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Truck Route Choice Modeling using Large Streams of GPS Data

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SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km

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16. Abstract
The primary goal of this research was to use large streams of truck-GPS data to analyze travel routes (or paths) chosen by freight trucks to travel between different origin and destination (OD) location pairs in metropolitan regions of Florida. Two specific objectives were pursued. The first objective was to measure and analyze the diversity in travel paths chosen by trucks between different OD locations in Florida. Various metrics were used to measure three different dimensions of diversity in truck route choice between any given OD pair. Further, statistical models of diversity metrics were estimated to gain insights on the determinants of various dimensions of truck route choice diversity between an OD pair. The second objective was to evaluate truck route choice set generation algorithms and derive guidance on using these algorithms for effective generation of choice sets for modeling truck route choice. Specifically, route choice sets generated from a breadth first search link elimination (BFS-LE) algorithm were evaluated against observed truck routes derived from large streams of GPS traces of a sizeable truck fleet in the Tampa Bay region of Florida. A systematic evaluation approach based on the algorithm's ability to generate relevant routes typically considered by travelers and generation of irrelevant (or extraneous) routes seldom chosen is presented. Based on this evaluation, the study offers guidance on effectively using the BFS-LE approach to maximize the generation of relevant truck routes while eliminating irrelevant routes. It was found that carefully-chosen spatial aggregation can reduce the need to generate a large number of routes for each trip. Finally, route choice models were estimated and applied on validation datasets to corroborate the findings.

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EXECUTIVE SUMMARY

Project Objectives

The primary goal of this research was to use large streams of truck-GPS data to analyze the travel routes (or paths) chosen by freight trucks to travel between different origins and destinations in metropolitan regions of Florida. To that end, the project used large streams of truck-GPS data acquired for two projects funded by the Florida Department of Transportation (FDOT)—one by the FDOT Central Office and another by FDOT District 7. The first project obtained more than 100 million raw GPS data points of several thousand trucks traveling in Florida to derive a variety of data products, including data on truck travel paths for more than 70,000 trips in Florida. Such raw GPS data were obtained from the American Transportation Research Institute (ATRI) for four months (April–July) in 2010. The details of this FDOT project and its outcomes can be obtained from the project report published by FDOT (Pinjari et al., 2014) The second project obtained more than 96 million raw GPS records from ATRI for the first 15 days in October 2015, December 2015, April 2016, and June 2016 for the Tampa Bay region of Florida. The truck-GPS data were used to develop route choice data for the Tampa Bay region and resulted in a database of more than 230,000 truck trips and corresponding routes (Tahlyan et al., 2017).

This is perhaps the largest amount of data used to date in the truck modeling literature to analyze truck route choice patterns. This offered an unprecedented opportunity to observe and analyze truck travel paths of a large number of trips between different origin and destination locations in Florida. Using such rich data, the following specific objectives were pursued in the project:

1. Measure and analyze diversity in truck route choice patterns in Florida.
2. Evaluate the performance of truck route choice set generation algorithms for developing truck route choice models in Florida.

Each of these objectives is briefly discussed in the following sections.

Objective 1: Measurement and Analysis of Truck Route Choice Diversity in Florida

This task involved measurement and analysis of the diversity of travel paths chosen by trucks between selected origin and destination (OD) locations in Florida. To measure the diversity in truck routes between a given OD pair, the research team developed the following six metrics: (1) number of unique routes, (2) average commonality factor, (3) average path size, (4) non-overlapping index, (5) standardized variance of route usage, and (6) standardized Shannon entropy of route usage. Each metric helped to measure one of the following three dimensions of diversity: (1) number of distinct routes used to travel between OD pairs, (2) extent of overlap (or lack thereof) among routes, and (3) evenness (or dominance) of the use of different unique routes. The diversity metrics were used to examine truck route choice diversity from more than 73,000 truck trips derived from more than 200 million GPS records of a large truck fleet. Descriptive analysis and statistical models of the diversity metrics offered insights on the determinants of various dimensions of truck route choice diversity between an OD pair. The research team compiled an extensive set of variables characterizing truck travel characteristics, OD location characteristics, and network structure characteristics between these OD pairs that could potentially influence the extent of route choice diversity. Negative binomial regression models were estimated to explore the influence of these variables on the number of unique routes traveled between an OD pair, and fractional response models were estimated to explore the determinants of average path size (overlap among routes) and standardized Shannon entropy (evenness) of route usage.

The analysis suggests that short-haul truck travel exhibit greater diversity in route choice than long-haul travel in terms of number of unique routes observed, the extent of non-overlap between unique routes, and the evenness of usage of different unique routes.

Objective 2: Performance Evaluation of Truck Route Choice Set Generation Algorithms

This task evaluated truck route choice set generation algorithms and derived guidance on using the algorithms for effective generation of choice sets for modeling truck route choice. Specifically, route choice sets generated from the breadth first search link elimination (BFS-LE) algorithm were evaluated against observed truck routes derived from large streams of GPS traces of a sizeable truck fleet in the Tampa Bay region of Florida. A carefully-designed evaluation approach was used to determine an appropriate combination of spatial aggregation and minimum number of trips to be observed between each OD location for evaluating algorithm-generated route choice sets. The evaluation was based on both the ability to generate relevant routes that are considered by the travelers and the generation of irrelevant (or extraneous) routes that are seldom chosen. Based on the evaluation, the research offers guidance on effectively using the BFS-LE approach to maximize the generation of relevant truck routes while eliminating irrelevant routes in a post-processing step. Finally, route choice models were estimated and applied on validation datasets to confirm findings from the above evaluation.

The results demonstrate the benefit of evaluating algorithm-generated choice sets against observed choice sets from large datasets at a spatially-aggregated OD-pair level (instead of performing trip-level evaluations). Doing so helped in evaluating the ability to generate relevant and irrelevant routes. Based on the evaluation results, it was found that a carefully-chosen spatial aggregation (of generated routes) can reduce the need to generate substantial numbers of routes for each trip. In the current empirical context of truck route choice, it was found that generating up to a maximum of five routes at the trip level and then aggregating such routes to a TAZ-level spatial aggregation (of up to 2 km^2) provided similar coverage of observed routes as that from generating more than 20 routes for each trip without spatial aggregation. The implication is that an effective and computationally-efficient use of the BFS-LE algorithm for generating truck route choice sets will generate a small number of routes at the disaggregate-level and then aggregate such routes from nearby OD locations.

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CHAPTER 1: INTRODUCTION

Freight is gaining increasing importance at all levels of government in the United States. Many states and regions are positioning themselves as hubs for international and domestic trade and freight flows to promote freight and logistics-led economic development. Accelerated growth in the volume of freight shipped on US highways has led to a significant increase in truck traffic, influencing traffic operations, safety, and state of repair of highway infrastructure. Traffic congestion, in turn, has impeded the speed and reliability of freight movement, leading to increased costs for producers and consumers, passenger traffic congestion, and environmental and economic impacts.

An essential step toward enhancing highway freight mobility is to gain a thorough understanding of freight truck travel behavior in the transportation network, including demand for travel between different origins and destinations, modes of travel, and routes of travel. An understudied dimension among these aspects is truck route choice. Measuring and monitoring the travel routes (or paths) taken by trucks and understanding why they do so can help design short-term truck routing policies aimed at congestion mitigation, improved reliability, and maintenance of good repair. In addition, it is essential for understanding and forecasting truck travel route choice and the aggregate level network performance for medium- to long-term decisions such as the designation of truck routes, addition of new truck corridors, and bypass routes. In addition, understanding individual truck route choice patterns can help in estimating link-level truck traffic volumes that have a bearing on highway pavement management decisions.

A primary challenge for all such investigations, however, is the lack of availability of observed data on truck routes. Traditional travel surveys do not allow for the observation of truck travel routes. In the absence of such data, transportation planners have to make assumptions on truck route choice behavior that may not necessarily hold true in the context of freight movement. Another challenge that also stems from the lack of availability of data is the dearth of truck route choice models that can be used to analyze and forecast truck travel routes and traffic volumes under alternative scenarios of traffic performance (congestion, reliability, etc.) and routing policies.

In the recent past, there has been an increasing interest in using alternate sources of data such as truck-GPS data (or probe data) to understand truck travel patterns. GPS technologies enable passive collection of large streams of data on truck movements over a wide range of temporal and spatial scales. Such data offer an unprecedented opportunity to observe and compare the route choices of a large number of trips, as opposed to observing only one of a few trips, between several origin and destination (OD) locations. Therefore, it is fruitful to use such data to understand freight truck route choice behavior.

The overarching goal of this research was to use large streams of truck-GPS data to analyze the travel routes (or paths) chosen by freight trucks to travel between different origins and destinations in metropolitan regions of Florida. To that end, the project used large streams of truck-GPS data acquired for two projects funded by the Florida Department of Transportation (FDOT)—one by the FDOT Central Office and another by FDOT District 7. The first project obtained more than 100 million raw GPS data points of several thousand trucks traveling in Florida to derive a variety of data products, including data on truck travel paths for more than 70,000 trips in Florida. Such raw GPS data were obtained from the American Transportation Research Institute (ATRI) for four months (April–July 2010). The details of this FDOT project and the outcomes of the project can be obtained from the project report published by FDOT (Pinjari et al., 2014). The second project obtained more than 96 million raw GPS records from ATRI for the first 15 days in

October 2015, December 2015, April 2016, and June 2016 for the Tampa Bay region of Florida. The truck-GPS data were used to develop route choice data for the Tampa Bay region and resulted in a database of more than 230,000 truck trips and corresponding routes (Tahlyan et al., 2017).

This is perhaps the largest amount of data used to date in the truck modeling literature to analyze truck route choice patterns and offered an unprecedented opportunity to observe and analyze truck travel paths of a large number of trips between different OD locations in Florida. Using such rich data, the following specific objectives were pursued in the project:

1. Measure and analyze diversity in truck route choice patterns in Florida.
2. Evaluate the performance of truck route choice set generation algorithms for developing truck route choice models in Florida.

To achieve these two objectives, two studies were conducted in this project, each focusing on one objective. Chapter 2 describes the first study, which was aimed at a comprehensive explanatory analysis of the truck route choice diversity in Florida. Chapter 3 describes the second study, which focused on performance evaluation of choice set generation algorithms for modeling truck route choice. Chapter 4 summarizes the findings from the two studies and identifies the avenues for future research. Please note that Chapters 2 and 3 are written so they can stand alone to reduce the need to refer to the reports of the FDOT projects that resulted in the route choice data used for this research (Pinjari et al., 2014; Tahlyan et al., 2017). However, the reader will benefit from skimming through these reports for details on ATRI's raw GPS data, the procedures used to convert the raw data into truck trips, and the procedures used to derive travel routes of the truck trips.

CHAPTER 2: COMPREHENSIVE EXPLORATORY ANALYSIS OF TRUCK ROUTE CHOICE DIVERSITY IN FLORIDA

2.1 Introduction

Highway freight mobility is critical to a region's economic growth. An essential step toward enhancing highway freight mobility is to improve our understanding of freight movement. For example, measuring and monitoring the routes that trucks use to travel from origins to destinations can help design short-term truck routing policies aimed at mitigating congestion and improving travel time reliability. Due to limited data on truck movements, however, truck route choice has been an understudied dimension of freight movement. The recent availability of global positioning systems (GPS) data has started to fill this gap. A few studies have used GPS data to understand route choice behaviors of freight trucks, passenger cars, and bicycles, and several studies have processed GPS data to derive freight performance measures (Brown and Racca, 2012; Chen-Fu, 2014; Liao, 2014; Wang et al., 2016; Woodard et al., 2017). However, not much attention has been paid to understanding the diversity of truck route choice.

This study pursues a comprehensive exploratory analysis of truck route choice diversity in Florida for both long-haul and short-haul travel segments. Specifically, the study addresses two broad questions: (1) How can the degrees of diversity in the routes trucks use to travel between an OD pair be measured? (2) What factors influence the diversity of truck route choice between an OD pair? To this end, six metrics were used to measure the following three different dimensions of diversity in route choice between a given OD pair: (1) number of different routes used between the OD pair, (2) extent of overlap (or lack thereof) among the routes, and (3) evenness (or the dominance) of the use of different unique routes between that OD pair. These metrics were applied to quantify truck route choice diversity using large streams of GPS data (200+ million GPS traces) from a large fleet of trucks traveling in Florida. Next, statistical models were estimated to explore the influence of various determinants on the three dimensions of route choice diversity between different OD pairs. The models provided insights into the influence of truck travel characteristics, OD location characteristics, and network structure characteristics between an OD pair on the diversity of route choice between that OD pair. These insights potentially can help travel modelers improve choice set generation algorithms for modeling truck route choice and help planners design resilient road systems for truck travel.

The next section describes the truck-GPS data used for this study, and the following section describes the metrics used to quantify diversity in truck route choice. Next, the statistical models used in this study are described, and empirical results are presented, beginning with a descriptive analysis of the diversity metrics followed by empirical findings from statistical models on the determinants of diversity. The last section summarizes and concludes the study.

2.2 Data Description

The truck-GPS data used in this study was provided by the American Transportation Research Institute (ATRI) for two FDOT funded projects (Pinjari et al., 2014; Tahlyan et al., 2017). The data used to derive long-haul truck trips (trips longer than 50 miles) comprised more than 145 million GPS records corresponding to a fleet of nearly 50,000 freight trucks. The long-haul GPS data spanned spatially over the state of Florida and temporally over a four-month period (March–June 2010). The data used to derive short-haul trips (trips shorter than 50 miles) comprised more than 96 million GPS records corresponding to a fleet of nearly 110,000 freight trucks and spanned six counties of the Tampa Bay region in Florida. Temporally, the short-haul data corresponded to first 15 days in October 2015, December 2015, April 2016, and June 2016.

The raw truck-GPS data first were converted into a database of truck-trips using algorithms developed by Thakur et al. (2015) and later refined by Pinjari et al. (2015) for the same data. To derive the chosen route for each trip, raw GPS records corresponding to each trip were map-matched using the procedure developed by Kamali et al. (2016) to high-resolution NAVTEQ roadway networks provided by FDOT. The 2010 NAVTEQ network used to derive long-haul routes comprised more than 1.5 million links and 5.8 million nodes whereas the 2015 NAVTEQ network used for short-haul routes comprised over 1.8 million links and more than 6.9 million nodes. Before map-matching, both networks were thoroughly checked for directional and topological consistency to detect any potential errors or disconnectivity in the network. After the map-matching and validation process, a database of more than 78,000 long-haul trips and 225,000 short-haul trips was retained, and a portion was used for the diversity analysis. Refer to Tahlyan et al. (2017) for more details on the procedures used to convert the raw GPS data to trips and corresponding routes.

