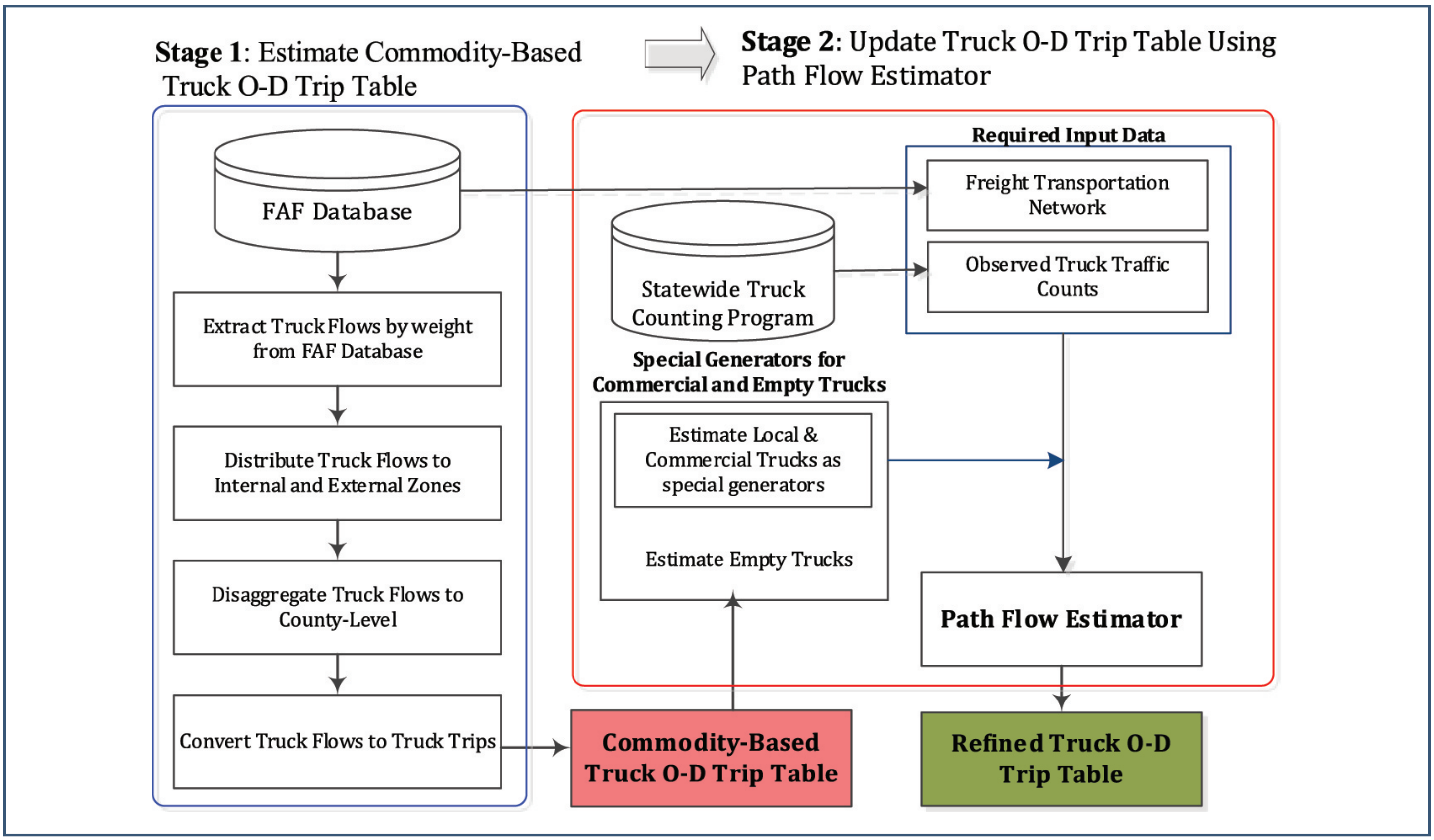
MOUNTAIN-PLAINS CONSORTIUM

MPC 14-269 | Sarawat Jansuwan, Seungkyu Ryu, Anthony Chen, and Kevin Heaslip| MAY 2014

A Two-Stage Approach for Estimating a Statewide Truck Trip Table



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A Two-Stage Approach for Estimating a Statewide Truck Trip Table

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May 2014

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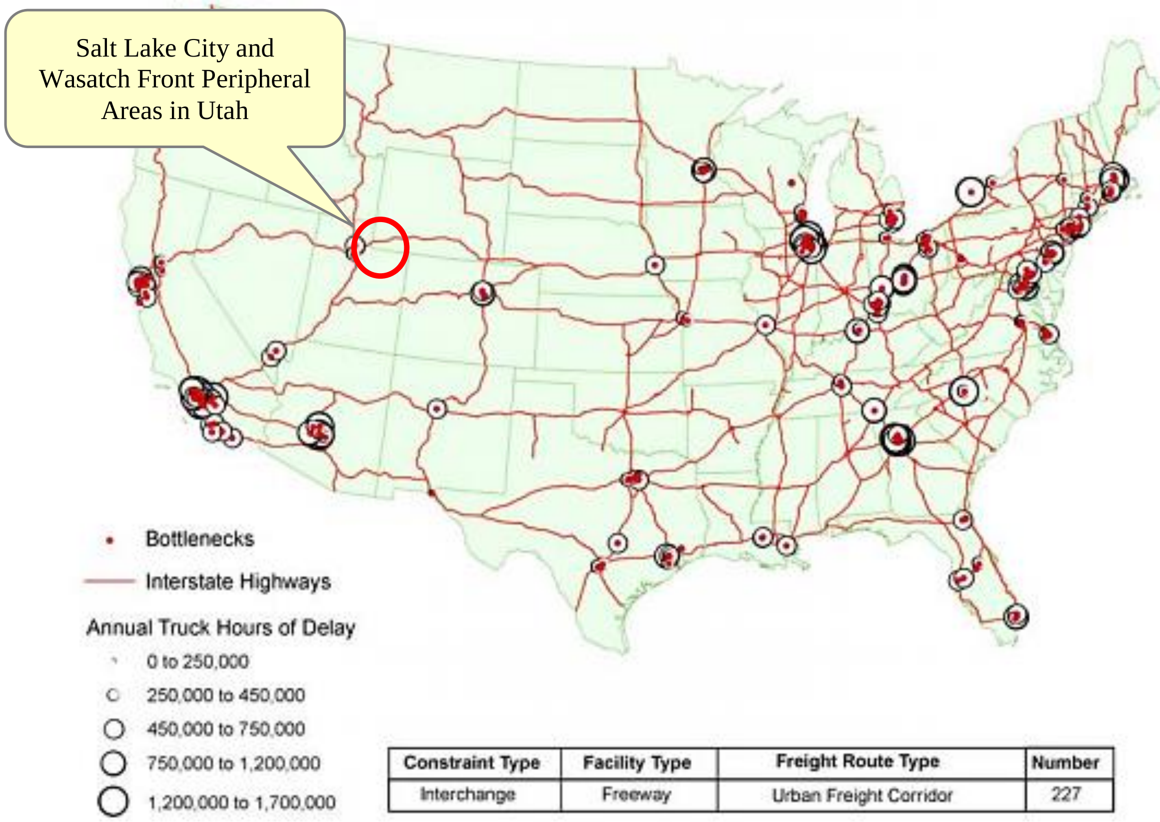
1. INTRODUCTION

