Tour-Based Urban Freight Travel Demand Models

by

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ABSTRACT

This dissertation is concerned with the enhancement of urban freight travel demand modeling by incorporating the trip chaining behavior of commercial vehicles. In this dissertation, two approaches were developed to accomplish the objective. One model focuses on estimating the tour flow distribution patterns in the aggregate level while the other attempts to simulate trip chaining behavior in the disaggregate level.

The first approach is aimed to estimate commercial vehicle tour flows distributed in urban networks using the concept of entropy maximization. The resulting entropy maximization formulations obtain the most likely set of tour flows that meet the system's aggregate-level constraints such as the number of trips produced by or attracted to each zone (trip production/attraction), and the total impedance of the entire network. The first-order conditions of the formulations show that the tour flow in a tour is a linear combination of the Lagrange multipliers associated with the trip productions/attractions along that tour, and the tour impedance variables.

The application of the tour-based entropy maximization approach requires a pre-specification of tours potentially visited by commercial vehicles and the associated impedances. In this context, a behavioral-based tour choice model was developed to generate a sufficient and effective set of tours as the input to the entropy maximization formulations.

The second approach is a tour construction model that generates commercial vehicle tours in order to satisfy a given commodity flow OD matrix as part of a hybrid micro-simulation framework. To shed light into key variables that affect trip chaining behavior, a behavioral approach was implemented, decomposing the tour decisions into two choices, i.e., the next destination choice and the tour termination decision. The corresponding discrete choice models were estimated to support the simulation of trip chaining decisions.

The test results show that both models reach good agreement with the trip chaining patterns observed in real world. The good performances of the two models indicate the feasibility of applying the proposed models to forecast urban freight travel demands.

1. Introduction

1.1 The importance of freight system modeling

Freight transportation, as an integral part of the transportation system, has proven to be a major factor contributing to economic growth and development. Its importance can be appreciated by noting that the nation's freight transportation system, all modes combined, carried 15.8 billion tons of raw materials and finished goods in 2002, which represented 4,506 billion ton-miles with a value of $10,460 billion (in 2000 dollars). In terms of modes used, trucks play a dominant role. Trucking moved the majority of freight by tonnage and by shipment value: 9.2 billon tons (58% of the total tonnage) and $6,660 billion (64% of the total value) in the national level. In large cities, their roles are even more significant: trucks account for around 80% of commodity tonnage moved and around 10% of the vehicle kilometers traveled (Outwater et al., 2005). Meanwhile, the demands on the freight system are rapidly growing. As an indication, it suffices to say that ton-miles have grown 24% since 1993, while value rose 45% (BTS, 2005). More importantly, higher growth rates have been forecasted in the future. The Oregon State Department of Transportation, as well as other ports and institutions all over the United States, are expecting an accelerating growth in freight in the near future, in excess of the historical growth rates in the freight handling infrastructures and vehicle fleets (Metro, 2004; SEMCOG, 2004).

Although much of the freight is a direct result of population growth and domestic economic activity, other factors, such as economic globalization and technological revolutions, play critical roles in increasing freight activity. These factors, on one hand, increase the size of the geographic areas covered, as well as the volumes of cargoes transported. On the other hand, the technological changes that have taken place in the last decades are bringing about major changes in the way the freight system operates. The rapid evolution and adoption of real-time, telecommunication-based information technologies have allowed the widespread adoption of electronic commerce as a means of placing contracts, tracking costs, and checking product status via the Internet. This, in turn, leads to new types of business partnerships, including new business arrangements between freight shippers, freight carriers, and a growing variety of third-party freight logistics agents. In addition, shopping on line, as a substitute for the traditional way, has increased the demand for lighter shipments of high-valued goods, and thus results in an increase in the amount of freight that has to be transported by truck, particularly in urban areas.

Concurrently, the negative externalities produced by freight transportation, such as congestion, accidents, pollution, noise, and vibrations, have become hotly contested public issues and the source of complaints by community and environmental groups (Forkenbrock, 1999; Rapaport, 2002; Nagurney and Toyasaki, 2003; Léonardi and Baumgartner, 2004). The combination of positive and negative externalities produced by freight, provide potent reasons to develop new methods to evaluate and improve the efficiency of freight transportation systems.

1.2 The complexity of freight activities

Achieving this goal is without any doubt, a major challenge due to the inherent complexity of freight activities (Ogden, 1992; Cambridge Systematics Inc., et al., 1996; Holguín-Veras and Thorson, 2003; Friesz and Holguín-Veras, 2005; Holguín-Veras and Patil, 2005). First, modeling freight demand needs to consider multiple dimensions of measurements (e.g., volume, weight, number of vehicle trips). These measurement units are associated with different types of flows (e.g., monetary, commodity or vehicle flows), and thus place specific requirements for the modeling approaches used. Second, freight movements are a result of complex interactions between a number of different decision makers including producers, shippers, carriers and receivers. These business interactions are usually commercially sensitive and difficult to observe. Third, it involves extremely diverse commodities with a wide spectrum of opportunity costs (ranging from low value commodities such as waste to high value commodities like computer chips that are worth $1 million per ton) that require various operational arrangements. Fourth, the freight activity flows, which have been overlooked in the past, reflect the fundamental economic interactions among different decision makers, and hence should be paid great attention in the modeling process.

1.3 Trip chaining behavior of urban commercial vehicle movements

Besides the fundamental characteristics mentioned before, freight transportation, particularly in urban areas, exhibit some unique features that make the modeling process even more challenging. Among them, it is important to highlight the significant importance of trip chaining behavior.

One of the most salient features of urban freight traffic is that commercial vehicles make a significant number of long trip chains (tours) as opposed to passenger transportation in which trip chains are the minority. For instance, the commercial vehicle movement survey conducted in the Denver metropolitan area revealed 3.2 stops per tour on a daily basis (Holgu ń-Veras and Patil, 2005). Compared to this, the typical range for passenger vehicles is 0-1 stops per tour depending on the tour purposes and the social-economic characteristics of travelers (McGuckin et al., 2005; Noland and Thomas, 2006). The trips made along a tour are integrated with each other by complex logistic arrangements, which break down the typical assumption of traditional freight demand forecasting models that vehicle trips are made independently. In this context, there is an urgent need to develop new freight demand models that consider the unique trip chaining behavior.

1.4 Challenge in modeling trip chaining behavior

The fundamental challenge in modeling trip chaining behavior of commercial vehicles comes from the fact that in a given area, there are three sets of flows taking place, which are associated with the monetary transactions, the commodities being made, and the vehicle trips derived. Though related, they represent different things. The monetary flows and the commodity flows result from economic interactions of production and consumption of commodities, while the vehicle flows reflect the logistics of transporting commodities. An example in Figure 1 illustrates the differences and the relationships between the three types of flows, in which a producer dispatches a single truck to send commodities to five customers in sequence. As can be seen, the monetary flows and the commodity flows represent transactions between the same producer-consumer pairs but in opposite directions – money passing from consumers to the producers while the commodities going in the other direction. In contrast to them, the vehicle flows exhibit a very different pattern: in terms of the flow directions, the vehicle trips are very different from the commodity flows and the monetary flows except of the starting and ending trips; in terms of magnitude, the amount of commodities delivered to or the money collected from each customer vary by customers although each delivery or monetary exchange may result in only one vehicle trip. These differences determine that the assumption of proportionality between commodity flows (or monetary flows) and vehicle flows is bound to introduce major errors in forecasting freight traffic. In this context, the urban freight demand models need to be developed in a way that the differences as well as the relationships between the three sets of flows can be captured simultaneously.

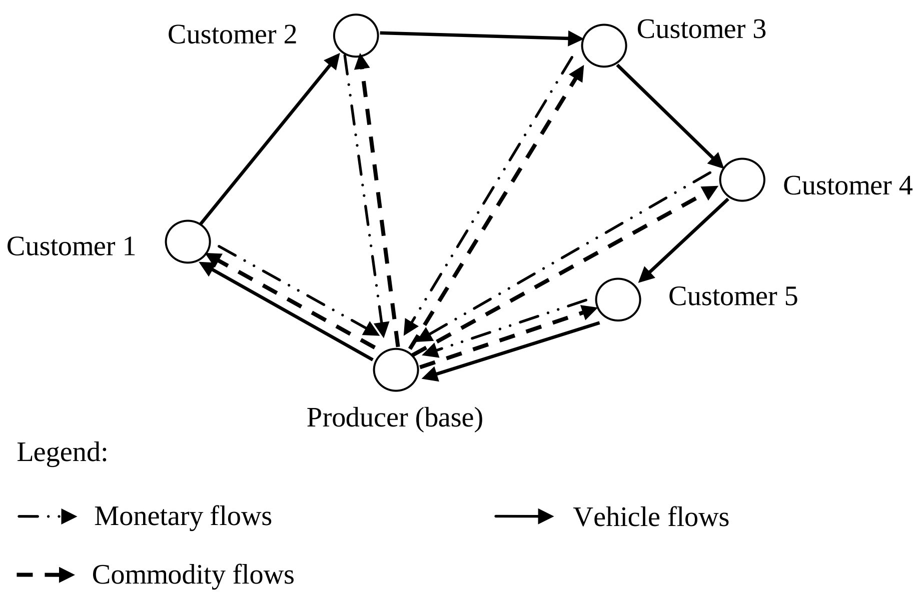


Figure 1: Relationships between monetary, commodity and vehicle flows in a urban freight network

1.5 Motivation

This dissertation is concerned with the enhancement of urban freight demand modeling by incorporating the trip chaining behavior of commercial vehicles. There are two major factors that motivate this dissertation.

The first factor is associated with the complexity of trip chaining behavior and the challenges of modeling it. As described previously, commercial vehicles in urban areas make a significant number of long trip chains in which trips are linked with each other by the underlying logistics operations. Meanwhile, trip chains, as a measurement of vehicle flows, are derived from commodity flows and monetary flows. Thereby, new urban freight demand modeling methodologies are required to represent the interactions between trips as well as the relationships between multiple freight flows.

The second major factor is concerned with the limitations associated with urban freight demand models. The efforts in urban freight demand modeling can be categorized into two groups, i.e., aggregate-level and disaggregate-level freight demand models, depending on whether the behavior of individual freight components (e.g., one vehicle or one unit of cargoes) or the bulk of freight movements is analyzed.

The aggregate-level approaches focus on the macroscopic patterns or attributes of freight movements in urban areas. The typical example is the four-step planning method that includes generation, distribution, mode split and traffic assignments of freight flows. They result in commercial vehicle trips rather than tours as the final outputs.

The popularity of the four-step planning method came from its simple estimation procedure, lower expenses for input data collection and its wide applications in traditional passenger-oriented travel demand forecasting. However, its fundamental assumption about the independency between trips has prevented its applications in large-scale urban freight systems where commercial vehicle trips are chained to tours by underlying logistic operations. In this context, developing tour-based aggregate models in urban areas is one major motivation behind this dissertation.

As the examples of disaggregate-level models, a handful of microsimulation-based disaggregate models have been formulated for urban freight movements. In these studies, tours are constructed either to satisfy commodity flows or to simulate the real-world trip chaining behavior. However, commercial vehicle tours are constructed in a way that either of two critical factors, i.e., the trip chaining behavior and the relationship between commodity flows and vehicle flows, is missing from the big picture. To address this issue, another major motivation of this dissertation is to develop a tour-based microscopic simulation model that considers the underlying decision making process behind each tour as well as the relationship between commodity flows and commercial vehicle flows.

1.6 Objectives

The major objective of this dissertation is to develop tour-based urban freight travel demand models to guide the progress of urban freight demand forecasting towards more realistic representations of urban freight operations. The resulting modeling frameworks must be mathematically tractable, empirically verifiable, theoretically grounded, and have the ability to incorporate trip chaining behavior.

In order to achieve the objective, the key factors that affect the trip chaining behavior of urban freight movements should be understood and assessed first. Then, different modeling frameworks that incorporate these factors should be developed, demonstrated and tested by cases in real world.

1.7 Overview of the modeling framework

In this dissertation, two types of urban freight demand models are proposed to incorporate trip chaining behavior, taking into account the availability of input data. One model is to estimate the tour distribution patterns of commercial vehicles given that the aggregate demand information is available. The other is to simulate the tour construction procedure in the disaggregate level given that commercial vehicle travel diaries are available for the behavioral modeling purposes. This section starts with a definition of important concepts used in the dissertation, and then presents the framework followed by each approach.

1.7.1 Definitions

Before the two approaches are introduced, it is important to define the concepts of "tour," "trip," and "tour flow." A "tour" is defined as the sequence of nodes visited by a vehicle, which starts and ends at the vehicle's home base. It is used interchangeably with "node sequence" in this dissertation. For instance, there is only one tour, i.e., base-1-2-3-4-5-base, in Figure 1. An individual vehicle movement connecting a stop to the next stop, for a specific purpose, is referred to as a "trip". For example, vehicle movements from home base to node 1 or from node 1 to node 2 make trips. The number of vehicle journeys following a specific tour during a certain time period is referred to as "tour flow." For instance, five vehicle visits could be made by following the same tour as base-1-2-3-4-5-base. These definitions are consistent with previous publications (Holgu ń-Veras and Patil, 2005).

1.7.2 Tour-based entropy maximization approach

The first approach is an aggregate-level model that estimates the tour distribution patterns using the concept of entropy maximization. The modeling framework is shown in Figure 2. As can be seen, the central component of the aggregate approach is the Entropy-based tour distribution model. In this part, a powerful concept, i.e., entropy maximization, is used to distribute commercial vehicle tour flows into the network. The final output of the entropy maximization formulations contains the most likely set of tour flows that meet the system's aggregate-level constraints such as the number of trips produced by or attracted to each node and the total impedance of the entire network.

Since the estimation of tour flows by using the entropy maximization formulations requires a pre-specification of potential tours visited by commercial vehicles, a tour choice model considering trip chaining behavior is developed in the dissertation. This model shares a similar framework as the tour construction procedure used in the hybrid microsimulation urban freight demand model. Both of them use two discrete choice models, i.e., the destination choice model and the tour termination model, to represent the carriers' trip chaining decisions. Differently, the tour choice model does not consider the impact of commodity flows but include the company attributes, the vehicle attributes and the handling time along each stop as the potential explanatory variables.

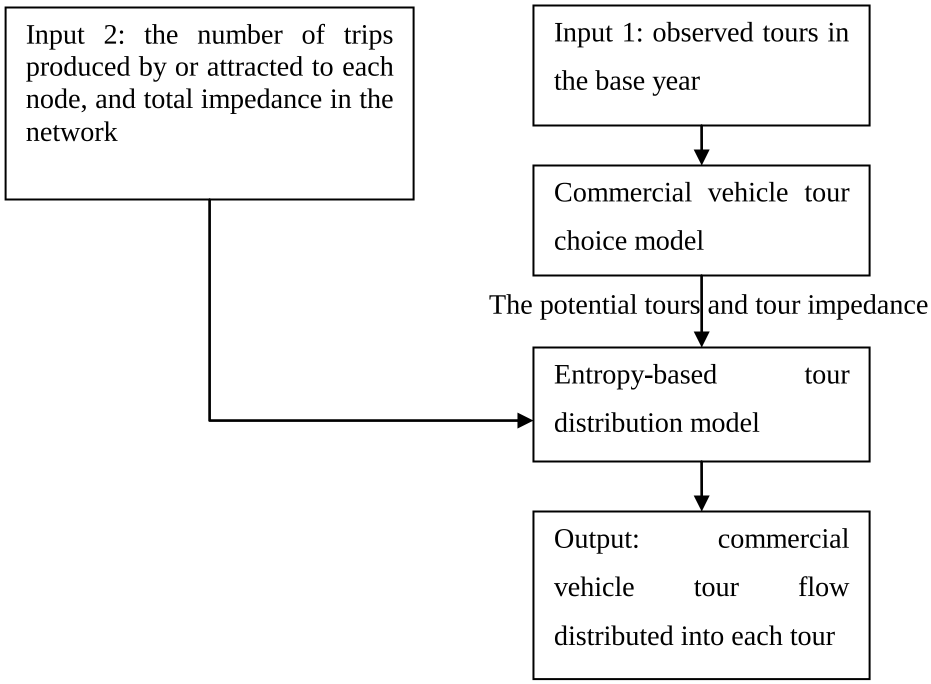


Figure 2: Framework of tour-based entropy maximization approach

1.7.3 Hybrid microsimulation urban freight demand model

The second type of models is to construct individual commercial vehicle tours that satisfy a given commodity flow OD matrix as part of a hybrid micro-simulation framework. This typical framework involves an input-output model to estimate the production and attraction of commodities in each zone, a gravity model to distribute commodity flows between OD pairs, and a tour-based microscopic simulation model to generate commercial vehicle tours. Due to the data availability, this dissertation only focuses on the third step, the tour construction procedure.

To shed light into the key variables that affect trip chaining behavior, a behavioral approach is implemented to construct individual tours, decomposing the tour decisions into two groups of choices: the choice of next destination location and the choice of terminating a tour. The corresponding discrete choice models are estimated in order to generate probabilities that help make the two types of decisions. The output of the tour construction procedure is a set of commercial vehicle tours that satisfy the given commodity flow OD matrix.

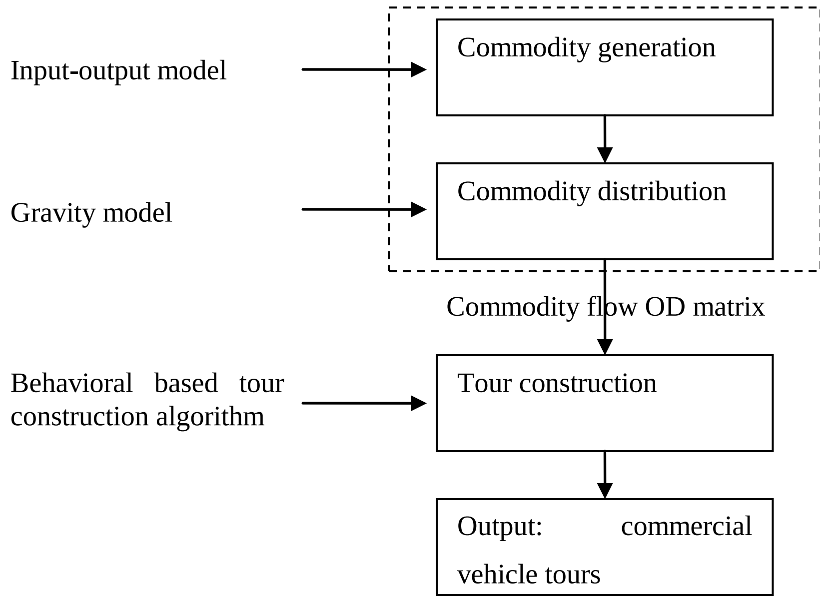


Figure 3: Typical framework of hybrid microsimulation urban freight demand model

1.8 Organization of the thesis

The dissertation is divided into six sections. Section 2 reviews the research efforts in urban freight travel demand modeling. Section 3 presents the entropy-based tour distribution model that is aimed to estimate tour demand in the network given the system's constraints such as the number of trips produced by or attracted to a zone, and the total impedance of the entire network. Section 4 discusses a behavioral based tour choice model that captures the sequential decisions made along a tour, e.g., the decision of choosing next destination and the decision of terminating a tour. Section 5 discusses a hybrid microsimulation framework proposed for modeling urban freight movements in the disaggregate level. Two types of discrete choice models, representing the destination choice behavior and the tour termination behavior respectively, are estimated by using a data set from the Integrative Freight Market Simulation (IFMS) (Thorson, 2005). Section 6 summarizes the major findings and the contribution of this dissertation, and describes the future research directions.

2. Literature in Urban Freight Travel Demand Models

Urban freight movements are different from freight movements over larger areas, such as states, regions, or nations. Urban freight movement is almost exclusively road-based due to the inefficiency of other modes over the smaller scale of urban areas (Ogden, 1992). Meanwhile, urban deliveries are characterized by short-distance movements, circular routes (or called tours) followed, and multiple stops made on one tour. This road-exclusive feature and the unique trip chaining behavior of commercial vehicle movements distinguish urban freight movements from passenger transportation, and have been attracting cumulative attentions from both researchers and practitioners.

Traditionally, urban freight movements have been overlooked in transportation planning. In the United States, beginning in the late 1950s, some undertaken transportation planning efforts identified truck trips as minor elements. They include the Detroit Transportation and Land Use Study, and the Chicago Area Transportation Study (Chatterjee, 1996).

During the 1970s, researchers, transportation planners, and government agencies especially in large cities, started to recognize that the majority of transport planning studies in the previous 10-15 years had almost completely neglected urban goods movement. Following this recognition, a series of studies and research projects were conducted to improve the level of knowledge about the features of urban freight flows, urban freight costs, problems and opportunities in US, Canada and Britain. Some examples include the review of Canadian freight research in the 1970s by Wood et al. (1979, 1982), the research projects of urban goods movement funded by the US Federal Government (Kearney, 1975, 1976), a number of studies of freight issues in specific urban areas in Britain (Corcoran and Christie, 1978).

Concurrently, new concepts and techniques that have their origin in urban passenger demand forecasting have been applied to model urban freight movements. The four-step planning method is one typical example. It was originally developed to forecast passenger travel demands, and then adopted to generate, distribute, split and assign freight flows. Treated similarly as passenger vehicles, the assigned freight-related vehicles were assumed to behave as independent individuals that tried to minimize their perceived transportation costs. They were assumed to make independent trips rather than tours composed of linked trips. During the modeling process, freight demand was measured either by the weight of commodities, or the number of vehicle trips. Therefore, the four-step methods branched into two different directions: the vehicle-trip-based approaches, and commodity-based approaches (Ogden, 1992; Holgu ń-Veras and Thorson, 2000, 2003).

In recent years, freight vehicle movement, with its dominant role in transporting goods in urban areas, has been attracting increasing attention. A lot of efforts have been dedicated to systematically analyze the complexity and characteristics of urban freight systems, aimed to replace the traditional four-step paradigm (Ogden, 1992; Holgu ń-Veras and Thorson, 2003; Holgu ń-Veras and Patil, 2005; Friesz and Holgu ń-Veras, 2005; Figliozzi, M., 2006; Thorson and Holguin-Veras, 2007). Among these studies, one unique feature of urban freight vehicle movements, i.e., trip chaining behavior, has been paid special attention. Some researchers have tried to accommodate trip chaining into their proposed models (Raothanachonkun et al., 2007; Donnelly, 2007; Stefan et al., 2005; Hunt and Stephan, 2007; Gliebe et al., 2007). These studies are referred as the tour-based models as opposite to the trip-based models mentioned above.

There are a number of different ways in which one would classify urban freight models. For the purposes of this review, it is useful to categorize all these modeling efforts as aggregate or disaggregate, depending on whether the overall patterns of freight movements or the behavior of individual freight agents are analyzed. Furthermore, each group of models is branched into different subgroups considering the different analysis units used (e.g., tons of commodities, trips or tours). The resulting classification is shown in Figure 4.

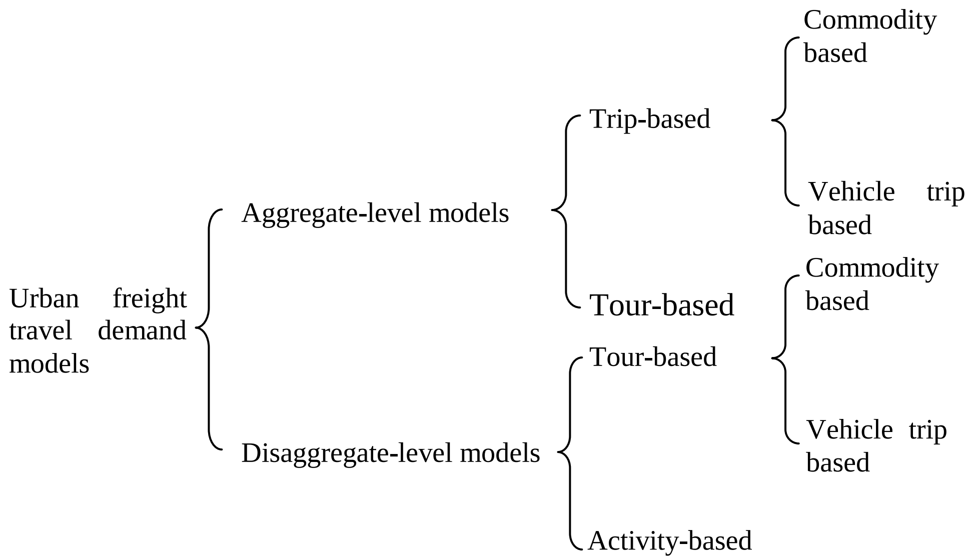


Figure 4: Summary of literature in urban freight travel demand modeling

2.1 Aggregate-level approaches

Aggregate-level approaches focus on modeling the conglomeration of user demand. The typical example is the four-step planning method that includes trip generation, trip distribution, mode split and traffic assignments. Different measurement units of freight demand used, e.g., commodities or vehicle trips, lead to commodity-based or vehicle-trip-based models. Regardless of the units used for measurement, these approaches result in commercial vehicle trips finally. Recently, some authors tried to introduce the concept of tours into aggregate freight planning models. These efforts are categorized into another group of models, i.e., the aggregate tour-based models. The following review focus on the three types of models.

2.1.1 Commodity-based Models

Commodity-based models are predicted on the facts that the freight system is essentially concerned with the movement of commodities. Hence, they focus on the directions and quantities of commodities being transported, and then estimate the corresponding traffic flows that are needed to satisfy these freight flows.

This type of models follows the general procedure shown in Figure 5. It is composed of two major steps: the step to forecast commodity flows, and the step to estimate the vehicle flows that are required to satisfy these commodity flows. In the first step, the amount of commodities produced by or attracted to each zone in the network is estimated at first, using either a commodity generation model or an input-output (I-O) model. Then, they are distributed to the network to get the commodity flows between origin-destination (OD) pairs. Furthermore, the estimated commodity flows are split into several subsets of commodity flows by mode. After it, the second step is applied to calculate the vehicle flows that are needed to transport these commodities. This step is composed of a vehicle loading model that convert commodity flows to loaded or empty trips, and a standard traffic assignment technique to dispatch vehicle flows to the road network.

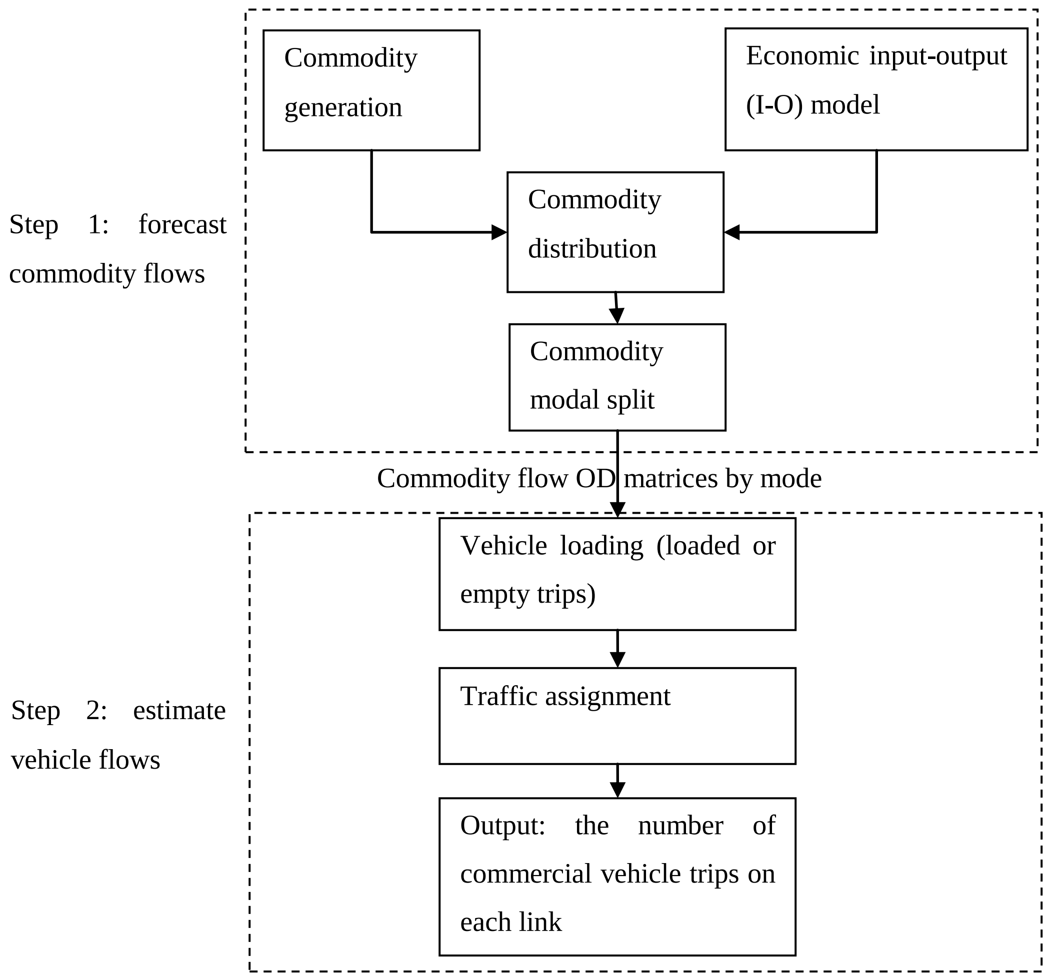


Figure 5: Estimation procedure of commodity-based models

The following literature review describes the methods used to forecast commodity flows and the vehicle loading models for converting commodity flows to vehicle trips. The standard traffic assignment techniques are not reviewed because of the lack of relevance.