To analyze route choice and the diversity therein, it is useful to aggregate trip end locations to larger spatial units. This allows analysts to observe a sufficient number of trips to get an uncensored view of the various routes trucks choose between two locations. Without aggregation, the number of trips observed between many OD pairs would be too small to observe the complete diversity of routes. Even if a substantial number of trips was observed between disaggregate OD locations, it might not exhibit the complete diversity in route choice due to lack of diversity in the truck drivers and/or operators and due to businesses imposing restrictions on truck routes. Aggregating trips from nearby locations potentially can help in observing the diversity in truck routes due to heterogeneity in truck drivers and operators and the businesses they serve. As such, practical implementations of route choice analysis and modeling consider spatially-aggregated units such as traffic analysis zones (TAZs). Therefore, in this study, all trip end locations were aggregated to the TAZs defined in Florida's statewide travel demand model. Further, only those TAZ OD pairs that had at least 50 trips for long-haul data and at least 30 trips for short-haul data were selected, as OD pairs with few trips might not offer a complete picture of truck route diversity. The final long-haul dataset used in this analysis comprised 277 TAZ OD pairs with a total of 30,263 trips that were longer than 50 miles. The short-haul dataset comprised 527 TAZ OD pairs totaling 42,884 trips that were 5–50 miles long. In the context of truck travel, trips shorter than 5 miles would not have many route choice options. Figure 2.1 presents the trip length distribution of all trips used for analyzing truck route diversity in this project for long-haul trips and short-haul trips.

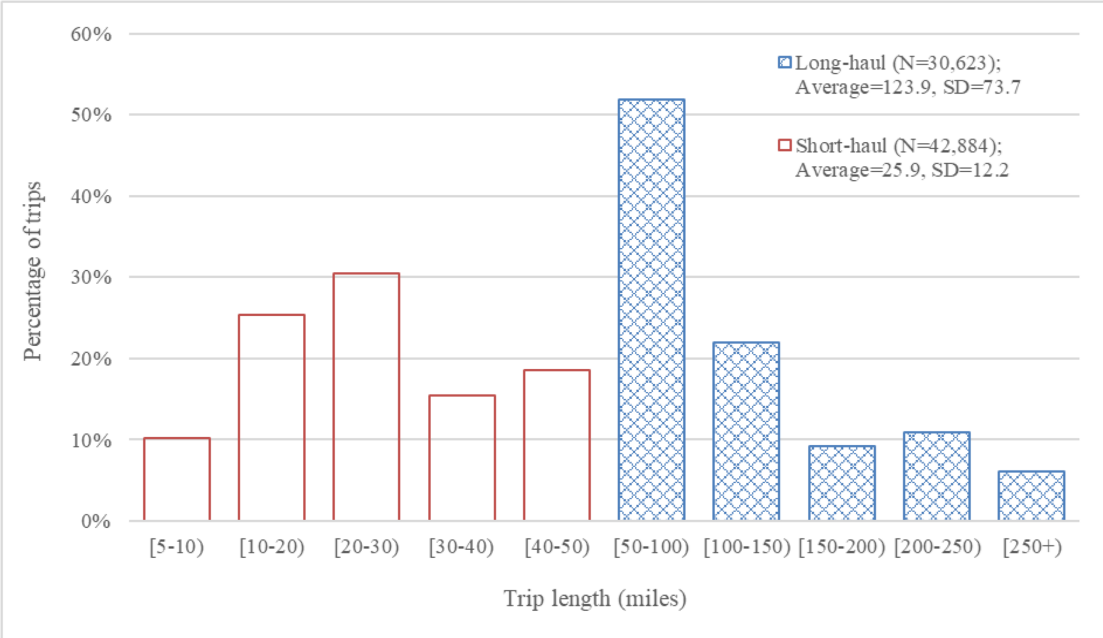

Figure 2.1 Trip Length Distributions of Long-haul and Short-haul Trips used for Route Diversity Analysis

2.3 Diversity Metrics

To measure diversity in truck route choice between a given OD pair, the following six metrics were employed: (1) number of unique routes, (2) average commonality factor, (3) average path size, (4) non-overlapping index, (5) standardized variance of route usage, and (6) standardized Shannon entropy of route usage. The first metric measures the number of unique routes traveled by trucks between an OD pair. The next three metrics measure the extent of overlap (or lack thereof) among the observed unique routes. The last two metrics measure the evenness (or, otherwise, dominance) in the usage of the routes between the OD pair. These three dimensions together provide a complete picture of the diversity in truck route choice between an OD pair. Each of the metrics are defined and discussed next.

2.3.1 Number of Unique Routes

Many routes traveled between an OD pair are different by only a few links. To determine a set of distinct or unique routes traveled between an OD pair, we used the commonality factor proposed by Cascetta et al. (1996). Commonality factor (C_{ij}) between routes i and j is defined as $C_{ij} = l_{ij}/\sqrt{L_i L_j}$, where L_i and L_j represent the length of routes i and j, respectively, and l_{ij} is the length of the shared portion between the two routes. The two routes are referred to as unique from each other if the commonality factor between the two routes is below 0.95. To determine the number of unique routes observed between an OD pair, all routes between that OD pair are arranged in an ascending order of route length. The shortest route is the first unique route. The commonality factor of each subsequent route is computed with respect to all previous unique routes to determine if it is a unique route (if C_{ij} is less than 0.95). The result of this process is a set of unique routes between an OD pair, where the commonality factor between any two unique routes is less than 0.95. The size of this unique route set represents the number of unique routes used between that OD pair.

2.3.2 Average Commonality Factor

Average commonality factor for a given OD pair is the mean value of the commonality factors computed across all pairs of unique routes between that OD pair. Since the earlier metric (number of unique routes) does not consider the extent of overlap (or lack thereof) between the unique routes, this metric measures the degree of overlap between all unique routes in an OD pair. Ranging between 0 and 1, an average commonality factor value closer to 0 (or 1) represents low (or high) overlap between the unique routes.

2.3.3 Average Path Size

Path size is a commonly-used metric in the route choice literature to measure the degree of overlap of two routes between an OD pair. Proposed by Ben-Akiva and Bierlaire (1999), the path size for a unique route i is defined as $PS_i = \sum_{a \epsilon \Gamma_i} \left(\frac{l_a}{L_i}\right) \frac{1}{\sum_{j \epsilon k} \delta_{aj}}$, where Γ_i is the set of all links composing route i, l_a is the length of link a, L_i is the length of route i, and δ_{aj} is equal to 1 if a route j belonging to the unique route set k uses link a, and zero otherwise. The maximum possible value of PS is 1, and the minimum value tends to 0. A route with no overlap with any other routes has a PS value 1. Average PS in an OD pair is the mean value of PS across all unique routes between that OD pair.

2.3.4 Non-overlapping Index

Complementary to the above two metrics, the degree of non-overlap among the unique routes between an OD pair is quantified using the non-overlapping index. This index is measured as the ratio between the total length of links (on unique routes) that were used only once to the total length of all links (on unique routes) that were used at least once. This index ranges between 0 and 1, where a value closer to 1 represents low overlap among unique routes.

2.3.5 Standardized Variance of Route Usage between an OD Pair

Another dimension of diversity is based on the evenness of the usage of different unique routes between an OD pair. The most even usage is when all observed trips between an OD pair are equally distributed among the observed unique routes between that OD pair. A complementary concept is the degree of dominance, when most trips are observed to have taken only one or a few unique routes.

To measure the degree of evenness in usage, the distribution of N trips among K different unique routes between a given OD pair may be characterized as a multinomial distribution, with each trip being allocated to any one of the K different unique routes. If the random variable X_k $(k = 1,2,3, \dots, K)$ indicates the number of trips choosing route k and p_k is the proportion of trips allocated to route k, vector $X = (X_1, X_2, \dots, X_K)$ follows a multinomial distribution with parameters N and p, where $p = (p_{1,} p_2, \dots, p_K)$. The variance of such multinomial-distributed random variables is $Var(X_k) = N * p_k * (1 - p_k)$.

The variance of route usage between an OD pair is defined as the sum of variances of usage frequency for each route, as: $N * \sum_1^K p_k * (1 - p_k)$. This metric is influenced by three factors: (1) total number of unique routes between the OD pair (more routes, higher the variance), (2) total number of observed trips between the OD pair (more trips, higher the variance), and (3) evenness of the distribution of the observed trips among various unique routes. To measure solely the nature of trip distribution without being influenced by the number of observed trips (N) or unique routes (K), this metric may be standardized as follows. For a given OD pair with N observed trips and K unique routes, the maximum possible value of variance of route usage is: $N * K * (1/K) * (1 - 1/K) = N * (1 - 1/K)$, when all trips are evenly distributed among all unique routes. Standardized variance of route usage is the ratio of the variance of usage to the maximum possible variance, defined as: $[\sum_1^K p_k * (1 - p_k)]/(1 - 1/K)$. The closer this metric is to its maximum possible value 1, the more evenly-distributed the observed trips are among various unique routes. For example, if there are 100 trips using two unique routes in an OD pair, the standardized variance of usage for that OD pair would be 1 if 50 trips take the first route and the other 50 trips take the second route. The value of this metric would become 0.36 if 90 trips take the first route and 10 trips take the second route.

2.3.6 Standardized Shannon Entropy of Route Usage between an OD Pair

Shannon entropy (Shannon, 2001) is a metric typically-used to measure the evenness of distribution of different entities among a given number of categories. Proposed in the field of information science, the concept of entropy has been applied widely by transportation researchers to quantify the degrees of geodiversity, etc., in a land use context (Brown et al., 2009; Li et al., 2016; Yabuki et al., 2009). The Shannon entropy of usage of K unique routes between an OD pair is defined as $\sum_1^K p_k \ln(p_k)$, where p_k is the proportion of trips taking the k^{th} unique route. The maximum value of the Shannon entropy of route usage is $K * (1/K) * \ln(1/K) = \ln(1/K)$ when all trips are equally distributed among the identified unique routes between an OD pair. To eliminate the effect of number of unique routes between an OD pair, the standardized Shannon entropy of route usage is computed as $[\sum_1^K p_k \ln(p_k)]/[\ln(1/K)]$, whose maximum possible value is 1 when all trips are evenly distributed among all unique routes.

2.3.7 Illustration

To illustrate the application of the above diversity metrics, Figure 2.2 presents examples of observed unique routes between two different OD pairs observed in the data. The first OD pair is from the long-haul data, with 8 unique routes that are 62 miles to 82 miles long. Note that many of the 8 unique routes overlap quite a bit with each other. Such overlap is measured by the average commonality factor and average path size. A total of 53 of the 65 trips observed between this OD pair used the first unique route, indicating the dominance of the first unique route. The second OD pair is from short-haul data, with 32 observed trips that are more evenly distributed among the different routes than those between the first OD pair. Such differences in dominance (or evenness) of route usage are measured by the standardized variance of usage and the standardized Shannon entropy of usage.

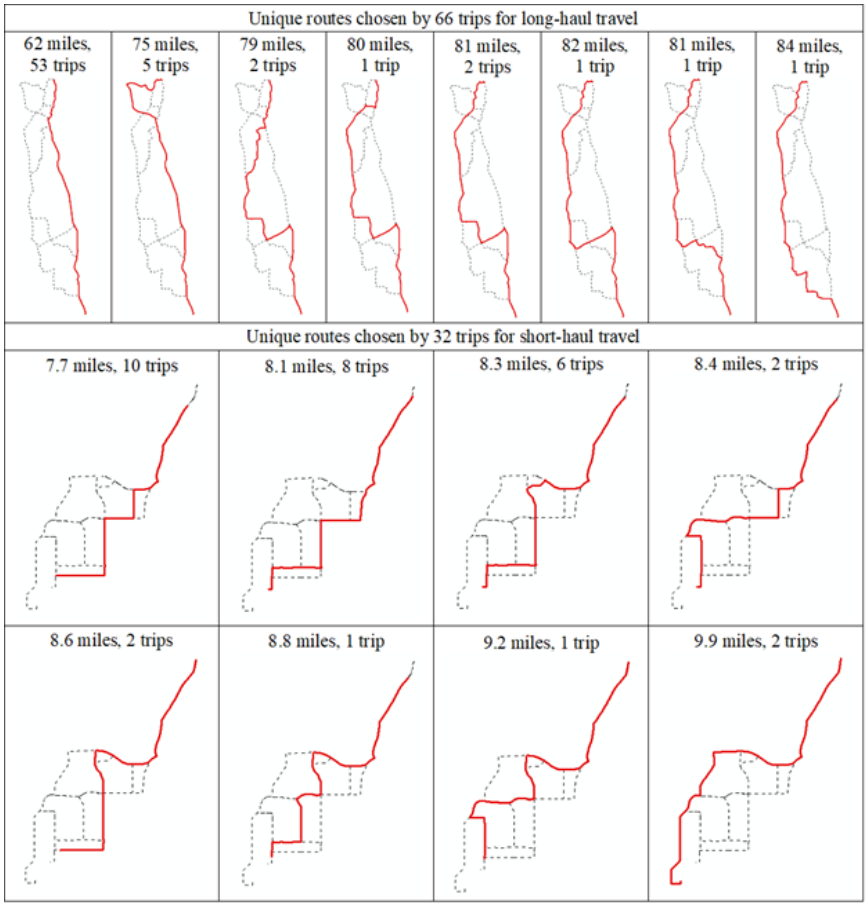

Figure 2.2: Examples of Unique Routes (*bold red lines*) for Long-haul OD Pair and Short-haul OD Pair

2.4 Modeling Methodology

This section explains the statistical model structures used to analyze the determinants of the following three of the six metrics developed in this study—number of unique routes between and OD pair, average path size of unique routes between an OD pair, and standardized Shannon entropy of route usage between an OD pair.

2.4.1 Count Data Models for Number of Observed Unique Routes between an OD Pair

Negative binomial (NB) regression (Washington et al., 2010) is an appropriate choice to model count data given by the number of observed unique routes in this research. Typically, Poisson regression is preferred if the mean of the count process is equal to the variance. If there is a significant difference between the mean and the variance of the count process, the data are said to be over-dispersed, and NB regression is preferred. Current empirical data supported the use of NB regression over Poisson regression, because of over-dispersion in the data.