1.1 Background

Statewide models, including passenger and freight movements, are frequently used for supporting numerous statewide planning activities. Many states use them for traffic impact studies, air quality conformity analysis, freight planning, economic development studies, project prioritization, and many other planning needs (Horowitz 2006). According to the databases from FHWA (2009) and Census Bureau (2010, 2012), the United States (U.S.) transportation system transported a total of 17.6 billion tons per year in 2011 to serve almost 117 million households and 7.4 million business establishments. The importance of truck demand has been increased in the statewide planning process because of its strong influence on the economy of the states and the nation overall. Truck is the dominant mode of freight transportation, with the industry hauling 11.9 billion tons in 2011, equating to approximately two-thirds (i.e., 67%) of all freight transported in the U.S. (FHWA 2009). According to the Freight Analysis Framework[3] (FAF) database, truck shares approximately 75% of the *domestic* freight shipments, and this trend is expected to continue until 2040. However, freight transportation capacity, especially roadway transportation, is expanding too slowly to keep up with demand (Cambridge Systematics 2005). This growth imbalance could significantly contribute to congestion at highway segments, interchanges, and highway bottlenecks (i.e., locations that are physically narrow and/or congested) and hence are very susceptible to incidents and disruptions. Congestion is also caused by restrictions on freight movement, such as the lack of space for trucks in dense urban areas (FHWA 2008) as posted on the roadways due to height, length, width, weight limits, incident, or construction.

Figure 1.1 shows the locations of highway interchange bottlenecks (i.e., solid dots) for trucks on the national highway network (Cambridge Systematics 2005). The bottlenecks in Utah include Salt Lake City and Wasatch Front peripheral areas. Truck origin-destination (O-D) trip table is an important component that can be used to help strategic transportation planners, providers, and government agencies to identify the potential bottlenecks in their areas. The subsequent results of truck trip table obtained from the proposed framework will be beneficial for assisting state departments of transportation (DOTs) and metropolitan planning organizations (MPOs) on evaluating operational strategies to address the consequent impacts due to truck traffic, including congestion, infrastructure deterioration, safety, and environment.



Constraint Type	Facility Type	Freight Route Type	Number
Interchange	Freeway	Urban Freight Corridor	227

Source: Cambridge Systematics, Inc. (*2005*)

Figure 1.1 Major highway interchange bottlenecks for trucks

1.2 Research Need

The current practice in estimating a statewide truck O-D trip table is through the use of truck trip rates estimated in the Quick Response Freight Manual (QRFM) developed by Cambridge Systematics (2007), or using a commercial freight database (e.g., TRANSEARCH, developed by IHS Global Insight, Inc.). However, because of the nature of the shared databases, the state DOT has to exert tremendous efforts to improve the accuracy of the estimations to match the local observations (e.g., truck counts, vehicle-miles of travel (VMT), etc.). The calibration process is usually lengthy and requires specialized technical staffs to operate. In addition, commercial freight databases (e.g., TRANSEARCH by Global Insight, Inc.) are typically proprietary, not available for public access. Many small states usually do not have sufficient resources to conduct freight surveys or house technical staffs to develop the freight demand model. Many existing models overlook this component or simply assume that freight trips follow some behavioral mechanism similar to passenger trips, i.e., truck traffic is estimated as a function of passenger-car traffic (Ogden 1992). This could be a potential weakness of truck demand modeling in the statewide model, where truck flow characteristics have been determined by other contributing factors such as location factors (i.e., places of production and market), physical factors (i.e., ways that goods can be transported: in bulk, tank, flat bed, or refrigerated container), geographical factors (the location and density of population may influence the distribution of end products), and so on (Ortuzar and Willumsen 2002).

Holguín and Thorson (2000) summarized different ways that could be used for modeling freight transportation demand and divided them into two major modeling approaches: trip-based and commodity-based. For trip-based modeling approach, the model has three major components: trip generation, trip distribution, and traffic assignment. The trip-based model does not need a modal split step as it assumes mode choice has already been selected. List *et al*. (2002), for instance, the trip-based modeling method is used to estimate a truck O-D trip table from partial and fragmentary truck observations in the New York region.

The main advantage of the trip-based modeling method is that it typically requires less data (i.e., only truck traffic counts) to reproduce an O-D matrix. However, the trip-based modeling method tends to overlook the behavioral characteristics of commodity flows. Commodity-based modeling method, on the other hand, uses the commodity flows to estimate truck flows produced and attracted by each zone in the study area. Sorratini and Smith (2000), for example, developed a statewide truck trip model using commodity flow data obtained from the commodity flow survey (CFS) and improve the estimation using the input-output (I-O) economic data. Although the commodity-based models have more advantages than trip-based models, as they can capture more accurately the fundamental economic mechanisms of freight movements, a truck O-D trip table estimated from this method often overlooks the *non-freight* truck trips (e.g., light commercial truck or empty truck trips).