2.1.1.1 Methods for forecasting commodity flows

Three sequential stages are involved in the step of forecasting commodity flows. They include: (1) the generation stage that estimates the amount of commodities produced by or attracted to each node in the network; (2) the distribution stage that obtains commodity flows between OD pairs; and (3) the mode split stage in which the estimated commodity flows are split to several subsets by mode.

In the first stage, the amount of commodities produced by or attracted to each node is estimated by either a commodity generation model or an economic input-output (I-O) model. The two types of models address the issue of commodity generation in different ways, and thus use different methodologies.

In the commodity generation models, the population, the employment, the land use type and the accumulation of households in a zone are considered as the major attributes that affect the generation of commodities. Therefore, the tonnages produced by or attracted to each zone in a network are usually modeled as a linear regression function of these attributes (Ogden, 1977). As an alternative way to estimate the commodity generation, the amount of commodities generated from each zone was forecasted by a set of commodity-type-specific growth rates, given the assumption that the land use patterns in the area of interest do not change much in the future (Waliszewski, et al., 2004).

In addition to commodity generation models, the economic input-output (I-O) models can also be used to estimate the commodity productions and attractions, given the fact that the freight demands are derived from the dollar valued trades in goods between areas. Originally proposed by Leontief (1941), the inter-industry I-O analysis is a macroeconomic approach focusing on industries' interactions in each region via business expenditure patterns. Since then, the inter-regional versions of I-O models have been adopted to estimate not only freight traffic generations and attractions but also the flows between regions as well as industries (Miller and Blair, 1985; Miller and Shao, 1990; Rey and Dev, 1997; Zhao and Kockelman, 2004). In the typical I-O analysis, the flow of goods is measured in monetary units, and the amount of products from a supply sector required by a demand section is determined by the inter-industry 'technical coefficients' and the final demand for the demand sector's output. Here, the technical coefficients represent the amount of given sector's products required to produce one dollar of another sector's product.

The main challenge in using I-O models to forecast freight demands comes from technical coefficients. Usually, obtaining technical coefficients require a great deal of data on regional economic activity and interregional flows. For compact areas with large numbers of zones, to get the technical coefficients is even more data demanding. Therefore, the I-O models are preferred by large scale systems, such as international, national or regional, and only a handful of applications have been done for urban areas. Among these applications, Fischer et al (2000) use the IMPLAN I-O models to determine the portion of each inbound commodity that goes to final demand by consumers and the use of each commodity by industry sectors in southern California. Commodity flows then were converted to truck trips, producing a set of trip tables that can be assigned to the regional roadway network using standard traffic assignment techniques. Giuliano et al. (2007) used a regional input-output transactions table, as well as widely available secondary data, to estimate intraregional commodity-specific trip attractions and productions at the level of small area units.

In the second stage of the commodity-based modeling framework, the generated commodity tonnage is allocated to OD pairs in the network by using commodity distribution models. Compared with commodity generation models, the commodity distribution models exhibit great diversity considering various factors that may affect this stage. Gravity models and spatial interaction models have been applied to estimate the commodity flows. In the typical gravity models, the tonnages between OD pairs are calculated as a function of the generation of the origin and the attraction of the destination weighted by an impedance term between the OD pair. The impedance variable could be distance or travel time. For example, the gravity distribution model developed by Ogden (1977) for Melbourne, Australia used the airline distance between each OD pair as the impedance.

Considering the complexity of freight systems, commodity distribution models with more complex forms were used to allocate commodity flows. One example is the fractional split distribution model developed for estimating inter-regional commodity flow volumes (Sivakumar and Bhat, 2002). This model adopted a multinomial logit form to determine the fraction of freight consumed at a destination zone that originated from each of the production zones. This idea is consistent with the basic postulates of freight systems, i.e., freight movements are generated by the demand of commodities at the destination that is met by the flow of commodities from one or more points. The application in Texas indicates that the fraction of total tonnage consumed in a zone that comes from each of production zones is a function of production zone size variables, impedance variables, and the production zone variables other than size. Meanwhile, the results from a nested likelihood ratio test show that the proposed model outperforms the typical gravity structure.

After the commodity distribution stage, the mode split models are used to split the estimated commodity flow OD matrix by mode as the last stage of the commodity flow forecasting procedure. The discrete choice models are usually used to split the commodity flows, and the utility of choosing a mode as a means to ship commodities between an OD pair is estimated as a function of mode-specific variables such as the travel cost by using that mode (Gray, 1982; Harker, 1985; Jeffs and Hills, 1990).

The commodity flow OD matrices estimated by the typical distribution models are zone based. However, since freight activities are likely to be even more heterogeneous within an industrial or retailing zone than household activities within a residential zone, aggregation bias could be greater in freight models calibrated on zonal data than in their passenger counterparts. To avoid the problems of spatial aggregation, some researchers attempt to generate commodities at the industrial or, preferably, the production unit or plant level. One example is from Wisetjindawat and Sano (2003). The modeling structure proposed by them is firm based and consists of two submodels: the commodity generation model and the commodity distribution model. In the commodity generation stage, the amounts of commodities produced and consumed by each firm were estimated as a regression function of firm size indicators such as the number of employees and the floor area. In the step of commodity distribution, the commodity flow between each shipper and customer pair was determined by the fraction that the customer purchases from the shipper. This fraction was calculated as a product of three types of probabilities: the distribution channel choice probability, the zone choice probability and the shipper choice probability. As found from a case study in the Tokyo metropolitan area, the zone choice probability was estimated from a discrete choice model with three groups of independent variables: zonal impedance variables (distance), the zonal attraction variables (the commodity production in a zone, the number of establishments of the corresponding industry type, the population, the size of the area and the number of employees), and correction variables (unknown scalar parameters). This modeling structure is a modification of the four-step planning method although firms instead of zones are used as the analysis units and the interactions between shippers and customers are taken into account by introducing a more complex distribution probability function.

In addition to the efforts mentioned above, a conceptual framework of modeling urban freight movement, called GoodTrip (Boerkamps, et al, 1999 and 2000), deserves special attention. This framework follows a similar procedure in Figure 5, but incorporates the aspects of supply chains into the modeling process. GoodTrip used activity types to define the nodes. These activity types include consumers, supermarkets, stores, offices, and distribution centers of retailers and producers. Then these nodes were linked to form supply chains. Meanwhile, land use was modeled by relating the activity types (or nodes) to the geographical zones of the model. In the procedure of estimation, the GoodTrip model started with estimating the volumes of end users' (customers') goods demand per goods type in every zone. Then, these estimated volumes were distributed to linkages (a linkage is defined as a trade relation between a shipper and receiver) in supply chains by the linkage-specific commodity distribution models. The mode split was conducted in the same stage as the commodity distribution. Once the goods flows by mode had been estimated, the flows of each goods type were combined and then assigned to vehicle tours that were generated by a vehicle loading and routing simulator. Finally, the tours per mode were assigned to their infrastructure networks, resulting in network loads. The authors also mentioned the future improvements that will include loading the network with autonomous traffic flows and establishing an iterative modeling process by updating the generalized OD travel times per mode.

2.1.1.2 Vehicle loading models

After the commodity flow OD matrices by mode are estimated, the vehicle loading models will be used to forecast the number of containers/vehicles/vessels required to move these commodities as shown in Figure 5. The loading process should take into account average, partial and empty loads, particularly for truck traffic forecasts.

Three models represent the early efforts in the vehicle loading methods that consider both loaded trips and empty trips. They are the naïve proportionality model, the formulation by Noortman and van Es (1978), and a model developed by Hautzinger (1984). Interested readers are referred to Holguín-Veras and Thorson (2003) for a detailed review of these methods.

The naïve proportionality model attempts to approximate the total number of trips from an origin to a destination as a function of the commodity flow in the same direction. Due to its simple formulation, the naïve proportionality model was used by a number of practical freight transport planning studies. However, this approach tends to reach unreasonable results due to the fact that no explicit distinction is made between trips with and without loads. As pointed out by Hautzinger (1984), if the commodity flows in a direction increases, it is likely that the flow of empty commercial vehicles in the opposite direction will also increase because of the return trips. This situation can not be addressed by the naïve proportionality model since the commodity flows and the vehicle flows are only one-way related in this model.

The formulation of Noorman and van Es (1978) moves one step forward by incorporating the commodity flows in the opposite directions to the loading function. It assumes that the number of empty trips from an origin to a destination is a function of the commodity flow in the opposite direction. The major limitation of the Noorman and van Es model lies in the implication from the developed equation, which is that the difference between the flows of commercial vehicles in two directions between an OD pair is a function of the difference between the commodity flows. However, according to Hautzinger, this implication is not consistent with the empirical evidence that even in cases of extreme difference between the commodity flows in two directions of an OD pair, the corresponding vehicle flows tend to be equal.

To overcome the limitations of the Noortman and van Es' approach, Hautzinger developed a formulation that takes into account the base location of the commercial vehicles. In the developed model, the total numbers of trips in both directions are equal regardless of the commodity flows.

Recently, Holguín-Veras and Thorson (2003) reviewed and modified the vehicle loading models mentioned above. As they summarized, both the Noortman and van Es' and Hautizinger's models are zero-order trip chain models which only considers the primary trips departing from home bases and the corresponding return trips. To improve these traditional models, they formed a first-order trip chain model that consider the flow of commercial vehicles, and specifically empty trips, as part of trip chains with one destination in addition to the primary trip. In this first-order trip chain model, the expected total number of trips from an origin to a destination is composed of three terms: the loaded trips, the empty trips from zero-order trip chains and the empty trips from higher-order trip chains. The general formulation is as following.

$$E(z_{ij}) = \frac{m_{ij}}{a_{ij}} + p\frac{m_{ji}}{a_{ji}} + (1-p)\gamma^{*}\sum_{h \neq j}\frac{m_{hi}}{a_{hi}}(P^{h}(j)P^{h}(E/j)) \qquad (2\text{-}1)$$

Where:

m_{ij}: Commodity flow between origin *i* and destination *j*;

a_{ij}: Average payload of the loaded vehicle trips from *i* to *j*;

p: probability of a zero order trip chain;

$(1-p)\gamma^{*}$: Parameter to be determined empirically;

$P^{h}(j)$: Probability that a vehicle that came from *h* to *i* chooses *j* as the next destination;

$P^{h}(E/j)$: Probability that a vehicle does not get cargo to *j* given that it follows tour *h*-*i*-*j*;

$P^{h}(j)P^{h}(E/j)$: Probability that a vehicle traveling in *h*-*i*-*j* goes empty to *j*.

As a further exploration, the destination probability $P^{h}(j)$ was specified as a function of the commodity flows and the corresponding trip impedance with four different forms. The parameters in these specifications were estimated by minimizing the sum of square of the differences between the observed total numbers of trips and the expected ones. The results from an application in Guatemala City show that the proposed vehicle loading model outperforms the Noortman and van Es' model in terms of the root mean squared error (RMSE). They also show that the destination choice probability will lead to a slightly better estimation when its formulation takes into account the length of the previous trip.

2.1.2 Vehicle-trip-based models

Vehicle-trip-based models focus on modeling the supply side of urban freight system, i.e., the movement of commercial vehicles. The most basic vehicle-trip-based freight models were modified from passenger-oriented models. Among them, the four-step process and the methods of OD synthesis account for the majority of the literature.

The first type of methods, i.e., the ones based on the four-step process, follow a procedure composed of trip generation, trip distribution, mode split and traffic assignment. The conventional four-step planning model introduced in the Quick Response Freight Manual (QRFM) (Cambridge Systematics et al., 1996) is a typical example. This model consists of four sequential steps: (1) trip generation for each traffic analysis zone (TAZ) by applying trip generation rates; (2) trip distribution between the TAZs by using the gravity model; (3) mode split that determines the commodity flow OD matrix by mode; and (4) traffic assignment that dispatch commercial vehicle trips to the urban network under the principle of user equilibrium. This proposed framework was applied successfully to predict truck traffic under different degrees of geographic resolution in Pennsylvania (Marker and Goulias, 1998).

In addition to the four-step method, origin-destination synthesis (ODS) models are a special class of vehicle trip based models. The fundamental objective of OD synthesis is to produce an estimate of the trip flow OD matrix that matches secondary data, link traffic counts or any other easily observable data. Different from the four-step planning method, it needs neither land use data to estimate the trip generation rates nor the complete base-year trip OD matrix to calibrate the trip distribution model. Therefore, OD synthesis has the potential of minimizing data collection costs and, ultimately, speeding up the process of model calibration and updating.

A number of OD synthesis methods have been developed to model vehicle trips. They can be categorized into the structured approaches and the unstructured approaches in terms of the methodologies involved (Willumsen, 1978; Ortúzar and Willumsen, 2001). The former imposes a model structure on the estimation problem which reduces it to a parameter estimation problem, subject to traffic count constraints while the latter uses general principles such as entropy maximization, information minimization or maximum likelihood to reduce the feasible space so that the problem has a unique solution. In terms of the variation in the time dimensionality and the underlying traffic assignment models used, these approaches can be further classified as: (1) static estimation and dynamic estimation; or (2) methods not requiring route choice, methods requiring proportional route choice, and methods requiring non-proportional route choice.

Compared with a significant amount of research conducted for passenger transportation, only a handful of OD synthesis methods were developed to estimate the freight trip OD matrices. Using the similar concept, the freight trip OD matrix was estimated by either an optimization programming that minimized the deviation of estimates from observations, or running an adaptive traffic assignment module. As an example of the former, Tamin and Willumsen (1988, reprinted in 1992) used both the non-linear least squares estimation method and the maximum likelihood estimation method to specify the parameters in the trip distribution models that best reproduce a given set of observed link freight traffic counts. Three types of trip distribution models, i.e., gravity (GR), opportunity (OP) and gravity-opportunity (GO) models were examined by a test data collected in Bali Province, Indonesia. As found, the gravity opportunity model produced an OD matrix which gave the best fit to the observed ones. As an example of the latter, a new commercial trip forecasting model was developed for the Baltimore Metropolitan Council (BMC) (Allen and Agnello, 2004). This model synthesized commercial vehicle counts at those locations where classification count data already existed. This method relies on a procedure that works backwards to develop trip tables from count data. The corresponding procedure consisted of three steps: first, a starting commercial vehicle trip table was obtained based on a model borrowed from another urban area; then, a procedure called adaptable assignment was used to assign the starting trip table, which systematically compared the resulting assigned link volumes to the counts and adjusted the trips to produce a closer match between assigned volumes and counts; consequently, the ratios between the new trip table and the starting trip table were calculated as the adjustment factor table for the future-year forecasting.

The major challenge of applying OD synthesis methods to model urban freight travel demand comes from the availability of data. In most urban areas, freight traffic counts are not collected or maintained as well as passenger traffic counts. Therefore, the freight-related OD synthesis methods have to explore all possible sources. Two studies have been dedicated to solve this issue. The first one is the work done by List and Turnquist (1994). They developed a formulation for estimating multi-class truck trip matrices in urban areas with the capability for a wide variety of input data in addition to link counts. In the proposed model, the estimation of trip matrices was treated as a large-scale linear programming problem in which the objective was to minimize the weighted sum of all deviations from the observed values, given: (1) the choice variable definitions provided by the user; (2) the network definition; and (3) the link use coefficients provided by the traffic assignment algorithm. The case study in Bronx in New York City confirms the effectiveness of this method. A total of nine OD matrices were estimated considering three time periods (a.m. peak, midday and p.m. peak) and three truck classes (vans, medium trucks and heavy trucks).

The other effort is from Rios et al. (2002) who assessed impact of different types of input information on the quality of estimation. Three types of observations were considered in this paper: (1) the origin and destination totals; (2) partial and aggregate OD entries; and (3) link counts. An optimization model, which combines the entropy maximization formulation and a weighted sum of squares of the differences between estimates and observations, was used to assess the quality of the estimate of the OD table that would likely result in given specific amounts of each type of information. These experiments indicate that link count information is very useful, followed by aggregate OD entries and the origin and destination totals.

Another challenge of applying the OD synthesis methods to forecast urban freight demand comes from the multiple flows existing in urban freight systems. As illustrated by Figure 1, three major flows, i.e., the monetary flow, the commodity flow, and the vehicle flow, are involved in urban freight movements. They represent different dimensions of freight systems, and thus need to be estimated by using different unidimensional demand modeling platforms. Since most of the OD synthesis techniques start with a re-calibrated demand model to adjust estimates to match observed secondary data, the introduction of different demand modeling platforms to the OD synthesis methods leads to various versions of the OD synthesis processes. The two studies reviewed previously (List and Turnquist, 1994; Rios et al., 2002) represents the vehicle-trip-based OD synthesis methods. They focus on the estimation of commercial vehicle trips flows, and adjusted the OD tables to match the link counts. Differently, Holgu ń-Veras and Patil (2008a and 2008b) used commodity-based formulations to estimate freight demands in order to consider the role of commodity type. They introduced a multi-commodity, single (generic) vehicle formulation of freight ODS model that combined a commodity-based model to estimate loaded truck trips and a complementary model of empty trips. As found, the integrated OD synthesis method that takes into account the empty trips and various commodity types substantially reduced the error associated with the estimation of observed traffic counts.

2.1.3 Aggregate tour-based model

A very little contribution has been made in aggregate tour-based planning models. The only related research found in the literature is the work conducted by Maruyama and Harata (2005). They developed three types of combined network equilibrium models that incorporate trip chaining behavior, including a combined trip distribution and assignment model for piston-type tours (tours with only one stop), a combined modal split and assignment model for the same type of tours, and a combined trip distribution and assignment model for general tours (tours with any number of stops). In these proposed models, the numbers of tours, rather than trips, were set as the decision variables. The processes of trip distribution, mode split and assignment were modeled as minimization problems under the constraints of trip chain flows, OD flows, route flows and link flows. Since these optimization problems are convex, a partial linearization method was used to find the optimal solution. However, because the modeling framework was proposed for overall traffic flows in the network, the potential applications and the corresponding issues in forecasting urban freight demand were not discussed.

2.2 Disaggregate-level approaches

In recent years, one of the unique features of urban commercial vehicle movements, i.e., trip chaining behavior, has been receiving more and more attentions. As discussed elsewhere (Ogden, 1992; Holguín-Veras and Thorson, 2003; Holguín-Veras and Patil, 2005), commercial vehicles tend to make multiple deliveries in one tour, and the corresponding trips are interrelated according to the underlying logistic decisions. These long tours break down the typical assumption implicit in trip-based demand models, which postulates that trips are made independent, and as consequence, trips between an origin-destination (OD) pair are only related to the zonal attributes and the travel impedance of the corresponding OD pair. Therefore, new paradigms of freight transportation models considering the interactions between commercial vehicle trips are needed for urban freight travel demand modeling.

In order to address this feature, a handful of tour-based models have been formulated at the disaggregate level to model urban freight movements. They modeled commercial vehicle tours as a vehicle routing problem, a simulated trip chaining process, or the byproduct of activity itineraries. In this context, these disaggregate-level models are categorized into three groups: (1) vehicle routing problems; (2) tour-based disaggregate models; and (3) activity-based disaggregate models.

2.2.1 Vehicle routing problems

In the majority of literature, finding tours visited by commercial vehicles is considered as a vehicle routing problem. As have been summarized by Cordeau (2002), Feillet (2005) among others, the vehicle routing problem (VRP) consists of designing *m* vehicle routes of least total cost, each starting and ending at the depot, such that each customer is visited exactly once, the total demand of any route does not exceed the vehicle capacity, and the length of any route does not exceed a preset maximal route length. The basic VRP can be extended by taking into account time windows of customers' requests, heterogeneity of vehicle fleets, tasks conducted by vehicles, the number of home depots, and operational restrictions faced by vehicles.

A number of algorithms have been developed to solve the VRP problem. They can be categorized as the exact algorithms or the heuristic methods depending on whether an exact optimal solution or an approximate solution is reached. The exact algorithms often used include various versions of branch and bound methods (Fisher, 1994) and the branch and cut technique (Araque et al., 1994; Ralphs, 2003). Suffering from the difficulty of deriving the sharp lower bounds of the objective values, the exact algorithms are found to be computationally expensive and inadequate to solve large instances of VRP problems. In this context, heuristic methods are commonly used in practice.

Several families of heuristics have been proposed for the VRP. As summarized by Laporte et al. (2000), they can be classified into two main groups: the classical heuristics developed mostly between 1960 and 1990, and the metaheuristics occurring in the last decade. The classical heuristics perform a relatively limited exploration of the search space and generally produce good quality solutions within modest computing times. The typical classical heuristics include the well-known savings algorithm (Clark and Wright, 1964), the sweep algorithm (Gillett and Miller, 1974), the petal algorithms (Balinski and Quandt, 1964; Ryan et al., 1993; Renaud et al., 1996), the cluster-first-route-second algorithms (Fisher and Jaikumar, 1981), and the improvement heuristics (Lin, 1965; Thompson and Psaraftis, 1993). Metaheuristics, with an emphasis on a deep exploration of the most promising regions of the solution space, are characterized by the various forms of tabu search heuristics (Gendreau et al., 1994; Tailard 1993; Xu and Kelly, 1996; Rego and Roucairol, 1996; Rochat and Taillard, 1995; Barr et al., 1995; and Golden et al., 1998), constraint programming (Shaw, 1998), colony optimization (Gambardella, 1999) and evolutionary computation techniques (Louis, 1999).

As one of the well developed area in transportation engineering as well as operations research, VRP has been solved widely to obtain commercial vehicle tours. However, it is only applied to small networks in most of cases due to the computational complexity of the problem. Meanwhile, its typical assumption of cost minimization may not represent the real-work urban freight operations in which participants compete with each other to maximize profits in short term and/or market shares in long term.

2.2.2 Microsimulation-based tour models

The microsimulation-based tour models can be categorized into the commodity-based tour models and the vehicle-trip-based models, depending on if the commodity flows or the commercial vehicle flows are addressed primarily. The former generate individual commercial vehicle tours one after another in order to satisfy the given or estimated commodity demands. In contrast, the latter neglects the role of commodity flows, while emphasizing the tour making process by taking into account the purposes, location visited and duration time spent.

2.2.2.1 Commodity-based tour models

This group of models addresses the relationship between commodity flows and commercial vehicle flows. In these models, commercial vehicle tours are constructed individually in order to satisfy the known commodity flows in the network.

One example is the microsimulation framework proposed by Raothanachonkun et al. (2007) in which the commercial vehicle movement was perceived as a demand derived from the needs of shipping commodities. In the proposed framework as shown in Figure 6, the commodity flow OD matrix was converted to the truck flow OD matrix in the Tokyo Metropolitan area by using the characteristics of freight such as average payload and average unloading weights. The overall commodity OD matrix was split into two groups according to the number of stops in the generated tours, i.e., the OD matrix of commodities shipped by the zero-order trip chains (round trips) and the one by the higher-order trip chains. For the commodity flow OD matrix belonging to the zero-order trip chains, the commodity flows were directly converted to commercial vehicle flows by using the average payload. For the commodity flow OD matrix belonging to the higher-order trip chains, a sequential procedure was used to expand a tour by adding one stop after another until the tour is completed. The average payloads were used as a criterion to select stops: the alternative traffic analysis zone with the maximum average payload shipped from current location was chosen as the next stop.

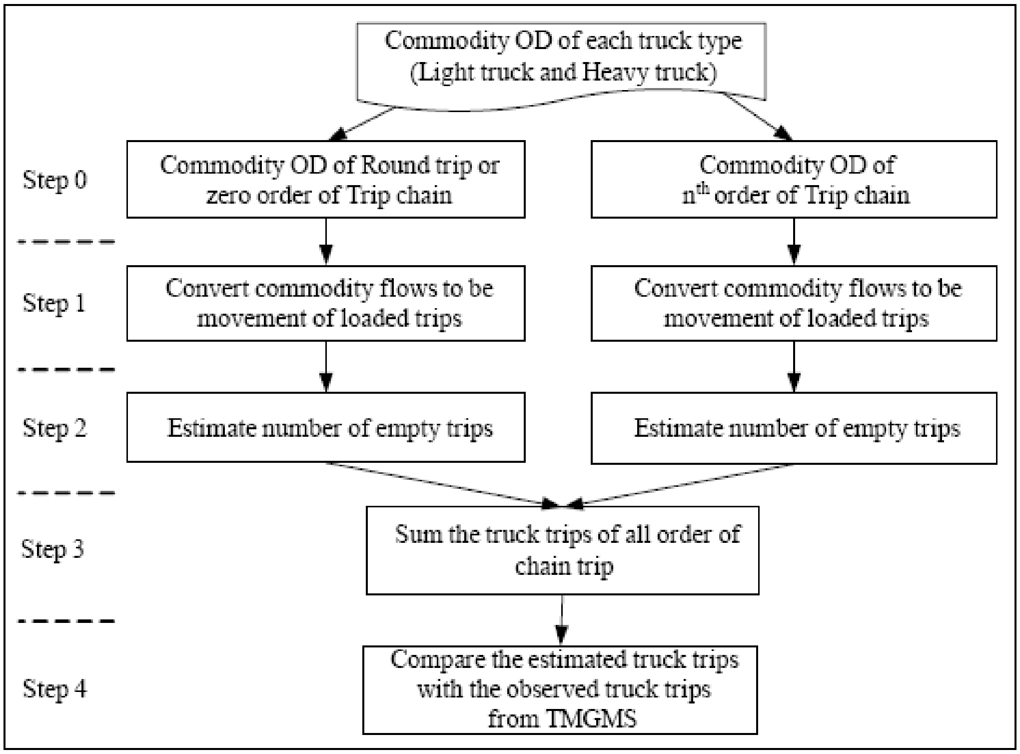


Figure 6: Logistics-based microsimulation framework (Raothanachonkun, et al., 2007)

This study is one of a very few freight demand models that address the relationship between commodity flows and commercial vehicle flows by incorporating trip chaining behavior of commercial vehicles. However, its several disadvantages limit its applications. One disadvantage comes from the trip chain patterns considered. The study focuses on only one shipment pattern, i.e., the trips chains composed of delivery trips, while ignoring other trips chains with mixed pick-up and delivery tasks. Another disadvantage is related to its criteria of choosing stops along a tour. Since the average payload, rather than distance or travel time, is used as the major criteria of choosing next destination, the resulting trip length distribution may not resemble the observed one in real world.

Donnelly (2007) developed a hybrid-microsimulation-based framework to distribute freight flows, in which solving a vehicle routing problem is a major step to consolidate multiple shipment tasks to tours. This framework is shown in Figure 7. It started with obtaining the commodity flow OD matrix from dollar flows between OD pairs by using value density functions derived from the Commodity Flow Survey (CFS) 1997. Then, the commodity flow of each commodity type between each OD pair was broken down into small pieces of shipments (discrete shipments) that are suitable for individual trucks. Considering the important role of trans-shipments (TF) points, e.g., warehouses, distribution centers, break-bulk and reload facilities, a probability was calculated to determine whether a trans-shipment stop is made during a discrete shipment or not. If the trans-shipment stop was made during a discrete shipment, the original discrete shipment is split into two independent shipments, i.e., the one from the origin to the trans-shipment facility, and the other from the trans-shipment facility to the destination. After the pool of discrete shipments was completed, they were assigned to shipper-receivers pairs, and then dispatched to carriers and vehicles using Monte Carlo techniques. The shipment list was next sorted by vehicle identifier. Then, a classical traveling salesman problem (TSP) was used to find the optimal tour that fulfills the shipment tasks assigned to each vehicle. Here, the objective of the TSP problem was to minimize the total distance traveled.

This paper addressed three major issues of freight movements that have been overlooked by previous studies: (1) the interactions between shippers, receivers and carriers; (2) the important role of trans-shipment points in freight movements; and (3) commercial vehicle tours. However, due to the unavailability of data, not much attention was paid to behavioral considerations in the simulation process. Random draws, rather than behavioral models, were used to decide the size of each discrete shipment, the assignment of shipments among shipper-receiver pairs, and the assignment of carrier and vehicle type. This may lead to estimations that are inconsistent with the observed trip chaining behavior.

