 100% →

Who pays penalty fees for late deliveries?

- ○ Company
- ○ Driver
- ○ Both
- ○ Not applicable

When do 'you' or 'drivers in your organization' consider changing your route? (Select all that apply)

- ☐ Never, the route is pre-planned and will not change.
- ☐ We consider changing routes if we encounter congestion.
- ☐ We consider changing routes if navigation apps tell us that a better route is now available.
- ☐ We consider changing routes if someone re-directs us to a different route.
- ☐ Not applicable

How much are you or your organization willing to pay to reduce one hour of travel time? (In Canadian dollars)

←

Survey Completion

0% 100%

→

## Trip Characteristics

On average, how many hours do 'you' or 'your drivers' drive daily?

| | |
|---|---|
| ○ 0 to 2 | ○ 6 to 8 |
| ○ 2 to 4 | ○ 8 to 10 |
| ○ 4 to 6 | ○ 10+ |

On average, how many consignees do 'you' or 'your drivers' have per trip?

- ○ 1
- ○ 2
- ○ 3
- ○ 4 or more

On average, what is the typical distance of truck trips conducted by 'you' / 'drivers in your organization'? (in kilometers)

- ○ Less than 100 km
- ○ 100 to 200 km
- ○ 200 to 400 km
- ○ 400 to 600 km
- ○ 600 to 800 km
- ○ 800 to 1000 km
- ○ More than 1000 km

←

Survey Completion

0% 100%

→

## Optional Questions

On average, what is the typical value of the commodities transported per trip? (in Canadian dollars)

Has technology changed your truck route decisions since you first started working in the trucking industry? Please elaborate if possible.

Do you (or your company) adjust the start time of truck trips based on external factors such as congestion or available personnel? Please elaborate if possible.

Has e-commerce influenced your shipping patterns? Please elaborate if possible.

Are there any programs supporting Equity, Diversity, and Inclusion (EDI) related challenges in your business? Please elaborate if possible.

←

Survey Completion

0% 100%

→

Thanks for participating in our study.
Feel free to leave any comments, questions or feedback here. (Optional)

In case your are interested in receiving a copy of the final survey results when they are available, please fill out the form below. (Optional)

Name

E-mail address

Company name

←

Survey Completion

0% 100%

Submit

# Appendix D: Ethics Certificate

The online survey had an ethics approval with certificate number e2019-125 initially approved on April 4th, 2019. The survey was deemed to have minimal risk on participants. The data was stored on secure Canadian servers. All information presented in the thesis is aggregated to preserve respondent confidentiality.