To fill this modeling gap, this research proposes a two-stage approach to estimate a statewide truck O-D trip table. The proposed approach is supported by two sequential stages: stage one estimates the commodity-based truck O-D trip table primarily derived from the commodity flow database, and stage two adopts the concept of path flow estimator (PFE) to refine the commodity-based truck O-D trip table using the observed truck counts. The proposed approach uses the secondary data sources available for public and research access such as the Freight Analysis Framework (FAF) database, statewide traffic counts, and socioeconomic and land use data to estimate statewide network truck traffic. A case study using the Utah statewide freight transportation network is conducted to demonstrate the application of the proposed method.

1.3 Objective of the Study

The goal of this research is to develop a two-stage approach for estimating truck O-D trip table using both commodity flows and truck counts. The specific objectives of this research include the following:

- Investigate and update the statewide truck data from the following data sources:
  - Freight Analysis Framework version 3 (FAF3), a newly released national commodity O-D database
  - The up-to-date statewide truck count programs
  - The Utah Statewide Travel Model (USTM)

- Develop a commodity-based truck trip table from FAF3 for the state of Utah
- Refine the commodity-based truck trip table using truck counts obtained from the statewide truck count program and the USTM.

1.4 Organization of the Report

The organization of this report is summarized as follows:

- Section 2 reviews the research studies for estimating the truck O-D trip table and the statewide freight demand modeling approaches. The review provides the background, features of the models, and potential capabilities for developing a two-stage approach for estimating the truck O-D trip table.

- Section 3 provides an overview of the statewide truck demand, including the freight transportation trends and the truck freight component in the Utah Statewide Travel Model (USTM).

- Section 4 describes the two-stage modeling approach for estimating truck O-D trip table: (1) using the commodity-based modeling technique and (2) using the PFE technique to update the results from the first stage with the observed truck traffic counts. The solution algorithm for solving the PFE is also provided in this section.

- Section 5 demonstrates the capability of the two-stage approach using a case study in Utah. Numerical results as well as the applications to the Utah statewide freight transportation network are summarized in this section.

- Section 6 concludes this research project and provides some suggestions for future research.

2. LITERATURE REVIEW

2.1 Literature Review on Truck O-D Estimation

Holguín and Thorson (2000) summarized different ways that could be used for modeling freight demand and divided them into two major modeling platforms: (1) trip-based modeling and (2) commodity-based modeling. Figure 2.1 depicts the modeling of these two approaches. This section provides a literature review based on these two modeling approaches.

2.1.1 Trip-based Modeling Approach

For trip-based modeling approach, the model has three major components: trip generation, trip distribution, and traffic assignment. The trip-based model begins with trip generation. In this step, regression models for trip production and trip attraction are estimated in conjunction with land use and socio-economic characteristics for each traffic analysis zones (TAZ). The next step is trip distribution, which is accomplished through a spatial interaction model (i.e., gravity model or growth factor method). The last step is to assign the trip table from the trip distribution step to the network. This trip-based modeling approach is also known as a three-step model as the mode choice has been already made in the truck freight model.

The current practice in estimating truck trip table is through the use of the truck trip rates estimated in the Quick Response Freight Manual (QRFM) II developed by Cambridge Systematics (2007). The QRFM provides truck trip generation rates based on the survey data collected from Phoenix, Arizona. Using trip rates to reflect the trip-making propensity based on land use configurations is a common practice, and provides an economical and reasonable estimate when planning resources are limited. Many researchers have also demonstrated that the estimation of truck O-D trip table could be achieved using secondary data sources based on the trip-based modeling approach.

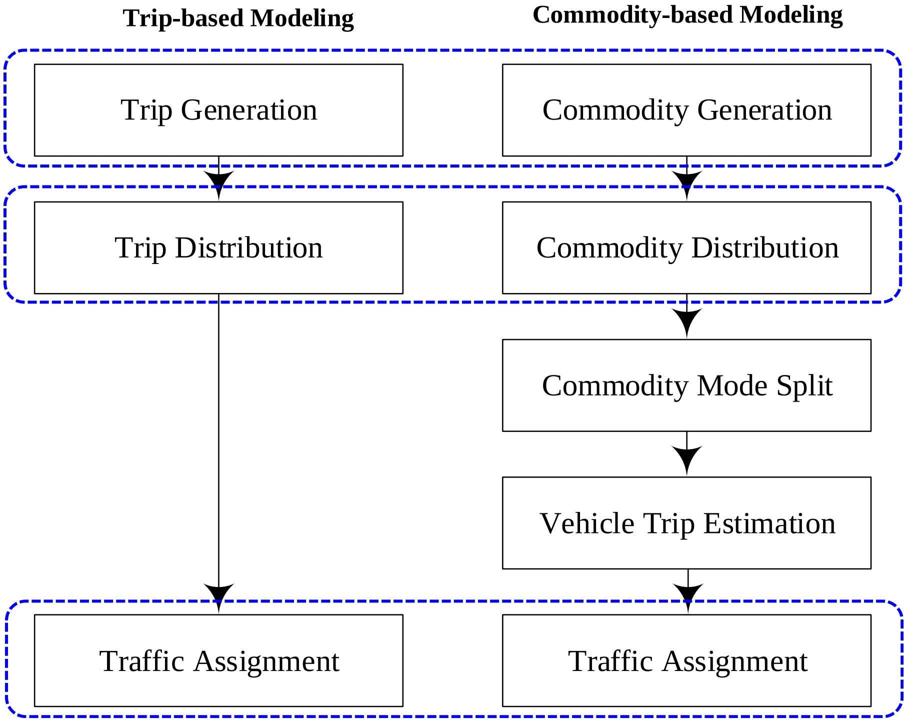


Figure 2.1 Trip-based and commodity-based approaches (modified from Holguín-Veras and Thorson 2001)

Tamin and Willumsen (1989) introduced a three-step model to estimate freight demand from observed traffic count data. They used two types of gravity models in the trip distribution step: the gravity model and the gravity-opportunity model. They proposed the nonlinear least square and maximum likelihood estimation methods to ensure that the models estimate link flows as close as possible to the observed data. List and Turnquist (1994) developed a linear programming (LP) method to synthesize the truck flow pattern from the observed truck counts on some links and cordon lines. This LP method minimizes the weighted sum of the residual between the estimated and observed values using fixed link-use coefficients for each O-D pair from a probabilistic path assignment procedure.