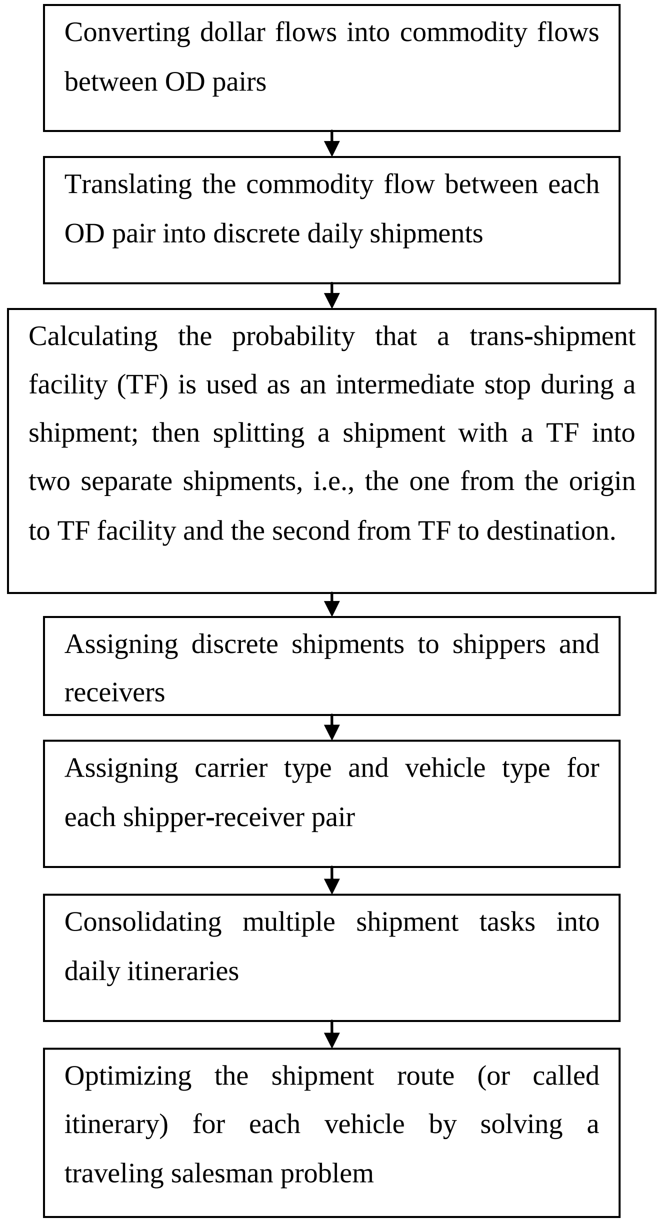


Figure 7: Hybrid-microsimulation-based modeling framework (Donnelly, 2007)

2.2.2.2 Vehicle-trip-based tour models

In urban areas, commercial vehicle flows are made for different purposes such as service, meeting and sales calls, in addition to the purpose of handling goods. In the city of Calgary in Canada, approximately 45% of all business stops were made to provide a service, with 25% transporting goods and 30% being performed by transportation handling companies providing the service of moving goods (Stefan et al., 2005).

Consistently, 35% and 37% of service trips, have been revealed in the city of Alberta (Hunt et al., 2006) and in the urban areas of Ohio State (Gliebe et al., 2007) respectively. The variety of trip purposes leads to different travel patterns. For instance, service related trips usually cover shorter distance and are more likely to use light vehicles while trips handling goods are characterized by relatively longer distance traveled and medium/heavy vehicles used. This feature requires models that can handle commercial vehicle tours with different purposes.

A system of modeling commercial movements for Calgary in Canada is one innovative attempt (Stefan et al., 2005; Hunt and Stephan, 2007). A tour-based microsimulation framework was developed for modeling commercial vehicle movements in Calgary in Canada as shown in Figure 8.

The authors used Monte Carlo techniques to construct each tour from a list of tours generated from each traffic analysis zone, by determining the tour purpose, vehicle type, next stop purpose, next stop location, and next stop duration sequentially. The Monte Carlo probabilities were estimated using a series of logit models, with coefficients estimated from a survey of commercial movements. As identified by these logit models, the decisions of choosing tour purposes, vehicle types, stop purposes and stop locations are affected by zonal attributes, cost factors, land use types and establishment types. These attributes, in total, determine the patterns of commercial vehicle tours.

This framework considered tours with different purposes and identified the key attributes that affect the travel pattern associated with each tour purpose. However, for goods-handling tours, the commodity movements that act behind the goods-handling tours were overlooked.

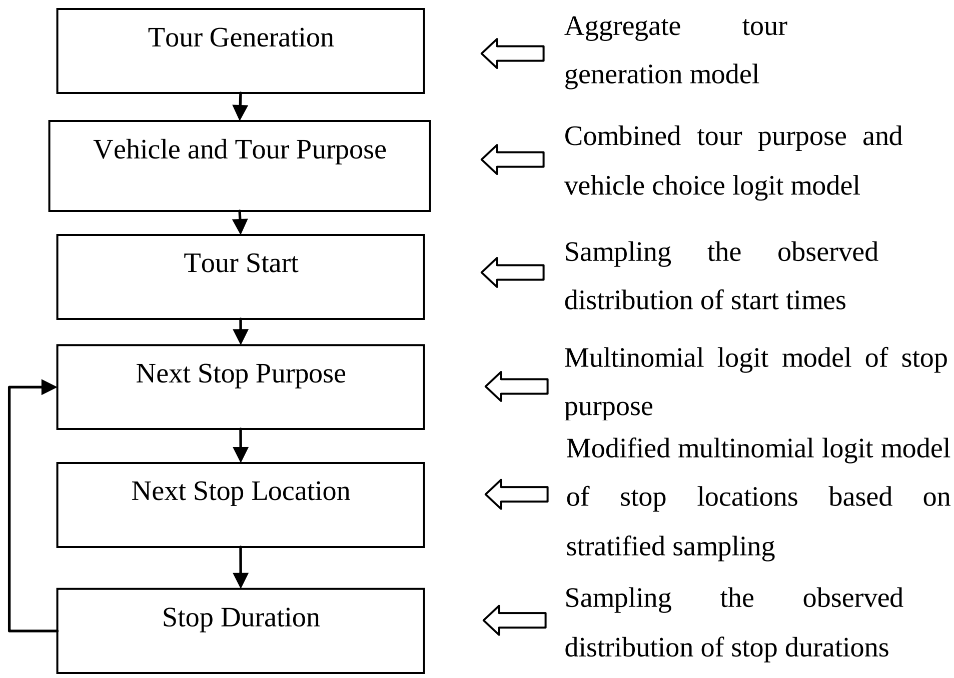


Figure 8: Commercial-vehicle-tour-based microsimulation framework (Hunt and Stephan, 2007)

2.2.3 Activity-based tour models

In recent years, activity-based modeling approaches, which were originally developed to estimate passenger travel demand, have been adopted to study urban commercial vehicle flows. This approach views travel as a derived demand from the need to pursue activities distributed in space (Bhat et al., 1999; Misra et al., 2003; Frusti et al., 2003). Since it focuses on the interactions between activities and travel, this approach is able to connect trips to form vehicle tours. Compared to the traditional four-step planning approach, it captures the link between trips along the time dimension rather than considering individual trips as the independent unit of analysis. This approach usually uses a microsimulation-based framework in which discrete choice models are specified to generate probabilities for simulating activity or travel itineraries. As an important step of model specification, this approach requires an expensive data collection procedure to provide revealed individual travel diaries.

The activity-based Disaggregate Commercial Model (DCM) proposed by Gliebe et al. (2007) is one application of the activity-based approach in modeling urban freight movements. The authors developed a method to model intra-urban commercial vehicle movements, focusing on the generation of activity patterns using a dynamic discrete choice model formulation, implemented in a microsimulation environment.

The structure of the activity-based model is shown in Figure 9. It started with the traveler generation in which a list of individual worker traveler records by industry type was created in each traffic analysis zone (TAZ) for the simulation day. Then, a vehicle was assigned to each traveler record for the entire day based on a binary logit model, considering establishment type and TAZ land use type. Following this, a starting time, which was randomly drawn from an empirical distribution of starting times, was assigned for the first departure from the establishment. Then, a dynamic activity pattern generation model was used to generate activity itineraries and the associated trip chains. The dynamic activity pattern generation model was composed of two discrete choice models, i.e., the next stop purpose choice model and the next stop location choice model. The objective of the next stop purpose choice model was to determine whether the vehicle is going to continue the current activity, move to a new activity stop or return to the establishment. A utility function was specified for each of the three alternatives. In order to assess the impact of time on the utility of each alternative, three time-variant factors, i.e., the elapsed time of current activity, the elapsed time of current tour and/or work shift, and the time-period specific effects, were introduced to these utility functions. Meanwhile, these utility functions were estimated for each type of current activity in order to take into account the variability of transition constants. As the second major component of the dynamic activity pattern generation formulation, the next stop location model was developed to determine which stop will be visited next, considering the establishment type and the stop purpose. A series of logit models were specified for choosing next stop locations, in which travel time and the attractiveness indicator of an alternative destination zone were included as independent variables.

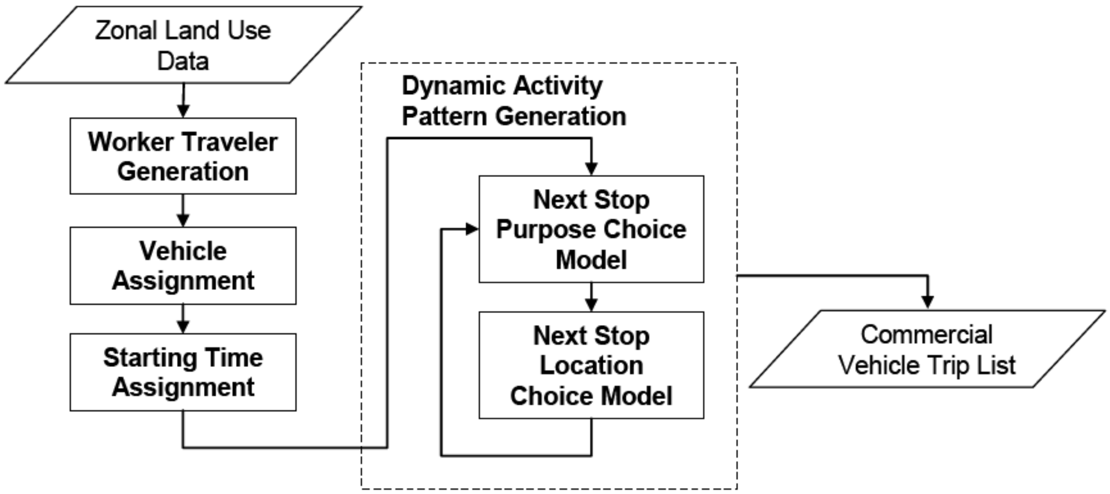


Figure 9: Activity-based disaggregate commercial model (DCM) (Gliebe et al., 2007)

The major advantage of these activity-based approaches is their behavioral soundness. The sequential choices made by each traveler in their daily activities are generated from either discrete choice modeling or observed data. Therefore, they represent the behavioral principles that travelers follow to arrange their commercial related activities and the corresponding travels in the real world. However, with their core interest in vehicle tours, the relationship between commodity flows and commercial vehicle tours is usually neglected in these approaches.

2.3 Literature review summary

In this section, literature relevant to the state of the art of urban freight travel demand modeling was summarized. The corresponding modeling efforts were categorized as aggregate or disaggregate approaches, depending on whether the overall patterns of urban freight movements or the behavior of individual freight participants are analyzed. Furthermore, each category was branched into different subgroups considering the different analysis units used (e.g., tons of commodities, trips or tours)

The aggregate-level approaches model the conglomeration of user demand. Depending on whether the demand side, i.e., the consignment of commodities, or the supply side of freight systems, i.e., the dispatching of vehicles, is the core interest, aggregate methods can be classified as commodity-based or vehicle-trip-based. The final outcome is the vehicle trips, which are either directly estimated from the vehicle-trip-based models or converted from the commodity flows obtained from the commodity-based models. As found, very little contribution has been made in the aggregate tour-based demand models.

In terms of the disaggregate-level approaches, only a handful of microsimulation-based models have been formulated to estimate urban freight demand. They focus on either individual tours or individual traveler’s activity itineraries. Thus, they were categorized into two groups: the tour-based disaggregate models and the activity-based disaggregate models. These approaches involved behavioral models to take into consideration the trip chaining decisions of commercial vehicles. However, they only focused on one dimension of freight movements, e.g., commodity flows, vehicle flows or activity flows while paying little attention on the relationships between them.

To address the issues and challenges identified in the literature review, the following chapters will introduce two approaches that consider trip chaining behavior of commercial vehicles. Chapter 3 and 4 will describe an entropy-based tour distribution model and its essential component, i.e., the tour choice model, in response to the lack of aggregate tour-based demand models. Meanwhile, Chapter 5 will focus on the development of a hybrid-microsimulation-based model that considers the trip chaining behavior as well as the relationship between commodity flows and vehicle flows.

3. Entropy-Based Tour Distribution Model

One of the major obstacles to urban freight demand forecasting is the lack of aggregate-level models that consider commercial vehicle tours. To bridge the gap, a powerful method, i.e., entropy maximization is adopted to develop tour-based urban freight travel demand models, given the aggregate information available in the network.

This method states that when no enough information is available to model the trip chaining behavior of individual commercial vehicles in an urban area, the individual flows of commercial vehicles expected to travel along any tour in the network are assumed to be equally probable unless information is available to the contrary; furthermore, of all the feasible ways to distribute commercial vehicle flows to the tours in the network, the most probable ones would be those that can be generated in the greatest number of ways under the constraints of the known aggregate information. Here, the known aggregate information includes the total number of commercial vehicle trips produced by (trip production) or attracted to (trip attraction) each node and the total travel impedance of the network. Based on this, the resulting entropy formulations are aimed to find the most likely set of tour flows that meet the system's constraints such as the trip production or trip attraction of each node and the total impedance of the entire network. Meanwhile, the total impedance constraints are added in order to assess the impact of tour impedance on the distribution of tour flows.

The rest of the chapter is organized as follows. Section 3.1 reviews the method of entropy maximization and its solution algorithms. Section 3.2 defines two variants of entropy maximization formulations for modeling commercial vehicle tour flows, taking into account different impedance variables. The theoretical solutions of tour flows and the characteristics of the proposed formulations are assessed afterwards. Section 3.3 presents the results from a case study in the Denver metropolitan area. Section 3.4 analyzes the impact of different impedance variables on the estimation performance. Based on the findings, section 3.5 discusses the potential applications of this approach for the purpose of urban freight demand forecasting. The chapter ends with conclusions.

3.1 Entropy maximization and its solution algorithms

Entropy maximization has been used as the foundation of model development in transportation since Wilson's seminal publication (Wilson 1967). In his work, trips are used as the analysis units, and three trip-related states are defined for the system of interest: (1) a micro state that consists of individual trip; (2) a meso state that specifies the number of trips between each OD pair; and (3) an even higher level of aggregation, a macro state, which represents the total numbers of trips produced by and attracted to each traffic analysis zone (TAZ) in the network. The entropy is defined as the number of ways of generating meso states in the network. In entropy maximization, the micro states are assumed to be equally probable unless information is available to the contrary. Meso states are not equally likely, and the most probable ones would be those that can be generated in a greatest number of ways. To maximize entropy is to find the greatest number of ways of generating meso states, given the relationships between the meso states and macro states as the constraints.

The method of entropy maximization is generally acknowledged as one of the most important contributions to transportation modeling theory as, among other things, provides theoretical support to a variety of models in transportation planning. Wilson (1967, 1969, and 1970) derived the gravity model of trip distribution, the mode split model and the route split model by using entropy maximization. Tomlin (1971) and Erlander (1977) proved that the entropy maximization formulation can easily lead itself to a combined distribution and assignment problem if the path flows replace the OD flows as the decision variables, and the relationship between the two types of flows are added to the constraint set. Depending on whether the link impedances or the path impedances are summed up as the total impedance, it can generate the traffic assignment model with the version of either user equilibrium or system optimization.

In order to solve the proposed models, researchers studied the property of entropy maximization formulations and the corresponding solution algorithms. The trip-based formulations were found to be convex. Hence, various convex optimization algorithms were used to solve the problems. The best known algorithms include Bregman's balancing method (Lamond and Stewart 1981), the multiplicative algebraic reconstruction technique (MART) (Lent 1976), and Newton's method (Eriksson 1980;

Erlander 1981). Interested readers are referred to Elfving (1980) for some other method schemes and their relationsips with the three algorithms mentioned above. In addition, other algorithms feasible for solving nonlinear convex programs have the potential to be applied. They include the convex combination algorithm (Frank and Volfe 1956) and the primal-dual interior method for optimization programs with convex objectives (PDCO) (SOL 2005; Paige and Saunders 1975; Saunder 1996; Saunder and Tomlin 1996).

PDCO is a primal-dual interior method developed for solving convex programs with linear constraints. The optimal solutions for both the primal and the dual problems are found using the following procedure. The original convex program is regularized at first to improve the stability of the solver. Then, an equivalent barrier subproblem is developed to replace the non-negativity constraints by the log barrier function. The necessary and sufficient Karush-Kuhn-Tucker (KKT) conditions are generated for the corresponding subproblem, which involve both the primal equations and dual equations. Finally, Newton's method is applied to solve the KKT conditions.

Among the potential solution algorithms, the PDCO method is chosen as the solution algorithm for two reasons. First, this algorithm has been found to be very efficient in solving large-scale entropy maximization problems. Second, it allows setting the lower and upper bounds for the decision variables, which enables the specification of the feasible ranges of decision variables according to reality.

3.2 Tour-based entropy maximization formulations

Before the problem is mathematically formulated, it is important to remind the concepts of "tour," "trip," and "tour flow." A "tour" is defined as the sequence of nodes visited by a vehicle, which starts and ends at the vehicle's home base. An individual vehicle movement connecting two consecutive stops is referred to as a "trip". The number of vehicle journeys following a specific tour during a certain time period is referred to as "tour flow." These definitions are consistent with previous publications (Holgu ń-Veras and Patil 2005).

In addition to the definitions above, the specification of the total impedance of a network needs special attention. For a given tour, its impedance is composed of two components: the summation of travel impedance in each trip along a tour (tour travel impedance), and the summation of handling impedance at each stop in the tour (tour handling impedance). The two impedance variables may have different effects on the tour flows. To address this issue, two cases are considered. In the first case, the two impedance variables are added to form the overall impedance of a tour (tour impedance). In the second case, the two impedance variables are considered separately so that their specific effects can be assessed independently.

Two variants of entropy maximization formulations are developed in order to accomplish this. The first formulation includes only one impedance-related constraint, the total tour impedance, i.e., the summation of tour impedances experienced by all tour flows in the network, while the second one uses the total tour travel impedance and the total tour handling impedance, separately as the impedance constraints. For each formulation, this section focuses on the following analysis: (1) the mathematical formulation; and (2) the first and second order conditions of the formulation.

3.2.1 Entropy maximization formulations

The entropy maximization formulations developed here intend to solve the tour distribution problem of commercial vehicles in an urban area. For modeling purposes, three states are defined for an urban freight system of interest (see Table 1).

Table 1: Definitions of tour-based system states

State	State variable
Micro state	Individual commercial vehicle journey starting and ending at a home base (tour flow) by following tour *m*;
Meso state	t_m : The number of commercial vehicle journeys (tour flows) following tour *m*;
Macro state	O_i : Total number of trips produced by node *i* (trip production); D_j : Total number of trips attracted to node *j* (trip attraction); Formulation 1: C : Total tour impedance in the commercial network; Formulation 2: C_T : Total tour travel impedance in the commercial network; C_H: Total tour handling impedance in the commercial network.

Note: $m \in \{1,2,\ldots,M\}$, and *M* is the total number of tours.

The first entropy maximization formulation is as following:

$$Max \qquad W = C_T^{t_1} \bullet C_{(T-t_2)}^{t_2} \bullet \ldots = \frac{T!}{\prod_{m=1}^{M} t_m!} \tag{3-1}$$

Subject to:

$$\sum_{m=1}^{M} a_{im} t_m = O_i, \qquad \forall i \in \{1,2,\ldots,N\} \tag{3-2}$$

$$\sum_{m=1}^{M} a_{jm} t_m = D_j, \qquad \forall j \in \{1,2,\ldots,N\} \tag{3-3}$$

$$\sum_{m=1}^{M} c_m t_m = C \tag{3-4}$$

$$t_m \geq 0, \qquad \forall m \in \{1,2,\ldots,M\} \tag{3-5}$$

Where:

W: System entropy that represents the number of ways of distributing commercial vehicle tour flows;

T: Total number of commercial vehicle tour flows in the network;

$C_T^{t_m}$: Combination of selecting the number of tour flow t_m from *T*;

M: Total number of possible tours in the system;

N: Total number of nodes in the system;

a_{im}: A binary variable indicating whether node *i* is in tour *m*: if yes, $a_{im} = 1$; otherwise, $a_{im} = 0$;

c_m: The impedance of tour *m*, which is the summation of the travel impedance and the handling impedance in the tour.

The formulation above is composed of one objective function and four groups of constraints. Statement (3-1) indicates that the objective of this problem is to find the most likely ways to distribute tours. The first group of constraints (equation (3-2)) is the trip production constraints. They indicate that the summation of the tour flows passing a node has to be equal to the total number of trips produced by this node. The second group of constraints, i.e., equation (3-3), is the trip attraction constraints, which indicates that the summation of the tour flows passing a node has to be equal to the total number of trips attracted to this node. Equation (3-4) is the total impedance constraint. It means that the summation of impedances of tour flows equals the total impedance in the network. The last group of constraints, i.e., equation (3-5), is the nonnegative constraints which mean that the resulting tour flows should be equal to or greater than zero.

Following Wilson (1967), the objective function can be simplified. Taking the natural logarithm, the objective function becomes:

$$Max \qquad z' = \ln(W) = \ln(T!) - \sum_{m=1}^{M} \ln t_m! \tag{3-6}$$

The term $\ln(T!)$ in equation (3-6) is a constant that can be dropped from the objective function, given that the total number of tour flows (T) is fixed. Since the maximization of $z' = \ln(W)$ is equivalent to the minimization of $z'' = -\ln(W)$, the objective function can be represented as below:

$$Min \qquad z'' = \sum_{m=1}^{M} \ln t_m! \tag{3-7}$$

Using the Stirling's formulation ($\log x! = x \ln x - x$), this objective function becomes:

$$Min \qquad z = \sum_{m=1}^{M} (t_m \ln t_m - t_m) \tag{3-8}$$

Meanwhile, since only tours are considered here, constraint (3-2) and (3-3) are redundant according to the principle of flow conservation for the tours. Therefore, either of them can be dropped out of the formulation. This results in an equivalent minimization program, as follows:

<u>Tour-based formulation 1:</u>

$$Min \qquad z = \sum_{m=1}^{M} (t_m \ln t_m - t_m) \tag{3-9}$$

Subject to:

$$\sum_{m=1}^{M} a_{im} t_m = O_i, \qquad \forall i \in \{1,2,..., N\} \qquad (\lambda_i) \tag{3-10}$$

$$\sum_{m=1}^{M} c_m t_m = C \qquad (\beta) \tag{3-11}$$

$$t_m \geq 0, \qquad \forall m \in \{1,2,..., M\} \tag{3-12}$$

Where:

λ_i = Lagrange multiplier associated with the trip production constraint of i^{th} node;

β = Lagrange multiplier associated with the total impedance constraint.

The second entropy maximization formulation considers the travel impedance and the handling impedance of a tour separately, while sharing the same objective function and the trip production/attraction constraints with the first formulation. It is specified as following:

Tour-based formulation 2:

$$Min \qquad z = \sum_{m=1}^{M} (t_m \ln t_m - t_m) \tag{3-13}$$

Subject to:

$$\sum_{m=1}^{M} a_{im} t_m = O_i, \qquad \forall i \in \{1,2,...,N\} \qquad (\lambda_i) \tag{3-14}$$

$$\sum_{m=1}^{M} c_{T\,m} t_m = C_T \qquad (\beta_1) \tag{3-15}$$

$$\sum_{m=1}^{M} c_{H\,m} t_m = C_H \qquad (\beta_2) \tag{3-16}$$

$$t_m \geq 0, \qquad \forall m \in \{1,2,...,M\} \tag{3-17}$$

Where:

c_{Tm} : Tour travel impedance in tour *m*;

c_{Hm} : Tour handling impedance in tour *m*;

C_T : Total travel impedance in the network;

C_H : Total handling impedance in the network;

β_1 : Lagrange multiplier associated with the total travel impedance constraint;

β_2 : Lagrange multiplier associated with the total handling impedance constraint.

As can be seen, two new impedance constraints (equation (3-15)-(3-16)) replaced the total impedance constraint (equation (3-11)) in formulation 1. The first impedance constraint indicates that the summation of tour travel impedances equals the total travel impedance in the network while the second requires that the summation of tour handling impedances equals the total handling impedance in the network. Since they consider the travel impedance and the handling impedance independently, they are associated with different Lagrange multipliers (β_1, β_2).

3.2.2 First and second order conditions of the formulations

In order to understand the characteristics of the entropy maximization formulations, the first-order conditions (or Karush-Kuhn-Tucker conditions (KKT) conditions) and the second-order conditions (Hessian matrix), are obtained for the two formulations, separately.

3.2.2.1 First-order conditions of formulation 1

The Lagrange function of the first formulation is:

$$L(t,\lambda,\beta)=\sum_{m=1}^{M}(t_m \ln t_m - t_m)+\sum_{i=1}^{N}\lambda_i(O_i-\sum_{m=1}^{M}a_{im}t_m)+\beta(C-\sum_{m=1}^{M}c_m t_m) \tag{3-18}$$

The partial derivative of the Lagrange function with respect to the number of tours t_m is:

$$\frac{\partial L(t,\lambda,\beta)}{\partial t_m}=\ln t_m-\sum_{i=1}^{N}\lambda_i a_{im}-\beta c_m \qquad \forall m\in\{1,2,...,M\} \tag{3-19}$$

Then, the first-order conditions of the model can be written as following. These conditions are necessary conditions for t^*,λ^*,β^* to be the optimal solutions of the model.

$$t_m^*\frac{\partial L(t^*,\lambda^*,\beta^*)}{\partial t_m}=0 \qquad \forall m\in\{1,2,...,M\} \tag{3-20}$$

$$\frac{\partial L(t^*,\lambda^*,\beta^*)}{\partial t_m}\geq 0 \qquad \forall m\in\{1,2,...,M\} \tag{3-21}$$

$$\frac{\partial L(t^*,\lambda^*,\beta^*)}{\partial \lambda_i}=0 \qquad \forall i\in\{1,2,...,N\} \tag{3-22}$$

$$\frac{\partial L(t^*,\lambda^*,\beta^*)}{\partial \beta}=0 \tag{3-23}$$

$$t_m^*\geq 0 \tag{3-24}$$

As can be seen, equation (3-22) and (3-23) are equivalent to constraint (3-10) and (3-11). Meanwhile, if the derivatives of the Lagrange function in (3-20) and (3-21) are replaced by (3-19), the first-order conditions for the model can be written explicitly as follows:

$$t_m^*(\log t_m^* - \sum_{i=1}^{N} \lambda_i^* a_{im} - \beta^* c_m) = 0 \qquad \forall m \in \{1,2,..., M\} \tag{3-25}$$

$$\log t_m^* - \sum_{i=1}^{N} \lambda_i^* a_{im} - \beta^* c_m \geq 0 \qquad \forall m \in \{1,2,..., M\} \tag{3-26}$$

$$\sum_{m=1}^{M} a_{im} t_m^* = O_i, \qquad \forall i \in \{1,2,..., N\} \tag{3-27}$$

$$\sum_{m=1}^{M} c_m t_m^* = C \tag{3-28}$$

$$t_m^* \geq 0 \tag{3-29}$$

Equation (3-25) is equivalent to:

$$t_m^* = \begin{cases} 0, \quad \text{if} \quad \ln t_m^* - \sum_{i=1}^{N} \lambda_i^* a_{im} - \beta^* c_m \neq 0 \quad \text{or} \quad t_m^* \neq \exp(\sum_{i=1}^{N} \lambda_i^* a_{im} + \beta^* c_m) \\ \quad \text{or} \\ \exp(\sum_{i=1}^{N} \lambda_i^* a_{im} + \beta^* c_m), \quad \text{if} \quad t_m^* \neq 0 \end{cases} \tag{3-30}$$

Equation (3-30) is equivalent to:

$$t_m^* \geq \exp(\sum_{i=1}^{N} \lambda_i^* a_{im} + \beta^* c_m) > 0 \tag{3-31}$$

This means that the optimal tour flows are positive. Therefore, the optimal solution defined by equation (3-30) is updated to:

$$t_m^* = \exp(\sum_{i=1}^{N} \lambda_i^* a_{im} + \beta^* c_m) \tag{3-32}$$

Thus, the first entropy maximization formulation results in a commercial vehicle tour distribution model in which the number of tour flows following a tour is an exponential function of the Lagrange multipliers associated with the trip productions/attractions of nodes along that tour and the tour impedance. If node *i* is in a tour, the number of tour flows along that tour will be affected by the exponential of the Lagrange multiplier associated with the trip production at that node (λ_i). If the tour impedance is increased by one, the number of tour flows on that tour will be changed by the exponential of the impedance-related Lagrange multiplier (β).