In NB regression, the probability $P(y_i)$ of an OD pair i having y_i number of unique routes is: $P(y_i) = \frac{\Gamma(1/\alpha + y_i)}{\Gamma(1/\alpha) y_i!}\left(\frac{1/\alpha}{(1/\alpha)+\lambda_i}\right)^{1/\alpha}\left(\frac{y_i}{(1/\alpha)+\lambda_i}\right)^{y_i}$, where $\Gamma(\cdot)$ is the gamma function, $\lambda_i = exp(\beta X_i + \varepsilon_i)$, X_i is a vector of explanatory variables, β is a vector of parameters to be estimated, and $exp(\varepsilon_i)$ is a Gamma-distributed disturbance term with unit mean and variance given by the dispersion parameter α. The model parameters can be estimated using a maximum likelihood estimation technique.

Depending on the count process being modeled, the regression can be right, left, or two-side truncated. To model the number of unique routes between an OD pair, count data models were left-truncated at 1, because any OD pair would have at least one unique route.

2.4.2 Fractional Response Models for Average Path Size and Standardized Shannon Entropy of Route Usage

It is worth noting that all diversity metrics proposed in this study, except the number of unique routes, ranged between 0 and 1. The fractional response model structure proposed by Papke and Wooldridge (1993) may be used to model such quantities whose values lie between 0 and 1. Although proportion data may be modeled by logit transformation of the dependent variable [$\text{i.e.}, ln(y_i/(1-y_i) = \beta X_i$] followed by ordinary least squares regression, this transformation cannot be used when the dependent variable might take values of 0 or 1. This issue can be resolved with the fractional response model (Papke and Wooldridge, 1993) whose expected value of the dependent variable is: $E(y_i|x_i) = G(x_i\beta),$ where $G(\cdot)$ is a known function with $0 < G(z) < 1 \; \forall z \in \mathbb{R}$. Two possible functional forms for $G(z)$ are (1) logistic function, $G(z) = exp(z)/(1 + exp(z))$ and (2) cumulative density function of a standard normal distribution. According to this model, the quasi likelihood of an OD pair with an observed value y_i is given by $\mathcal{L}_i(\beta) = y_i * log[G(x_i\beta)] + (1 - y_i) * log[1 - G(x_i\beta)]$. The parameter estimation is done using maximization of the quasi log-likelihood function.

2.5 Descriptive Analysis

This section provides a descriptive analysis of various metrics of diversity derived for both long-haul and short-haul datasets and the potential determinants of diversity.

2.5.1 Diversity Metrics

Table 2.1 summarizes the mean and standard deviation values of all diversity metrics calculated for the long-haul and short-haul datasets used in this study. There were 19 OD pairs in the long-haul data and 22 OD pairs in the short-haul data that had one observed unique route. Except for the number of unique routes metric, all other diversity metrics reported in the table were computed after excluding such OD pairs with a single unique route.

Table 2.1: Descriptive Statistics of Diversity Metrics

No.	Diversity Metrics	Long-haul		Short-haul	
		Average	*SD*	*Average*	*SD*
1	Number of unique routes	8.61	6.54	9.03	6.51
2	Average commonality factor	0.69	0.17	0.68	0.18
3	Average path size	0.28	0.12	0.29	0.14
4	Non-overlapping index	0.26	0.13	0.32	0.15
5	Standardized variance of usage	0.62	0.26	0.65	0.25
6	Standardized Shannon entropy of usage	0.57	0.21	0.61	0.21

From Table 2.1, a noteworthy pattern shows that the short-haul routes exhibit greater diversity than long-haul routes with higher average values of observed unique routes, non-overlapping index, standardized variance of route usage, and standardized Shannon entropy of route usage. The standard deviations are also higher for short-haul data, suggesting a greater incidence of higher values for this data. In other words, short-haul routes are move diverse than long-haul routes from the standpoint of lower overlap as well as lower dominance in their usage.

2.5.2 Potential Determinants of Diversity

To explore the correlates of diversity in route choice between various OD pairs, a variety of factors describing observed travel demand, OD locations, and network structure between the OD pairs were extracted. These explanatory variables are presented in Table 2.2 and briefly discussed next.

Table 2.2: Descriptive Statistics of Explanatory Variables for Route Diversity Analysis

No.	Potential Determinants of Diversity		Long-haul		Short-haul	
			Average	*SD*	*Average*	*SD*
1	No. of trips observed for an OD pair		109.3	99.7	81.1	123.7
2	No. of trucks observed for an OD pair		19.7	16.6	68.3	113.5
3	OD airway distance (mi)		109.8	69.6	21.9	11.0
4	Travel time of trips taking most used route (min)	SD	7.5	3.6	4.8	18.4
5		Average	146.1	73.9	31.4	13.0
6		95th percentile	158.5	77.4	35.9	14.3
7		5th percentile	136.9	71.7	27.8	12.1
8	Ratio of most used route length to airway OD distance		1.2	0.1	1.2	0.4
9	Employment density of OD TAZs (1000 jobs/sq. mi.)	All types	7.0	5.5	5.7	4.0
10		Industrial	1.5	1.1	0.9	0.7
11		Service	3.4	3.1	3.0	2.8
12		Commercial	2.1	1.9	1.8	1.3
13	Average area of OD TAZs (mi^2)		2.2	2.8	2.3	3.4
14	Indicator if both OD TAZs are urban		0.8	0.3	0.9	0.3
15	Average distance from centroid of all trip ends to each trip end (mi)		0.4	0.5	0.8	1.0
16	Average distance from the TAZ centroid to major arterials (mi)		6.0	3.5	4.7	3.2
17	Length of major arterials (mi)	Long ellipse	331.8	411.8	27.1	27.9
18		Short ellipse	274.2	386.1	15.7	17.5
19		Ending buffers	29.0	23.6	8.8	10.0
20	Length of minor arterials (mi)	Long ellipse	621.4	855.4	42.6	49.4
21		Short ellipse	502.6	800.1	18.2	25.9
22		Ending buffers	62.8	60.2	17.8	24.0
23	Length of collectors (mi)	Long ellipse	1276.6	1561.8	110.5	114.3
24		Short ellipse	1031.3	1446.2	48.7	62.2
25		Ending buffers	137.9	96.0	48.1	56.7
26	Length of local roads (mi)	Long ellipse	10155.1	14471.0	673.1	639.2
27		Short ellipse	9867.2	11496.5	311.3	349.2
28		Ending buffers	1212.1	768.9	259.8	279.2
29	Toll roads (mi)	Long ellipse	81.4	117.6	5.8	8.2
30	No. of rest stops	Long ellipse	9.2	12.1	1.0	1.4
31		Short ellipse	8.1	11.6	0.6	1.0
32		Ending buffers	0.3	0.9	0.4	0.8
33	No. of interchanges	Long ellipse	84.4	124.6	9.3	12.1
34		Short ellipse	60.5	107.6	4.0	6.7
35		Ending buffers	18.1	24.3	4.2	7.1
36	No. of traffic signals	Long ellipse	728.6	1043.8	59.2	86.3
37		Short ellipse	532.9	901.4	25.0	47.4
38		Ending buffers	136.2	168.4	29.1	53.0

2.5.2.1 Trip characteristics

The first category of variables includes the number of trips observed for each OD pair and the number of trucks taking those trips (a measure of truck travel demand), spatial separation (straight-line distance or direct distance) between the OD locations, and travel conditions measured between the OD pair (particularly on the most used route). For the most used unique route, travel time variability and level of route circuity (defined as the ratio of route length to the direct OD distance) were measured.

2.5.2.2 OD location characteristics

Characteristics of origin and destination TAZs include land-use descriptors (employment densities, TAZ size, urban/rural classification) and spatial dispersion of freight activity centers (calculated as the average distance of all trip end centroid to each trip end location).

2.5.2.3 Network Structure

To explore the impact of network structure on the diversity of observed routes, two different areas of influence between OD pairs were hypothesized, as illustrated in Figure 2.3. In the first hypothesis, the diversity of route choice between an OD pair was provided by the entire road network inside an elliptical area of influence connecting that OD pair, referred to as the long ellipse (see illustration on left side in Figure 2.3). The long ellipse's major axis was assumed to be the same distance and orientation of the straight line connecting the centroids of origin and destination TAZs. Its minor axis was set to be one-third of the major axis length. In the second hypothesis, the diversity of route choice between an OD pair was differentially impacted by two different areas of influence. The first area of influence was a circular area around the OD TAZ centroids, referred to as circular buffers. The buffer radii explored were 1, 2, and 5 miles for direct distances of 5–10, 10–20, and more than 20 miles, respectively. The second area of influence was elliptically shaped, referred to as the short ellipse, with the major axis as the difference of straight-line distance and radius of the circular buffers on each end (see illustration on right in Figure 2.3).

Figure 2.3 Long Ellipse, Short Ellipse, and Circular Buffers

Within these hypothesized areas of influence for each OD pair, densities of various road types (major arterials, minor arterials, collectors, and local roads) were computed to characterize the network structure between the OD pair. In addition, other facilities along the roadway, such as traffic signals, intersections, interchanges, truck rest stops, were counted within long and short ellipses and circular buffers.

2.6 Estimation Results

Statistical models were estimated separately for long-haul and short-haul datasets to analyze the determinants of diversity metrics, including number of unique routes, average path size, and standardized Shannon entropy. This section presents the empirical model results.

2.6.1 NB Regression Model for Number of Unique Routes

Table 2.3 presents the NB regression estimation results for the number of unique routes between an OD pair, separately for long-haul and short-haul travel segments. Both model results indicate that OD pairs with a higher number of observed trucks are likely to have more unique routes. This was an expected result because more trucks traveling between an OD pair may lead to greater diversity in route choice due to heterogeneity in preferences of truck drivers, operators, and the businesses they serve. Similarly, OD pairs with more observed trips had more unique routes, in both long- and short-haul travel segments (specifically, when there are more than 150 trips in the short-haul segment). More trips represent a greater demand for travel and may lead to greater diversity in route choices as well.

The next variable in the long-haul model, indicating high travel time variability (when the difference between 95th and 5th percentile travel time on the most used route is greater than 15 minutes), suggests more unique routes since the variability in travel conditions or low reliability in travel time causes travelers to prefer alternative routes. Furthermore, in the long-haul model, deviation of the most used route from the straight-line OD distance (measured as the ratio of the most used route length to straight-line distance) had a positive influence on the number of observed unique routes. When the most-used route is more circuitous, more available routes in the network may exist (or travelers may look for more alternatives), which decreases trucker preference for any particular route. Interestingly, neither travel time variability nor route circuity had a significant influence in the short-haul segment.

In the context of OD location characteristics, OD pairs with larger OD TAZs were likely to have lower number of unique routes in both travel segments, perhaps because those TAZs were typically in areas with sparse network, population, and employment density and, therefore, had fewer network options to travel. For the same reason, both OD locations being in an urban zone is associated with a higher number of unique routes in the short-haul model. In the context of direct distance, OD pairs within 200 miles separation are likely to have more unique routes than those that are farther from each other. In the short-haul segment, the diversity of route choice appears to increase as spatial separation increases from small (<10 miles) to moderate (10–20 miles) and then decreases in the highest length segment. This may be because the network does not offer too many route options both for short-length (<10 miles) or long-length (>40 miles) travel. In the short-haul model, employment densities at the OD TAZs were positively correlated with the number of unique routes, perhaps because a greater employment density is a surrogate for the heterogeneity of businesses served by freight trucks, which leads to a greater diversity in route choice.

Similarly, the average distance between the TAZ-centroid of the trip ends and each trip’s end coordinates (a measure of spatial dispersion of the freight activity generators in the OD TAZs) is positively associated with the number of unique routes observed between an OD pair (only in the short-haul model). The next variable in the short-haul model, average distance from TAZ-centroids to the nearest major arterial, is a surrogate for how quickly the trucks can reach a major arterial, which is negatively correlated with the number of observed unique routes.

Table 2.3 Estimation Results of Truncated Negative Binomial Regression of Number of Unique Routes for Long-haul and Short-haul Datasets

Variable Description	Long-haul Data		Short-haul Data	
	Coefficient	*t-stat*	*Coefficient*	*t-stat*
Trip Characteristics				
Logarithm of number of truck IDs	0.293	5.53	0.358	10.93
Logarithm of number of trips	0.379	4.97	--	--
Indicator (1 if more than 150 trips, 0 otherwise)	--	--	0.159	1.80
Travel time variability on most used route indicator (1 if difference of 95th and 5th percentile of travel time greater than 15 minutes, 0 otherwise)	0.172	1.86	--	--
Ratio of length of most used route to direct OD distance (mi/mi)	1.486	3.51	--	--
OD Characteristics				
Average area of OD TAZs (mi^2)	-0.040	-1.85	-0.036	-3.85
Indicator if both OD TAZs are urban zone	--	--	0.277	3.83
Indicator if direct OD distance indicator between 50 and 200 miles	0.381	3.59	N/A	N/A
Indicator if direct OD distance between 10 and 20 miles	N/A	N/A	0.128	2.84
Indicator if direct OD more than 40 miles	N/A	N/A	-0.671	-6.52
Industrial employment density (1000 jobs/mile^2)	--	--	0.215	6.41
Commercial employment density (1000 jobs/mile^2)	--	--	0.059	2.95
Average distance from centroid of all trip ends to each trip end (mi)	--	--	0.283	12.54
Average distance from TAZ centroids to nearest major or minor arterials (mi)	--	--	0.042	4.87
Network Structure				
Ratio of toll roads to major arterials in long ellipse (mi/mi)	1.283	3.09	--	--
Density of major and minor arterials in 5-mile buffers around both endings (mi/mi^2)	-0.583	-2.87	--	--
Density of collectors in 5-mile buffers around both endings (mi/mi^2)	0.340	2.29	--	--
Density of major, minor arterials and collectors in short ellipse (mi/mi^2)	0.231	2.12	--	--
Density of minor arterials and collectors in the long ellipse (mi/mi^2)	--	--	0.108	2.70
Proportion of major arterials to total length of major, minor arterials and collectors in long ellipse (miles/mile)	--	--	-0.534	-2.41
Proportion of minor arterials and collectors to total length of major and minor arterials and collectors in short ellipse (mi/mi)	1.375	2.24	--	--
Constant	-3.997	-5.06	-0.254	-1.41
Dispersion parameter	0.235	5.78	0.075	5.80
Number of observations (OD pairs)	277		527	
Log likelihood at convergence	-782.90		-1372.45	
Log likelihood for constant-only model	-842.92		-1617.90	
Adjusted ρ^2 with respect to constant-only model	0.056		0.141	

Note: For variables that have significant influence in one model but not in other, "--" appears in place of parameter estimate and t-stat for that variable in latter model. N/A used when variable not applicable to specific model.