Later, List *et al*. (2002) used a similar technique to estimate a large-scale truck O-D trip table in the New York region. The model was implemented in a two-step process: the first step estimates the trip production and trip attraction at each TAZ; the second step uses the link-use coefficients based on a multi-path traffic assignment procedure to estimate the truck O-D trip table. Crainic *et al*. (2001) used a bi-level optimization program to adjust the target freight demand matrix such that the differences between the observed and assigned truck flows in the upper level are minimized. The lower level for this bi-level program is a system optimum (SO) traffic assignment procedure. They implemented the bi-level programming method in the Strategic Planning of Freight transportation (STAN) software, an interactive-graphic transportation planning package for multimodal multiproduct freight transportation. The main advantage of the trip-based modeling approach is that it typically requires less data (i.e., only truck traffic counts) with some existing planning data (e.g., trip production, trip attraction, partial or full size of target trip table) to estimate an O-D matrix. However, the main disadvantage of the trip-based modeling approach is that it tends to overlook the behavioral characteristics of commodity flows in the urban and regional models. Holguín-Veras *et al*. (2001) noted that trip-based models have a limited range of applicability to account for major changes of the study areas such as changes in land use and that it could be difficult to model multimodal systems using this modeling approach.

2.1.2 Commodity-based Modeling Approach

The commodity-based modeling approach, on the other hand, uses the commodity flows to estimate truck flows produced and attracted by each TAZ. In the United States, the FAF estimates commodity flows over the national highway networks, waterways, and rail systems among the states and regions. The current version of the FAF commodity O-D database (FAF version 3) provides estimates of commodity flows by origin, destination, and by mode for the base year 2007 and the forecast years from 2010 to 2040 with a five-year interval. Note that the FAF commodity O-D database was developed using the 2007 Commodity Flow Survey (CFS) and other public data sources. To estimate truck demand from the CFS data, the commodity flows in tonnage have to be disaggregated from the state to the finer zonal level such as TAZ by county and then convert them to truck trips using the truck payload equivalent factor (TPEF).

Because the CFS database is based on survey data established through a shipper-based survey, the commodity-based models can better capture the fundamental behavioral characteristics of commodity flows. Sorratini and Smith (2000), for example, developed a statewide truck trip model using the commodity flow data obtained from the CFS database and improved the estimation using the I-O economic data. A similar technique was also adopted by Fischer *et al*. (2005) for estimating the heavy-duty truck O-D trip table for the Southern California Association of Government (SCAG) region. The commodity-based modeling approach is often used in statewide and regional practices. Zhang *et al*. (2003), for instance, estimated the intermodal freight flow patterns of highway, railway, and waterway networks for the state of Mississippi using the CFS database and public domain data. They further developed a simulation model to assess the freight operations and the modal shift effect (i.e., from truck to intermodal barge/truck). Al-Battaineh and Kaysi (2005) used a genetic algorithm (GA) procedure to find the best O-D matrix that gives the minimum deviation between observed and estimated data when the O-D matrix is assigned to the network. Trip production and trip attraction derived from the trip generation step were also used to preserve the spatial distribution of the commodity flow pattern. However, it is known that GA cannot guarantee finding the global optimum. Stefan et al. (2005) noted that it may be difficult to obtain the I-O data for certain regional and urban areas.

While the commodity-based models have more advantages than the trip-based models, as they can capture more accurately the fundamental economic mechanisms of freight movements, a truck O-D trip table estimated from the commodity-based method often overlooks the non-freight truck trips (e.g., commercial truck or empty truck trips). Hybrid models have been developed to bridge the modeling gap of trip-based and commodity-based models. Holguín-Veras and Patil (2008) developed a multi-commodity O-D estimation model that combined two submodels: (1) a commodity-based model and (2) a complementary model of empty truck trips. The findings of this study highlights the significant benefits of considering an empty truck trip model in the estimation process as it can improve the ability to replicate the observed traffic counts.

The hybrid approach was also adopted in the SCAG's truck demand model. Hybrid models forecast the internal-internal truck trips through the use of a trip-based model and forecast the external truck trips through the use of a commodity flow survey. Some of the truck freight demand modeling approaches, including trip-based, commodity-based, and hybrid models, are summarized in Table 2.1.

Table 2.1 Freight demand modeling approaches, methods, and data sources

Authors	Modeling approaches		Methods	Data sources
	Trip-based	Commodity-based		
List and Turnquist (1994)	●		Linear programming model	Observed truck counts for some links and cordon lines
Sorratini and Smith (2000)		●	I-O model	CFS, TRANSEARCH
List et al. (2002)	●		Linear programming model	Observed truck counts for some links and cordon lines
Zhang et al. (2003)		●	Planning and simulation models	CFS, TRANSEARCH, intermodal databases
Al-Battaineh and Kaysi (2005)		●	I-O model, Genetic Algorithm	Commodity flows, observed truck counts
Liedtke (2006), Wisetjindawat et al. (2006)		●	Micro-simulation	Commodity flow surveys
Fischer et al. (2005)	■	■	Hybrid model	Shipper and receiver surveys (for internal trips), commodity flow surveys (for external trips)
Houlguin-Veras and Patil (2008)	■	■	Hybrid model, least square method	Multi-commodity flows, estimated empty truck trips, observed truck counts

Note: ■ represents a hybrid model

2.2 Literature Review on Truck O-D Estimation

State-of-the-practice in truck freight modeling approaches can be classified broadly into the following eight categories based on the objective, methodology, and data requirements: (1) link-based factoring method, (2) O-D factoring method, (3) three-step truck model, (4) four-step commodity flow model, (5) economic activity model, (6) hybrid model, (7) logistics/supply chain model, and (8) tour-based model (see details and discussions in Fischer *et al*. 2005).

2.2.1 Link-based Factoring Method

The link-based factoring method uses the growth factors based on the historical freight trend analysis or economic growth forecasts for scaling the base-year link volumes to obtain the future-year link volumes. For instance, this method was applied in the Quick Response Freight Manual II (Cambridge Systematics 2007). Though this method is simple and requires less data to conduct the analysis, the drawback of this method is the lack of behavioral basis for modeling freight traffic. In some cases, it assumes freight trips follow a behavioral mechanism similar to the passenger trips; that is, truck traffic is estimated as a function of passenger-car traffic (Ogden 1992).