3.2.2.2 First-order conditions of formulation 2

The Lagrange function associated with the second formulation ((3-13)-(3-17)) is as follows:

$$L(t,\lambda,\beta)=\sum_{m=1}^{M}(t_m \ln t_m - t_m)+\sum_{i=1}^{N}\lambda_i(O_i-\sum_{m=1}^{M}a_{im}t_m)$$
$$+\beta_1(C_T-\sum_{m=1}^{M}c_{Tm}t_m)+\beta_2(C_H-\sum_{m=1}^{M}c_{Hm}t_m) \tag{3-33}$$

The partial derivative of the Lagrange function with respect to the number of tours t_m is:

$$\frac{\partial L(t,\lambda,\beta)}{\partial t_m}=\ln t_m-\sum_{i=1}^{N}\lambda_i a_{im}-\beta_1 c_{Tm}-\beta_2 c_{Hm} \qquad \forall m \tag{3-34}$$

Following the same procedure, the first-order conditions of the second formulation are as follows:

$$t_m^*(\log t_m^*-\sum_{i=1}^{N}\lambda_i^* a_{im}-\beta_1^* c_{Tm}-\beta_2^* c_{Hm})=0 \qquad \forall m\in\{1,2,...,M\} \tag{3-35}$$

$$\log t_m^*-\sum_{i=1}^{N}\lambda_i^* a_{im}-\beta_1^* c_{Tm}-\beta_2^* c_{Hm}\geq 0 \qquad \forall m\in\{1,2,...,M\} \tag{3-36}$$

$$\sum_{m=1}^{M}a_{im}t_m^*=O_i, \qquad \forall i\in\{1,2,...,N\} \tag{3-37}$$

$$\sum_{m=1}^{M}c_m t_m^*=C \tag{3-38}$$

$$t_m^*\geq 0 \tag{3-39}$$

Similar as has done before, the optimal solution defined by equation (3-35)-(3-36) is equivalent to:

$$t_m^*=\exp(\sum_{i=1}^{N}\lambda_i^* a_{im}+\beta_1^* c_{Tm}+\beta_2^* c_{Hm}) \tag{3-40}$$

Equation (3-40) indicates that the number of tour flows following a tour is an exponential function of the Lagrange multipliers associated with the trip productions/attractions of nodes, the tour travel impedance and the tour handling impedance along that tour. The effects of the impedance variables are quantified by the Lagrange multipliers (β_1^* and β_2^*). If β_1^* and β_2^* are different, it means that the tour travel impedance and the tour handling impedance have different impacts on the number of tour flows distributed along a tour. Otherwise, the resulting tour distribution model from formulation 2 (equation (3-40)) is equivalent to the ones from formulation 1 (equation (3-32)).

3.2.2.3 Second-order conditions

To determine whether the formulations are convex or not, the Hessian of each objective function was computed to see if it is positive definite. Since the two formulations have the same objective function, they have the same second-order derivatives as defined below:

$$\frac{\partial z^2(\bar{t})}{\partial t_i \partial t_j} = \begin{cases} \dfrac{1}{t_i} & for \quad i = j \\ 0 & otherwise \end{cases} \qquad \forall i, j \in \{1,2,...,M\} \tag{3-41}$$

This indicates that the Hessian is a diagonal matrix with the elements in the main diagonal equal to $\frac{1}{t_i}$, given equation (3-41). This Hessian is positive definite, so the objective function is convex. Meanwhile, since the constraints are linear, the two entropy maximization formulations are both convex. Therefore, the two formulations have unique optimal solutions.

3.2.3 Linkages to classic formulations

It is important to discuss how the model developed here compares to the classic trip-based entropy model. Their characteristics are compared in Table 2. On one hand, the two groups of formulations have similar macro states and constraints. On the other hand, the micro states of the tour-based formulation are individual tour flows while the ones for the classic model are trips. This difference leads to different objectives and conclusions. The tour-based formulation looks for the most likely way of distributing tour flows while the trip-based formulation aims at the most likely way of distributing trips. Meanwhile, the resulting function of tour flows is more complex than the one for trips. For instance, both the tour-impedance-related Lagrange multiplier (β , or β_1 and β_2), and the production/attraction-related Lagrange multipliers (λ_i) need to be calibrated in the tour flow function in the former case. In contrast, only trip-impedance-related Lagrange multiplier (β) is required for computing the number of trips between each OD pair in the latter case.

Table 2: Comparison between the tour-based and the trip-based entropy maximization formulations

Characteristics	Tour-based formulation	Trip-based formulation
States of the system		
Micro state	Individual TOUR FLOW following a tour	Individual TRIP between an OD pair
Meso state	Number of TOUR FLOWS following a tour	Number of TRIPS between an OD pair
Macro state	Trip production and attraction in each node	Trip production and attraction in each node
Inputs		
Trip generation	Total number of trips produced by or attracted to each node	Total number of trips produced by or attracted to each node
Tour impedance	Tour impedance in a tour, including the travel impedance and the tour handling impedance	Trip impedance between an OD pair, including travel impedance only
Total impedance	Formulation 1: total impedance in the network ; Formulation 2: total travel impedance and total handling impedance	Total travel impedance in the network
Spatial related	The set of tours	The set of OD pairs
Objective	Maximizing the number of ways of distributing TOUR FLOWS to the known tours	Maximizing the number of ways of distributing TRIPS between the known OD pairs
Constraints	Total number of trips produced by each node; and the total impedance of the system	Total number of trips produced by or attracted to each node; and the total impedance of the system

Models	From formulation 1: $$t_m = \exp(\sum_{i=1}^{N} \lambda_i a_{im} + \beta c_m)$$ From formulation 2: $$t_m = \exp(\sum_{i=1}^{N} \lambda_i a_{im} + \beta_1 c_{T\,m} + \beta_2 c_{H\,m})$$	$t_{ij} = A_i O_i B_j D_j \exp(\beta c_{ij})$

3.3 Case study

In order to test the feasibility of the models developed here, they were applied to a case study. This section describes the results obtained by applying the tour-based entropy maximization formulations to the data collected by the Denver Regional Council of Governments (DRCOG) in the Denver metropolitan area. This data set was chosen because it is the largest scale commercial vehicle travel diary data available to the authors.

The corresponding Travel Behavior Inventory (TBI) survey was conducted between 1998 and 1999. It contained a business survey and a commercial vehicle travel diary survey. The business survey was to collect information on business characteristics and vehicle ownership. Of the population of 90,558 businesses in the eight countries of the Denver metropolitan area, 4,903 businesses (5.4%) were randomly picked and surveyed. If they owned at least one vehicle, the travel diary survey was conducted for the selected vehicles. Among the 1,624 vehicles selected, 832 (51%) vehicles completed the travel diary survey, though only 502 vehicles (31%) made at least one trip on the survey day. The information collected in the travel diary survey includes the traffic analysis zones (TAZs) where the vehicles stopped to do something, the arrival and departure time at each TAZ, trip purpose, the handling time at each stop (minutes) and the travel times between adjacent stops (minutes). Various expansion factors related to businesses surveyed, vehicles selected and trips collected were used to expand the raw data. After sample expansion, it was estimated that the sample represents 343,500 commercial vehicle trips made per average weekday in the Denver metropolitan area. The interested readers are referred to Holguín-Veras and Patil (2005) for details.

The commercial vehicle travel inventory data was processed to get tours. As found, 613 different tours were identified, representing a total of 65,385 journeys made on these tours per day. A total of 919 TAZs in the area were visited. These tour flows are aggregated to get the total number of trips produced by each TAZ and the total impedance as the input to the entropy maximization formulations.

Meanwhile, the information of individual tours in the data was used to determine the coefficients in the constraint set of the entropy maximization formulations. To accommodate the data used, the definition of a_{im} in equation (3-10) and (3-14) was modified to allow for the aggregation of nodes. In the survey, the nodes visited by each tour were aggregated into different TAZs. Therefore, a TAZ may be visited more than once in a tour. Considering this, a_{im} is redefined as the number of times TAZ i is visited along tour m rather than as a binary variable indicating whether node i is in tour m or not. In equation (3-11) of formulation 1, the observed tour time that represents the summation of the travel time in each trip and the handling time at each stop in a tour, is used as the tour impedance. In equation (3-15) and (3-16) of formulation 2, the summation of the observed trip travel times along a tour and the summation of handling times at stops in the tour are used as the tour travel impedance and tour handling impedance respectively.

After the trip productions/attractions, the total impedance, the total tour travel impedance and the total tour handling impedance were calculated, the PDCO algorithm was used to solve the two variants of entropy maximization formulations. The set of optimal solutions include: (1) the primal optimal solutions for the tour flows on the 613 observed tours (t_m); (2) the impedance-related Lagrange multipliers (β for formulation 1, or β_1 and β_2 for formulation 2); and (3) the optimal values for 919 production/attraction-related Lagrange multipliers (λ_i).

The calibrations of the models took two seconds to solve the problem by using the PDCO algorithm. The results indicate an excellent match between the observed and estimated tour flows. The mean absolute percentage errors (MAPE) of the estimated tour flows are 6.71% for formulation 1 and 6.61% for formulation 2 (see Table 3).

Table 3: The MAPE and the impedance-related Lagrange multipliers

Estimated results	**Formulation 1**	**Formulation 2**
MAPE	6.71%	6.61%
Impedance-related Lagrange multipliers:		
Tour-time-related Lagrange multiplier ((β)	-0.000228	/
Tour-travel-time-related Lagrange multiplier (β_1)	/	-0.00190
Tour-handling-time-related Lagrange multiplier (β_2)	/	0.000183

As the consequence of the good match obtained, the estimated distributions of tour time, tour travel time and tour handling time resemble the observed ones. The observed tour length distributions are show in Figure 10. As found, the best fitting regression model for the tour time distribution is a gamma function of tour time with the form of equation (3-42) while the best one for the tour travel time distribution or the tour handling time distribution is an exponential function of the corresponding time variable with the form of equation (3-43). The findings are consistent with the study conducted by Holgu ń-Veras and E. Thorson (2000).

$$freq = a_0 e^{a_1 tt_1} tt_1^{a_2} \tag{3-42}$$

$$freq = a_0 e^{a_1 tt_2} \tag{3-43}$$

Where:

freq= Frequency of tour times, tour travel times or tour handling times (%);

a_0, a_1, a_2= Parameters of tour length distribution functions;

tt_1, tt_2= Tour time and tour travel time (or tour handling time) respectively.

The closeness of the estimated distributions to the observed ones is confirmed by the *t* statistics test in Table 4, which shows that none of the parameter values of these estimated distribution functions are statistically different from the observed distribution parameters.

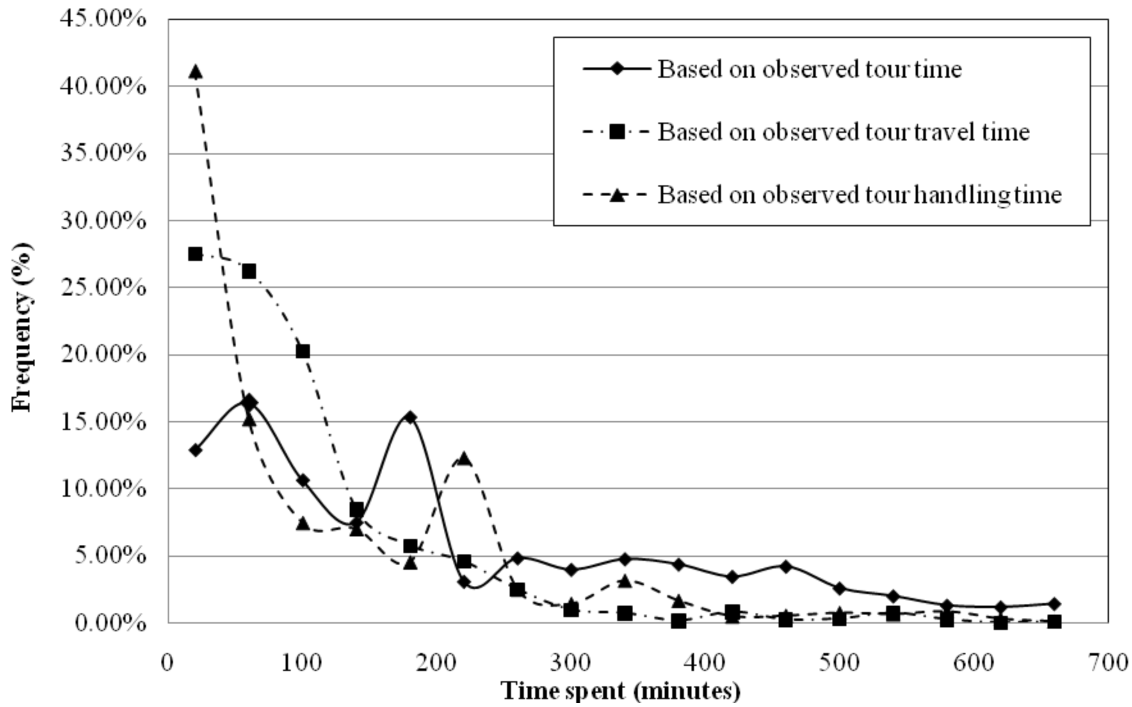


Figure 10: The observed tour length distributions

Table 4: Model parameters and *t* test statistics for tour length distributions resulting from the entropy maximization formulations

Frequency of	a_0	$s_e(a_0)$	a_1	$s_e(a_1)$	a_2	$s_e(a_2)$
Observed tour time	0.0218	1.210	-0.00767	0.00101	0.564	0.274
Estimated tour time	0.0212	1.203	-0.00769	0.00100	0.570	0.273
Observed tour travel time	0.288	0.323	-0.00900	0.000822	/	/
Estimated tour travel time	0.293	0.326	-0.00906	0.000831	/	/
Observed tour handling time	0.238	0.268	-0.00729	0.000683	/	/
Estimated tour handling time	0.240	0.267	-0.00731	0.000679	/	/
Hypothesis:	*t* statistic	Result	*t* statistic	Result	*t* statistic	Result
Tour time distribution: estimated	-0.00148	Accept	-0.0660	Accept	0.0728	Accept

= observed						
Tour travel time distribution: estimated = observed	0.0522	Accept	-0.212	Accept	/	/
Tour handling time distribution: estimated = observed	0.0234	Accept	-0.0856	Accept	/	/

Note: Each hypothesis is tested at the 95% confidence interval.

The impedance related Lagrange multipliers are the second group of optimal solutions reached by the PDCO algorithm. When the tour time is considered as the only impedance constraint (formulation 1), the Lagrange multiplier (β) associated with the tour time (-0.000228) has a negative sign as expected. This indicates that the higher the tour length is the less likely tour flows will be made on that tour. On the contrary, when the impacts of the tour travel time and the tour handling time are assessed separately (formulation 2), the corresponding Lagrange multipliers (β_1 and β_2) present significant difference: the one associated with the tour travel time has a negative sign (-0.00190) while the one with the tour handling time has a positive sign (0.000183). The potential reason may lie in the difference in the underlying meanings of the two impedance variables. The tour travel time, as a pure indicator of travel impedance, discourages travel as expected. Compared with it, the tour handling time, though considered as an impedance variable, may represent the amount of customers' requests available in a tour, due to the proportionality of handling time to the efforts spent serving customers. Therefore, longer handling time requested in a tour may induce more travels made on this tour.

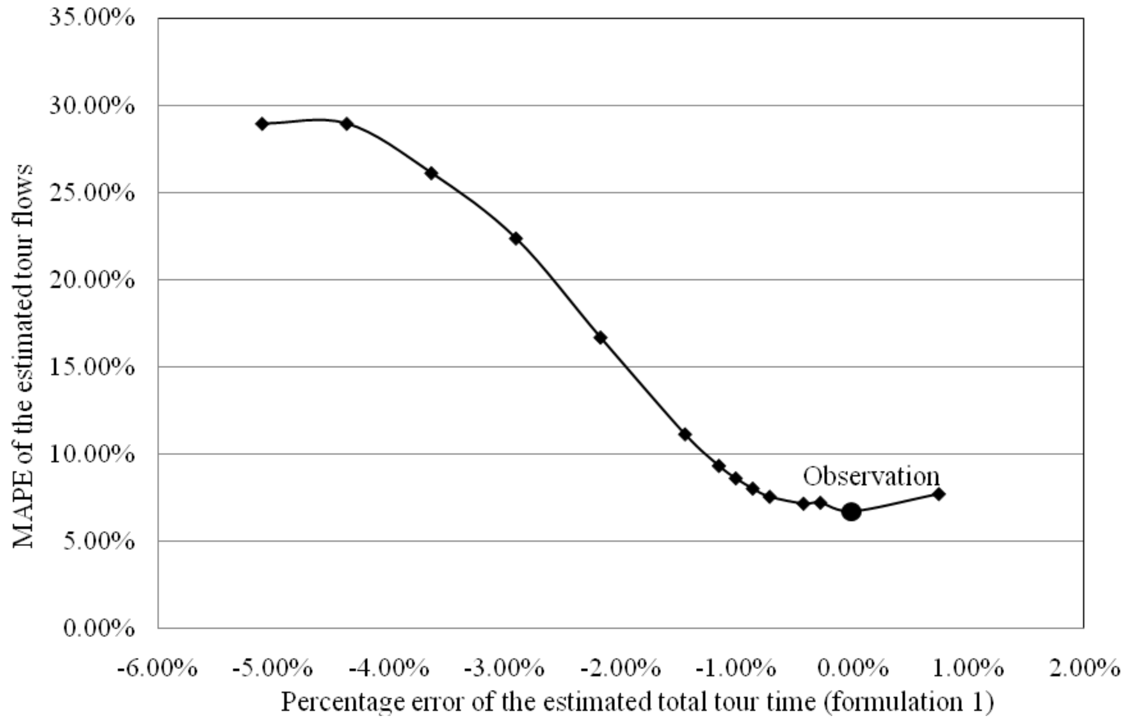
In addition to the tour flow and the impedance related Lagrange multipliers described above, the PDCO algorithm also returns the optimal values for the Lagrange multipliers associated with the trip production of each TAZ in the network. These multipliers are zone-specific and could be either positive or negative, and no obvious patterns were observed from these Lagrange multipliers.

3.4 Sensitivity analysis

In real world applications, it is not likely that the total impedance of the network is estimated accurately. Considering this, sensitivity analyses were conducted to assess how the level of accuracy in the estimation of impedance variables affects the estimation performance of entropy maximization formulations. For the case study in the Denver metropolitan area, the impacts of the total tour time, the total tour travel time and the total tour handling time are described separately as follows.

3.4.1 Sensitivity of estimation performance with respect to the error of total tour time (formulation 1)

For the first formulation, the total tour time in the Denver metropolitan area is the only impedance variable considered. Its impacts on the estimation performance and the estimated Lagrange multipliers (β) are shown in Figure 11 and Figure 12. Figure 11 illustrates the relationship between the mean absolute percentage error (MAPE) of the estimated tour flows and the error of total tour time. As can be seen, the MAPE increases with the error of total tour time. Meanwhile, the MAPE is very sensitive to the estimation error of total tour time: the elasticity of MAPE with respect to the total tour time in the decreasing proportion of the curve ranges from -80.23 to -15.54. This indicates that the pre-specified total tour time has a significant impact on the performance of the entropy maximization formulations in estimating tour flows. When the total tour time used as input is significantly different from the actual one, the estimated tour flows may deviate dramatically from the observed ones.



Note: (1) the observed total impedance is 13,698,291 minutes; (2) the percentage error of the estimated total tour time = [(estimated total tour time-observed total tour time)/observed total tour time]*100%.

Figure 11: Mean absolute percentage error (MAPE) vs. total tour time (from formulation 1)

In addition to the MAPE of the estimated tour flows, the total tour time can also affect the Lagrange multiplier associated with tour time (β). Figure 12 shows the pattern. As can be seen, the error of total tour time has an impact on the values of β as the calibration error in β decreases with the error in total tour time.

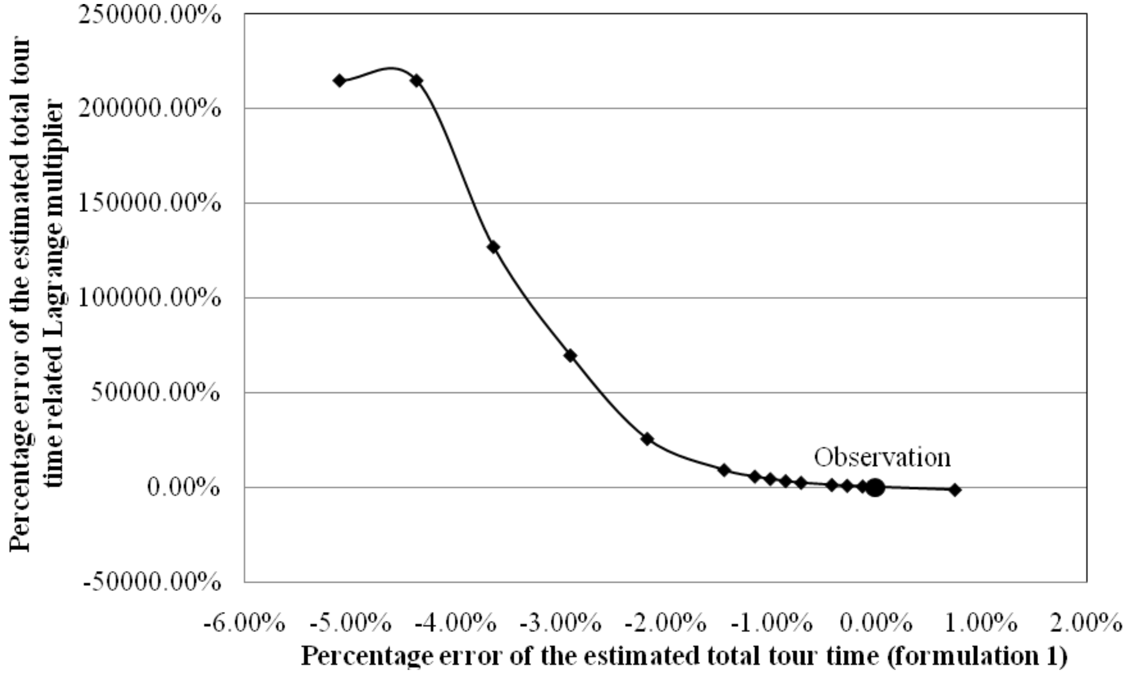
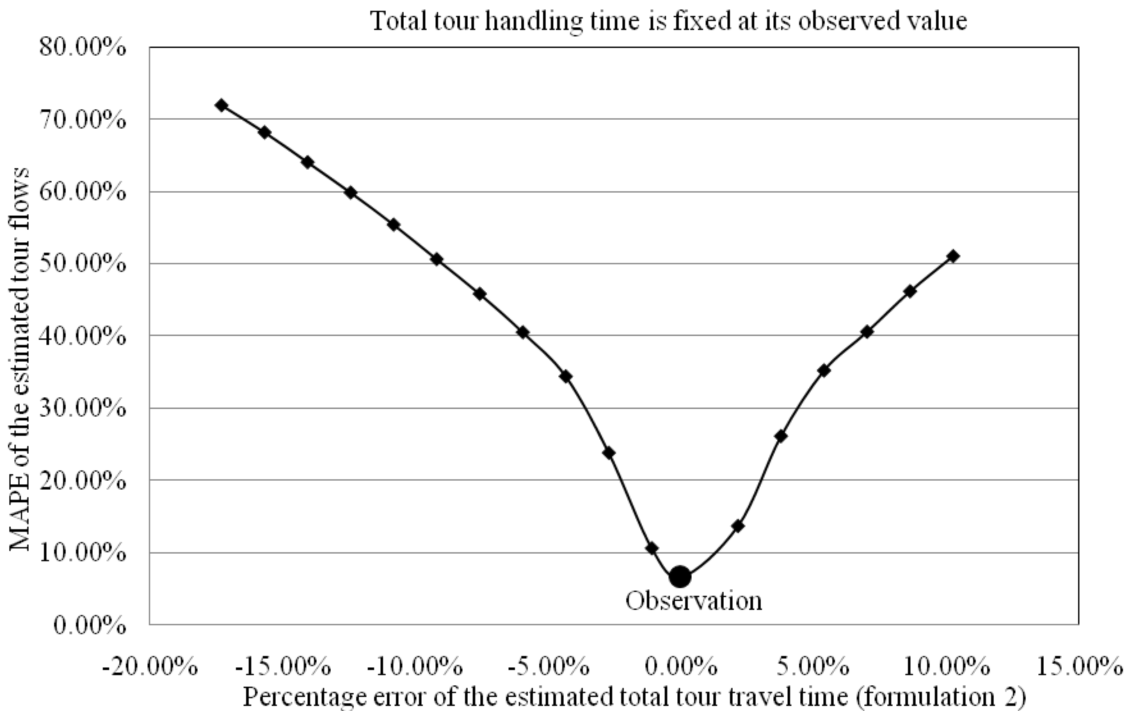


Figure 12: Tour-time-related Lagrange multiplier (β) vs. total tour time (from formulation 1)

3.4.2 Sensitivity of estimation performance with respect to the errors of separated tour impedances (formulation 2)

In the second proposed formulation, the total tour time is split into the total tour travel time and the total tour handling time as the impedance variables. Considering this, their impacts are analyzed separately by varying one while fixing the other in its observed value.

The impacts of the total tour travel time on the estimation performance and the calibration of Lagrange multipliers (β_1 and β_2) are shown in Figure 13 and Figure 14. As illustrated by Figure 13, the MAPE of the estimated tour flows decreases as the total tour travel time increases. It reaches the minimum at the observed total tour travel time. Meanwhile, the MAPE fluctuates from 6.61% to 71.93% with the change of the total tour travel time, and the corresponding elasticity of MAPE with respect to the total tour travel time varies dramatically from -96.81 to 80.24. This indicates that inaccurate total tour travel time may cause significant error in the estimated tour flows.



Note: (1) the observed total tour travel time and total tour handling time are 6,167,617 minutes and 7,530,674 minutes respectively; (2) the percentage error of the estimated total tour travel time = [(estimated total tour travel time-observed total tour travel time)/observed total tour travel time]*100%.

Figure 13: MAPE vs. total tour travel time (from formulation 2)

Figure 14 shows the relationships between the impedance-related Lagrange multipliers and the error of total tour travel time given that the total tour handling time is fixed at its observed value. On one hand, the errors of calibrating the two Lagrange multipliers increase with the error in total tour travel time. On the other hand, the change of total tour travel time has larger marginal impact on the tour-travel-time-related Lagrange multiplier (β_1) than on the tour-handling-time-related Lagrange multiplier (β_2).