In the context of network characteristics, long-haul OD pairs with a higher ratio of toll roads to major arterials captured in the long ellipse are likely to have more unique routes, because truck operators might look for alternative routes to avoid tolls. However, this variable is insignificant in the short-haul model mostly because the study region for the short-haul segment does not have many toll roads. In the long-haul model, OD locations with a higher density of major and minor arterials in circular buffers around trip ends likely are associated with a lower number of unique routes, whereas the OD locations with a higher density of collectors likely are associated with more unique routes. This may be because access to more major and minor arterials at the OD locations reduces the need to search for alternative routes. On the other hand, OD pairs with a higher density of major and minor arterials and collectors in the short ellipse are likely to have more unique routes, probably because of an increased number of route options. For similar reasons, OD pairs with a greater proportion of minor arterials and collectors (with respect to major and minor arterials and collectors) in the short ellipse are likely to have a greater number of observed unique routes in the long-haul model. In the short-haul model, whereas the density of the minor arterials and collectors in the long ellipse has a positive influence on the number of observed unique routes, the influence of the proportion of major arterials (with respect to major, minor arterials and collectors) is negative. All these results highlight subtle but notable differences in the influence of network structure on the diversity of truck route choice between long-haul and short-haul travel segments.

2.6.2 Fractional Response Models for Average Path Size and Standardized Shannon Entropy of Usage

Table 2.4 presents the fractional response model estimation results for average path size estimated for OD pairs with at least two observed unique routes.

Table 2.4 Estimation Results of Fractional Response Models for Average Path Size

Variables in Average Path Size Model	Long-haul Data		Short-haul Data	
	Coefficient	*t-stat*	*Coefficient*	*t-stat*
Number of unique routes	-0.068	-9.66	-0.056	-9.74
Proportion of trips on the most used route	0.534	3.72	0.705	6.25
Direct OD distance (mi)	--	--	-0.012	-5.71
Direct OD distance indicator (1 if more than 200 miles, 0 otherwise)	-0.175	-1.95	--	--
Constant	-0.665	-4.73	-0.539	-4.70
Number of observations (OD pairs)	258		505	
Log pseudo likelihood at convergence	-101.08		-202.11	
Log pseudo likelihood for constant-only model	-106.37		-211.61	
Rho-square with respect to constant-only model	0.050		0.045	

Table 2.5 presents the fractional response model estimation results for standardized Shannon entropy of usage, estimated for OD pairs with at least two observed unique routes.

With regard to the average path size models, as expected, OD pairs with a higher number of observed unique routes are likely to have lower average path size (i.e., greater overlap) in both models. OD pairs with a higher proportion of trips on the most used route are likely to have higher average path size (i.e., lower overlap) in both models. The presence of a dominant route may imply the presence of other longer routes that do not overlap much and are less preferable. A greater spatial separation of OD pairs is associated with a smaller value of path size (i.e., greater overlap) of the different unique routes in both models; perhaps because an increase in spatial separation may reduce the number of travel routes offered by the network.

Table 2.5 Estimation Results of Fractional Response Models for Standardized Shannon Entropy of Usage

Variables in Standardized Shannon Entropy Model	Long-haul Data		Short-haul Data	
	Coefficient	***t-stat***	***Coefficient***	***t-stat***
Number of unique routes	0.059	5.76	0.052	6.37
Number of trips	-0.003	-4.83	-0.002	-3.74
Average path size	-1.345	-1.78	-1.667	-4.31
Average distance from centroid of all trip ends to each trip end (mi)	--	--	0.255	4.60
Constant	0.498	1.81	0.462	2.80
Number of observations (OD pairs)	258		505	
Log pseudo likelihood at convergence	-119.19		-224.05	
Log pseudo likelihood for constant-only model	-126.39		-241.98	
Rho-square with respect to constant-only model	0.057		0.074	

As expected when modeling standardized Shannon entropy, OD pairs with a higher number of observed unique routes are likely to have a higher Shannon entropy (i.e., more even distribution of trips among unique routes) in both models. OD pairs with a higher number of observed trips are likely to have a more even usage of the routes in both models. OD pairs with a higher average path size (or lower overlap) among unique routes demonstrate a more uneven usage of different routes in both models. Such OD pairs with less overlapping routes are likely to have one or few dominant routes that are largely preferred over other routes. In the short-haul model, OD pairs with a greater average distance from the centroid of the trip end TAZs to all trip ends (i.e., greater spatial dispersion of freight activity generators) are likely to be associated with a more even distribution of trips among different unique routes. This suggests the influence of heterogeneity or spatial dispersion in trip ends on the heterogeneity of preferences for truck routes.

2.7 Summary and Conclusions

This study presents a comprehensive exploratory analysis of truck route choice diversity in Florida for both long-haul and short-haul truck travel segments. To measure the diversity in truck routes between a given OD pair, the following six metrics were developed: (1) number of unique routes, (2) average commonality factor, (3) average path size, (4) non-overlapping index, (5) standardized variance of route usage, and (6) standardized Shannon entropy of route usage. The first of these metrics measured the number of distinct routes traveled by trucks between an OD pair. The next three metrics measured the extent of overlap (or lack thereof) among the routes whereas the last two metrics measure the evenness (or, otherwise, the dominance) of the usage of the routes between the OD pair. These three dimensions together provide a complete picture of the diversity in truck route choice between an OD pair. The diversity metrics were used to describe truck route choice diversity in Florida from a database of more than 73,000 truck trips, which were, in turn, derived from more than 200 million GPS traces of a large fleet of trucks traveling in Florida. A rich database of diversity metrics was derived for 277 TAZ OD pairs for long-haul travel (trips longer than 50 miles) in Florida and 527 TAZ OD pairs for short-haul travel (trips between 5–50 miles) in the Tampa Bay region. In addition, an extensive set of variables characterizing the truck travel characteristics, OD location characteristics, and network structure characteristics between these OD pairs that could potentially influence the extent of route choice diversity was compiled. Negative binomial regression models were estimated to explore the influence of these variables on the number of unique routes traveled between and OD pair, and fractional response models were estimated to explore the determinants of average path size (overlap among routes) and standardized Shannon entropy (evenness) of route usage.

The analysis suggests that short-haul truck travel exhibits greater diversity in route choice than long-haul travel in terms of number of unique routes observed, extent of non-overlap between unique routes, and evenness of usage of different unique routes. Within the long-haul segment, OD pairs farther than 200 miles from each other exhibited lower diversity than those that were closer. Among the short-haul OD pairs, short distance (<10 miles) travel and long-distance travel (>40 miles) exhibited lower diversity than medium distance travel. OD pairs in urban zones were associated with a greater diversity in route choice because urban areas offer wider network options for route choice, and OD pairs with a greater number of trips and/or trucks observed (i.e., greater demand for travel) were associated with a higher number of unique routes. OD pairs with greater variability in travel conditions (travel time) and those with routes that deviate more from a straight-line had more diverse traveled routes. In addition, the network structure variables had a considerable influence on the diversity of truck route choices. OD pairs with a higher number of observed unique routes had greater overlap (i.e., lower average path size) and lower dominance of route usage, whereas OD pairs with fewer overlapping routes exhibited greater dominance of usage. Another important finding is that the determinants and their extent of influence differed between short-haul and long-haul travel segments. For example, OD TAZ land use (employment density and diversity of freight activity locations) had a significant influence on route choice diversity only in the short-haul segment. Furthermore, network structure variables had differential impacts on route diversity between the two segments.

The findings from this study can be used for improving the algorithms used in the literature for generating choice sets for truck route choice modeling. Route choice set generation algorithms can be customized based on truck travel demand, OD location, and network structure characteristics found to be influential in this analysis. An enhanced understanding of truck route choice diversity also can help improve truck routing policies and inform routing decisions during emergency situations.

CHAPTER 3: PERFORMANCE EVALUATION OF CHOICE SET GENERATION ALGORITHMS FOR MODELING TRUCK ROUTE CHOICE: INSIGHTS FROM LARGE STREAMS OF TRUCK-GPS DATA

3.1 Introduction

Route choice set generation is an essential precursor to analyzing traveler route choice. Route choice set for a given OD location pair is a subset of feasible alternative routes offered by the transportation network between that OD pair. However, the number of feasible routes in real life networks is typically very large, computationally difficult to enumerate, not readily distinguishable from each other (due to overlaps), unknown to travelers, and varies substantially from one OD pair to another (Bovy, 2009). Therefore, extraction of the set of routes known to and potentially considered by travelers (which comprises the consideration set) (Hoogendoorn-Lanser, 2005; Ton et al., 2017)) is a challenging task. A variety of different choice set generation algorithms have been used in the literature to generate route choice sets (Ben-Akiva et al., 1984; Bovy and Fiorenzo-Catalano, 2007; de la Barra et al., 1993; Frejinger et al., 2009; Prato and Bekhor, 2006; Rieser-Schüssler et al., 2013; Schuessler and Axhausen, 2009). Most of these algorithms focus on generating alternative routes that are behaviorally realistic (for example, acyclic routes) and diverse (i.e., routes that do not overlap too much to become indistinguishable), with a primary goal to maximize the generation of relevant routes that are likely to be taken by travelers while reducing the generation of irrelevant routes that are not typically considered by travelers (for example, routes that involve large detours from shortest paths). As the composition of choice sets potentially can have a significant impact on route choice model estimation and prediction results (Bliemer and Bovy, 2008; Prato and Bekhor, 2007), evaluation of the generated choice sets is an important step prior to using them for route choice analysis.

A widely-used approach to evaluate route choice set generation algorithms is to measure the extent to which the generated choice sets include the observed travel routes. This approach operates at a trip level, where for each observed trip, it is assessed whether the generated route choice set includes the observed route within a certain tolerance level (Bekhor et al., 2006; Prato and Bekhor, 2007). The proportion of observed trips for which the generated choice sets include the observed routes is called the coverage. Many studies in the literature report coverage ranging from 22% to 96.6% for tolerance levels ranging from 0% to 30% for various route choice set generation algorithms (Bekhor et al., 2006; Hess et al., 2015; Prato and Bekhor, 2006, 2007; Rieser-Schüssler et al., 2013; Ton et al., 2017). Using this evaluation approach, coverage can be improved by generating more routes (which may increase the computation time), improving the algorithm itself, using a better algorithm, or combining the choice sets from different algorithms. In doing so, however, one may end up with numerous irrelevant routes, which may not be considered by travelers and, therefore, potentially cause bias in estimation of choice model parameters and choice probabilities. The trip-level evaluation approach does not offer simple ways to evaluate the generation of irrelevant routes, because the analyst cannot observe the traveler consideration set from a single trip.

One way to overcome issues associated with trip-level evaluation is to perform an evaluation at an OD pair level. That is, if one can observe the routes of a sufficiently large number of trips between a given OD pair, one might get close to observing the travelers' consideration set for that OD pair. At the least, it is reasonable to assume that any feasible routes between an OD pair that are not used even after observing a sufficiently large number of trips are unlikely to be in traveler consideration choice sets and, therefore, need not be included in the choice sets used for analyzing route choice. With increasing availability of large data sources (such as GPS data), it is now possible to observe a substantial number of trips made by multiple travelers between a given OD pair. Therefore, using such data sources, analysts can compare observed choice sets with algorithm-generated choice sets at an OD pair level to evaluate the algorithm's ability to generate observed (i.e., relevant and/or considered) choice sets as well as the extent of generation of irrelevant routes. An evaluation of both aspects—the ability to generate relevant routes and the generation of irrelevant routes—can help improve choice set generation algorithms by increasing the capture of relevant routes while reducing irrelevant routes. Another appeal behind generating and evaluating choice sets at the OD pair-level is that typical application of route choice models for transport modeling and planning is anyway at some level of spatial aggregation in OD locations (such as traffic analysis zones).

There are a few practical issues associated with evaluating choice set generation algorithms at an OD pair level. First, for any given OD pair, a sufficiently large number of trips should be observed for an unbiased evaluation of the choice set generation algorithms. Using a small number of observed trips is likely to cause biased evaluation because those trips might provide only a censored view of the traveler consideration choice sets. The natural question is, how many trips are necessary to observe the complete (or uncensored) consideration choice set between an OD pair? Conceptually, a rather substantial number of trips should be observed for each OD pair, but the data requirements may become prohibitively large to do so. Therefore, it may be pragmatic to determine a certain minimum number of trips that is, for practical purposes, sufficient to observe most of the consideration choice set.

The second practical issue is related to the spatial aggregation of trip ends (or OD locations). A disaggregate-level representation of OD locations for route choice analysis purposes is the link-level, where the OD pair is represented in the form of the network links at the trip ends; i.e., the first link of the route starting from the origin and the last link of the route ending at the destination. With such disaggregate spatial units, however, even with large data sources, it may not be easy to observe sufficient number of trips at the OD pair level. In addition, even if one observes a sufficient number of trips for a link-level OD pair, the observed route choices might not be diverse enough as these trips are typically made by only one or a few travelers (or, in case of freight travel, one or a few trucks belonging to only one or a few trucking companies). One way to overcome these issues is the consideration of spatially-aggregated OD pair locations, so it becomes easier to (1) observe sufficient number of trips for each (spatially) aggregated OD pair and (2) capture the diversity in route choices due to diversity in the travelers and their OD locations (or, in case of freight, diversity in the establishments trucks serve at the OD locations). Of course, spatial aggregation comes with its issues such as aggregation over large spatial units causing spurious diversity in route choices (due to the trip end locations being too far from each other) and aggregation over observed choices of multiple travelers (or trucks) masking individual-level heterogeneity in choice sets. The key lies in choosing spatial units that are neither too large to cause spurious diversity nor too small to censor true diversity in route choices between an OD pair. Carefully-selected spatial aggregation might help in observing routes that are different due to difference in the starting and/or ending network link for trips beginning and/or ending from same locations. Although aggregation leads to homogeneous choice sets for different travelers between the same OD locations, it is not inconceivable that route alternatives chosen by one traveler are relevant to (and potentially considered by) another traveler. In fact, application of route choice models for prediction purposes in transport model systems with spatially-aggregated OD pairs potentially will benefit from allowing such aggregated choice sets that are inclusive of differences in traveler and spatial characteristics (Hoogendoorn-Lanser and Van Nes, 2004).

In summary, evaluation of generated choice sets against observed choice sets from a sufficient number of trips between optimally aggregated spatial units potentially can provide insights on the strengths of choice set generation algorithms as well as ways to improve the quality of generated choice sets. The question to be addressed here is, what is the optimal combination of the spatial aggregation and the minimum number of trips to observe for each OD pair?