2.2.2 O-D Factoring Method

The O-D factoring method also applies the growth factors to scale the base-year trip table and assigns the updated demand to the road network. The base-year truck O-D trip table is usually analyzed from some freight surveys such as the commodity flow data (e.g., Commodity Flow Survey (CFS) by BTS, or private freight database such as the TRANSEARCH database by IHS Global Insight, Inc.). These databases typically characterize the commodity flows or long-haul truck traffic, but lack the details of freight flows such as local, service, and empty truck trips.

2.2.3 Three-step Truck Model

The three-step truck model follows the traditional travel demand forecasting process, including trip generation, trip distribution, and traffic assignment, without the modal split step. Mode choice is assumed to have already been made in the three-step truck model. The trip generation step can be accomplished using trip generation rates or equations based on the characteristics of the local sites, including existing and forecast zonal employment and population data, to generate truck productions and attractions. The trip distribution step is then applied to generate a truck O-D trip table, and the traffic assignment step assigns the truck O-D trip table to the road network. This method has often been criticized as it does not capture other possible modes and/or multimodal freight demand.

2.2.4 Four-step Commodity Flow Model

The four-step commodity flow model follows a similar structure as the traditional four-step model for passengers. The commodity-based trip generation model estimates the tonnage commodity flows between origins and destinations based on the national or commercial freight database (i.e., Freight Analysis Framework (FAF) or TRANSEARCH by IHS Global Insight, Inc.). The commodity flows are then disaggregated to TAZ based on the county's population and employment data. The trip distribution step estimates a trip table using the gravity model. The modal split step assumes that the base year truck share or truck proportion remains the same in the future year. The average payload factors are further used to convert the daily commodity flows (in tonnage) to the daily truck trips. An all-or-nothing (AON) traffic assignment procedure is typically used to preload the freight truck traffic by allocating all the truck trips from each O-D pair to the shortest free-flow time path, and a user equilibrium (UE) traffic assignment procedure is then used to assign the passenger trips. A multiclass traffic assignment procedure can also be used to simultaneously assign both passenger and truck trips in the statewide travel demand model (e.g., the Florida Intermodal Statewide Highway Freight Model (FISHFM) and the Southern California Associations of Government (SCAG) model). Figure 2.2 provides a graphical illustration of the four-step commodity flow modeling process.

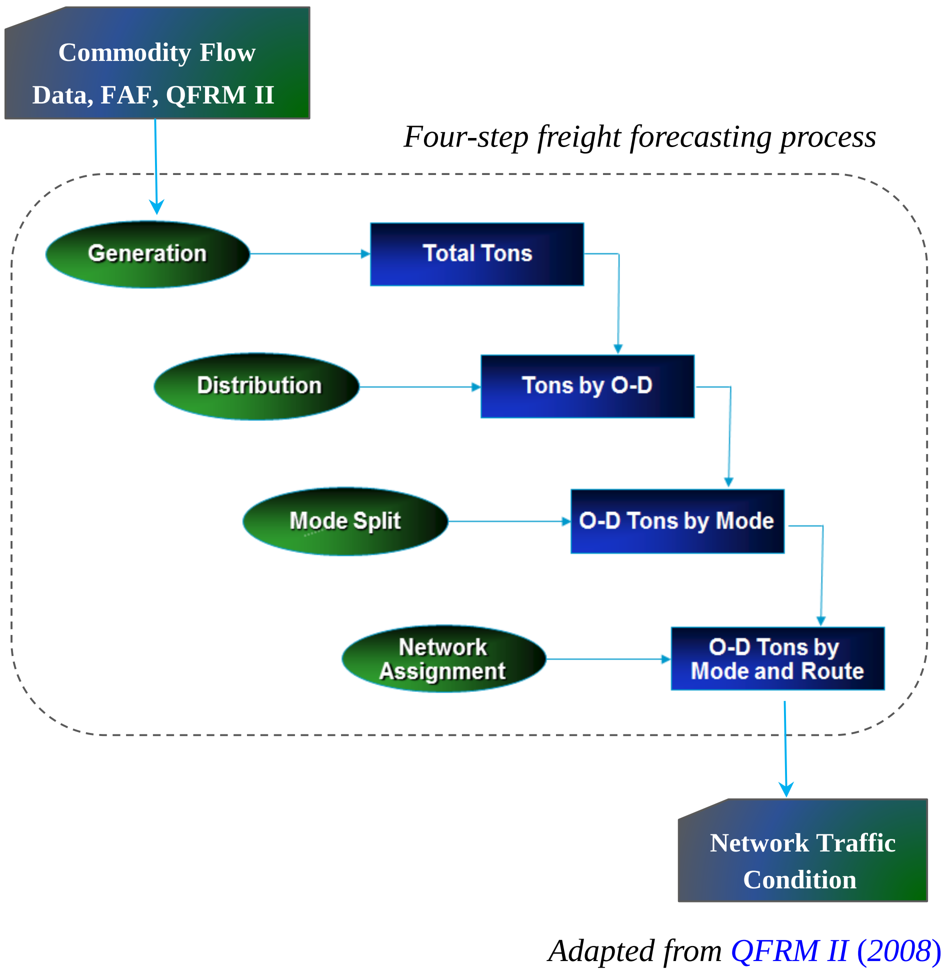


Figure 2.2 Four-step commodity flow modeling process

2.2.5 Economic Activity Model

The economic activity model is largely driven by the economic activity data or existing economic and land-use models such as the spatial I-O model. The model uses the I-O structure to estimate the economic relationship between industries and between industries and households. Network flows are then derived and aggregated from these particular structures (see the Oregon statewide model as an example).

2.2.6 Hybrid Model

The hybrid model attempts to bridge the gaps between the commodity flow modeling techniques and freight truck modeling techniques. The commodity-based model has some advantages over the trip-based model as it can better capture the fundamental economic mechanisms of freight movements; however, a truck O-D trip table estimated from this method often overlooks the non-freight truck trips (e.g., light commercial truck and/or empty truck trips) in urban areas. The hybrid model typically adopts a trip generation model to compensate these undercounted truck trips based on the socio-economic data of each TAZ, and uses a trip distribution model (e.g., a gravity model) to estimate the truck O-D trip table. The model has the flexibility to incorporate special trip generators (e.g., warehouses, distribution centers, terminals, etc.) and external trips obtained from additional freight surveys.