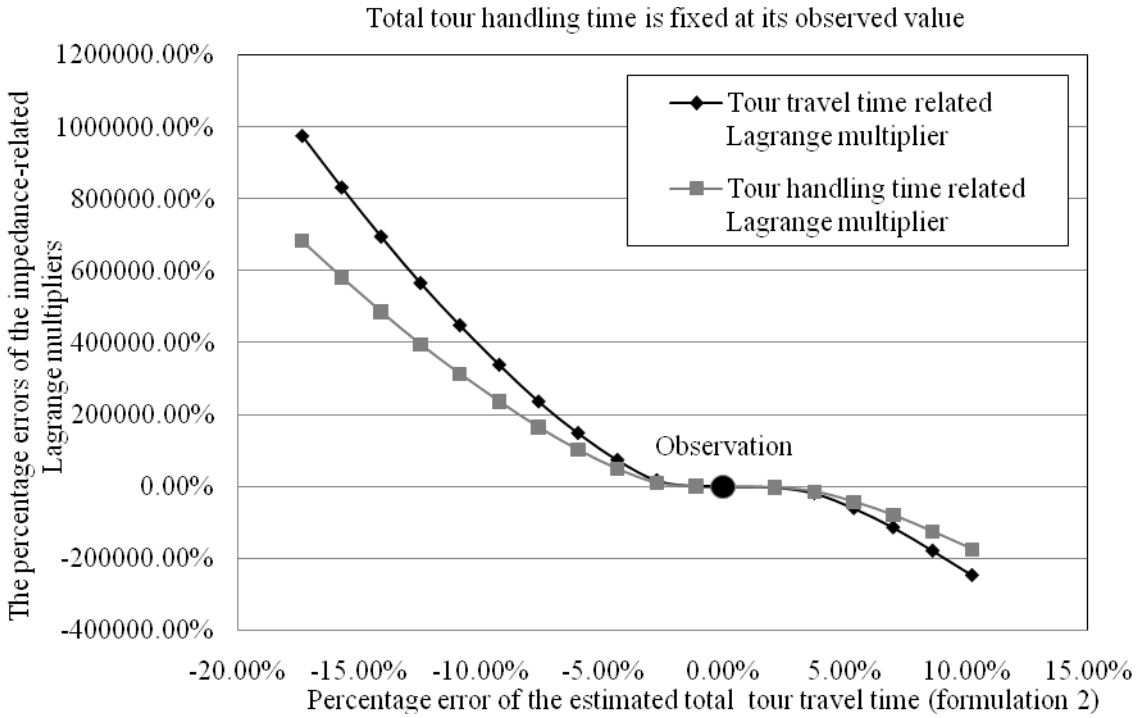
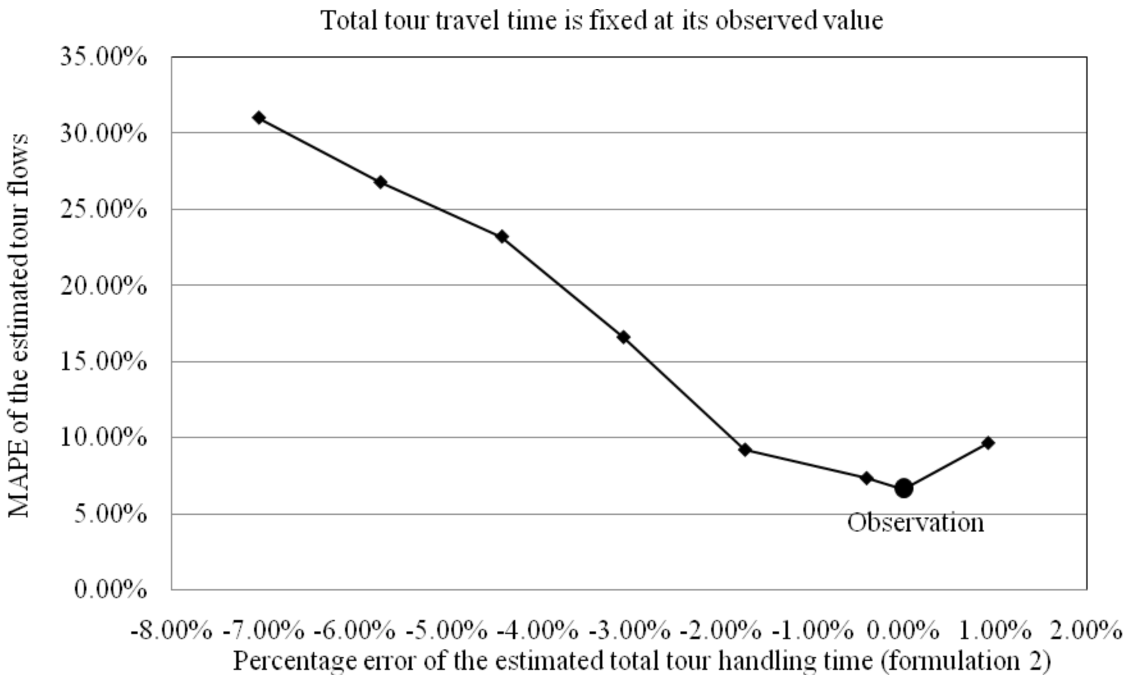


Figure 14: Impedance-related Lagrange multipliers vs. total tour travel time (from formulation 2)

The total tour handling time exhibits similar impacts on the estimation performance and the calibrated Lagrange multipliers though the magnitude is smaller. Figure 15 illustrates the MAPE of the estimated tour flows as a function of the percentage error of the estimated total tour handling time given that the total tour travel time is fixed at its observed value. The MAPE increases with the error of the total tour handling time. The elasticity of the MAPE ranges from -57.23 to 50.45, which indicates a high sensitivity of the estimation performance with respect to the estimated total tour handling time.



Note: (1) the observed total tour travel time and total tour handling time are 6,167,617 minutes and 7,530,674 minutes respectively; (2) the percentage error of the estimated total tour handling time = [(estimated total tour handling time -observed total tour handling time)/observed total tour handling time]*100%.

Figure 15: MAPE vs. total tour handling time (from formulation 2)

Figure 16 shows the change patterns of the two impedance related Lagrange multipliers with respect to the error in total tour handling time. As shows, the calibration errors of the two Lagrange multipliers approach zero as the absolute error of total tour handling time decreases. Meanwhile, the change of the total tour handling time dramatically impacts the calibrated value of tour-travel-time-related Lagrange multiplier while only slightly affecting the tour-handling-time-related Lagrange multiplier.

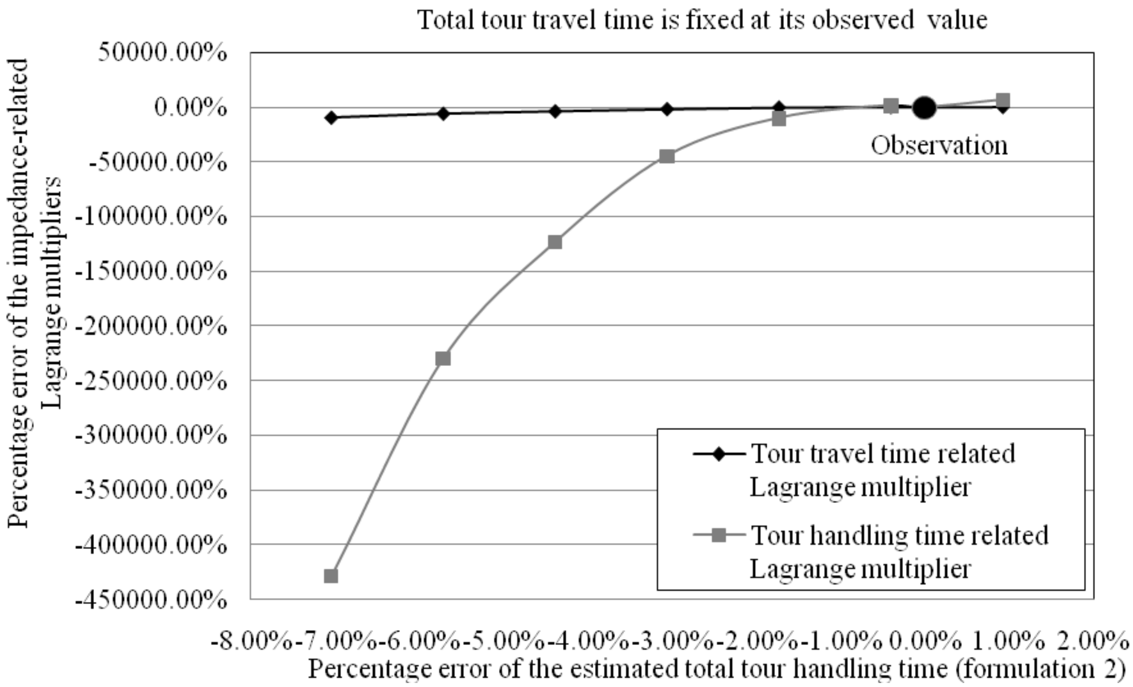


Figure 16: Impedance-related Lagrange multipliers vs. total tour handling time (from formulation 2)

3.5 Potential Applications in Urban Freight Planning

The proposed approach can be applied in two different ways depending on data availability, as shown in Figure 17. The first application entails the use of the base-year information as the input to estimate the parameters, i.e., λ_i, β or $\lambda_i, \beta_1, \beta_2$ of the corresponding models. Then, the distribution models can be used to estimate the tour flows in the future year. In order to do this, the same procedure that the case study followed can be applied: first, the observed tour flows in the base year are aggregated to get the trip productions/attraction at the TAZs and the total impedance of the network; then, the PDCO solver is used to search the optimal values for the parameters in the tour distribution models (equation (3-32) and (3-40)). Once the parameters are estimated, the future-year tours can be forecasted by using the tour distribution models given that the potential tours visited in the future year and the associated tour impedances are estimated in advance.

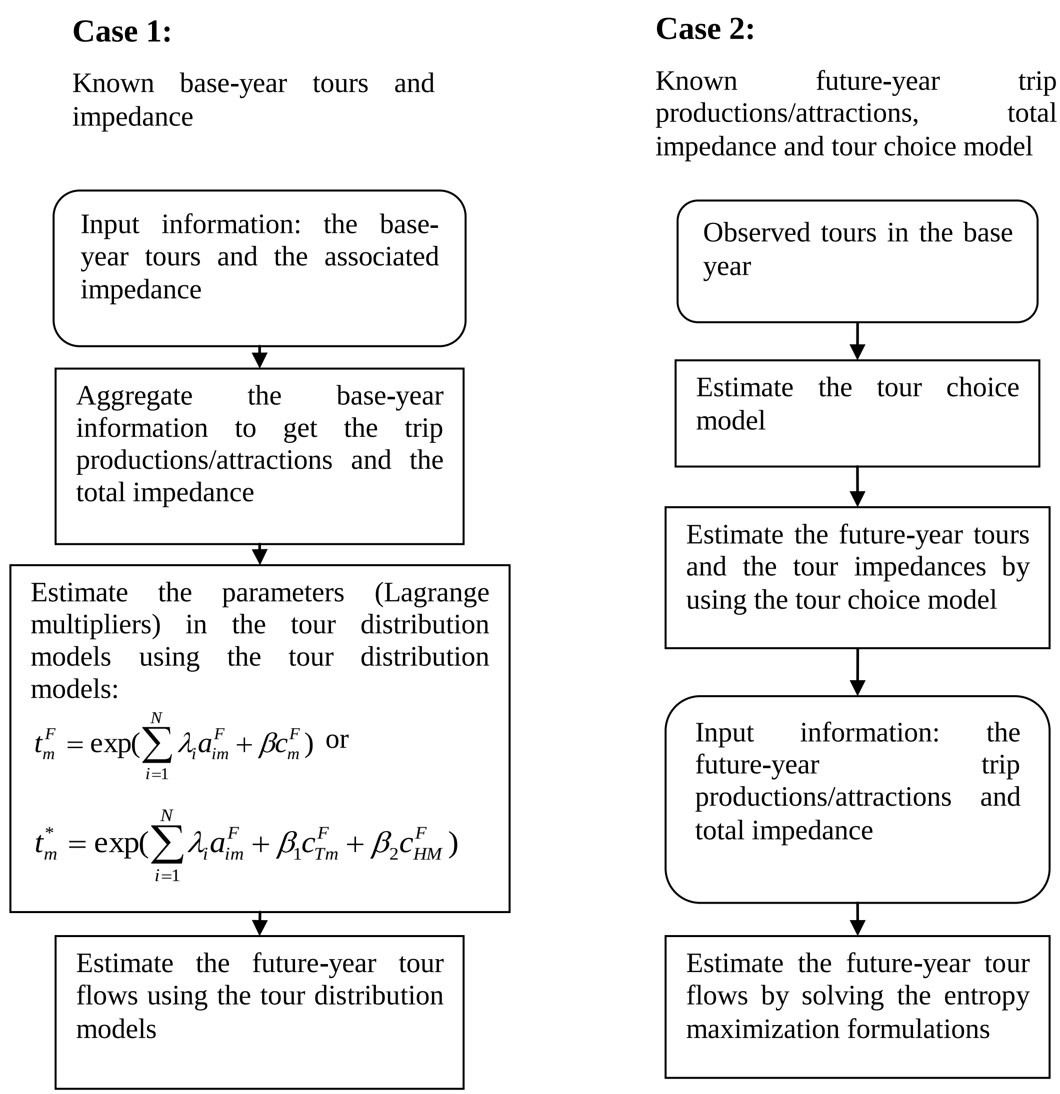


Figure 17: The applications of the tour-based entropy maximization approach in urban freight travel demand forecasting

In the second application, the future-year trip productions/attractions and the total impedance in the network are estimated as the input of the entropy maximization formulations. Given the future-year information, the entropy maximization formulations are used directly to estimate future-year tours by following the procedure below: first, the potential commercial vehicle tours in the future year are generated by using a tour choice models so that the trip production/attraction constraints can be set properly; then, the tour impedances along these tours are estimated as the coefficients of the impedance constraints; at the end, the PDCO solver is applied to search the optimal way to distribute tour flows in the future year. As can be seen, the essential component of this approach is to develop the tour choice models in order to estimate the tours and the associated tour impedance for the future year. Given the limited space available, the corresponding issues associated with this component will be addressed in another study.

3.6 Conclusions

This chapter describes two variants of entropy maximization formulations that were developed to estimate the commercial vehicle flow that are expected to travel along a given tour in the network. The numbers of trips produced by each node and the total impedance of the entire network are used as constraints during the estimation. The first formulation includes only one impedance variable which is the summation of the total tour travel impedance and the total tour handling impedance, while the second one uses the total tour travel impedance and the total tour handling impedance separately as impedance variables.

The first and second order conditions are derived to gain insight from the entropy maximization formulations. The first-order conditions show that the number of commercial vehicle journeys made in a tour is a function of the Lagrange multipliers associated with the trip productions/attractions of nodes along that tour, and the tour impedance. The second-order conditions indicate that the proposed formulations are convex programs with a convex objective function and a set of linear constraints. The corresponding optimization problems are solved using the primal-dual interior method for optimization programs with convex objectives (PDCO) because of its efficiency in solving large-scale entropy problems.

The proposed formulations are applied to the Denver metropolitan area. The estimation results indicate that the entropy maximization formulations are a feasible and efficient way to accommodate the commercial vehicle tours into the aggregate-level urban freight demand modeling. The estimated tour flows closely match the observed ones with the mean absolute percentage error as 6.71% for the first formulation and 6.61% for the second formulation. As the consequence of the good match obtained, the estimated tour length distributions resemble the observed ones as well.

Based on the findings, the chapter discusses two possible ways of applying this approach to forecast urban freight demand. As indicated by the second application, the forecast of commercial vehicle tour flows in the future requires the estimation of potential tours visited by commercial vehicles and the associated tour impedances, which itself is a complex problem considering the combinatorial number of possible ways to generate tours. To address this issue, tour choice models will be developed in next chapter as an extension of this approach.

4. Commercial Vehicle Tour Choice Model

As discussed in Chapter 3, modeling commercial vehicle tours require the use of two models: the first one focuses on estimating tour choice, i.e., the set of tours the commercial vehicles are expected to consider; while the second one focuses on estimating the vehicle flows along each tour, which is what the entropy-based tour distribution models do in Chapter 3. This chapter describes a behavioral tour choice model that is intended to complement the entropy-based tour distribution models in Chapter 3 by providing the set of tours to be considered.

The estimation of the set of tours to be specified as an input to the entropy maximization problem is a very complex problem. The first issue is the combinatorial number of possibilities. In the most general case, the number of possibilities follows the equation below:

$$NT = C_1^{N_{HB}} \sum_{i=1}^{S_{\max}} P_i^{N-1} \tag{4-1}$$

Where:

NT : The number of possible tours that may be considered by commercial vehicles;

N_{HB}: The number of home bases contained in the network of interest;

$C_1^{N_{HB}}$: The number of combinations of choosing one home base as the start node of a tour;

$S_{\max}$: The maximum number of destinations allowed in a tour;

N : The number of nodes contained in the network of interest;

P_i^{N-1}: The number of permutations of choosing i nodes as the intermediate stops of a tour from the remaining nodes (except of the chosen home base) in the network.

Table 5: Relationship between the number of possible tours and the size of the network

Number of nodes in the network (N)	Number of possible tours (NT)
50	7.116×10^{31}

100	1.0564×10^{39}
1000	8.1024×10^{59}

Note: the maximum number of intermediate stops in a tour is assumed to be less than or equal to 20.

As shown in Table 5, the number of possibilities is astronomical in a large network. Obviously, complete enumeration of tours is not possible as this would have a very detrimental impact on computing performance, though doing so would still enable the entropy-based tour distribution models to find the optimal tours. At the other end of the spectrum of possibilities, one could specify only a handful of tours. In this case, the computational expense will be minimal though the model may suffer from a major specification error as this small set of tours is not likely to contain the optimal tours. These tradeoffs could be illustrated with the assistance of Figure 18. All of this implies that there is an optimal specification somewhere in between the two extreme solutions. This chapter attempts to define a procedure to select a set of input tours based on behavioral principles, and assess its performance in assisting the entropy-based tour distribution models to estimate tour flows.

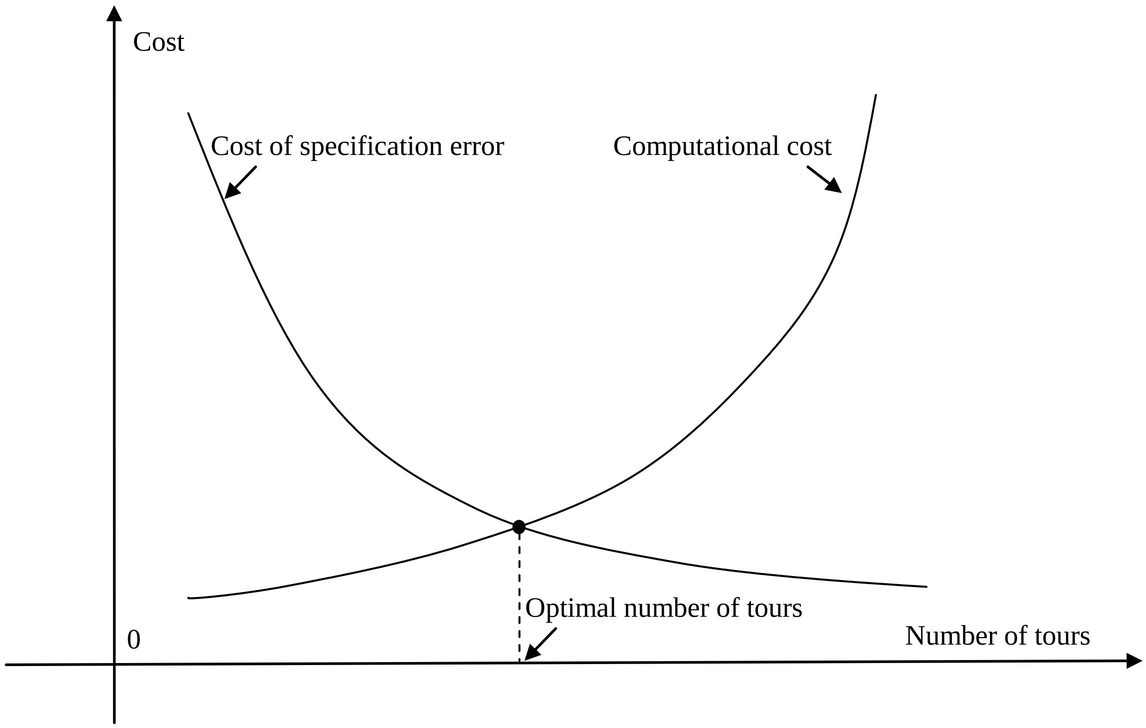


Figure 18: Specification error vs. computational cost in tour estimation

The fundamental challenge is that the tours considered as the input to the entropy maximization formulations need to be sufficient and effective to ensure estimation accuracy and computational efficiency of the entropy-based tour distribution models. On one hand, estimation accuracy requires that the tours generated represent the observed routing behavior. On the other hand, computational efficiency requires discarding as many ineffective tours as possible to make sure that the optimal solution of the entropy-based tour models is reached in a reasonable amount of time. Inefficient tours here include those that are overly circuitous, longer than work hour limits, or rarely used in the real work will only slow down the estimation process.

However, the methods available in the literature were not designed to identify tours in the way needed here. Vehicle routing problems, the formulations most widely used to determine commercial vehicle routes, are not suitable because they require previous knowledge of the customers to be visited. Enumeration algorithms are not suitable either because of the exponentially increasing computing time. In this context, new algorithms are required to pre-specify a sufficient and effective set of tours as the input to the entropy maximization formulations.

To meet the needs, a tour choice model is developed in this chapter. This model involves a micro-simulation procedure in which the individual tours are constructed by taking into consideration of two important trip chaining decisions, i.e., which node to be visited as the next destination (destination choice), and whether or not to return to the home base from the current location (tour termination choice). The final output is a set of tours that is to be used as the input to the entropy-based tour distribution models.

The objectives of this tour choice model are: (1) to integrate the important decisions made along a tour, such as the destination choice and tour termination choice, into the tour choice model; (2) to identify the key attributes that affect the destination choice and the tour termination choice made along a tour by using discrete choice modeling; and (3) to develop algorithms to generate a set of sufficient and effective tours based on the estimated behavioral choice models.

The rest of the chapter is organized as follows. Section 4.1 describes the proposed tour choice model. Section 4.2 concentrates on two types of discrete choice models that capture the decisions of whether to return to the home base or not, and which node will be the next destination if not returning. In section 4.3, the tour flows estimated from the entropy maximization formulations are compared with the observed tours to evaluate the performance of the tour choice model.

4.1 Methodology

The proposed tour choice model is shown in Figure 19. This algorithm involves a framework that is composed of three main loops: (1) the inner loop that updates the destinations for a tour; (2) the middle loop that updates the tour set for a home base; and (3) the outer loop that updates the home bases in the network.

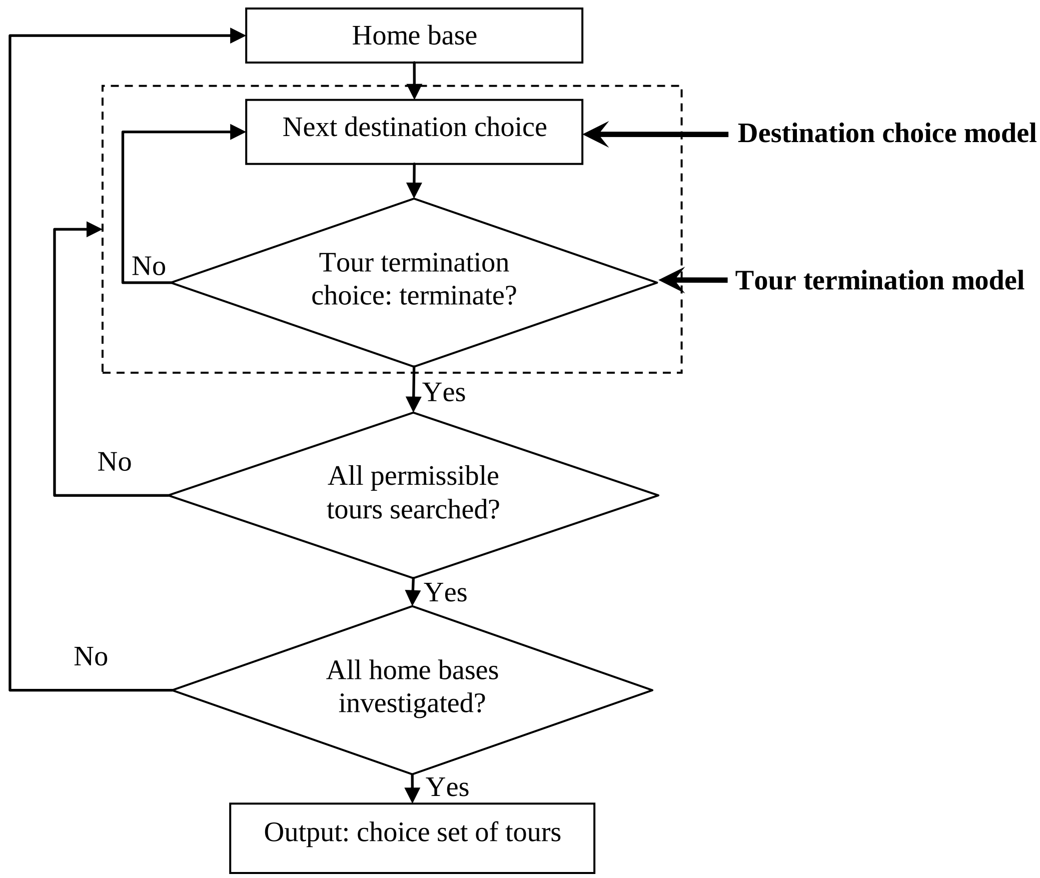


Figure 19: Framework of commercial vehicle tour choice model

The inner loop is to expand a tour by adding new destinations before it is terminated. The tour construction process is decomposed into two decisions: (1) the tour termination decision determining if the tour terminates at the current location (unless it is a home base) or continues; and (2) the destination choice decision indicating which node to be visited next if the tour continues. Two behavioral choice models, i.e., the tour termination model and the destination choice model, are used to represent the two types of decisions respectively. Based on the probabilities generated from the two models, each tour progresses as below: a tour starting from a home base continues to add new destinations that are selected by the destination choice model until either of the following termination criteria is met: (1) if the tour termination model indicates returning; or (2) if the maximum number of stops is reached. In order to take into consideration the randomness of the termination decision, a Monte Carlo simulation combined with the tour termination model is applied as the first criterion. A random number between 0 and 1 is generated for each current location along a tour. If the value is greater than the return probability calculated by the termination model, the tour is completed by adding the home base as the last node.

The middle loop is to search new tours for the current home base. To avoid enumeration of all alternative tours, a search algorithm is developed to restrict the search space as it explores the effective tours. This algorithm takes advantage of the probabilities generated by the destination choice model, and searches the tours that are composed of the destinations with high probabilities to be visited. It follows a depth-first search structure in which a search progresses by expanding the first active node that may branch off in the search tree, and thus goes deeper and deeper until the stem explored meets the tour termination criteria. Then the search backtracks, returning to the most recent active node it has not finished exploring. This process keeps expanding and searching until all the expanded stems are terminated. The generated stems, which are called permissible tours later, form a dynamic search tree as illustrated in Figure 20.

The logic of this search algorithm is described below:

Step 0 (Initialization): Initialize three vectors associated with the nodes off which the search tree of tours may branch: *NodeSet*={*HB*}, *NodeStatus*={1}, *NodePosition*={0}; define the sets storing the incomplete and complete tours as *Tours_IC*={{*HB*}} and *Tours_C*=ϕ respectively.

Here, *NodeSet* contains the IDs of the nodes that may branch. *NodeStatus* stores the status of these nodes: 1 means a node is active for branching, 0 otherwise. *NodePosition* indicates the position of each node on its tour: 0 represents the home base (*HB*) while i denotes the i^{th} destination of a corresponding tour, i ranging from 1 to the maximum number of destinations allowed in a tour.

Step 1 (Main Step): Repeat the following steps until *NodeStatus* is a zero vector.

Step 1.1: Find the index of the first non-zero entry in *NodeStatus*, and store it as the index of the current node (*CN_Index*);

Step 1.2: Determine the current node (*CN*) and its properties: (1) set the current node as *CN* = *NodeSet*(*CN_Index*); (2) find the position of the current node along a tour: *CN_Position*= *NodePosition* (*CN_Index*); and (3) set the status of the current node as dead: *NodeStatus* (*CN_Index*) = 0;

Step 1.3: If *CN*=*HB*, go directly to Step 1.6; else, go to step 1.4;

Step 1.4: Append the current node to the first incomplete tour: *Tours_IC*(1)= *Tours_IC*(1)+ {*CN*}; then, set it as the current tour: *CNS*= *Tours_IC*(1);

Step 1.5: Check if *CNS* is terminated or not using the three termination criteria mentioned before.

If terminate, do the following: add *CNS* to the set of COMPLETE tour: *Tours_C*=*Tours_C*⋃{*CNS*}; delete *CNS* from the set of INCOMPLETE tour: *Tours_IC*= *Tours_IC* \{*CNS*}; and then go back to Step 1;

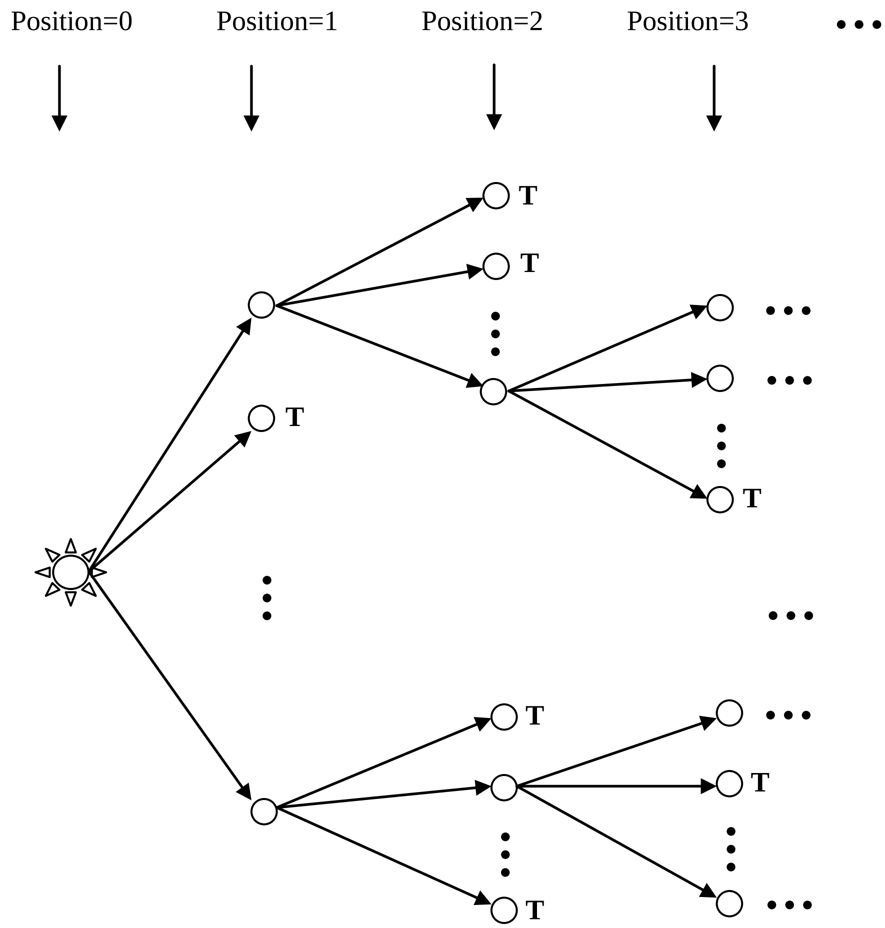
Else: go to next step.