To improve choice set generation, a potentially effective approach that has not receive much attention in the literature is to aggregate algorithm-generated choice sets over appropriately-defined spatial units or OD pairs (similar to aggregating observed routes for evaluation purposes). Doing so can help in gaining the diversity needed in generated choice sets without having to generate too many routes for each disaggregate-level trip in the spatially aggregated OD pairs. A relevant question to be addressed here is, which is a better approach—generation of a large choice set at a disaggregate OD pair level or aggregation of small choice sets generated at a disaggregate OD pair level to a spatially-aggregated OD pair? Also, how many routes should be generated at a disaggregate level, if they are aggregated to a spatially-larger OD pair, and how can irrelevant route alternatives be reduced while increasing the capture of relevant alternatives in the choice set? Addressing these questions potentially can lead to substantial improvements to and/or effective use of existing choice set generation algorithms for route choice analysis.

3.1.1 Current Research

The primary goal of this research was to evaluate truck route choice set generation algorithms and derive guidance on the use of such algorithms for effective and computationally efficient generation of choice sets for modeling truck route choice. Specifically, this study focused on the evaluation (and effective use) of the breadth first search link elimination (BFS-LE) algorithm, proposed by Rieser-Schüssler et al. (2013), which has been gaining traction in the recent literature for generating route choice sets in high resolution transportation networks.

For evaluating route choice set generation algorithms, the study provides a carefully-designed evaluation approach that takes advantage of recently-emerging large data sources that enable analysts to observe a large number of trips between a given OD pair. The evaluation design was based on determining the optimal combination of (a) the spatial aggregation to represent trip OD locations and (b) the minimum sufficient number of trips to observe for each OD pair. Further, the evaluation used metrics to assess the ability of route choice set generation algorithms to generate relevant routes (and the diversity therein) as well as the extent of generation of irrelevant (or extraneous) routes.

Based on findings from the evaluation, the study offers guidance on using the BFS-LE approach to maximize the generation of relevant routes while eliminating irrelevant routes for the purpose of freight truck route choice modeling. Specifically, it was examined whether and to what extent spatial aggregation could help in reducing the need to generate large number of routes for each trip within a spatially-aggregated OD pair (and thereby reduce the computational burden of generating large number of diverse routes for each trip). In addition, the attributes of the BFS-LE generated routes and observed routes were compared to understand the systematic differences between relevant routes and extraneous routes. An understanding of such differences can assist in reducing the generated choice set by eliminating extraneous routes in a post-processing step.

Finally, route choice models were estimated and applied (on validation datasets) using different choice sets to confirm the hypotheses discussed above on effectively using BFS-LE to generate truck route choice sets that maximize the capture of relevant routes.

All of the above explorations were conducted using truck route choice data derived from large streams of truck GPS traces (more than 96 million truck GPS records) from more than 110,000 trucks traveling in the Tampa Bay Region of Florida in an FDOT-funded project (Tahlyan et al., 2017). The raw GPS traces were map-matched to a high-resolution transportation network to derive more than 225,000 truck trips and their routes for use in this analysis. Given that the majority of route choice studies, other than a few exceptions (Arentze et al., 2012; Feng et al., 2013; Hess et al., 2015; Knorring et al., 2005), are in the context of passenger car or bicycle route choice, this study contributes to a currently small body of literature on generating route choice sets for modeling freight truck route choice.

In the remainder of this chapter, Section 3.2 describes the data used. Section 3.3 discusses the BFS-LE algorithm for route choice set generation, its implementation in this research, and the design of the evaluation approach, including the different combinations of spatial aggregations and minimum number of trips considered to generate and observe choice sets for each OD pair, and the metrics used to evaluate the algorithm-generated choice sets. Section 3.4 presents the performance evaluation results and findings and guidance on generating high quality route choice sets. Section 3.5 presents results of route choice models for different combinations of spatial aggregation and number of trips observed for each OD pair, along with the application of such models to validation datasets to validate the findings from Section 3.4. Section 3.6 summarizes and concludes the chapter.

3.2 Data

The primary data for this analysis, provided by the American Transportation Research Institute (ATRI), is truck-GPS data of more than 96 million GPS traces from a large fleet of trucks carrying GPS receivers (see Tahlyan et al., 2017). Geographically, the data spanned six counties of the Tampa Bay region in Florida—Hillsborough, Pinellas, Polk, Pasco, Hernando, and Citrus—and 15 miles beyond the six-county region. Temporally, the data were obtained for the first 15 days in October 2015, December 2015, April 2016, and June 2016. The raw data were first converted into a database of truck trips using GPS-to-trip conversion algorithms developed by Thakur et al. (2015) and refined by Pinjari et al. (2015). Specifically, the algorithm identifies trip ends by detecting potential stops (based on travel speed) of a certain minimum duration (five minutes) and using detailed land-use information to eliminate traffic stops and stops at rest areas. More than 1 million truck trips were generated along with the information on the OD location of each trip and other attributes such as trip start and end times and travel time. Subsequently, validation procedures were used to eliminate potentially problematic trips (due to GPS error or algorithmic error), highly circuitous trips with large detours potentially due to the algorithm missing a stop in between (detected by the ratio between direct OD distance and trip length less than 0.7), and trips less than five miles in length (as short truck trips would not have many route options). This resulted in more than 650,000 trips.

For the trips generated above, the traveled routes were not necessarily readily-observable in the form of network links and nodes traversed between the OD locations. The raw GPS data of those trips had to be map-matched to the roadway network to derive the traveled routes. In this study, we used a high-resolution NAVTEQ roadway network available from FDOT comprising more than 1.8 million links and 1.4 million nodes in the state. The network was thoroughly checked for missing links, topological and directional consistency, and strong connectivity (i.e., every node is reachable by every other node) and converted into a directed weighted graph for later use in choice set generation.

To derive traveled routes for the truck trips generated from the GPS data, the GPS data were map-matched to the roadway network employing the procedures used in Kamali et al. (2016) and refined later by Luong et al. 2017. High-frequency (i.e., closely spaced) GPS data are necessary for accurately deriving the traveled routes. GPS data for only about 50% of the derived truck trips were sufficient and spaced closely enough to avoid missing links in the routes derived from map-matching. For another 10% of the trips, some GPS data points could not be map-matched to an accurate network link, because the GPS data was not close to any link. After eliminating all such trips, traveled routes were derived for more than 228,000 trips. For all these derived routes, an algorithm was developed and implemented to identify loops (or cycles) and routes that were too far from the original GPS data. Routes with loops and those that spatially deviated considerably from the raw GPS data were not considered for further analysis. Of the remaining 212,800 trips, 300 randomly-chosen routes were validated for consistency in the direction of travel, feasibility, and presence of large detours by evaluating the sequence of links in the route and visualizing the routes on Google Earth. The validation exercise indicated high accuracy in the derived traveled routes. Such derived traveled routes were considered as observed routes against which route sets generated using choice set generation algorithms are evaluated.

The 212,800 trips were distributed as follows in each of the following trip length categories: 9% in 5–10 miles, 17% in 10–20 miles, 16% in 20–30 miles, 11% in 30–40 miles, 12% in 40–50 miles, 10% in 50–60 miles, 7% in 60–70 miles, 6% in 70–80 miles, 5% in 80–90 miles, 4% in 90–100 miles, and 3% in 100–150 miles. For each of these trips, the derived route included information on the trip OD coordinates, corresponding TAZs defined in Florida's statewide travel demand model (FLSWM), and all the network links traversed by the truck between the OD locations. In addition, for each trip, several route attributes were computed, including route length, free flow travel times (from link-level speed limit information), travel costs (derived using the procedures by Torrey et al., 2014), number of intersections, left turns, right turns, and exit/entry ramps (each of these attributes was computed per mile and per minute of travel), proportion of toll road length, and proportion of roads of several types (interstate highways, major arterials, minor arterials, collectors, local roads). For most of these computations, R codes were written to extract the information for each route from the network. In addition, to account for the similarity (or degree of overlap) of a route with other routes in the choice set for that same OD pair, a path-size attribute was computed as (Ben-Akiva and Bierlaire (1999): $PS_i = \sum_{a\epsilon\Gamma_i}\left(\frac{l_a}{L_i}\right)\frac{1}{\sum_{j\epsilon C_n}\delta_{aj}}$, where Γ_i is the set of all links in path i between the OD pair n, l_a is the length of link a, L_i is the length of path i, C_n is the choice set of routes between the OD pair n, and δ_{aj} is equal to 1 if a route $j\epsilon C_n$ uses link a, 0 otherwise. The value of path-size for a route ranges between 0 and 1 (excluding zero), where a greater path-size value indicates smaller extent of overlap (and no overlap if path-size = 1).

3.3 Choice Set Generation and Evaluation Methodology

3.3.1 BFS-LE Algorithm and Its Implementation

The BFS-LE approach for route choice set generation belongs to the class of algorithms based on repeated least cost path search and is well-suited for extracting routes from large-scale, high-resolution networks represented as strongly connected, weighted, directed graphs. Specifically, it is a link elimination (Azevedo et al., 1993) based on a repeated least cost search approach, where links on the current shortest path are eliminated, one by one, to find subsequent least cost paths.[1] What distinguishes BFS-LE from other link elimination approaches is its use of a tree structure in which each node is a network. Beginning with the original network (which is the root node of the tree), any unique network obtained after the elimination of a link from a current least cost path is a node of the tree, as long as the network offers at least one feasible route for the OD pair under consideration. The nodes are arranged at various depths (d) in the tree based on the number of links eliminated. That is, d = 1 for a network obtained after removing any one link from the first least cost path between the OD pair in the root node (i.e., the original network), d = 2 for a network obtained after removing a link from the current least cost path between the OD pair in any of the nodes (or networks) at depth 1, and so on. For each node (network) at each depth, the links on the current shortest path between the OD pair under consideration comprise the breadth. The breadth first approach finishes the search for the next least cost path within a depth level, by removing links (one by one) on the current shortest paths in all nodes at that depth (i.e., across all breadths in that depth), before proceeding to the next depth level. The algorithm is aborted when a certain pre-defined number of routes are generated, a pre-defined time threshold is reached, or there are no more feasible routes to be found. The choice of the cost function to use (for least cost path search), the maximum number of routes to generate, and the time threshold are at the discretion of the analyst. To improve the computational performance of BFS-LE, Rieser-Schüssler et al. (2013) employ a topologically-equivalent network reduction in which nodes that are not junctions of more than two links or dead-ends are eliminated and the corresponding links are merged to form a reduced (yet topologically equivalent) network for use in choice set generation. In addition, they use the A-star landmarks routing algorithm (Lefebvre and Balmer, 2007) instead of Dijkstra's algorithm (Dijkstra, 1959) for a quicker search of the least cost path.

In this study, the original network was coded and reduced to a topologically-equivalent network, and the BFS-LE algorithm was implemented in the Python programming language.[2] For the least cost path search, the free flow travel time was used as a cost function. Following Dhakar and Srinivasan (2014), to avoid premature termination of the algorithm in situations with fewer than two outgoing links at the origin of a trip, the BFS-LE least cost search was started from the next junction or intersection in the route that had at least two outgoing links. In addition, the BFS-LE generates routes were different from each other even by one small network link. Since travelers may not consider routes with small deviations from each other as distinct, we considered a generated route to be a *unique* route (and, therefore, a part of the choice set) only if it is different from previously generated routes by at least 5% (see Dhakar and Srinivasan (2014)). Specifically, for a given OD pair, *unique* routes are determined (on the fly) using the commonality factor metric proposed by Cascetta et al. (1996), which determines the degree of similarity between two routes. Commonality factor (C_{ij}) between two routes i and j is: $C_{ij} = l_{ij}/\sqrt{L_i L_j}$, where l_{ij} is the length of shared portion between two routes and L_i and L_j are the lengths of the routes i and j, respectively. For a given OD pair, at every instance a route was generated from the BFS-LE algorithm, we considered it *unique* (and a

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[1] Other variants of repeated least cost search algorithms are (1) simulation (Bierlaire and Frejinger, 2005; Prato and Bekhor, 2006; Ramming, 2001), where stochasticity in travelers' perceptions of travel costs and/or their preferences is simulated to generate multiple least cost routes, (2) path labeling (Ben-Akiva et al., 1984), where several least cost paths are obtained based on different criteria/labels for the cost function, and (3) link penalty (de la Barra et al., 1993), where links in the current shortest path are penalized with additional impedance before searching for the next least cost path.

[2] The Python code written for implementing BFS-LE in this study is available upon request.

part of the choice set) only if the commonality factors between that route and all previously generated unique routes were less than or equal to 0.95.

3.3.2 Evaluation Design

To evaluate the choice sets generated from the BFS-LE approach, we compared them to the observed route choice sets derived from large streams of GPS data. An important aspect of this evaluation was aimed at finding the appropriate combination of spatial aggregation and minimum number of trips to be observed for each OD pair. These aspects are discussed first, followed by a discussion of the metrics used to evaluate how well the generated choice sets capture observed choice sets while not generating irrelevant routes that are not in the observed choice sets.

3.3.2.1 Spatial Aggregation and Minimum Number of Trips to be Observed

Link-level aggregation: For all observed trips and their routes derived from the GPS data, the OD locations were represented in the form of network links at the trip ends; i.e., the first link of the route starting at the origin and the last link of the route ending at the destination. Such a link-level aggregation comprises the most disaggregate representation of OD locations.

XY-level aggregation: The GPS locations of trip ends were aggregated by simply rounding off the longitude and latitude values from five decimal places to two decimal places. All trips with the OD coordinates matching up to the second decimal place were combined into a single XY-level OD pair. Such rounding leads to a spatial aggregation of roughly 1 km^2 at each of the trip ends.

TAZ level aggregation: The observed trips were aggregated based on the TAZs defined in the Florida Statewide Travel Demand Model (FLSWM), in which the state is divided into 5,403 TAZs. The size of these TAZs varies from 0.0067 km^2 to 232.45 km^2 depending on their population and employment densities. Most of the large-size zones covered large waterbodies and/or rural locations. To avoid spurious diversity in the generated routes due to large-sized zones, we did not consider TAZ-level OD pairs with O/D TAZ sizes beyond 10 km^2. Further, we considered TAZ-level OD pairs with the following three levels of maximum TAZ size: 2 km^2, and 5 km^2, and 10 km^2.