2.2.7 Logistics/Supply Chain Model

The logistics/supply chain model combines the economic I-O model with a logistics model to form an integrated model. The economic I-O model calculates the supply-demand interactions from different economic sectors, while the logistics/supply chain model assigns the goods to determine the spatial commodity flow pattern. Examples of the logistics/supply chain model include the Strategic Model for Integrated Logistics Evaluation (SMILE) of the Dutch Ministry of Transport and the GoodTrip model (Boerkamps 1999).

2.2.8 Tour-based Model

The tour-based model follows the concept of the activity-based model for passenger travel demand modeling. It focuses on the tour characteristics of truck trips, especially in the urban freight movements. The tour-based model typically uses a micro-simulation model to simulate the commodity flow movements and assess different scenarios of urban freight distribution (e.g., see Liedtke [2006]; Wisetjindawat et al. [2006]; de Jong and Ben-Akiva [2007]; Ruan et al. [2011]). This tour-based truck model combined with logistics/supply chain model has been developed for modeling the regional freight network traffic in the Chicago region to address the present weaknesses identified in the current freight travel demand forecasting models (i.e., lack of detailed information about freight delivery systems, long- and short-haul demands, and trip chain). Although this modeling approach provides a much finer resolution of truck flows over time periods, this technique is data demanding and computationally expensive. It is more suitable for assessing truck operations of urban freight traffic than strategic planning of regional freight traffic.

Figure 2.3 provides a summary of the truck freight modeling approaches based on two metrics: modeling platforms (i.e., trip-based or commodity-based methods) and application horizons (i.e., strategic planning, tactical, and operational). As can be seen, the economic activity, logistics/supply chain, and tour-based models are more suitable for tactical and operational applications, while the three-step, four-step, and hybrid models are often used for long-term strategic planning applications. Note that these tactical and operational models typically require much more input data to capture the details of truck operations in urban areas. As a result, these models require much more effort in the calibration and validation processes.