Step 1.6: Calculate the probabilities of being chosen as the next destination for all the feasible destinations; previously selected destinations on the corresponding tours are regarded as infeasible;

Step 1.7: Rank these feasible destinations by probabilities, and choose the first *N*(*CN_Position*) destinations as the permissible destinations; set the status of these permissible destinations as 1 (active), and set the positions of them as *CN_Position* +1;

Step 1.8: Replace the entries of *CN* in *NodeSet*, *NodePosition*, and *NodeStatus* with the corresponding information associated with the selected permissible destinations respectively;

Step 1.9: Replicate *CNS* *N*(*CN_Position*) times and replace *Tours_IC*(1) with the replicated tours.



Note: T means the corresponding tour is terminated.

Figure 20: Search tree of permissible tours

In the search algorithm described above, the number of permissible destinations into which a current node can branch off (N(*CN_Position*)) needs to be carefully specified since the product of them determines the maximum number of tours that the search tree may contain as shown in equation (4-1). Setting this value for each current node position is a tradeoff between the estimation accuracy and the computational efficiency. When it is exactly equal to the number of alternative destinations available to a current position, the search process becomes an exhaustive search that requires enormous computational efforts. When it takes a small number, some optimal tours may be missed during the search. To balance the two requirements, experiments are suggested determining the values. The selected values are reasonable if the tours generated for each home base cover the observed spectrums of tour attributes such as tour length distribution and the distribution of the number of stops.

$$NNS_{\max} = N(0) * N(1) * \cdots * N(S_{\max} - 1) \tag{4-2}$$

Where:

$NNS_{\max}$: The maximum number of tours that the search tree may contain;

$N(i)$: The number of highly probable alternative destinations (permissible destinations) into which the tour can branch off next from the currently selected i^{th} destination;

$S_{\max}$: The maximum number of destinations allowed in a tour.

The outer loop in the tour choice model updates the home bases. After all the permissible tours have been explored for a home base, the process moves to next home base and continues to search new permissible tours associated with the newly selected home base until all the home bases in the network of interest are traversed. The final output from this search algorithm is a set of permissible tours.

4.2 Destination choice and tour termination choice models

In the tour choice model discussed previously, two types of discrete choice models, i.e., the destination choice model and the tour termination model, play a central role. They are estimated to represent the destination choice and the termination decision made along a tour, and thus determine the patterns of the constructed tours. This section focuses on the data used for model specification, the estimation methodology and the estimation results for the models.

4.2.1 Description of data set

The same commercial vehicle travel inventory data collected by the Denver Regional Council of Governments (DRCOG) in the Denver metropolitan area in 1998 is used for the discrete choice modeling purposes. As has been described in Chapter 3, 613 different tours were observed in this data set, representing a total of 65,385 tours made on these tours per day. These tours were made for various purposes, including business meeting, drop-off/pick-up people, fuel/service vehicle, personal business, pickup/deliver a load, and service call among others. A total of 919 TAZs in the network were visited. Among them, 182 TAZs served as the home bases of the observed tours. The interested readers are referred to Holgu ń-Veras and Patil (2005) for details.

Two data sets are generated from the observed tour data for different modeling purposes. To model the destination choice, each observed trip in the original tour data is regarded as an observation in which the destination of the trip is defined as the choice made among the alternative destinations available to the origin node of this trip. The travel impedance associated with this trip and the tour where the trip belongs to are considered as the potential explanatory variables for the destination choice. This results in a destination choice data composed of 2,514 observations. To model the tour termination decision, the same data of the observed trips, with the exception of the first trip on each tour, are taken as observations to generate the choice data: if the chosen destination of a trip is the home base of the corresponding tour, the revealed choice of this observation is set as returning; otherwise, not returning. This leads to 1,908 valid observations that are recorded with their attributes in the tour termination choice data.

For the purposes of modeling the destination choice, the travel impedance associated with the observed destinations as well as those associated with the alternative destinations need to be known in advance. However, the Denver commercial vehicle travel inventory data provides only the former. To solve the issue, a travel impedance matrix collected by the Denver Regional Council of Governments (DRCOG) in 1997 is used as a complementary data set. The travel impedance in the matrix are specified for each OD pair in the Denver metropolitan area, denoting: (1) the distance; (2) the travel time including terminal and intra-zonal time for the peak hours and off-peak hours respectively; (3) the in-vehicle travel time for the peak hours and off-peak hours respectively, which does not include terminal and intra-zonal time; and (4) the vehicle operation cost in terms of dollar values.

4.2.2 Estimation methodology

As introduced in the previous section, the approach discussed in the chapter is based on two models: a destination choice model and a tour termination model. From the analytical standpoint, the tour termination model is the simplest as it only contains two choices: returning to the base or not returning after the vehicle visits the current node. Therefore, the binary logit models are used to represent the perceived utilities of choices. In contrast, the destination choice model has to consider a huge number of elemental alternative destinations, which makes the estimation process next to impossible. To overcome this problem, a stratified importance sampling method was used. In the sampling procedure, the elemental alternatives are aggregated to several strata. Then, a desired number of elemental alternatives are sampled from each stratum to form the choice set. In this case, the decision to choose alternative *i* among the sampled choice set as the next destination can be represented by a modified Multinomial Logit model as shown below (Ben-Akiva and Lerman, 2000):

$$p_n(i \mid D) = \frac{\frac{1}{q_{in}} e^{\mu^* \overline{V_{in}} + \mu' \ln(M_i) + \mu' \ln(B_{in})}}{\sum_{j \in D} \frac{1}{q_{jn}} e^{\mu^* \overline{V_{jn}} + \mu' \ln(M_j) + \mu' \ln(B_{jn})}} \tag{4-3}$$

Where:

$p_n(i \mid D)$: The conditional probability of alternative *i* being chosen given the choice set *D* for observation *n*;

q_{in}: The selection probability of sampling a desired number of alternatives from the stratum where alternative *i* belongs to, for observation *n*. It can be used as the expansion factor for alternative *i*;

$\overline{V_{in}}$: The expected utility of choosing alternative *i* for observation *n*;

M_i: The number of alternatives in the stratum where *i* belongs to;

B_{in} -The measure of the variability of the utilities of alternatives in the stratum where alternative *i* belongs to;

$\mu' = \mu^* / \mu$: The nonnegative ratio of the corresponding scale parameters.

For alternatives within the same stratum, the correlation coefficient between them is equal to $(1-\mu'^2)$. Therefore, μ' needs to satisfy:

$0 \le \mu' < 1$

When μ' is equal to 1, the correlation coefficient between alternative utilities is zero. In this case, the parameters of the specified choice model are not dependent on the definition of the strata. Therefore, μ' can be used to measure the efficiency of stratifying alternatives.

B_{in}, as a measure of the variability of the choice utilities in a stratum, is usually difficult to be observed or modeled. Considering this, it is assumed that B_{in} is approximately equal among strata. Therefore, the equation (4-3) is simplified as:

$$p_n(i \mid D) = \frac{\frac{1}{q_{in}} e^{\mu^* \overline{V_{in}} + \mu' \ln(M_i)}}{\sum_{j \in D} \frac{1}{q_{jn}} e^{\mu^* \overline{V_{jn}} + \mu' \ln(M_j)}} \tag{4-4}$$

A distance-based strategy is used to sample alternative destinations. Under this strategy, for each observed trip, all the elemental alternative destinations are divided into four non-overlapping strata by using the origin zone of this trip as the center (Figure 21). These strata include: (1) the circular region with the radius less than or equal to 1.5 miles from the origin zone; (2) the donut shaped region with distance greater than 1.5 miles and less than or equal to 10.0 miles from the origin zone; (3) the donut shaped region with distance greater than 10.0 miles and less than or equal to 20.0 miles from the origin zone; (4) the region covering the remaining alternative destinations. Then, for each observation, the observed destination is taken as the selected sample from the stratum in which this zone is found while one alternative destination is randomly sampled from each of the other strata. This creates a choice set with four alternatives in total for each observation. Here, the thresholds used to determine the strata represent the quartiles of the observed trip distances in the data set. To determine the best sampling method, several other ways were tested, including two strata with four alternatives sampled and four strata with seven alternatives sampled. The sampling method which was ultimately chosen, i.e., four strata with four alternatives, stands out in terms of the least correlation it causes between the alternative destinations in the same stratum.

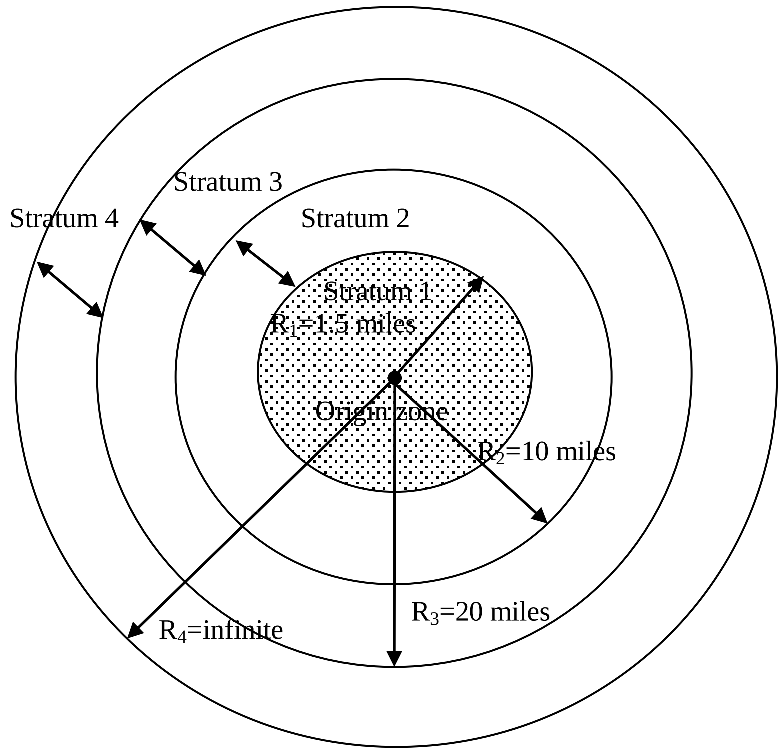


Figure 21: Strata defined to sample alternative destinations (for the commercial vehicle tour choice model)

4.2.3 Destination choice model

The purpose of this model is to identify the key variables that affect the choice of destination location in each trip along a tour. The potential explanatory variables to be included in this model can be categorized into three groups: (1) variables associated with each alternative destination; (2) variables related to the current location (the origin zone of the current trip); and (3) the memory variables representing the cumulative travel impedance of a tour up to the current location. These variables are listed in Table 6.

Table 6: The potential explanatory variables of the destination choice model

Potential variable	Definition
Destination specific variables _ travel impedance related:	
DIST	Distance from the current location to next destination (miles)
TT	Travel time from the current location to next destination (minutes), including

	terminal and intra-zonal time
IVTT	In-vehicle travel time from the current location to next destination (minutes), NOT including terminal and intra-zonal time
ATCOST	Vehicle operation cost from the current location to next destination (dollar value in year 1996)
Destination specific variables _ stratum related:	
LOGSIZE	Natural logarithm of the number of alternative destinations available in the corresponding stratum
Land use indicators of the current location (LU_LAND):	
LU_LAND	A binary variable indicating if the land use of the current location belongs to certain type: if yes, 1; otherwise, 0. The land use types considered include: agriculture, construction, manufacturing, mining, open space, public building, residential, retail, service, transportation and wholesale. The corresponding binary variables are LU_AGRI, LU_CONS, LU_MANU, LU_MINE, LU_OPEN, LU_PUBL, LU_RESI, LU_RETL, LU_SERV, LU_TRAN and LU_WHOL
Memory variables:	
CDIST	Cumulative distance traveled up to the current location in a tour (miles)
CTTIME	Cumulative travel time spent up to the current location in a tour (minutes), including terminal and intra-zonal time
CIVTT	Cumulative in-vehicle travel time spent up to the current location in a tour (minutes), NOT including terminal and intra-zonal time
CHTIME	Cumulative handling time spent up to the current location in a tour (minutes)
CATCOST	Cumulative vehicle operation cost spent up to the current location in a tour (dollar value in year 1996)

It should be mentioned that distance, travel time, in-vehicle travel time and vehicle operation cost between each OD pair, are highly correlated, which would lead to severe estimation problems. To avoid multicollinearity, only one cost variable is included in the destination choice models. Distance (DIST) was finally chosen because of its superior modeling performance.

A number of multinomial logit models were tested, in which different combinations of explanatory variables were included. A vast majority of them were estimated with the piecewise distances as the explanatory variables. The best model that is both statistically significant and conceptually valid is presented in equation (4-5) and Table 7.

$$U(i) = \alpha_{0S_{i \in S}} + \sum_j \alpha_{1j} DISTPIECE_j + \sum_k \alpha_{2k} DIST * LU\_LAND_k + \alpha_3 LOGSIZE_{S_{i \in S}} \quad (4\text{-}5)$$

Where:

$U(i)$: The perceived utility of choosing the i^{th} alternative destination as the next destination by a commercial vehicle;

$\alpha_{0S_{i \in S}}$: Alternative specific constant associated with the S^{th} strata where the i^{th} alternative destination belongs to;

α_{1j}: Coefficient of the j^{th} piecewise distance, j=1, 2, 3, 4;

α_{2k}: Coefficient of the k^{th} interaction term between the distance (DIST) and the k^{th} binary indicator of the land use type of the current location;

LU_LAND: a vector of binary variables indicating if the land use type of the current location belongs to certain category, LU_LAND =[LU_AGRI, LU_CONS, LU_MANU, LU_MINE, LU_OPEN, LU_PUBL, LU_RESI, LU_RETL, LU_SERV, LU_TRAN, LU_WHOL];

α_3: Coefficient of the natural logarithm of the number of alternative destinations contained in the stratum where the i^{th} destination belongs to ($LOGSIZE_{S_{i \in S}}$).

Table 7: Multinomial logit model for choosing destination locations (for the commercial vehicle tour choice model)

Variable	Definition	Coefficient (β)
Alternative specific constants:		
$CONSTANT_2$	Alternative specific constant associated with the alternative destination in the 2nd stratum	0.5066 (26.855)
$CONSTANT_3$	Alternative specific constant associated with the alternative destination in the 3rd stratum	0.9517 (36.164)
$CONSTANT_4$	Alternative specific constant associated with the alternative destination in the 4th stratum	1.1231 (34.455)
Piecewise distances:		

$DISTPIECE_1$	Piecewise distance from the current location to next destination between 0 and 1.5 miles	-0.8362 (-85.938)
$DISTPIECE_2$	Piecewise distance from the current location to next destination between 1.5 and 10 miles	-0.3317 (-169.401)
$DISTPIECE_3$	Piecewise distance from the current location to next destination between 10 and 20 miles	-0.1378 (-69.698)
$DISTPIECE_4$	Piecewise distance from the current location to next destination above 20 miles	-0.0736 (-55.471)
Interaction terms associated with distance and land use type (interaction=DIST*LU_LAND):		
DISTAGRI	Interaction between the distance from the current location to next destination (DIST) and a land use binary variable indicating whether the land use type of the current location is agriculture area or not (LU_AGRI)	0.0485 (13.358)
DISTMANU	Interaction between DIST and the land use binary indicator of manufacturing areas (LU_MANU)	-0.0106 (-7.480)
DISTMINI	Interaction between DIST and the land use binary indicator of mining areas (LU_MINI)	0.0580 (33.180)
DISTOPEN	Interaction between DIST and the land use binary indicator of open space (LU_OPEN)	-0.0793 (-23.854)
DISTPUBL	Interaction between DIST and the land use binary indicator of public building (LU_PUBL)	-0.0503 (-40.056)
DISTRESI	Interaction between DIST and the land use binary indicator of residential areas (LU_RESI)	-0.0245 (-22.522)
DISTRETA	Interaction between DIST and the land use binary indicator of retail areas (LU_RETA)	-0.0181 (-17.908)
DISTSERV	Interaction between DIST and the land use binary indicator of service areas (LU_SERV)	-0.0368 (-37.157)
DISTTRAN	Interaction between DIST and the land use binary indicator of transportation areas (LU_TRAN)	-0.0457 (-25.821)
DISTWHOL	Interaction between DIST and the land use binary indicator of wholesale areas (LU_WHOL)	-0.0482 (-37.210)
DISTBASE	Interaction between DIST and a binary variable indicating whether the current location is home base	0.0284 (40.962)

Size measurement of the stratum:		
LOGSIZE	Natural logarithm of the number of locations available in the corresponding stratum	0.7241 (158.006)

Note: (1) the values in the parentheses are the *t* statistic; (2) LU_LAND represents the binary indicators of the land use type of the current location.

The estimated models show that the distance from the current location to a potential destination (DIST) has a nonlinear effect on the utility of choosing the destination. The absolute value of the DIST coefficient associated with the stratum close to the current location is larger than the ones associated with the strata that are farther. To accommodate this, the distance variable was split into four pieces, DISTPIECE1 (the piece less than 1.5 miles), DISTPIECE2 (the piece greater than or equal to 1.5 and less than 10.0 miles), DISTPIECE3 (the piece greater than or equal to 10.0 and less than 20.0 miles) and DISTPIECE4 (the piece greater than 20 miles), as demonstrated in Figure 22. Same as the ones used to determine the strata, the thresholds used here represent the quartiles of the observed trip distances.

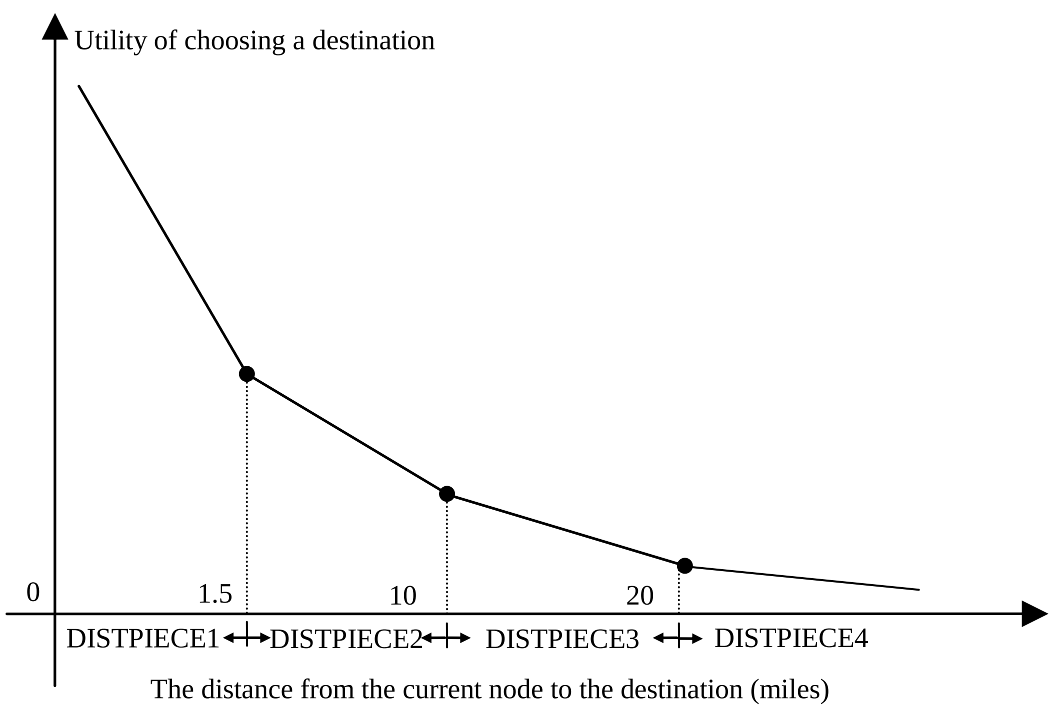


Figure 22: Nonlinear effect of the distance on the utility of choosing a destination (from the commercial vehicle tour choice model)

As shown, the distance from the current location to next destination as well as the interaction terms associated with it remains significant in the model as the memory variables dropped out. The signs of the piecewise distance variables (DISTPIECE1, DISTPIECE2, DISTPIECE3 and DISTPIECE4) are all negative, demonstrating that the perceived utility of choosing a destination is a deterrence function of the distance from the current node to this destination. The longer the distance is, the less likely the destination will be chosen. This finding is consistent with the previous studies of truck trip length distributions (Holguín-Veras and Thorson, 2000). Meanwhile, the marginal effect of the distance is nonlinear as discussed before. Because of the highly non-linear relationship, destinations close to the current node are preferred. However, as the distance increases, the relative importance of distance decreases.

In addition to the direct effect of trip distance (DIST), the modeling process revealed the existence of interaction effects between distance and the land use type of the current zone. As indicated by the estimated coefficients of the interaction terms between DIST and the binary indicator of the land use type of the current location, the land use type of the current location may affect commercial vehicles' perception of distance in determining their choices of next destination. For instance, if the land use type of the current location is manufacturing (LU_MANU), open space (LU_OPEN), public building (LU_PUBL), residential (LU_RESI), retail (LU_RETA), service (LU_SERV), transportation (LU_TRANS) or wholesale area (LU_WHOL), commercial vehicles are willing to visit the nodes nearby as the next destination. On the contrary, a longer trip to next destination is more likely to be made given the land use type of the current location is agriculture (LU_AGRI) or mining (LU_MINI). This is consistent with the fact that the agriculture or mining areas are usually located on the periphery of the urban areas and thus require longer trips to make connections with the potential destinations in urban areas.

In this model, the coefficient of the size measurement variable (LOGSIZE) is close to 1. As has been explained in equation (4-4), this indicates that the specification of the destination choice model does not depend on the definition of strata.

4.2.4 Tour termination model

The second model represents the decision of whether to terminate the tour, or continue to visit another destination. Since there are only two alternatives, terminating the tour or not, a binary logit model is used. As shown in Table 8, the potential variables that may affect the termination decision include the variables associated with the return travel impedance, the land use indicators and the memory variables.

Table 8: The potential explanatory variables for the tour termination model

Potential variable	Definition
Return travel impedance variables:	
RETNDIST	Return distance from the current location to the home base (miles)
RETNTT	Return travel time from the current location to home base (minutes), including terminal and intra-zonal time
RETNIVTT	Return in-vehicle travel time from the current location to home base (minutes), NOT including terminal and intra-zonal time
RETNATCOST	Vehicle operation cost from the current location to home base (dollar value in year 1996)
Land use indicators of the current location (LU_LAND):	
Same as in Table 6	
Memory variables:	
Same as in Table 6	

The best model found is shown in equation (4-6) and Table 9. Three groups of variables are included in the tour termination model: (1) the in-vehicle travel time back to the home base from the current location (RETNIVTT); (2) interaction terms between RETNIVTT and the binary indicators of the land use type of the current location; and (3) two memory variables, i.e., the cumulative travel time spent in a tour up to the current location in the unit of minutes (CTTIME) and the cumulative handling time spent in a tour up to the current location (CHTIME).

$$U(RETURN) = \beta_0 + \beta_1 RETNDIST + \beta_2 CTTIME + \beta_3 CHTIME$$

$$+ \sum_i \beta_{1i} RETNDIST * LU\_LAND_{1i} \quad (4\text{-}6)$$

$$= \beta_0 + (\beta_1 + \sum_i \beta_{1i} LU\_LAND_i) * RETNDIST + \beta_2 CTTIME + \beta_3 CHTIME$$

Where:

U(RETURN): the perceived utility of returning to the home base from the current location;

β_0: Alternative specific constant associated with the choice of returning to the home base;

β_i: Coefficients of RETNDIST, CTTIME, and CHTIME respectively, *i*=1, 2, 3;

β_{1i}: Coefficient of the i^{th} interaction term between the return in-vehicle travel time (RETNIVTT) and the i^{th} binary indicator of the land use type of the current location;

Due to the interaction terms introduced, the marginal effect of the return in-vehicle travel time (RETNIVTT) on the perceived utility of terminating a tour is quantified by the summation of the estimated coefficient of this variable and the estimated coefficients of the corresponding interaction terms as indicated in equation (4-6). In this context, the land use type of the current location affects the role of the return in-vehicle travel time significantly. For instance, if the land use of the current location is construction (LU_CONS), manufacturing (LU_MANU), mining (LU_MINE), residential (LU_RESI), retail (LU_RETL), service (LU_SERV), transportation (LU_TRAN) or wholesale (LU_WHOL) area, the sign of the combined coefficient of RETNIVTT is negative. This indicates that commercial vehicles tend to visit nodes close to their home base before actually returning to home base. On the contrary, given the land use of the current location is agricultural area (LU_AGRI), open space (LU_OPEN) or public building (LU_PUBL), the overall impact of RETNIVTT on the perceived utility of returning becomes positive. This implies that the tours with these three types of areas as the last destinations have a strong tendency to return even though these destinations are far away from the home base.

The cumulative travel time up to the current location (CTTIME) and the cumulative handling time up to the current location (CHTIME) play different roles in determining if a tour returns to the home base or not. As indicated by the signs of their estimated coefficients, the increase in the cumulative travel time spent up to the current location discourages returning while the increase in the cumulative handling time spent up to the current location increases the likelihood of returning. Meanwhile, the marginal effect of the cumulative handling time is higher than that for the cumulative travel time as shown by the absolute values of the estimated coefficients. The opposite effects of the two memory variables can be explained by the difference in meanings of them. On one hand, the cumulative handling time up to the current location quantitatively represents the amount of requests made by customers along a tour due to the proportionality of handling time to the efforts spent serving customers. The cumulative travel time up to the current location, on the other hand, serves as a pure indicator of travel impedance. Since commercial vehicle tours are essentially made for serving customers' requests, a long travel time spent along a tour may induce more travel until certain requests are satisfied. On the contrary, if a large amount of customers' requests have been satisfied in a tour, or in other words, a lot of handling time has been spent to serve these requests; the likelihood for a truck to return to its base will be high. This implies that, the cumulative handling time, as an indicator of customers' requests or demands satisfied in a tour, significantly impacts the trip chaining behavior of commercial vehicles, particularly the tour termination decision; its role is so different from the one of the cumulative travel time that its impact should be analyzed separately.

Table 9: Binary logit model for tour termination (for the commercial vehicle tour choice model)

Variable	Definition	Coefficient
Alternative specific constant:		
CONSTANT	Alternative specific constant for the choice of returning	-0.4994 (-52.229)
Return travel time:		
RETNIVTT	In-vehicle travel time of returning from the current location to the home base (minutes)	-0.0061 (-2.481)

Cumulative travel impedance:		
CTTIME	Cumulative travel time spent in a tour up to the current location	-0.0038 (-64.155)
CHTIME	Cumulative handling time spent in a tour up to the current location	0.0044 (78.501)
Interaction terms associated with RETNIVTT (interaction= RETNIVTT*LU_LAND) :		
IVTTAGRI	Interaction between the in-vehicle travel time of returning to the home base from the current location (RETNIVTT) and a land use binary variable indicating whether the land use type of the current location is agriculture area or not (LU_AGRI)	0.0333 (8.104)
IVTTCONS	Interaction between RETNIVTT and the land use binary indicator of construction areas (LU_CONS)	-0.0134 (-5.208)
IVTTMANU	Interaction between RETNIVTT and the land use binary indicator of manufacturing areas (LU_MANU)	-0.0354 (-12.528)
IVTTMINI	Interaction between RETNIVTT and the land use binary indicator of mining areas (LU_MINI)	-0.1173 (-20.181)
IVTTOPEN	Interaction between RETNIVTT and the land use binary indicator of open space (LU_OPEN)	0.1230 (21.261)
IVTTPUBL	Interaction between RETNIVTT and the land use binary indicator of public building (LU_PUBL)	0.0422 (16.196)
IVTTRESI	Interaction between RETNIVTT and the land use binary indicator of residential areas (LU_RESI)	-0.0429 (-16.641)
IVTTRETA	Interaction between RETNIVTT and the land use binary indicator of retail areas (LU_RETA)	-0.0352 (-13.964)
IVTTSERV	Interaction between RETNIVTT and the land use binary indicator of service areas (LU_SERV)	-0.0156 (-6.179)
IVTTTRAN	Interaction between RETNIVTT and the land use binary indicator of transportation areas (LU_TRAN)	-0.0326 (-7.363)
IVTTWHOL	Interaction between RETNIVTT and the land use binary indicator of wholesale areas (LU_WHOL)	-0.0634 (-23.217)

Note: (1) the values in the parentheses are the *t* statistic; (2) LU_LAND represents the binary indicators of the land use type of the current location.

4.3 Case study

In order to evaluate the performance of this tour choice model, the models were applied to the Denver case study. In this case, there are 919 TAZs among which 182 TAZs contain home bases of commercial vehicles. As found, 613 different tours were included in the data set, representing a total of 65,385 tours made on these tours per day. These observed tours are aggregated to get the total number of trips produced by each TAZ (trip production) and the total travel impedance as the inputs to the entropy maximization formulations. A detailed description of the data set can be found in Chapter 3.