Spatial clusters: Since large TAZs potentially cause spurious diversity in routes, spatial clustering was used to aggregate trip ends in larger (than 10 km^2) TAZs into smaller spatial clusters. After preliminary experimentation with different clustering techniques, the leader clustering technique (Hartigan, 1975) was used to divide the trip ends belonging to large TAZs into smaller clusters of radius 2 km while retaining the TAZ boundaries. An advantage of the leader clustering technique over the commonly used k-mean clustering technique is that the number of clusters need not be defined *a priori* but an output of the algorithm.

Minimum number of trips to be observed: As discussed earlier, it is necessary to observe a sufficiently large number of trips for an uncensored view of route choice sets in the data. Therefore, only OD pairs that have at least a minimum number of observed trips should be considered for a fair evaluation of choice set generation algorithm. To determine the minimum required number of trips, for each of the above-discussed aggregations, we considered OD pairs with the minimum number of trips of 20, 30, 50, and 100.

3.3.2.2 Observed and Generated Unique Routes for Each Combination of Spatial Aggregation and Minimum No. of Trips

For each OD pair in each of the above categories, the observed routes of all trips (derived from the GPS data) were reduced to a set of unique routes using Cascetta et al.'s (1996) commonality factor formula described earlier and applying an overlap threshold of 0.95. In the unique route set for each OD pair, the commonality factor of a given route with respect to all other routes was less than 0.95. In addition to deriving the set of observed unique routes for each OD pair, the number of trips observed to have taken each unique route was also recorded. Specifically, all trips that have a commonality factor greater than or equal to 0.95 with respect to a unique route were assumed to have taken that route.

For each link-level OD pair corresponding to all trips reported in Table 1, the BFS-LE algorithm was run to generate unique route choice sets at the link-level. For each link-level OD pair, the BFS-LE algorithm was run up to a maximum of 15 unique routes generated or for 1 hour, whichever was earlier, unless the algorithm stopped earlier due to completion of the search tree. Such link-level generated choice sets were aggregated into other, larger spatial units reported using Cascetta et al.'s (1996) commonality factor formula described earlier and applying an overlap threshold of 0.95. For example, unique routes for different link-level OD pairs in a same TAZ-level OD pair were aggregated to generate a set of unique routes for the TAZ-level OD pair. The hypothesis is that such aggregation, if done at a carefully-selected spatial aggregation, will help in better capturing the observed routes.

3.3.2.3 Evaluation Metrics

Let the set of observed unique routes for an OD pair n be $O_n = \{o_1, o_2, \dots, o_i, \dots, o_{I_n}\}$ and the set of generated unique routes for that OD pair be $G_n = \{g_1, g_2, \dots, g_j, \dots, g_{J_n}\}$, where i is the index for an observed unique route, j is the index for a generated unique route, I_n is the number of observed unique routes in the n^{th} OD pair and J_n is the number of generated unique routes for that OD pair. Let k_i be the number of trips observed to have taken the unique route i (i.e., all observed trips between that OD pair whose routes have a commonality factor greater than 0.95 with the unique route i). To measure the performance of BFS-LE-based choice set generation implemented in this study, we devised three metrics to compare the observed and generated unique route sets at an OD pair level—(1) false negative error, (2) weighted false negative error, and (3) false positive error—each of which is discussed next.

False negative error (ε_n^-): False negative error for an OD pair *n* is the proportion of observed unique routes that are not generated by the choice set generation algorithm (i.e., not present in the generated unique routes set). Mathematically, $\varepsilon_n^- = 1 - \frac{\sum_{i=1}^{I_n} \delta_i}{I_n}$, where $\delta_i = 1$ if the commonality factor C_{ij} between the observed unique route i and any of the generated unique routes $j \in G_n$ is greater than 0.95, zero otherwise. ε_n^- ranges between 0 and 1; the most desirable value is 0 (when all observed routes are generated) and least desirable value is 1 (when none of the observed routes is generated).

Weighted false negative error (ε_{wn}^-): Weighted false negative error is the proportion of observed trips (not unique routes) whose observed unique routes are not generated by the choice set generation algorithm. It is a weighted version of the false negative error, where the capture (by the choice set generation algorithm) of each observed unique route is weighted by the proportion of trips taking that route. Specifically, $\varepsilon_{wn}^- = 1 - \frac{\sum_{i=1}^{I_n} k_i \delta_i}{\sum_{i=1}^{I_n} k_i}$. It is observed in the data that only a few of the observed unique routes are used by majority of the trips. The ε_n^- metric equally penalizes the choice set generation algorithm for not capturing any observed unique route, regardless of the usage of that route. The weighted metric overcomes this shortcoming by penalizing an uncaptured route based on the extent of its usage.

False positive error ($\boldsymbol{\varepsilon_n^+}$): False positive error for an OD pair *n* is the proportion of generated unique routes that are not presented in the observed unique routes set. This metric provides a measure of the irrelevant (or extraneous) routes generated that are not observed to have been chosen by the traveler. Specifically, $\varepsilon_n^+ = 1 - \frac{\sum_{j=1}^{J_n} \delta_j}{J_n}$, where $\delta_j = 1$ i if the commonality factor C_{ji} between the generated unique route j and any of the observed unique routes $i \in O_n$ is greater than 0.95, zero otherwise. ε_n^+ ranges between 0 and 1; the most desirable value is 0 (when all generated routes are observed) and least desirable value is 1 (when none of the generated routes are observed). As discussed earlier, a trip-level evaluation of the choice set generation algorithms doesn't allow one to evaluate false positives (i.e., the generation of extraneous routes).

3.3.2.4 Performance Evaluation

First, to evaluate the performance of the implemented BFS-LE approach, the above discussed error metrics were compared at various levels of spatial aggregation and minimum number of trips per OD pair. The same metrics were used to determine the appropriate combination of spatial aggregation and minimum number of trips for the performance evaluation. Second, for OD pairs with the determined spatial aggregation and minimum number of observed trips, the error metrics were recomputed by reducing the threshold value of commonality factor between the observed and generated choice sets from 0.95 to 0.90, 0.85, and 0.80 to assess how much the error measures would decrease. Third, for various spatial aggregations ranging from link-level to TAZ-level, we recomputed the error metrics for generated choice sets constructed out of implementing BFS-LE with the following limits on the maximum number of routes generated for each link-level OD pair: 5, 10, 15, 20, and no limit. The time limit to abort the algorithm was set to 1 hour in all cases. The resulting error metrics were analyzed to determine which is a better approach – generation of a large choice set at a disaggregate OD pair level or aggregation of small choice sets generated at a disaggregate OD pair level to a spatially aggregated OD pair? To further examine this, choice models were estimated and applied (on validation datasets) using choice sets constructed at link-level and TAZ-level aggregations; constructed from a maximum of 5 and 15 BFS-LE routes generated at the link-level. Finally, various attributes of routes that were observed as well as algorithm-generated were compared with those of the extraneous routes that were generated but not observed. These comparisons shed light on identifying extraneous routes for eliminating them in a post-processing step after choice set generation. For routes that were common between the observed and the generated choice sets, there were two values of path size, one with respect to observed routes and the other with respect to generated routes.

3.4 Evaluation Results

3.4.1 OD Pair-level Evaluation of Choice Set Generation Algorithm at Different Combinations of Spatial Aggregation and Minimum Number of Observed Trips

Table 3.1 presents the evaluation results for each combination of spatial aggregation and minimum number of observed trips considered at an OD pair level. Various observations and inferences can be made from this table, each of which are discussed next.

Table 3.1: Comparison of Number of Observed Unique Routes, Generated Unique Routes, and Errors in OD Pairs with at Least 20, 30, 50, and 100 Observed Trips at Various Levels of Aggregation

Aggregation Level	Minimum Number of Trips	No. of OD Pairs	No. of Trips	No. of Observed Unique Routes		No. of Generated Unique Routes		False Negative Error		Weighted False Negative Error		False Positive Error	
				Mean	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*
Link level	20	615	29,003	2.6	2.3	9.2	4.4	0.34	0.34	0.17	0.32	0.81	0.19
	30	335	22,327	2.8	2.4	8.9	4.5	0.38	0.35	0.19	0.35	0.81	0.19
	50	145	15,315	3.0	2.9	8.3	4.4	0.43	0.35	0.19	0.36	0.81	0.19
	100	48	8,995	3.4	2.8	7.2	4.5	0.53	0.33	0.26	0.41	0.79	0.2
XY cluster	20	1071	51,556	4.0	3.3	17.7	10.7	0.39	0.31	0.19	0.29	0.87	0.10
	30	615	40,654	4.6	3.6	18.3	11.2	0.44	0.29	0.18	0.28	0.87	0.10
	50	282	28,266	5.0	4.2	18.9	12.7	0.45	0.30	0.17	0.27	0.86	0.10
	100	80	15,008	6.2	5.4	19.9	14.3	0.55	0.24	0.19	0.29	0.86	0.09
Spatial cluster	20	966	58,774	5.5	4.3	26.0	20.1	0.41	0.29	0.18	0.25	0.87	0.09
	30	574	49,491	6.4	4.9	26.7	20.3	0.45	0.29	0.18	0.25	0.86	0.09
	50	294	39,001	7.4	5.7	28.0	19.8	0.49	0.27	0.18	0.26	0.86	0.10
	100	111	26,417	9.4	7.4	29.6	22.1	0.52	0.24	0.17	0.25	0.84	0.11
TAZ level (max. 2 km^2)	20	373	16,851	6.0	4.1	32.2	22.1	0.38	0.27	0.15	0.21	0.89	0.07
	30	205	12,989	6.8	4.5	32.6	22.6	0.43	0.26	0.14	0.19	0.88	0.07
	50	84	8,211	7.6	5.2	33.0	28.5	0.47	0.23	0.11	0.15	0.88	0.07
	100	28	4,336	8.3	6.2	33.4	28.4	0.54	0.21	0.11	0.18	0.88	0.08
TAZ level (max. 5 km^2)	20	723	40,229	6.8	4.7	36.9	28.4	0.38	0.26	0.17	0.22	0.88	0.07
	30	423	33,181	7.8	5.1	38.8	29.6	0.41	0.26	0.16	0.20	0.88	0.07
	50	196	24,602	8.9	5.8	39.2	27.1	0.44	0.23	0.14	0.19	0.87	0.07
	100	74	16,307	11.0	6.5	43.3	34.0	0.48	0.21	0.15	0.19	0.86	0.08
TAZ level (max. 10 km^2)	20	1152	70,494	7.7	5.8	41.4	33.2	0.38	0.25	0.18	0.23	0.88	0.08
	30	697	59,726	9.0	6.6	44.1	36.5	0.41	0.25	0.18	0.24	0.87	0.09
	50	336	46,047	10.7	7.8	47.6	38.0	0.44	0.24	0.17	0.23	0.87	0.09
	100	132	31,986	13.1	9.6	51.1	42.5	0.47	0.22	0.16	0.22	0.85	0.11

First, the columns titled "No. of OD Pairs" and "No. of Trips" present the observed data available for each combination of spatial aggregation and minimum number of observed trips. For example, at least 20 trips of data were available for 615 OD pairs at the link-level. In addition, a total of 29,003 trips were observed between these OD pairs. As expected, for a given spatial aggregation, the number of OD pairs with available data decreased as the minimum number of trips increased from 20 to 100. Likewise, for a given minimum number of trips, the number of OD pairs with available data increased from a finer spatial resolution to a higher spatial aggregation. From the initial 212,800 trips, there are 82,738 trips available for each spatial aggregation that belong to 23,112 link-level OD pairs.

The column titled "No. of Observed Unique Routes" reports the average number of observed unique routes (and the standard deviation) across all OD pairs in each combination of spatial aggregation and minimum trips. One can infer from this column that the number of observed unique routes per OD pair increased with increase in spatial aggregation and/or with increase in the minimum number of trips observed. Although the increase in the minimum number of trips from one spatial resolution to another was considerable, a visual inspection of trip ends in different OD pairs suggested that increasing the TAZ size beyond 2 km^2 led to a spurious increase in unique routes due to the trip ends within a TAZ becoming too far from each other. For any given spatial aggregation, the average number of unique routes increased with an increase in the minimum number of trips observed. The number did not stabilize even after observing a minimum of 50 trips per OD pair, suggesting a possibility that one may have to observe many more trips per OD pair to get an uncensored view of the actual route choice set. However, it can be noted that the increase occurred at a decreasing rate, with the lowest increase in the number of additional observed unique routes per unit increase in the minimum number of trips observed occurring between 50 to 100 minimum trips per OD pair. There were some outlier OD pairs (which have very high number of observed unique routes) among those with a minimum of 100 trips that skewed the reported average values in Table 3.1. Given all this and for pragmatic reasons (such as not to lose a lot of data), we determined that observing a minimum of 50 trips per OD pair was sufficient to derive an observed route choice set for evaluation purposes.

The column titled “No. of Generated Unique Routes” reports the average number of generated unique routes (and standard deviation) across all OD pairs for each combination of spatial aggregation and minimum number of trips. It can be observed from comparing this column to the preceding column that the number of generated routes was generally greater than the number of observed routes for an OD pair. Further, as expected, the number of generated unique routes increased with increase in spatial aggregation, but at a higher rate than the increase in the number of observed unique routes.

The error metrics—false negative error, weighted false negative error, and false positive error—are reported in the last three sets of columns in Table 3.1. These columns report the average and standard deviation of the OD pair-level error measures across all OD pairs. Several observations can be made from these columns. First, the weighted false negative errors, ranging from 11% to 26%, were smaller than their unweighted counter parts, which range from 34% to 55%. As discussed earlier, the unweighted metric did not take into consideration the extent of usage of a route; whereas the weighted metric computes the errors based on usage of routes, with the errors on more (less) used routes carrying a greater (lower) weightage. In fact, the average weighted false negative errors were under 20% for most combinations of spatial aggregation and minimum number of observed trips. Therefore, one can infer that the BFS-LE performs well in capturing the more frequently-used routes than the less frequently used routes.

Second, for a given minimum number of trips between an OD pair, the weighted false negative errors were lowest at a spatial aggregation of TAZs of up to 2 km^2. This suggests that choice sets created by aggregating the generated routes over a spatial resolution of TAZs of up to 2 km^2 can help in improving capture of observed routes. Interestingly, the improvement in weighted false negative errors was lost when larger-sized TAZs were included, perhaps because the observed routes between larger TAZs would have spurious diversity due to the trip ends being too far from each other. Also, the error rates for spatial aggregations of XY-level and spatial clusters were higher than those of small-sized TAZs. This is likely because TAZs are typically created keeping in view the transportation network structure around (as opposed to the other aggregations we created) and that small-sized TAZs provided an optimal mix of diversity in trip-starting and trip-ending links (which results in diverse routes between the TAZs), while keeping the trip ends within a concentrated area to avoid spurious diversity. It is also interesting to note that the standard deviations of weighted negative errors were smallest for the spatial aggregation of TAZ-level of up to 2 km^2. All these results suggest that route choice sets created out of aggregating routes generated between different trip-end links of small-sized TAZ pairs can potentially capture a large share of observed routes.