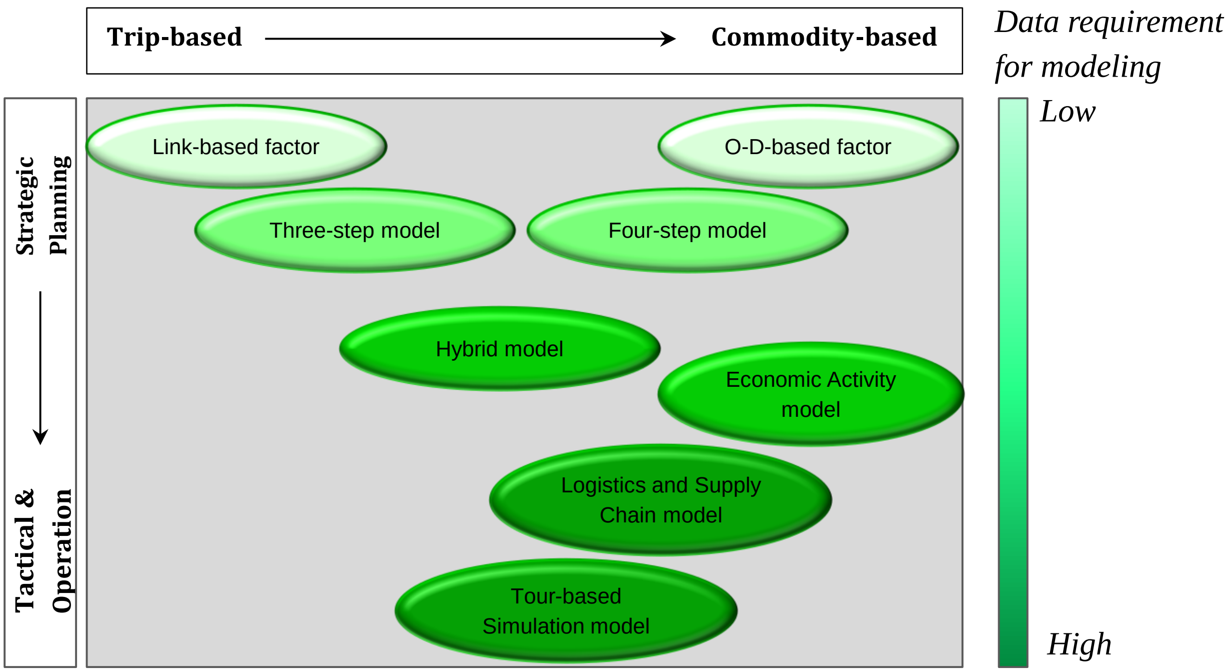


Figure 2.3 Truck freight demand modeling metrics

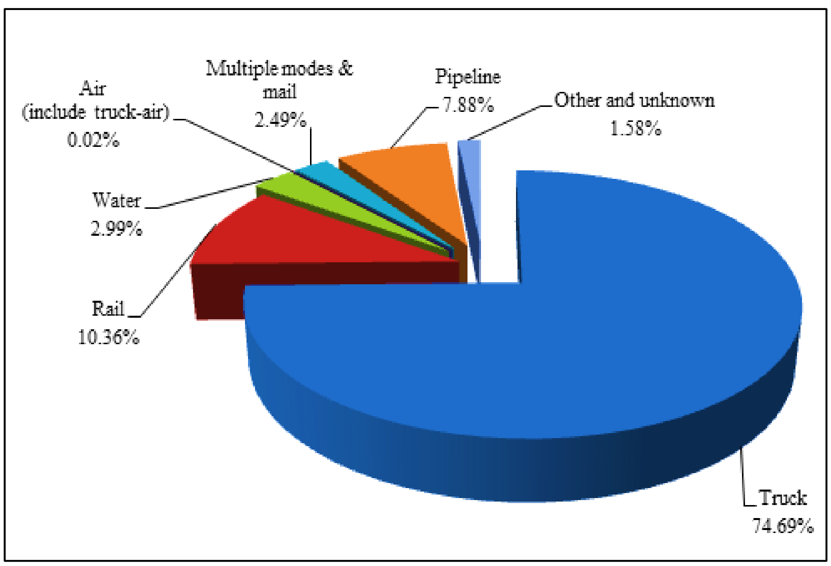
3. STATEWIDE TRUCK DEMAND OVERVIEW

3.1 Freight Trends

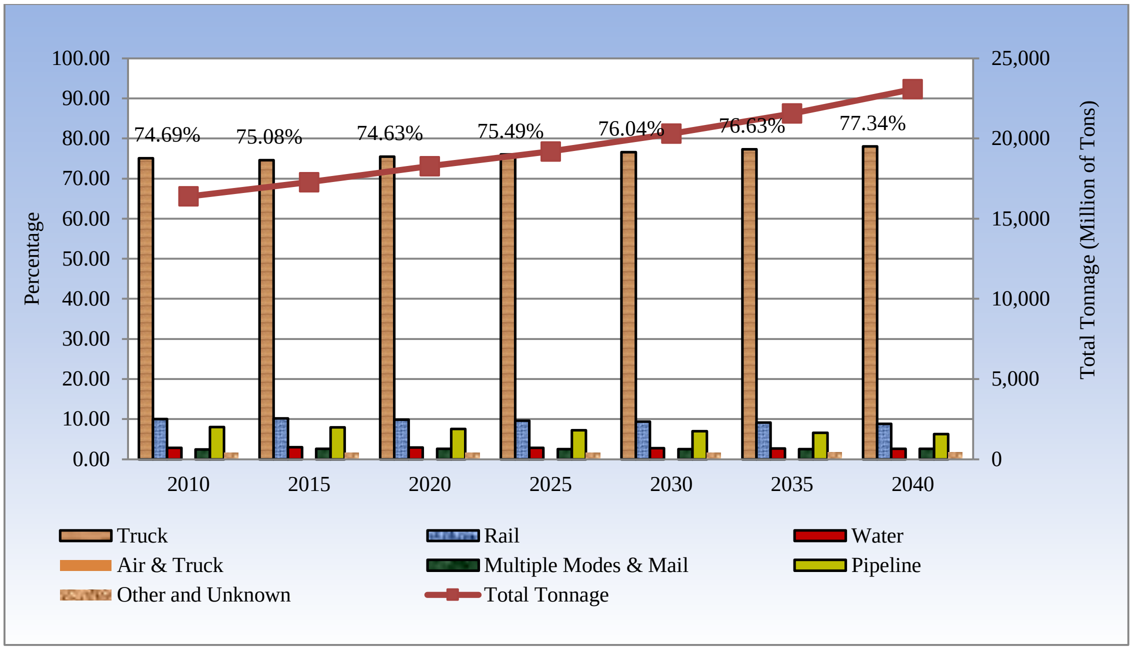
Demand of passenger and freight upon the nation's transportation networks is expected to increase significantly. Estimated and forecast total freight volumes in FAF3 have indicated a steady growth from year 2007 to 2040. Freight volumes will increase approximately 40% from 2007 to 2040 and the majority of them will be transported by trucks. This section provides an overview of the freight transportation trends in the nation and in Utah. It should be noted that FAF3 provides comprehensive national and state-level estimates and forecasts of freight flows covering 131 freight analysis zones, including 123 domestic regions and eight international regions for import and exports (FHWA 2009). This particular database is a crucial component in our study as it will be used to develop a commodity-based truck trip table for the state of Utah.

3.1.1 National Freight Transportation Trends

This section provides information about the freight transportation trends from 2007 to 2040 in the United States. Figure 3.1(a) shows the modal share of freight shipment by volume for the base year 2007. As can be seen, the majority of the freight shipment measured in volume (in tonnage) is carried out by trucks, followed by rail, pipeline, water, and multiple mode, respectively. Trucks alone account for 74.69% in volume for domestic freight transportation, indicating the importance of trucking service for the nation's freight transportation and economic development. Figure 3.1(b) depicts the domestic (DOM) freight transportation trends by percentages of mode share in volume (millions of tons) and value (billions of dollars) from 2007 to 2040.



(a) Modal share of freight shipment by volume in 2007 (National)



(b) Projection of freight growth and mode share by volume from 2007 to 2040 (National)

Figure 3.1 National freight transportation trends

As can be seen, the projection of freight growth is increasing steadily, and the nation's freight volumes are expected to increase nearly 37% from 2007 to 2040. This will pose a challenge in capacity planning to adequately address freight demand, especially the growing truck traffic on the nation's infrastructure.

3.1.2 Utah Freight Transportation Trends

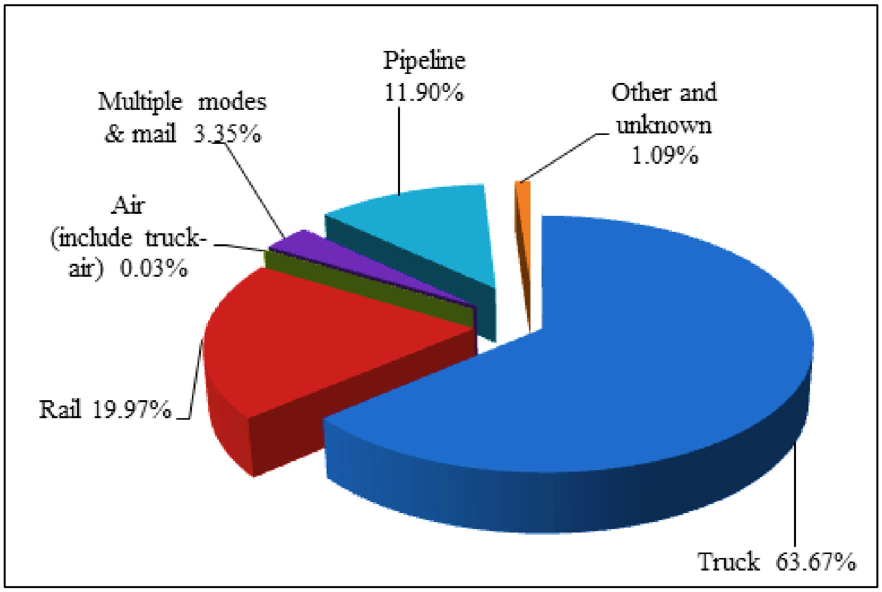
In Utah, the demand for freight transportation, especially truck, has been rising steadily and the forecast shows a continuous growth at least over the next two decades. Using the FAF3 Domestic Database, this section provides a brief summary of the freight movement trends for the state of Utah. Table 3.1 summarizes the modal share of freight shipments in Utah by volume and value for the base year 2007.