The proposed tour choice model (Figure 19) is applied to generate a set of tours. The vector containing the number of permissible destinations into which the i^{th} order destination can branch off (N(*CN_Position*)) is set as $[10, 10, 2, 1, 1, \ldots, 1]_{1\times 20}$ for each home base based on a number of experiments. This leads to 15,728 effective tours that represent wide spectrums of observed tour attributes in terms of the possible values of tour length and the number of stops in a tour. The resulting tours are then used to define the entries, a_{im}, in the coefficient matrix A of the entropy maximization formulations: if a tour m includes node i, a_{im} equals 1; otherwise, 0. With the given coefficient matrix and the previously aggregated information of trip productions and total impedance factors, the corresponding entropy formulations are solved to get an optimal solution of the number of tour flows loaded in each tour. To evaluate the effectiveness of the tour choice model, the estimated tours are compared with the observed tours in terms of the tour length distributions.

4.3.1 Results associated with entropy maximization formulation 1

The generated tours are used as the input to the first entropy maximization formulation in which the tour time constraint is the only travel impedance related constraint. In the optimal solution reached, the total 65,385 vehicle flows are distributed to 536 tours, leaving other tours irrelevant.

The tour time distributions of the estimated tours and the observed tours are shown in Figure 23. The two distributions follow a very similar pattern with the percentage of trips increasing first and then decreasing as the tour time increases. For the two histogram distribution curves, the best fitting regression model for the tour time distribution is a gamma function of tour time with the form below:

$$freq = a_0 e^{a_1 tt_1} tt_1^{a_2} \tag{4-7}$$

Where:

freq= Frequency of tour times (%);

a_0, a_1, a_2= Parameters of tour time distribution functions;

tt_1 = Tour time.

Consistent with the patterns exhibited, the estimated parameters in the two distributions are very similar. As shown in Table 10, none of the parameter values of the estimated tour time distribution are statistically different from the parameters of the observed distribution. These findings indicate that the first entropy maximization formulation combined with the proposed tour choice model can reach a set of estimated tour flows that are good enough to resemble the patterns of observed tour flows.

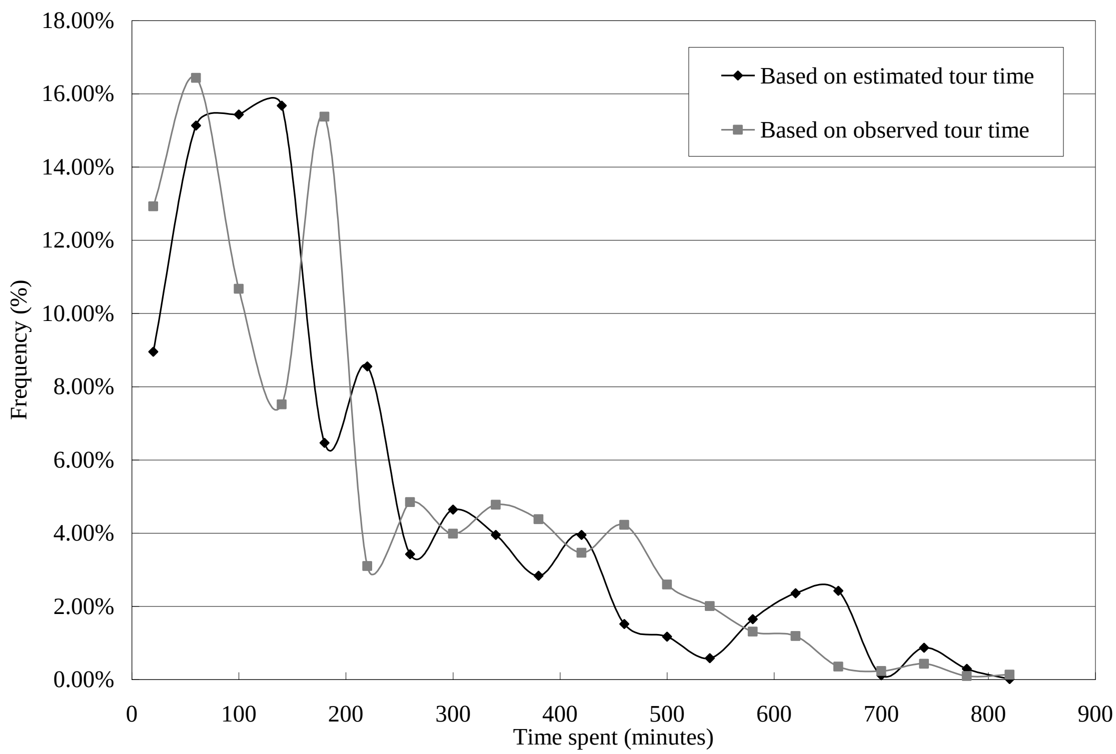


Figure 23: Tour time distributions, estimated (from formulation 1) vs. observed

4.3.2 Results associated with entropy maximization formulation 2

The same set of generated tours is used as input to the second entropy maximization formulation. In this formulation, two components of the tour time, i.e., the tour travel time and the tour handling time, are considered respectively by using two constraints. As found in the optimal solution from the second entropy maximization formulation, 65,385 vehicle flows are distributed to 449 tours.

The tour travel time distributions as well as the tour handling time distributions for the estimated tours and the observed tours are illustrated in Figure 24 and Figure 25 respectively. As found, the best fitting regression model for two distributions is an exponentail function of the corresponding impedance variable with the form below:

$$freq = a_0 e^{a_1 tt_2} \tag{4-8}$$

Where:

tt_2 = Tour travel time or tour handling time.

As shown in Table 10, none of the parameter values of the estimated tour travel time distribution are statistically different from the parameters of the observed distribution. In contrast, the parameter associated with tour handling time (a_2) in the estimated tour handling time distribution is significantly different from the one specified for the observed distribution. The likely reason of causing it may come from the method of determining the handling time at each current location along a tour. In the process of generating tour, the handling time spent on each destination along a tour was randomly sampled from the observed distribution of handling time. Taking the summation of these randomly sampled handling times in a tour tends to stretch out the original pattern of tour handling time, and thus results in a gentler and smoother curve as shown in Figure 25.

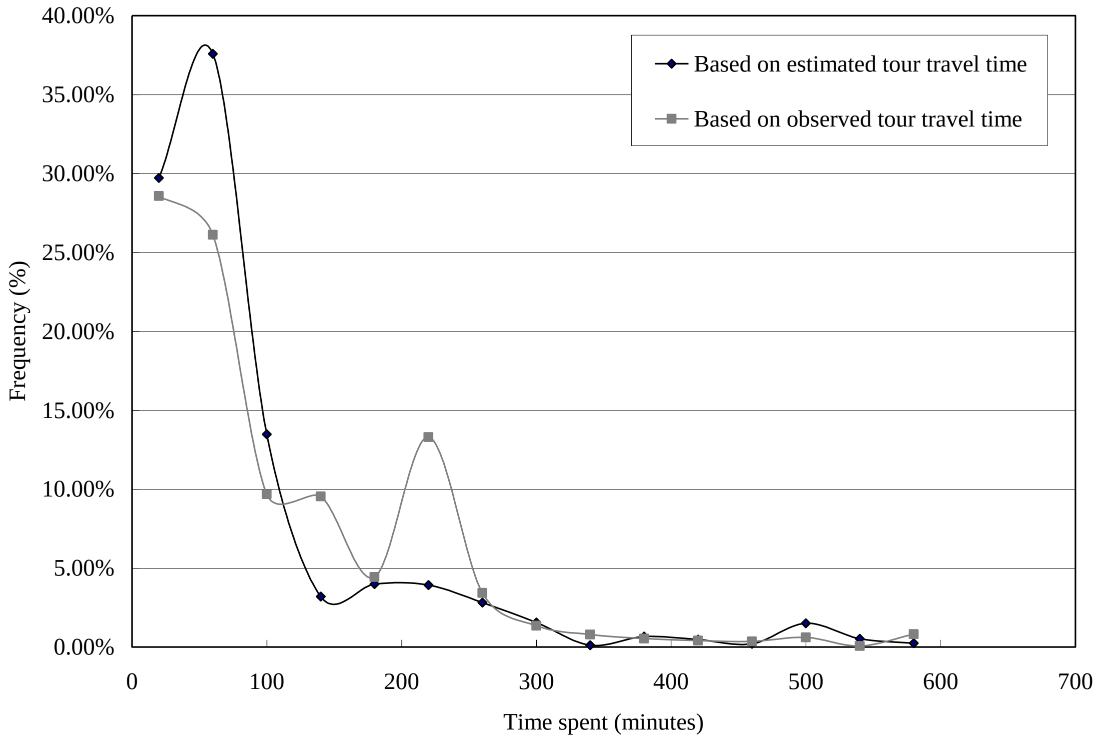


Figure 24: Tour travel time distributions, estimated (from formulation 2) vs. observed

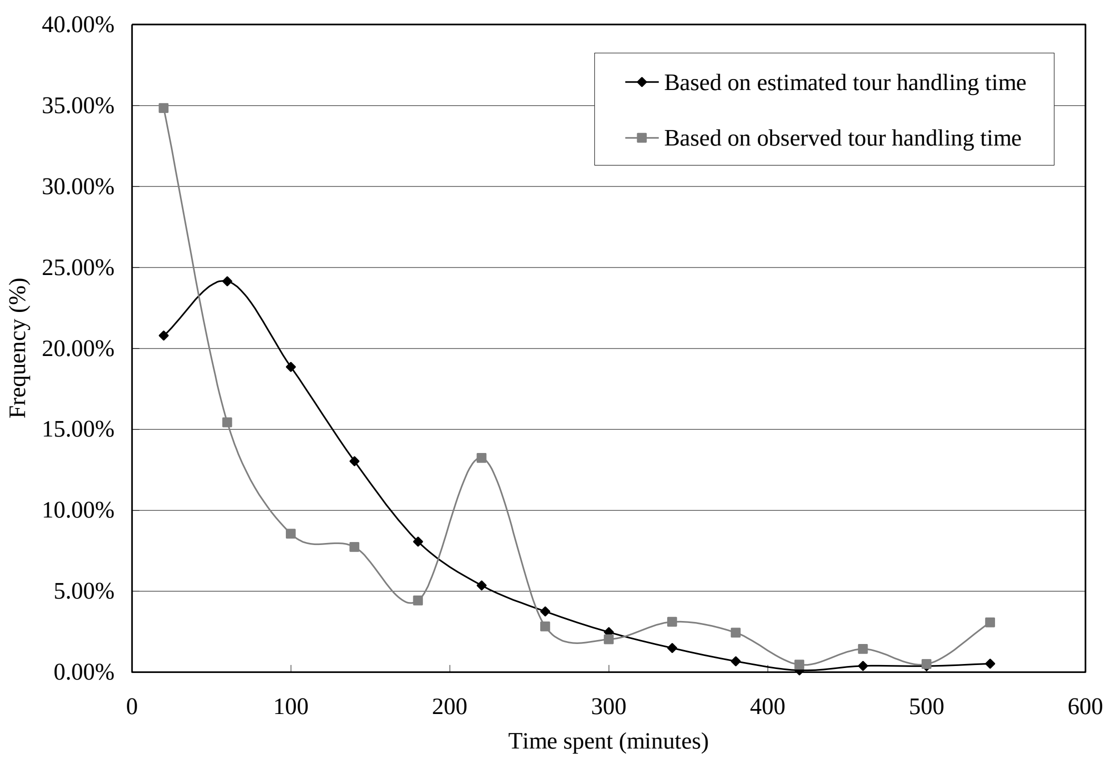


Figure 25: Tour handling time distributions, estimated (from formulation 2) vs. observed

Table 10: Model parameters and t test statistics for the tour length distributions resulting from the tour choice model

Frequency of (%)	a_0	*se* (a_0)	a_1	*se* (a_1)	a_2	*se* (a_2)
Observed tour time	0.022	1.210	-0.00767	0.00101	0.564	0.274
Estimated tour time	0.011	2.290	-0.00855	0.00201	0.729	0.524
Observed tour travel time	0.288	0.323	-0.00900	0.000822	/	/
Estimated tour travel time	0.220	0.492	-0.00843	0.00142	/	/
Observed tour handling time	0.238	0.268	-0.00729	0.000683	/	/
Estimated tour handling time	0.395	0.339	-0.00984	0.00105	/	/
Hypothesis:	*t* statistics	Result	*t* statistics	Result	*t* statistics	Result
Tour time distribution: estimated = observed	-0.019	Accept	-1.788	Accept	1.276	Accept
Tour travel time distribution: estimated = observed	-0.444	Accept	1.345	Accept		
Tour handling time distribution: estimated = observed	1.357	Accept	-7.622	Reject		

Note: each hypothesis is tested at the 95% confidence interval.

4.4 Conclusions

In this chapter, a commercial vehicle tour choice model is developed to generate a set of tours as the input to the entropy maximization formulations. In this model, the tour generation process is decomposed into two decisions: (1) the destination choice decision indicating which node will be visited next if the tour continues; and (2) the tour termination decision determining if a tour needs to return to the home base from the current location or continue to visit another destination. Two behavioral choice models, i.e., the tour termination model and the destination choice model are specified to represent them respectively. As identified by the destination choice model, the distance from the current location to next potential destination and the land use type of the current location are two key variables that determine the choice of next destination. As expected, the perceived utility of choosing a node as next destination is a deterrence function of distance. Meanwhile, because of the highly non-linear relation, destinations closer to the current node are preferred. However, as the distance increases, the relative importance of distance decreases.

In addition to the negative effect of distance, it was found that the impact of distance varies by the land use type of the current location: if the land use type of the current location is manufacturing, open space, public building, residential, retail area, service, transportation or wholesale, commercial vehicles are willing to visit the nodes nearby as the next destination. On the contrary, a longer trip to next destination is more likely to be made given the land use type of the current location is agriculture or mining.

The estimation revealed that the tour termination model is a function of three types of variables: (1) the in-vehicle travel time back to the home base; (2) the interaction terms between the return travel time and the binary indicators of the land use type of the current location; and (3) two memory variables measuring the cumulative travel time and the cumulative handling time spent up to the current location in a tour. Due to the interaction terms introduced, the impact of return travel time on the perceived utility of returning is significantly affected by the land use type of the current location. Meanwhile, the two memory variables play opposite roles in making the termination decision: the increase in the cumulative travel time may discourage returning while the increase in the cumulative handling time will increase the likelihood of returning instead.

In order to evaluate the performance of this tour choice model, the proposed methodology is applied to a case study in the Denver metropolitan area. The generated tours are used to define the coefficient matrix in the entropy maximization formulations. As found, the estimated tour length distributions from the entropy maximization formulations resemble the observed ones. This indicates the efficiency of the proposed tour choice model.

5. Hybrid Microsimulation Urban Freight Demand Model

In the previous two chapters, the tour-based entropy maximization formulations combined with a behavioral-based tour choice model were proposed to estimate the aggregate distribution patterns of commercial vehicle tour flows in urban areas. As a prerequisite condition of this approach, the trip productions/attractions and the total impedance of the network are required as the input information, which may not be available for all planning purposes. In this context, this chapter describes a hybrid micro-simulation framework that focuses on the construction of individual tours, looking forward to providing an alternative way to forecast urban freight travel demand.

Similar to traditional hybrid micro-simulation methods used by others, this framework involves a sequential procedure that is composed of three stages: (1) the first stage is to estimate the commodity flow origin-destination (OD) matrix that captures the production-consumption relationships. This may require an input-output model to estimate the total number of tons produced and attracted by each node in the network; (2) the second stage is to distribute the tons to origin-destination pairs by using gravity models or other forms of spatial interaction models; and (3) following these, commercial vehicle tours are constructed in the third stage to satisfy the estimated commodity OD matrix. The proposed method is different from previous methods in that, behavioral models, rather than a simplistic Monte Carlo simulation, are used to generate individual tours. This is accomplished by means of two discrete choice models that focus on destination choice and tour termination decision. Due to the unavailability of the data, this study only focuses on the tour construction stage, assuming that the commodity flow OD matrix is known as an input.

The data used for the discrete choice modeling are from the Integrative Freight Market Simulation (IFMS) conducted by Thorson (2005). This synthetic data contains tours generated using a spatial price equilibrium formulation. Using synthetic data has some advantages. First, the analyst has full knowledge of the experimental conditions. Second, the analysis can focus on the key aspects of the problem under analysis. Third, when properly generated, research using synthetic data has been found to lead to significant insight into complex problems and is routinely used in areas such as discrete choice modeling (Gopinath et al., 2005; Walker, 2001)

The chapter is divided into six sections. Section 5.1 describes the modeling framework proposed and assumptions made in this study. Section 5.2 analyzes the data and the sampling technique used for discrete choice modeling. Section 5.3 presents the estimated discrete choice models to capture the decisions of whether to return to the base or not, and which node will be the next destination if not returning. Section 5.4 describes the results obtained from the application of the modeling framework to a test case. This chapter ends with conclusions.

5.1 Methodology and assumptions

The fundamental assumption used here is that the tour construction process can be decomposed into two parts: the destination choice, and the tour termination decision. Figure 26 shows the proposed procedure. Obviously, this is a simplification of the decisions about which destinations to visit and in what order are when related. As a result, each tour is constructed based on the probability of choosing each destination and the probability of whether to terminate the tour or not in the current destination. These probabilities are generated by two different logit models: (a) the destination choice model; and (b) the tour termination model. More details about these models are discussed in the next section. After a new destination is chosen, the corresponding trip from the previous location to the chosen destination is added to the tour. This trip is determined to be loaded or empty based on the availability of commodity flows: if no cargo is available between the corresponding OD pair, the trip is empty; otherwise, the trip is loaded with the average payload. The process of adding trips to a tour continues until the tour termination model indicates returning to the home base or the maximum number of destinations is reached. After a tour is completed, the commodity flow OD matrix is updated by subtracting the amount of cargoes shipped by the tour. Tours are constructed one by one until all the cargoes are shipped.

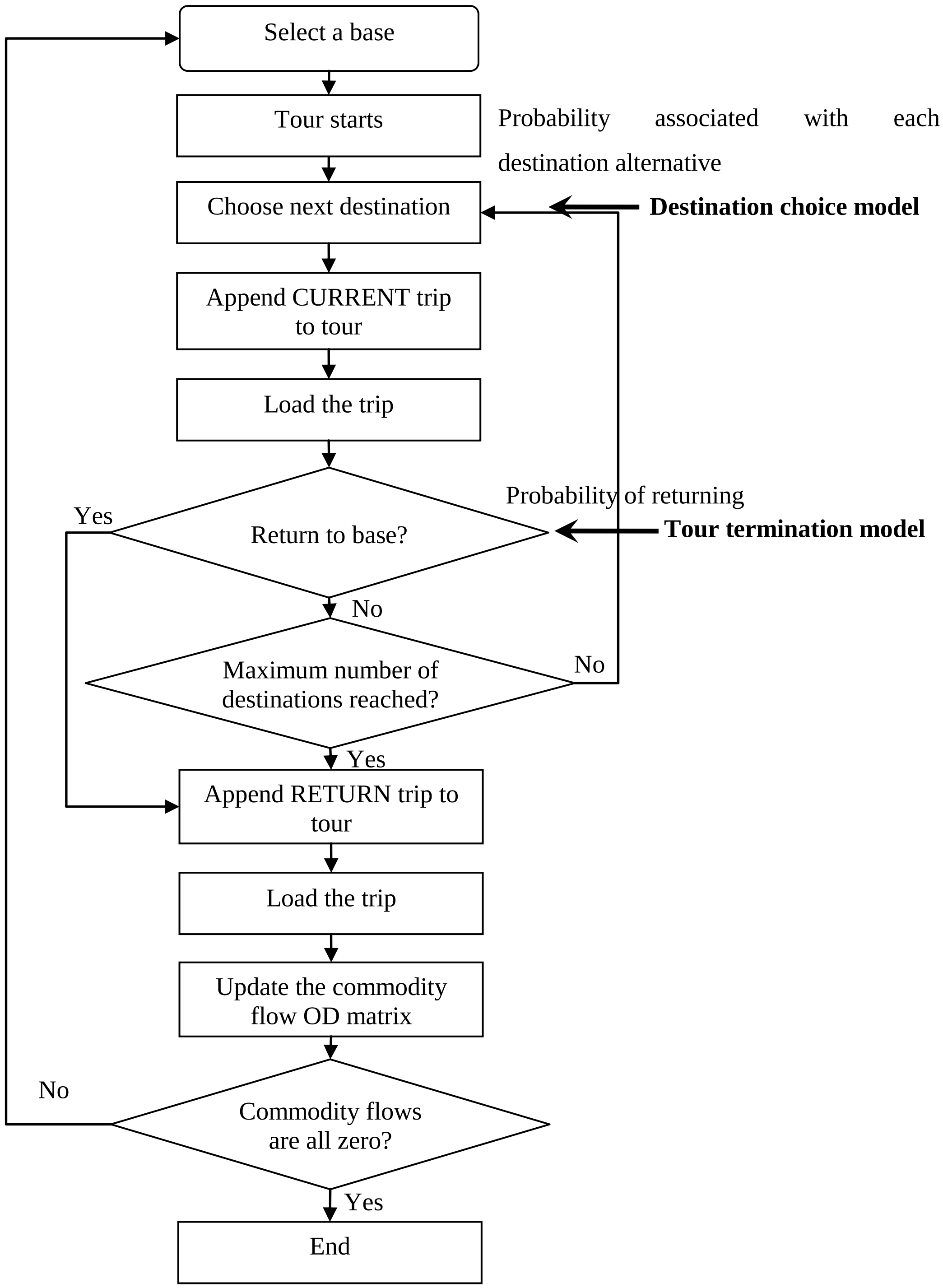


Figure 26: Procedure of constructing goods-related vehicle tours

Estimating the tours taking place in the entire area requires a sequential process by which the carriers located in the study area are allowed to take part in the transport of commodity flows. In doing this, the carriers are selected probabilistically on the basis of their fleet size as shown below.

$$p(k) = \frac{F_k}{\sum_{l=1}^{K} F_l} \tag{5-1}$$

Where:

$p(k)$: The probability that the common carrier located at home base k is assigned a token to dispatch a truck.

F_k : The total number of trucks owned by the carrier located at home base k.

K: The total number of carriers (or bases) operating in the freight network.

The following assumptions are made in order to simplify the procedure of constructing commercial vehicle tours:

(1) A single, generic commodity is being transported;
(2) Trucks are identical and have the same capacity;
(3) Each carrier is assumed to own enough trucks to satisfy the demand of shipments;
(4) The fleet size of each carrier is assumed to be known.

5.2 Disaggregate choice Models

In this study, each tour is constructed by choosing the destination for a given trip, and modeling the decision to terminate (or not) the tour, trip by trip, until the truck finally returns to its base. In order to do this, two discrete choice models are estimated to capture the decisions pertaining to destination choice, and tour termination. This section describes the data set used for modeling purposes and the sampling technique used for the disaggregate modeling of destination locations.

5.2.1 Description of data set

This paper uses a synthetic data set generated by Thorson (2005) that contains a set of tours that satisfy spatial price equilibrium conditions in an urban area. This data set was generated as part of research on the Integrative Freight Market Simulation (Holguín-Veras, 2000). The IFMS involves the development of a comprehensive freight transportation demand model based on game theory which depicts both commodity flows and vehicle tours. Since the tours were constructed under the condition that Nash Equilibrium was obtained among common carriers competing in the urban freight market, they are consistent with common carriers' market equilibrium and profit maximization. In other words, they are a representation of common carriers' trip chaining behavior in a competitive urban freight market. Therefore, using this data is expected to help gain insights about the key factors that affect the trip chaining decisions.

In this data set, there are 86 tours constructed using spatial price equilibrium principles. For each tour, the available information includes the number of destinations, the total profit, the total travel time, destination location, and the associated amount of cargoes that need to be picked up or delivered. The number of destinations in each tour ranges from 6 to 19, and the average is 12.5. The tour profit varies from \$354.9 to \$876 with the average as \$604.6. The total travel time is from 5.6 to 9.9 hours with the average as 7.7 hours, which is consistent with truck drivers' work hours.

As shown in Table 11, these tours were generated from different games that vary in the number of common carriers, the number of available nodes, and the number of contested nodes. Therefore, this data set covers different market situations in which the level of competition between common carriers vary.

Table 11: Summary of tours in terms of games

Game	Number of common carriers	Number of nodes in the network	% of contested nodes	Number of trip chains (tours)
A	2	80	0	6
B	2	80	10	6
C	2	80	20	6
D	2	80	25	7
F	2	120	30	10
F'	4	120	30	9
G	4	150	50	11
H	8	150	30	15
I	8	150	50	16

For modeling purposes, the data set was broken down into two subsets. The first subset is for modeling the destination choice. In this data set, each observed trip in the original tour data is regarded as an observation in which the destination of the trip is defined as the choice made among the alternative destinations available to the origin node of this trip. The attributes associated with this trip and the tour where the trip belongs to are considered as the potential explanatory variables for the destination choice. This results in a destination choice data composed of 1151 observations. The second data set is for modeling the tour termination decision, given that current location is chosen. To generate it, the same data of the observed trips, except of the first trip on each tour, are taken as observations to generate the choice data: if the chosen destination of a trip is the home base of the corresponding tour, the revealed choice of this observation is set as returning; otherwise, not returning. 1072 valid observations are recorded with their attributes in the tour termination choice data.

5.2.2 Estimation methodology

As introduced in the previous section, the approach discussed in the paper is comprised of two discrete choice models: a destination choice model and a tour termination model. From the analytical standpoint, the tour termination model is the simplest as it only contains two choices: returning to the base or not returning after the vehicle visits the current node. Therefore, the binary logit models are used. On the other hand, the destination choice model has to consider a huge number of elemental alternative destinations, which makes the estimation process next to impossible. To overcome this problem, a stratified importance sampling method was used. As described in Chapter 4, sampling procedures could be effective in reducing the dimensionality of the problem. The procedure used is summarized below: the elemental alternatives are first aggregated to several strata; then, a specified much smaller number of elemental alternatives is sampled from each stratum to form the destination choice set. By using this method, the decision to choose alternative *i* among the choice set as the next destination can be represented by a modified Multinomial Logit model as shown in equation (5-2) (Ben-Akiva and Lerman, 2000).

$$p_n(i \mid D) = \frac{\frac{1}{q_{in}} e^{\mu^* \overline{V_{in}} + \mu' \ln(M_i)}}{\sum_{j \in D} \frac{1}{q_{jn}} e^{\mu^* \overline{V_{jn}} + \mu' \ln(M_j)}} \tag{5-2}$$

Where:

$p_n(i \mid D)$: The conditional probability of alternative *i* being chosen given the choice set *D* for observation *n*;

q_{in}: The selection probability of sampling the desired number of alternatives from the stratum where alternative *i* belongs to, for observation *n*. It can be used as the expansion factor for alternative *i*;

$\overline{V_{in}}$: The expected utility of choosing alternative *i* for observation *n*;

M_i: The number of alternatives in the stratum where *i* belongs to;

$\mu' = \mu^* / \mu$: The nonnegative ratio of the corresponding scale parameters.

For alternatives within the same stratum, the correlation coefficient between them is equal to $(1-\mu'^2)$. Therefore, μ' needs to satisfy:

$0 \leq \mu' < 1$

When μ' is equal to 1, the correlation coefficient between the utilities of alternative destinations is zero. In this case, the parameters of the specified choice model do not depend on the definition of the strata. Therefore, μ' can be used to as a criterion to measure the efficiency of the stratified sampling method.

Three different ways of stratified importance sampling were tested to see which one caused the least correlation between the stratified alternatives, e.g., the strategy with two strata and four alternatives, the one with four strata and four alternatives, and the one with four strata and seven alternatives. Table 12 shows the estimated coefficient (μ') for the measure of stratum size ($\ln(M)$) and the corresponding correlation coefficient between alternatives for each strategy. As can be seen, strategy 1 with two strata and four alternatives causes the least correlation between the alternatives in the defined strata. In other words, the parameters of the specified choice model are least dependent on the definition of the strata. Therefore, strategy 1 is used as the sampling method.

Table 12: Correlation coefficient between alternatives for different stratified sampling strategies

Stratification strategy	Stratum ID	Radius of stratum,	Number of sampled	Coefficient of the measure of	Correlation coefficient between alternative

		(distance units)	alternatives	stratum size (μ') (1)	utilities $(1-\mu'^2)$
1	1	<=0.3	2	0.792	0.373
	2	>0.3	2		
2	1	<=0.2	1	0.055	0.997
	2	>0.2 and <=0.3	1		
	3	>0.3 and <=0.5	1		
	4	>0.5	1		
3	1	<=0.2	2	0.711	0.494
	2	>0.2 and <=0.3	2		
	3	>0.3 and <=0.5	2		
	4	>0.5	1		

Note: (1) μ' is the coefficient of the natural log of the stratum size as shown in equation (5-2).