Third, as can be observed from the column titled “False Positive Error”, the proportion of extraneous/irrelevant routes in the generated choice sets increased from the link-level to any other spatial aggregation considered in this study. As expected, increasing the capture of relevant routes (i.e., decreasing weighted false negative error rates) through spatial aggregation comes with an increase in extraneous routes as well. Interestingly, however, the average false positive error rates were not very different across different spatial aggregations other than the link-level.

Overall, the above-discussed results suggest the potential benefits of OD pair-level evaluation of choice set generation algorithms over the traditionally used trip-level evaluation. As importantly, aggregating the generated choice sets over carefully-defined spatial units (which happens to be TAZs of up to 2 km^2 in this empirical analysis) can help improve the capture of relevant routes for subsequent route choice modeling and prediction.

3.4.2 Comparison of OD Pair-level Evaluation Results to Trip-level Evaluation Results

Note that the errors reported in Table 3.1 are OD pair level errors, as opposed to trip-level errors typically reported in the literature, which is simply the proportion of observed routes of all trips not captured in the generated routes[3]. The trip level error computed out of all 82,738 trips used in this study is 0.25—i.e., observed routes for 25% the trips were not present in the generated choice sets. When we examined only those trips belonging to OD pairs with a minimum of 20 trips at various spatial aggregations, the corresponding trip-level errors ranged from 0.18 for all 16,851 trips between TAZs of up to 2 km^2 size to 0.28 for all 58,774 trips between spatial clusters. These errors are not reported in the tables, but their OD-pair level counterparts are reported as weighted false negative errors in Table 3.1, which range from an average value of 0.15 for 373 OD pairs at the TAZ-level (of up to 2 km^2 size) to an average value of 0.18 for 966 OD pairs at the spatial cluster level. It is interesting to note that both the trip-level errors and OD pair-level average errors are smallest for a spatial aggregation of TAZs (of up to 2 km^2 size).

The trip-level errors from various studies in the literature that use repeated shortest path choice set generation methods, including those from the current study, are reviewed in Table 3.2. Table 3.2 presents trip-level false negative errors reported in the literature for different levels of tolerance thresholds for the difference between observed and generated routes—0%, 5%, 10%, and 20%—along with salient features of the choice set generation algorithms in the literature. Although it is difficult to compare errors reported in different studies due to differences in the modes of travel, the choice set generation algorithms, and the specifics of implementation, one can observe from the reported errors of the current study and those in another truck route choice study by Hess et al. (2015) that the use of BFS-LE approach to generate route choice sets for truck travel seems to result in relatively small trip-level errors compared to that for other modes of travel. To examine this further, we analyzed (for all 82,738 trips used in Table 3.1) how different are the observed routes from their corresponding shortest time routes and shortest distance routes on the network, again using the commonality factor metric between each observed route and the corresponding shortest route. Interestingly, more than 80% of the observed routes had commonality factors above 0.9 with respect to their corresponding shortest time route. On the other hand, only about 70% of the observed routes had commonality factors above 0.9 with respect to their corresponding shortest distance route. It appears that the BFS-LE approach based on repeated shortest time search performs well for truck route choice set generation because the chosen routes are not very different from the shortest time routes. Another plausible reason the current study had a small error rate (when compared to that in other studies) is perhaps because we generated up to 15 *unique* route alternatives that were different from each other by at least 5% (using a

[3] To be precise, most studies in the literature report trip-level coverage, which is 1 minus trip-level error.

commonality factor threshold of 0.95). Most (if not all) other studies consider generated routes as different from each other even if they are different from each other by a small link and generate up to 15 or 20 such routes (which are not very different from each other). This limits the diversity of generated routes and, therefore, limits the capture of diverse observed routes.

Table 3.2: False Negative Errors for Various Choice Set Generation Algorithms

Algorithm	Study	Mode	Max. Number of Alternatives	Important Features of Used Generation Algorithm	False Negative Error (%)		
					Tolerance (%)		
					0	*10*	*20*
Breadth-first-search link elimination	Present study	Truck	15**	Use of free-flow travel time as cost function to generate routes that are at least 5 percent different from each other.	25 (at 5% tolerance)		
	Rieser-Schüssler et al. (2013)	Car	20*	Use of free-flow travel time as cost function	37	N.T.	N.T.
			100*		27	N.T.	N.T.
	Hess et al. (2015)	Truck	15*	Use of generalized cost function that includes penalties that reflect other sources of inconvenience occurring on minor rods	26	N.T.	N.T.
	Halldórsdóttir et al. (2014)	Bicycle	20*	Use of generalized cost function taking into account road types, cycle lanes, and land use	34	28	22
	Ton et al. (2017)	Bicycle	20*	Use of distance as travel cost	99	98	97
	Dhakar and Srinivasan (2014)	Car	20**	Use of commonly factor to generate routes that are at least 5% different from each other	N.T.	51	N.T.
Link elimination	Bekhor et al. (2006)	Car	N.R.	Elimination of links on shortest path (in sequence) to generate new routes	40	37	29
	Prato and Bekhor (2007)	Car	10*	Elimination from shortest path of links that takes driver farther from destination and closer to origin or compels driver to turn from high hierarchical road to low hierarchical road	42	42	30
`Labeling	Bekhor et al. (2006)	Car	3*	Generation of routes to minimize distance, free-flow time. and time	61	56	48
			16*	Use of 16 different labels to generate various routes	28	24	15
	Prato and Bekhor (2007)	Car	4*	Generation of routes to minimize distance, free-flow time, travel time, and delay	60	60	60
	Broach et al. (2010)	Bicycle	9*	Use of 11 different labels to generate various routes but still making sure that no generated route deviate from shortest path by more than 100%	80	75	65
	Ton et al. (2017)	Bicycle	N.R.	Use of various labels to generate routes	99	98	96
Calibrated labeling	Broach et al. (2010)	Bicycle	20*	Generation of routes using multiple labels and cost function parameters, calibrated using observed distribution of shortest path deviation	78	71	58
Link penalty	Bekhor et al. (2006)	Car	40*	Shortest route generation after gradual increase of impedance of all links on shortest path	43	33	20
			15*		44	34	22
	Prato and Bekhor (2007)	Car	15*	Iterative shortest route generation after increasing impedance of shortest path by factor of 1.05	46	46	38
Simulation (low variance)	Prato and Bekhor (2007)	Car	N.R	Generation of shortest path by drawing link impedances from truncated normal distribution with mean travel to travel time, variance equal to 20% of mean, left truncation limit equal to free-flow travel time, right truncation limit equal to time for speed of 10km/h	51	51	46
Simulation (high variance)	Prato and Bekhor (2007)	Car	N.R	Generation of shortest path by drawing link impedances from truncated normal distribution with mean travel to travel time, variance equal to 100% of mean, left truncation limit equal to free-flow travel time, right truncation limit equal to time for speed of 10km/h	39	38	29
Doubly stochastic generation function	Fiorenzo-Catalano et al. (2004)	Multi-modal	1600*	Repeated shortest path generation by considering stochasticity in travelers' perception of network attributes and preferences for different trip components	22	N.T.	N.T.

N.R: Maximum number of generated alternatives not reported in study.
N.T: Particular tolerance level not tested in study.
** Generated route alternatives were elemental alternatives (i.e. two route alternatives considered separate alternatives even if they differ from each other by one link.)*
*** Generated alternatives were unique alternatives (i.e. two route alternatives considered separate alternatives if they differ from each other by a certain minimum non-overlap.*

3.4.3 Evaluation of Generated Choice Sets at Different Thresholds of Overlap between Observed and Generated Choice Sets

In all the analysis above, the generated unique choice sets were compared to the observed unique choice sets using a threshold value of 0.95 for the commonality factor. That is, an observed unique route was considered to be captured in the set of generated unique routes if the commonality factor between the observed route and any of the generated routes was at least 0.95. Table 3.3 provides false negative and weighted false negative errors computed for OD pairs with a minimum of 50 trips at the spatial aggregation of TAZ-level (of up to 2 km^2) for different thresholds values of commonality factors—0.95, 0.90. 0.85, and 0.80. It can be observed that the weighted false negative error values decreased substantially as the threshold value decreased. For example, an average of only 4% observed routes were not captured in the generated choice sets for a commonality threshold value of 0.90. This value decreased to 1% for a threshold value of 0.80. The false positive error values also decreased substantially with a decrease in the threshold value. Although threshold values of 0.90 or more might be a bit too high for trips of mid-rage to long distance, the error measures in Table 3.3 suggest that most of the uncaptured observed routes (with a 0.95 threshold value) were not substantially different from the generated routes. This again highlights the performance of the BFS-LE algorithm implemented in this study.

Table 3.3: Comparison of Errors at Various Overlapping Thresholds in OD Pairs with at Least 50 Trips at TAZ Level (Max. Area = 2 km^2) Aggregation

Overlapping Threshold		False Negative	Weighted False Negative	False Positive
0.95	Mean	0.47	0.11	0.88
	S.D.	0.23	0.15	0.07
0.9	Mean	0.16	0.04	0.79
	S.D.	0.19	0.08	0.14
0.85	Mean	0.09	0.02	0.76
	S.D.	0.16	0.07	0.17
0.8	Mean	0.06	0.01	0.74
	S.D.	0.12	0.03	0.20

3.4.4 Which is Better: Spatial Aggregation of a Limited Number of Generated Routes or Increasing the Number of Routes Generated from BFS-LE?

Findings from Table 3.1 suggested that spatial aggregation of generated routes can potentially help in increasing the capture of observed routes. We examined if one can achieve a high capture of observed routes by generating a small number of routes at the link-level OD pairs and then spatially aggregating them to TAZ-level (instead of generating large number of routes at the link level and then aggregating them). The hypothesis was that generating a smaller number of unique routes at the link-level and aggregating them spatially (to a TAZ-level, in this case) will lead to sufficient diversity in the generated choice sets. In doing so, we can reduce the computational burden of generating a large number of unique routes at the disaggregate level.

To test the above hypothesis, Table 3.4 presents error measures for choice sets generated from different limits on the maximum number of generated unique routes at the link-level—5, 10, 15, 20, and no limit—for two different spatial aggregations—TAZ-level (of up to 2 km^2 size) and link-level. Recall that the error measures presented in Table 3.1 were generated when the BFS-LE was run for up to a maximum of 15 unique routes at the link-level and then aggregated to various spatial aggregations. It is remarkable to note that the average weighted false negative values (and the corresponding standard deviations) for the TAZ-level aggregation did not vary from choice sets constructed out of a maximum of 5 unique BFS-LE routes to those generated out of 20 or more (see the column titled "Weighted False Negative" under the TAZ Level columns). The same can be observed for the link-level aggregation as well (see the column titled "Weighted False Negative" under the link-level columns).

Table 3.4: Comparison of Errors at Various Limits on Maximum Number of Routes to Generate in OD Pairs with at least 50 Trips at TAZ Level (Max. Area = 2 Km^2) and Link Level Aggregation

No. of Unique Routes Limit	Value	TAZ Level (max. 2 km^2)				Link Level			
		No. of Generated Unique Routes	*False Negative*	*Weighted False Negative*	*False Positive*	*No. of Generated Unique Routes*	*False Negative*	*Weighted False Negative*	*False Positive*
5	Mean	21.10	0.49	0.11	0.83	4.50	0.45	0.20	0.75
	S.D.	10.23	0.23	0.16	0.09	0.97	0.35	0.37	0.20
10	Mean	27.90	0.47	0.11	0.86	7.04	0.43	0.19	0.80
	S.D.	16.75	0.23	0.15	0.07	2.91	0.35	0.36	0.19
15	Mean	32.16	0.47	0.11	0.88	8.28	0.43	0.19	0.81
	S.D.	22.11	0.23	0.15	0.07	4.44	0.35	0.36	0.19
20	Mean	36.19	0.46	0.11	0.88	8.59	0.42	0.19	0.81
	S.D.	25.19	0.23	0.15	0.07	4.98	0.35	0.36	0.19
No limit	Mean	37.56	0.46	0.11	0.89	8.68	0.42	0.19	0.81
	S.D.	26.69	0.23	0.15	0.07	5.24	0.35	0.36	0.19

Overall, these results suggest that route choice sets constructed out of aggregating (to a TAZ level) unique routes from running BFS-LE (at the link level) for a maximum of 5 unique routes provide a better capture of observed routes than those generated from running BFS-LE (at the link-level) for a maximum of 20 or more unique routes. This is probably because the BFS-LE algorithm may not consistently generate up to 20 unique routes within a time span of one hour (recall that we had set a time limit of one hour per link-level OD pair); see column titled "No. of Generated Unique Routes" under the "Link Level" column, where the average number of generated routes does not increase beyond 8.68. Since our search was for unique routes that are different from each other by at least 5%, the BFS-LE would not generate as many routes as needed within one hour. Also notice that while the average number of generated unique routes at the link level increased from 4.50 to 8.68 when the maximum limit increased from 5 routes to no limit, the average weighted false negative error did not decrease discernably (it decreased from 0.20 to only 0.19), but the false positive errors increased from 0.75 to 0.81. Therefore, an effective and computationally-efficient alternative to increase the diversity of generated choice sets (and thereby increase the coverage of observed routes) was to aggregate a limited number of link-level choice sets generated from close by locations. In the current case, it was sufficient to generate up to only 5 unique routes at the link level and then aggregate all such choice sets from trips starting and ending in a same TAZ pair (of up to 2 km^2 size). Of course, the false positive errors increased with spatial aggregation.

3.4.5 Estimation and Validation of Route Choice Models with Different Choice Sets

To further test the above hypothesis that aggregating a limited number of BFS-LE routes leads to better choice sets than generating a large number of routes from the BFS-LE without aggregation, we estimated different route choice models from choice sets at link-level and TAZ-level aggregations constructed from up to a maximum of 5 or 15 BFS-LE alternatives. The empirical specification in all models was based on the path-size logit structure. The path-size model structure was used for all the models. Further, all models were estimated on the same sample of 2,888 trips and applied on a validation sample of 722 trips to evaluate the impact of choice set composition on the model's prediction ability. The choice sets used for all model estimations were augmented with the chosen routes (if the chosen routes were not already generated). On the other hand, the choice sets used for validation would include the chosen route only if it was generated. The metric used for validation was based on the expected overlap of each route in the choice set with the chosen route. Specifically, for a trip with a chosen route r, the expected overlap was $E(O) = \sum_{i=1}^{I} p_i C_{ir}$, where p_i is the probability of choosing route i from the choice set (computed using the path-size logit model estimates) and C_{ir} is the proportion of route i common with the chosen route r.