Under this strategy, for each current location, all the available destinations were grouped into two strata by using the current location as the center, one with the radius less than or equal to 0.3 distance units and the other covering the remaining area (Figure 27). This threshold was used because it is the median node-to-node distance in the data set. Then, for each observation, one alternative node was randomly sampled from the stratum in which the observed destination node is, and two alternative nodes were sampled from the other stratum. This creates a choice set with four alternatives in total.

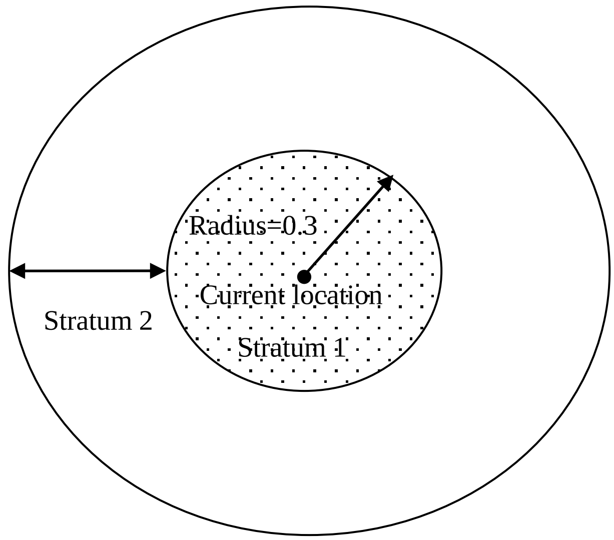


Figure 27: Strata defined to sample alternative destinations (for the microsimulation-based tour construction procedure)

5.3 Estimation results

Two sets of discrete choice models were estimated by using the IFMS data and the stratified alternative sampling. The estimation results discussed in this section correspond to the destination choice model and the tour termination model.

5.3.1 Destination choice model

The purpose of this modeling process is to identify the key variables that affect the choice of destination location in a tour. The potential explanatory variables to be included in this model can be categorized into two groups: (1) variables associated with an alternative destination such as the distance from the current location to this destination (STOPDIST), the amount of cargoes available for picking up at the destination (STOPPROD), the amount of cargoes available for delivering to the destination (STOPATTR), and the natural logarithm of the number of available destinations in the corresponding stratum (LOGSIZE); and (2) memory variables representing the history of a tour, i.e., the cumulative distance covered up to the current location (ELAPDIST), and the cumulative amount of cargoes picked-up (ELAPPROD) or delivered up to the current location (ELAPATTR). In order to take into consideration the effects of aggregating alternatives, a measure of the stratum size (LOGSIZE) is included as an explanatory variable (Ben-Akiva and Lerman, 2000).

A number of multinomial logit models were tested, in which different combinations of independent variables were included. The estimated models show that the distance from the current location to the potential destination (STOPDIST) has a nonlinear effect on the perceived utility. The coefficients of STOPDIST for the first two utility functions belonging to the first stratum are greater in absolute value than the coefficients in the utility functions associated with the second stratum. To address this issue, the distance variable was broken down into four pieces, e.g., STOPDIST1 (the piece less than or equal to 0.2 distance units), STOPDIST2 (the piece greater than 0.2 and less than or equal to 0.3 distance units), STOPDIST3 (the piece greater than 0.3 and less than or equal to 0.5 distance units) and STOPDIST4 (the piece greater than 0.5 distance units), as demonstrated in Figure 28. The thresholds used are the first, second and third quartiles of the observed trip distances respectively.

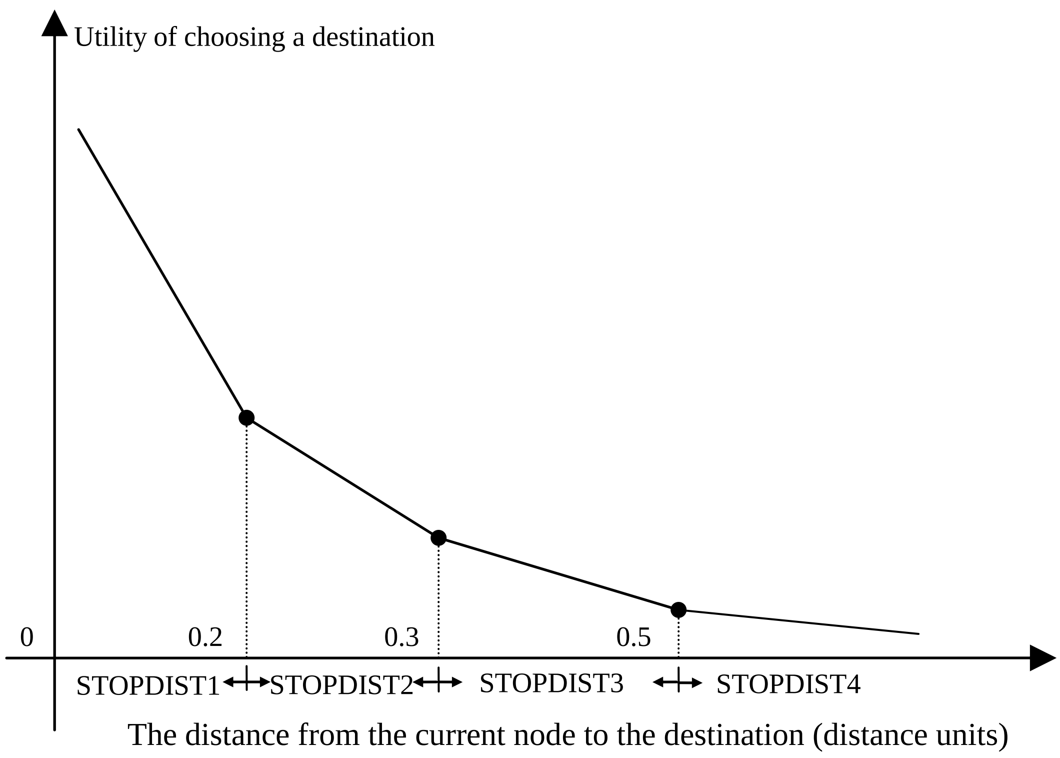


Figure 28: Nonlinear effect of the distance on the utility of choosing a destination (from the microsimulation-based tour construction procedure)

New models were estimated for the piecewise distances. The one with both statistical significance and theoretical soundness is presented in Table 13. As shown, only the variables in the first group are significant, as the memory variables dropped out. The signs of the distance variables (STOPDIST1, STOPDIST2, STOPDIST3 and STOPDIST4) are all negative, which demonstrates that the perceived utility of choosing a destination is a deterrence function of the distance from the current node to the alternative destination. The longer the distance is from the current node to a potential destination, the less likely the destination will be chosen. This is consistent with the previous studies of truck trip length distributions (Holguín-Veras and Thorson, 2000). Meanwhile, similar as has been found in the destination choice model developed in Chapter 4, the marginal effect of the distance is nonlinear. The piece of distance within the range of 0.2 distance units has the greatest impact on the perceived utility of choosing a destination (-11.406), and the impact decreases to the least when the piece falls into the range of above 0.5 distance units. This demonstrates the logic that common carriers use to choose the next destination: within the nodes close to the current location, they would like to pick the nearest one; when the nodes are far away, it does not matter much whether a relatively close node or a little more distant node is chosen.

There are two variables that measure the attractiveness of an alternative destination, the amount of cargoes available for pick-up (STOPPROD) and the amount of cargoes available for delivery (STOPATTR). Both of them increase the probability of a destination being chosen. Similar as STOPDIST, their coefficients vary by strata. As shown, the coefficients in the first stratum are smaller than the ones associated with the second stratum, 0.073 vs. 0.144 for STOPPROD, and 0.044 vs. 0.163 for STOPATTR. This indicates that one unit increase in the amount of cargoes available at a destination increases the attractiveness of this destination more when it is farther than 0.3 distance units away from the current location.

In this model, the coefficient of the size measurement variable (LOGSIZE) is close to 1. As explained in equation (5-2), this indicates that the specified model has little dependency on the strata defined.

Table 13: Multinomial logit model for destination choice (for the microsimulation-based tour construction procedure)

Utility \ Variables	Alternative specific constant	STOPDIST1	STOPDIST2	STOPDIST3	STOPDIST4	STOPPROD	STOPATTR	LOGSIZE
U(STOP1)	/	-11.406	-8.329	/	/	0.073	0.044	0.791
		(-44.609)	(-22.371)			(12.799)	(7.67)	(23.279)
U(STOP2)	-0.194	-11.406	-8.329	/	/	0.073	0.044	0.791
	(-1.234)	(-44.609)	(-22.371)			(12.799)	(7.67)	(23.279)
U(STOP3)	-0.508	-11.406	-8.329	-8.243	-4.540	0.144	0.163	0.791
	(-5.014)	(-44.609)	(-22.371)	(-21.3)	(-19.649)	(14.635)	(17.602)	(23.279)
U(STOP4)	-0.899	-11.406	-8.329	-8.243	-4.540	0.144	0.163	0.791
	(-8.727)	(-44.609)	(-22.371)	(-21.3)	(-19.649)	(14.635)	(17.602)	(23.279)

Definition of the independent variables:

STOPDIST1: the piecewise distance from the current location to next destination between 0 and 0.2 distance units;

STOPDIST2: the piecewise distance from the current location to next destination between 0.2 and 0.3 distance units;

STOPDIST3: the piecewise distance from the current location to next destination between 0.3 and 0.5 distance units;

STOPDIST4: the piecewise distance from the current location to next destination above 0.5 distance units;

STOPPROD: the units of cargoes available for pick up in next destination;

STOPATTR: the units of cargoes available for delivery in next destination;

LOGSIZE: the number of locations available in the corresponding stratum; the first two alternatives, STOP1 and STOP2, belong to the first stratum with its radius less than or equal to 0.3 distance units; and the last two alternatives, STOP3 and STOP4, belong to the second stratum with its radius greater than 0.3 distance units.

Note: the values in the parentheses are the *t* statistic.

5.3.2 Tour termination model

The second model is intended to represent the decision of either terminating the tour and returning to the base, or continuing to another destination. Since there are only two alternatives, terminate the tour or not, a binary logit model is used. The variables that could affect the decision include the return distance from the current location to the base (DISTTODE), the cumulative distance covered up to the current location (ELAPDIST), the cumulative amount of cargoes picked up until the current location (ELAPPROD), and the cumulative amount of cargoes delivered up to the current location (ELAPATTR). The last three are memory variables.

The estimated model is shown in Table 14. Several findings are generated. First, the perceived utility of returning to the home base decreases with the distance from the current location to the base. This indicates that commercial vehicles tend to choose their last visits as close to their bases as possible. Second, if the cumulative amount of cargoes that has already been delivered along the tour is large, the likelihood for a truck to return to its base will be high. This is expected since vehicles that accomplish more delivery tasks will be more likely to return to their bases for rest or maintenance.

Table 14: Binary logit model for tour termination (for the microsimulation-based tour construction procedure)

Utility	Variable	Definition	Coefficient	*t* statistic
U(RETURN)	Constant	Alternative specific constant	/	/
	DISTTODE	Return distance from the current location to the home base (distance units)`	-2.62	-3.55
	ELAPATTR	The cumulative units of cargoes delivered up to the current location	0.18	9.60
U(NOTRETURN)	Constant	Alternative specific constant	6.69	8.41

5.4 Case study

The test network in the study is an 84-node urban freight market in which two common carriers are competing for the commodity flows between eight contested nodes.

Two nodes are served as the bases for the two carriers respectively. The carriers are assumed to have the equal chances to dispatch their vehicles. The network and the corresponding commodity flow OD matrix were adopted from one game produced in the Integrative Freight Market Simulation (IFMS) by Thorson (2005).

The destination choice model and the tour termination model discussed in the previous section were applied to the test network. Fifteen tours were constructed in total to satisfy the preset commodity flow OD matrix, nine for carrier 1 and six for carrier 2. The average number of destinations in a tour is 9.6, and the average tour length is 3.07 distance units.

The trip length distributions were estimated to see if the constructed truck tours are consistent with the trip chaining behavior found in the test case. As can be seen in Figure 29, the estimated trip length distribution resembles the one in the test case. Both of them follow an expected pattern: the largest percentage of commercial vehicle trips occurs at the short distance and the number of trips decreases as the travel distance increases. The two distributions also exhibit some differences. The trip length distribution estimated from the proposed model tends to cover wider range of distance compared with the one from the IFMS. The average trip distance is 0.29 distance units with the standard deviation of 0.18 distance units in contrast to 0.17 distance units on average with the standard deviation of 0.10 distance units. This may be a consequence of stratified sampling. When the stratified sampling method was used, only two alternatives were taken from each stratum, and less variation of distance was captured in the discrete choice modeling process. Therefore, the perceived utility of choosing a destination is less sensitive to the distance than it should be, and thus tends to adopt destinations with a wider range of trip distance.

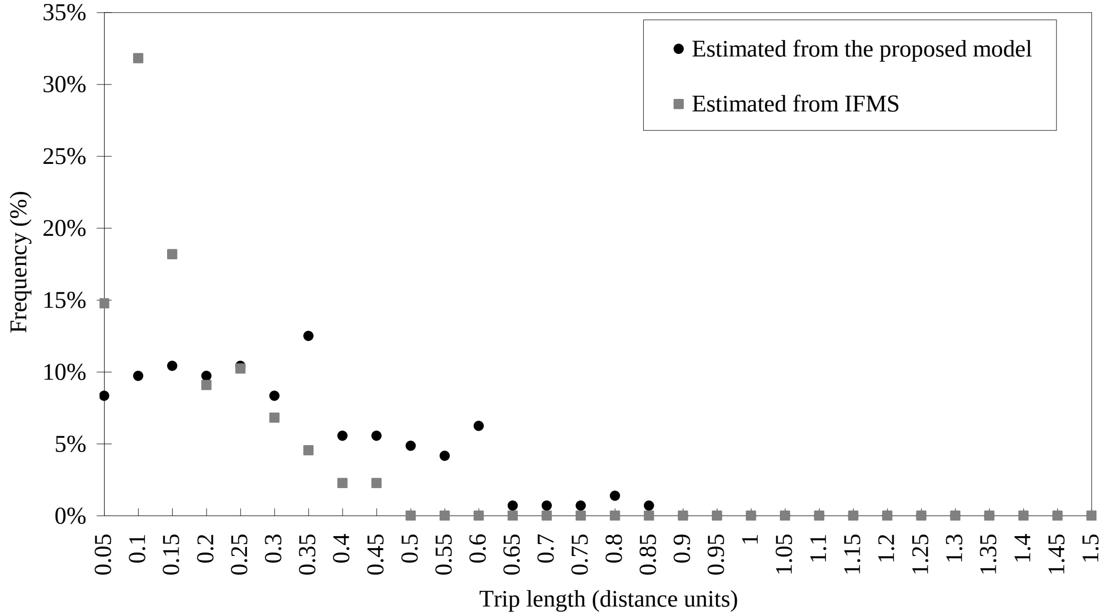


Figure 29: Trip length distribution (estimated vs. IFMS results)

5.5 Conclusions

In this chapter, a two-level hybrid-simulation modeling framework was proposed to construct commercial vehicle tours that satisfy a known commodity flow OD matrix. The proposed formulation has two key components: a destination choice model, and a tour termination model. The former is used to select the destination of a given trip, while the latter is used to decide when to terminate the tour. The models were estimated using a data set from an Integrative Freight Market Simulation (IFMS). The proposed framework was applied to an 84-node urban freight network. The estimated trip length distribution was found consistent with the trip chaining behavior in the test case.

The discrete choice modeling process identified several key variables that affect the choices of destination location and the decisions of returning to the base or not. First, the distance, the amount of cargoes available for pick up, and the amount of cargoes available for delivery at a given location are the key variables that determine the decision of choosing a destination. As expected, the distance to a given location has a negative relation with the probability of selecting a destination; while both the amount of cargoes to be picked-up, and to the delivered to, have a positive relationship. One very interesting finding is that the marginal effect of distance is nonlinear. A shorter distance has more negative impact on the perceived utility of choosing a destination than the large ones. Meanwhile, the attractiveness increases when the distance is 0.3 distance unit farther away from the current node. It is worthy of mention that none of the variables found to be significant in the destination choice model were memory variables, i.e., those that provide a measure of the amount of work already done.

The estimation revealed that the tour termination model is a function of the distance to the base, and of a memory variable that measures the amount of cargoes the truck has delivered up to the current location. In the case of distance, the farther the location is the less likely it is to return from that location. This reflects the fact that truck tours tend to follow the pattern shown in Figure 1, in which the truck gets farther and farther from the base, and at some point starts making deliveries or pick-ups getting increasingly closer to the base. The modeling process also revealed that the more cargoes the truck has delivered, the more likely it will be that it returns to the base and terminates the tour.

These results provide insight into the factors that must be taken into account at the moment of conducting hybrid micro-simulations of urban freight flows. The specified discrete choice models imply that the destination choice is a function of the attributes of the destination and the separation between the current location and alternative destinations; and that the tour termination decision is a function of the distance to the base, and a memory variable that is a proxy for the amount of work already done.

6. Conclusions, Research Contributions, and Future Research

This dissertation is concerned with enhancing urban freight demand modeling by incorporating one unique feature of urban freight movements, i.e., trip chaining behavior. In this context, the main objective of the dissertation is to develop tour-based freight travel demand models to guide the progress of urban freight demand forecasting towards more realistic representations of freight operations.

Two different urban freight demand models were proposed to fulfill the objectives in response to different situations. The first approach is the entropy-based tour distribution models that are aimed to estimate the commercial vehicle flow along each tour given that the aggregate information of commercial vehicle movements is available. Since the application of these entropy-based models require a specification of the potential tours visited by commercial vehicles, a behavioral-based tour choice model is developed to determine the possible tours as the input to the entropy-based models. The second approach involves a hybrid microsimulation-based procedure that generates individual tours to satisfy the known commodity demand given that the detailed commercial vehicle travel diaries in the base year are available for capturing the trip chaining behavior. The test results show that both models reach good agreement with the observed patterns, indicating the feasibility of the proposed models for forecasting urban freight demands. The conclusion from each major chapter, the contributions, and the future research areas are summarized as below.

6.1 Conclusions

In the first approach, the concept of entropy maximization was used to support the development of aggregate-level urban freight demand models. The resulting formulations are the maximization programming programs aimed to obtain the most likely set of tour flows (or called the entropy of the system) that meet the system's aggregate-level constraints such as the total number of trips produced by each node (trip productions), the total number of trips attracted to each node (trip attractions) and the total impedance in the network.

The analysis suggested that different impedance variables may have different impacts on the model's performance. Considering this, two entropy maximization formulations were introduced. The first formulation included one impedance constraint, i.e., the total time constraint that accounts for both the total travel time and the total handling time, while the second one included two impedance constraints considering the total travel time and the total handling time respectively.

The first and second order conditions were derived to gain insight from the entropy maximization formulations. The first-order conditions resulted in a tour distribution model, showing that the number of commercial vehicle visits made in each tour is a linear combination of the Lagrange multipliers associated with the trip productions/trip attractions of nodes along that tour, and the tour impedance variables. The second-order conditions indicate that each formulation is a convex program with a convex objective function and a set of linear constraints. Given the convexity, the primal-dual interior method for optimization programs with convex objectives (PDCO) was chosen as the solution algorithm, considering its efficiency in solving large-scale entropy problems.

The proposed formulation was applied to the Denver metropolitan area. The estimation results indicate that the entropy-based tour distribution model is a feasible and efficient way to incorporate the commercial vehicle tours into the aggregate freight demand modeling. The estimated tours closely match the observed ones with the mean absolute percentage error (MAPE) as 6.71% for the first entropy maximization formulation and 6.61% for the second formulation. As the consequence of the good match obtained, the estimated tour length distribution resembles the observed one as well.

As one outcome of this approach, two potential ways of applying the entropy maximization formulations were proposed for the purpose of forecasting urban freight demands in the future. The first application is to use the base-year information as the input to calibrate the parameters in the tour distribution model developed for the future year. The second application is to use the entropy maximization formulations to directly estimate the optimal future-year tour flows given that the future-year trip productions/attractions, the total impedance in the network, and the potential tours visited by commercial vehicles have been estimated in advance.

The estimation of the future-year tours flows by using the entropy-based tour distribution model requires a pre-specification of the possible tours visited by commercial vehicles in the future year. Considering this, a commercial vehicle tour choice model was developed next to generate a set of tours as the input to the entropy-based tour distribution model.

The proposed tour choice model involved a framework that consists of two major trip chaining decisions: (1) the destination choice decision indicating which node will be visited next if the tour continues; and (2) the tour termination decision determining if a tour needs to return to the home base from the current location or continue to visit another destination. Two behavioral choice models, i.e., the tour termination model and the destination choice model were specified to represent the two types of decisions respectively, using the tour travel diaries collected in the Denver Metropolitan area in 1998. As identified by the destination choice model, the distance from the current location to next potential destination and the land use type of the current location are two key variables that determine the choice of next destination. As expected, the perceived utility of choosing a node as next destination is a deterrence function of distance. Meanwhile, the marginal effect of distance decreases with the increase of distance. In addition to the negative effect of distance, the impact of distance varies by the land use type of the current location: if the land use type of the current location is manufacturing, open space, public building, residential, retail area, service, transportation or wholesale, commercial vehicles are willing to visit the nodes nearby as the next destination. On the contrary, a longer trip to next destination is more likely to be made given the land use type of the current location is agriculture or mining.

The estimation revealed that the tour termination model is a function of three types of variables: (1) the return in-vehicle travel time from the current location back to the home base; (2) the interaction terms between the return in-vehicle travel time and the binary indicators of the land use type of the current location; and (3) two memory variables representing the cumulative travel time and the cumulative handling time spent up to the current location in a tour. Due to the interaction terms introduced, the impact of return in-vehicle travel time on the perceived utility of returning is significantly affected by the land use type of the current location. Meanwhile, the two memory variables play opposite roles in affecting the tour termination decision: the increase in the cumulative travel time may discourage returning while the increase in the cumulative handling time will increase the likelihood of returning instead.

In order to evaluate the performance of this tour choice model, the proposed framework is applied to a case study in the Denver metropolitan area. The generated tours were used to define the coefficient matrix in the entropy maximization formulations. As found, the estimated tour length distributions from the entropy maximization formulations resembled the observed ones.

As the second approach of this dissertation, a two-level hybrid-simulation modeling framework was discussed in order to construct commercial vehicle tours that satisfy a known commodity flow origin-destination (OD) matrix. This dissertation focuses on the second level, i.e., a tour-based microscopic simulation model to generate commercial vehicle tours, assuming that the commodity flows have been estimated by the first level which consists of an input-output model to generate commodity from or to each node and a gravity model to distribution commodities flows between OD pairs. To shed light into the key variables that affect trip chaining behavior, behavioral modeling was conducted, decomposing the tour decisions into two groups of choices: the choice of next destination location, and the choice of terminating a tour. The corresponding discrete choice models were estimated using a data set from an Integrative Freight Market Simulation (IFMS). They were then used to generate probabilities that helped make the two types of decisions. The proposed framework was applied to an 84-node urban freight network used in the IFMS. The estimated trip length distribution was found consistent with the trip chaining behavior in the test case.

The discrete choice modeling process identified several key variables that affect the choices of destination location and the decisions of returning to the base or not. As found, the destination choice decision is affected by the distance from the current location to the potential destination, the amount of cargoes available for picking up and the amount of cargoes available for delivery at this destination. As expected, the distance to a potential destination has a negative relation with the probability of selecting this destination; while both the amount of cargoes to be picked up, and to the delivered to, have a positive relationship. Similar as has been found in the tour choice model, the marginal effect of distance is nonlinear. A shorter distance has more negative marginal impact on the perceived utility of choosing a destination than the large ones. Meanwhile, the attractiveness, indicated by the amount of cargoes available for pick-up and delivery, increases when the distance is farther than 0.3 distance units away from the current node. It is worthy of mentioning that none of the memory variables measuring the amount of work already done was found to be significant in the destination choice model.

The estimation revealed that the tour termination model is a function of the distance to the base, and of a memory variable that measures the amount of cargoes the truck has delivered up to the current location. In the case of distance, the farther the location is less likely it is to return from that location. This reflects a logic commercial vehicles tend to follow to make tours: they tend to get closer and closer to the home base when they are about to return. The modeling process also revealed that the more cargoes the truck has delivered, the more likely it will be that it returns to the home base and terminates the tour.

6.2 Contributions

The major contributions made by this research can be summarized as follows:

(1) It systematically analyzed the key variables that affect the trip chaining behavior. As found, one of the major decisions made along a tour, i.e., the choice of next destination location, is affected by the distance from the current location to the potential destination, the land use type of the current location, and the amount of cargoes available for pick-up and delivery. Meanwhile, another major decision of making a tour, i.e., the tour termination decision, is determined by the return distance or in-vehicle travel time, the land use type of the current location and the memory variables indicating the cumulative travel impedance or shipment accomplishments up to the current location;

(2) It provided the first closed-form aggregate model to estimate the flow of commercial vehicles along a given tour;

(3) It proved that the tour flow distributed to a tour is a function of the tour impedance, and a linear combination of the Lagrange multipliers associated with the trip productions/attractions of nodes along the tour;

(4) It developed a tour-based hybrid microsimulation model that considers the trip chaining behavior as well as the relationship between commodity flows and

commercial vehicle flows. To the best of the author's knowledge, this is the first application that addresses the two issues simultaneously.

6.3 Areas of future work

Though the two types of models developed in this dissertation performed reasonably well according to the test results, more work is needed to improve the performance of these tour-based urban freight travel demand models. This section discusses future research on this subject.

The implicit behavioral assumptions in the commercial vehicle tour choice model in Chapter 4 and the tour construction procedure in Chapter 5 are that the trip chaining process can be decomposed to two decisions, i.e., the destination choice and the tour termination decision and they are made sequentially. These assumptions enable to simplify the complex behavioral choice modeling process into the independent estimations of the destination choice model and the tour termination model. These two models were then used sequentially to construct tours by adding a new trip after another until a tour is terminated. However, intuition suggests that the two decisions may be made simultaneously. Moreover, the decision of choosing one destination is correlated with the decisions made for choosing previous destinations as well as the potential choices for the following destinations. In this context, behavioral choice models that involve multiple decision layers should be tested in the future to see if the trip chaining behavior can be represented more accurately. Meanwhile, other decisions made along a tour, such as the handling time spent on each destination, the overall purpose of a tour, and the specific task assigned to each trip in a tour, should be considered jointly with the two decision mentioned above in order to form a sophisticated behavioral-based modeling framework.

The entropy-based tour distribution models also need more researches. As discussed previously, the accuracy of the estimated tour flows depends on the input value of total impedance in the network. This presents a challenge to the freight demand forecasting procedure because obtaining the accurate total impedance itself requires significant data collection, while forecasting what the total impedance would be in the future is complicated furthermore by the fact that the value of total impedance varies with the traffic equilibrium patterns in the network. The latter could be obviated if the assumption of parameter stability is invoked, though no one could guess how valid such assumption is.

Moreover, the entropy maximization formulations deserve more investigations, particularly for the purpose of developing commodity-based tour models. Given the limited data available, the entropy-based tour distribution models developed in this dissertation are vehicle movement based: the given demand is measured by the total number of vehicle trips produced by or attracted to each node in the network while the total travel impedance involves only travel time or handling time commercial vehicles spent along a tour. In this context, the resulting tour demand models are a function of the variables associated with vehicle movements only, i.e., the marginal effects of trip productions/attractions of nodes along the tour, the travel time and handling time spent in a tour. However, the fundamental component that derives commercial vehicle movements, i.e., the commodity movements, and its impact on the distribution pattern of tour flows are missing from the models derived. To address this issue, more sophisticated entropy-based tour distribution models can be developed to incorporate the commodity flow demands, the profit earned from as well as cost spent in shipping the commodities.

As a further extension, the concept of entropy maximization can be combined with the methodology of OD synthesis (ODS) in order to estimate the distribution patterns of commercial vehicle tour flows given link traffic counts or any other easily collected secondary data. This approach enables to reduce the data collection efforts by taking advantage of the ODS framework while limiting the feasible solution space by using the concept of entropy maximization. The decision variables in the entropy-based formulation can be specified as the tour flows distributed along the potential tours in the network. The objective of this formulation can be defined as the maximization of the number of ways of distribution tours flows (or called system entropy). Further work needs to be concentrated on the specification of the relationship between tour flows and the observed secondary data.

Another area of improvement is related to the lack of consideration of the empty trips in the hybrid microsimulation-based procedure proposed in Chapter 5. In this procedure, the decision of loading or unloading cargoes to a trip in a tour is simplified as a process that solely depends on the availability of cargoes: if there are commodity flows available between the OD pair associated with the trip, the vehicle is loaded with the average payload; otherwise, the trip is assumed to be empty. However, the behavior of making empty trips is much more complicated. It is determined by many other factors in addition to the availability of commodities. How to incorporate the empty trips to the behavioral-based tour construction procedure will be another challenging topic for the future research.

Finally, the impedance associated with commercial vehicles is only represented by travel distance, travel time and handling time. However, other impedance variables, such as toll cost, operational cost, extra work hour cost and delay cost all play significant roles in trip chaining behavior. In this context, these impedance factors and their impacts need to be investigated in the future.

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