The model estimation results in Table 3.5 suggest that routes with a lower travel time, smaller proportion (in length) of tolled routes, smaller number of intersections and turns and ramps per minute, and those with a higher proportion of road length on major highways were preferred over other routes. The last row of Table 3.5 reports average value (and standard deviation) of the expected overlap with the chosen route over all trips in the validation data. It can be observed from this row that the average expected overlap with the chosen route was higher for models with TAZ-level choice sets than those with link-level choice sets. For example, the model with TAZ-level choice sets built out of up to 5 BFS-LE generated routes at the link level yields a better expected value (hence, better predictive ability) than the model with link-level choice sets of up to 15 BFS-LE generated routes at the link-level. These results suggest the benefit of spatial aggregation in generating route choice sets.

Table 3.5: Path Size Logit (PSL) Model Estimation Results for Four Different Choice Sets

Variable Description	Choice Set at Link Level with up to 5 BFS-LE Alternatives		Choice Set at Link Level with up to 15 BFS-LE Alternatives		Choice Set at TAZ Level (max. area = 2 km^2) Aggregated from up to 5 BFS-LE Alternatives at Link Level		Choice Set at TAZ Level (max. area = 2 km^2) Aggregated from up to 15 BFS-LE Alternatives at Link Level	
	Parameter Estimate	***t-stat***	***Parameter Estimate***	***t-stat***	***Parameter Estimate***	***t-stat***	***Parameter Estimate***	***t-stat***
Travel time (min)	-0.032	-1.951	-0.123	-7.313	-0.168	-13.722	-0.228	-18.795
Proportion of tolled portion of a route	-15.678	-14.276	-17.375	-16.512	-13.479	-15.425	-13.126	-16.598
No. of left turns per minute	I.S.	N/A	I.S.	N/A	-0.742	-3.605	-0.667	-3.341
No. of right turns per minute	-4.364	-5.006	-2.950	-3.612	I.S.	N/A	C.I.	N/A
No. of intersections per minute	-3.241	-22.146	-3.371	-24.163	-2.185	-22.135	-2.225	-23.380
No. of ramps per minute	-3.435	-16.030	-3.296	-16.491	-2.195	-13.108	-1.745	-13.685
Proportion of interstate portion of a route[1]	17.118	10.837	27.284	13.637	18.766	15.377	24.494	19.794
Proportion of major arterial portion of a route	16.464	9.859	22.573	11.001	14.442	10.763	18.596	14.210
Proportion of minor arterial portion of a route	21.367	12.992	29.983	14.535	18.525	15.169	23.623	19.062
Proportion of collector portion of a route	14.105	8.534	20.314	9.786	11.121	8.547	13.955	10.486
Natural log of path size	-2.509	-13.585	-1.9110	-19.848	-1.9174	-20.436	-1.487	-20.770
No. of cases	2888		2888		2888		2888	
Log-likelihood at convergence	-2156.98		-2779.109		-4045.61		-4528.52	
Log-likelihood for equal shares model	-4734.48		-7140.021		-8234.46		-9343.65	
Rho-square	0.544		0.611		0.508		0.515	
Adjusted rho-square	0.542		0.609		0.507		0.514	
Average of expected overlap with chosen route over validation dataset of 722 trips (standard deviation in parentheses)	0.765 (0.383)		0.785 (0.365)		0.774 (0.351)		0.792 (0.330)	

I.S. – Estimated parameter insignificant at 95% confidence interval. Hence, model re-estimated without corresponding variable.
C.I. – Estimated parameter removed as it had counter intuitive sign. Hence, model re-estimated without corresponding variable.
N/A – t-stat not available, as corresponding parameter not estimated.
1 Any given link in network can be classified into one of five categories: Interstate, Major Arterial, Minor Arterial, Collector, and Local Road.

3.4.6 Comparison of the Characteristics of Observed and Generated Choice Sets

Table 3.6 presents a comparison of routes that were observed as well as generated (i.e., relevant routes captured in generated choice sets) to routes that were generated but not observed (i.e., extraneous routes). This comparison suggests that extraneous routes were generally longer, have a greater proportion of tolled roads and involve a greater proportion of the route through smaller roads (such as minor arterials, collectors, and local roads), more network links per mile, and more intersections and turns than relevant routes captured by the choice set generation algorithm. This is reasonable because trucks typically do not consider routes that involve going through many smaller roads and turns. A visual examination of the extraneous routes suggested that many such routes involve getting off an interstate highway to smaller roads and then getting back on to the interstate highway.

Table 3.6: Comparison of Route Characteristics of Observed and Generated Routes in OD Pairs with at least 50 Trips at TAZ Level (Max. Area = 2 Km^2) Aggregation

Route Characteristics	Relevant Routes Captured in Generated Choice Sets (i.e., Observed and Generated)		Irrelevant/Extraneous Routes (i.e., Generated but not Observed)	
	Mean	***S.D.***	***Mean***	***S.D.***
Length (mi)	43.35	22.36	45.05	22.64
Proportion of ramps	0.037	0.039	0.049	0.034
Proportion of tolled roads	0.00	0.062	0.028	0.063
Proportion of interstate highways and major arterials	0.784	0.284	0.667	0.255
Proportion of minor arterials	0.137	0.222	0.173	0.19
Proportion of collectors	0.061	0.105	0.131	0.101
Proportion of local roads	0.018	0.04	0.029	0.047
No. of links	214.9	123.92	253.2	119.1
No. of links per mile	5.75	3.07	6.46	2.82
No. of intersections	89.77	77.01	119.30	72.51
No. of intersections per mile	2.58	2.07	3.22	1.96
No. of right turns	1.95	1.52	4.75	2.26
No. of left turns	1.92	1.29	4.85	2.48
Average path size	0.29[4] (0.09)[5]	0.19 (0.06)	0.14	0.06

A potential use of such comparison is in devising strategies to remove extraneous routes in a post-processing step. For example, further analysis may be conducted to identify deterministic thresholds on selected route attributes such as maximum route length, maximum travel time, or maximum number of turns per mile. Once such thresholds are identified, generated routes that do not meet the threshold criteria may be removed from the choice set. Another approach is to devise a probabilistic sampling approach that assigns sampling probabilities to routes based on how likely a route is to be extraneous. Exploration of such strategies is an avenue for future research.

[4] Pathsize of observed relevant routes with respect to observed routes.
[5] Pathsize of generated relevant routes with respect to generated routes.

3.5 Summary and Conclusions

This study evaluated truck route choice set generation algorithms and derived guidance on using the algorithms for effective generation of choice sets for modeling truck route choice. Specifically, route choice sets generated from the breadth first search link elimination (BFS-LE) algorithm were evaluated against observed truck routes derived from large streams of GPS traces of a sizeable truck fleet in the Tampa Bay region of Florida. A carefully-designed evaluation approach is presented to arrive at an appropriate combination of spatial aggregation and minimum number of trips to be observed between each OD location for evaluating algorithm-generated route choice sets. The evaluation was based on both the ability to generate relevant routes that are considered by travelers and the generation of irrelevant (or extraneous) routes that are seldom chosen. Based on the evaluation, the study offers guidance on effectively using the BFS-LE approach to maximize the generation of relevant truck routes while eliminating irrelevant routes in a post-processing step. Finally, route choice models were estimated and applied on validation datasets to confirm findings from the above evaluation.

The results demonstrate the benefit of evaluating algorithm-generated choice sets against observed choice sets from large datasets at a spatially-aggregated OD-pair level (instead of performing trip-level evaluations). Doing so helps in evaluating the ability to generate relevant routes as well as the generation of irrelevant routes. Based on the evaluation results, it was found that a carefully-chosen spatial aggregation (of generated routes) can reduce the need to generate substantial number of routes for each trip. In the current empirical context of truck route choice, it was found that generating up to a maximum of 5 routes at the trip-level and then aggregating such routes to a TAZ-level spatial aggregation (or up to 2 km^2) provided a similar coverage of observed routes as that from generating more than 20 routes for each trip without spatial aggregation. The implication is that an effective and computationally-effective use of the BFS-LE algorithm for generating truck route choice sets is to generate a small number of routes at the disaggregate-level and then aggregate such routes from nearby OD locations.

The findings of this study also suggest that extraneous routes generated by the BFS-LE are generally longer, have a greater proportion of tolled roads, and involve a greater proportion of the route through smaller roads (such as minor arterials, collectors, and local roads), more network links per mile, and more intersections and turns than observed routes. Using such results, future research can focus on the development of approaches to eliminate extraneous routes from generated choice sets prior to embarking on route choice modeling.

CHAPTER 4: SUMMARY AND CONCLUSIONS

4.1 Summary

The primary goal of this research was to use large streams of truck-GPS data to analyze the travel routes (or paths) freight trucks choose to travel between different origins and destinations in metropolitan regions of Florida. To this end, the project used large streams of truck-GPS data acquired for two projects funded by the Florida Department of Transportation (FDOT)—one by the FDOT Central Office and another by FDOT District 7. The first project obtained more than 100 million raw GPS data points of several thousand trucks traveling in Florida to derive a variety of data products, including data on truck travel paths for more than 70,000 trips in Florida. Such raw GPS data was obtained from the American Transportation Research Institute (ATRI) for four months (April–July 2010). The details of this FDOT project and the outcomes of the project can be obtained from the project report published by FDOT (Pinjari et al., 2014). The second project obtained more than 96 million raw GPS records from ATRI for the first 15 days in October 2015, December 2015, April 2016, and June 2016 for the Tampa Bay region of Florida. The truck-GPS data were used to develop route choice data for the Tampa Bay region and resulted in a database of more than 230,000 truck trips and corresponding routes (Tahlyan et al., 2017).

This is perhaps the largest amount of data used to date in the truck modeling literature to analyze truck route choice patterns. This offered an unprecedented opportunity to observe and analyze truck travel paths of a large number of trips between different origin and destination locations in Florida. Using such rich data, the following specific objectives were pursued in the project:

1. Measure and analyze diversity in truck route choice patterns in Florida.
2. Evaluate the performance of truck route choice set generation algorithms for developing truck route choice models in Florida.

Each of these objectives is briefly discussed next.

4.1.1 Measurement and Analysis of Truck Route Choice Diversity in Florida

This task involved the measurement and analysis of diversity of travel paths chosen by trucks between selected OD locations in Florida. To measure the diversity in truck routes between a given OD pair, the research team developed the following six metrics: (1) number of unique routes, (2) average commonality factor, (3) average path size, (4) non-overlapping index, (5) standardized variance of route usage, and (6) standardized Shannon entropy of route usage. Each of these metrics helped in measuring one of the following three dimensions of diversity: (1) number of distinct routes used to travel between the OD pair, (2) extent of overlap (or lack thereof) among the routes, and (3) evenness (or the dominance) of the usage of different unique routes. The diversity metrics were used to examine truck route choice diversity from more than 73,000 truck trips that were derived from more than 200 million GPS records of a large truck fleet. Descriptive analysis and statistical models of the diversity metrics offered insights on the determinants of various dimensions of truck route choice diversity between an OD pair. The research team compiled an extensive set of variables characterizing the truck travel characteristics, OD location characteristics, and network structure characteristics between these OD pairs that potentially could influence the extent of route choice diversity. Negative binomial regression models were estimated to explore the influence of these variables on the number of unique routes traveled between an OD pair, and fractional response models were estimated to explore the determinants of average path size (overlap among routes) and standardized Shannon entropy (evenness) of route usage.

The analysis suggests that short-haul trucks travel exhibit greater diversity in route choice than long-haul trucks in terms of number of unique routes observed, extent of non-overlap between unique routes, and evenness of usage of different unique routes.

4.1.2 Performance Evaluation of Truck Route Choice Set Generation Algorithms

This task evaluated truck route choice set generation algorithms and derived guidance on using the algorithms for effective generation of choice sets for modeling truck route choice. Specifically, route choice sets generated from the breadth first search link elimination (BFS-LE) algorithm were evaluated against observed truck routes derived from large streams of GPS traces of a sizeable truck fleet in the Tampa Bay region. A carefully-designed evaluation approach was used to determine an appropriate combination of spatial aggregation and minimum number of trips to be observed between each OD location for evaluating algorithm-generated route choice sets. The evaluation was based on both the ability to generate relevant routes that are considered by travelers and the generation of irrelevant (or extraneous) routes that are seldom chosen. Based on the evaluation, the research offers guidance on effectively using the BFS-LE approach to maximize the generation of relevant truck routes while eliminating irrelevant routes in a post-processing step. Finally, route choice models were estimated and applied on validation datasets to confirm findings from the above evaluation.

The results demonstrate the benefit of evaluating algorithm-generated choice sets against observed choice sets from large datasets at a spatially aggregated OD-pair level (instead of performing trip-level evaluations). Doing so helped in evaluating the ability to generate relevant and irrelevant routes. Based on the evaluation results, it was found that a carefully-chosen spatial aggregation (of generated routes) can reduce the need to generate a substantial number of routes for each trip. In the current empirical context of truck route choice, it was found that generating up to a maximum of five routes at the trip level and then aggregating such routes to a TAZ-level spatial aggregation (of up to 2 km^2) provided a similar coverage of observed routes as that from generating more than 20 routes for each trip without spatial aggregation. The implication is that an effective and computationally-efficient use of the BFS-LE algorithm for generating truck route choice sets is to generate a small number of routes at the disaggregate-level and then aggregate such routes from nearby OD locations.

4.2 Opportunities for Future Research

Findings from the diversity analysis described in Chapter 2 can be used for improving the algorithms used in the literature for generating choice sets for truck route choice modeling. Route choice set generation algorithms can be customized based on the truck travel demand, OD location, and network structure characteristics found to be influential in this analysis. An enhanced understanding of truck route choice diversity can also help improve truck routing policies and inform routing decisions during emergency situations. Findings from the evaluation of route choice set generation algorithms suggest that extraneous routes generated by the BFS-LE are generally longer, have a greater proportion of tolled roads and involve a greater proportion of the route through smaller roads (such as minor arterials, collectors, and local roads), more network links per mile, and more intersections and turns than observed routes. Using such results, future research can focus on the development of approaches to eliminate extraneous routes from generated choice sets prior to embarking on route choice modeling.

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