Table 3.1 Modal share of freight shipment in Utah by volume in 2007 (unit: MTon)

Mode	Within UT		UT → Other States		Other States → UT		UT → International		International → UT	
	MTon	%	MTon	%	MTon	%	MTon	%	MTon	%
Truck	93.30	86.17	15.51	28.43	17.79	49.39	0.56	24.17	0.71	22.87
Rail	8.21	7.59	24.16	44.29	7.34	20.37	0.67	28.97	0.67	21.79
Air	0.00	0.00	0.02	0.03	0.03	0.09	0.00	0.10	0.00	0.03
Multiple modes	0.06	0.05	3.40	6.23	3.20	8.89	0.96	41.66	0.40	12.79
Pipeline	6.25	5.77	9.98	18.29	7.44	20.65	0.00	0.00	1.31	42.25
Other & unknown	0.46	0.42	1.49	2.73	0.22	0.61	0.12	5.11	0.01	0.29
Total	**108.28**	**100.00**	**54.56**	**100.00**	**36.01**	**100.00**	**2.31**	**100.00**	**3.10**	**100.00**

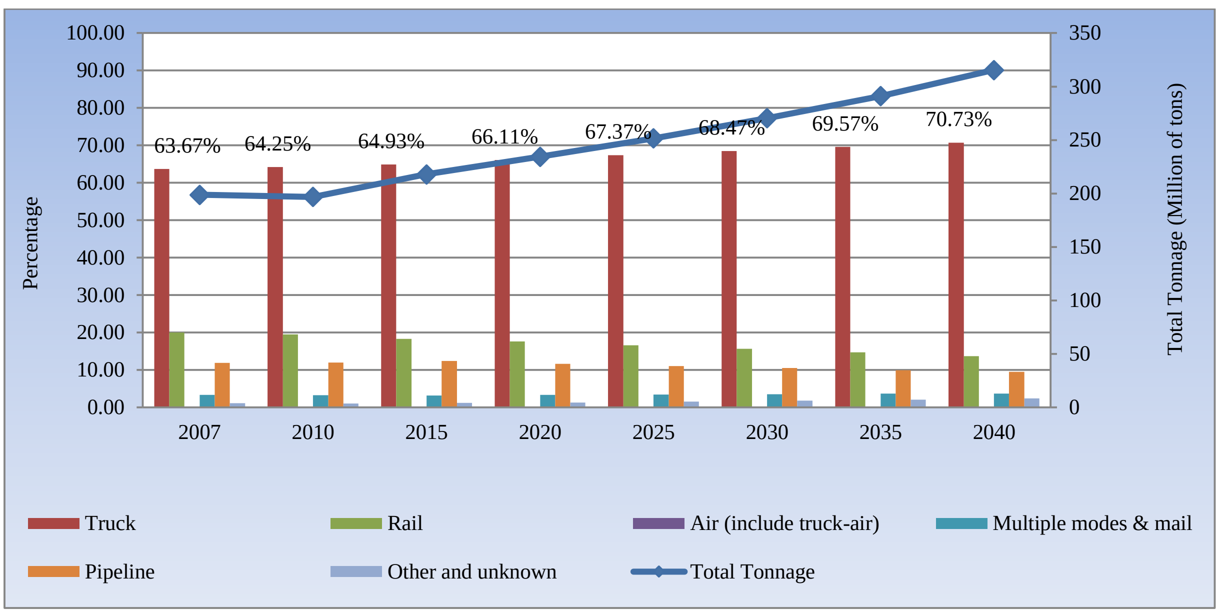
The results indicate that nearly 200 million tons of freight were moved from, to, and within Utah in 2007. Specifically, 108 million tons were moved within Utah, 55 million tons were moved out of Utah, 36 million tons were moved into Utah, and 5.4 million tons were international freight.

The value of these freight shipments was approximately $195 billion. Freight volume measured in tonnage carried by truck accounts for 64% of the modal share by volume and 67% by value. The freight value transported by truck was about $125 billion in 2007 and is expected to increase to $291 billion by 2040. Figure 3.2 shows the modal share of freight shipments by volume for the base year 2007 in Utah. Similar to national level trends, the majority of freight shipments measured in volume is carried out by trucks. The projection of freight growth in Utah, shown in Figure 3.3, appears to increase at a faster rate than the national average (i.e., nearly 60% from 2007 to 2040).



Modal share of freight shipments by volume in 2007 (Utah)

Figure 3.2 Utah freight transportation trends



Projection of freight growth and mode share by volume from 2007 to 2040 (Utah)

Figure 3.3 Utah freight transportation trends (cont.)

3.1.3 Top 10 Commodity Flows in Utah

In order to provide a better understanding of freight transportation demand in Utah, the top 10 commodity flows are described in this section. Table 3.2 and Table 3.3 provide a summary of the top 10 commodities by volume and value in Utah for 2007 and 2040. These tables indicate that coal and nonmetal mineral products are the top commodities by volume from 2007 to 2040. In 2040, precision instruments will become the top commodity by value. The top value commodity from Utah to other states is mixed freight and also the top value commodity from other states to Utah for 2007 and 2040, respectively. For the shipments within Utah, the top value commodity is machinery for 2007 and 2040. In addition, the top volume commodity shipped from, to, and within Utah remains to be nonmetal mineral products for 2007 and 2040. The highlighted commodities in these tables are the commodities that are also the top commodities transported by truck. Please refer to Appendix A for the top commodities transported by truck shipped from, to, and within Utah.

Table 3.2 Top 10 commodities by volume in Utah for 2007 and 2040

Commodity	2007 (Millions of tons)	Commodity	2040 (Millions of tons)
Coal	25.84	Nonmetal min. prods.	35.48
Nonmetal min. prods.	20.29	Coal	34.23
Gravel	19.19	Gravel	26.82
Waste/scrap	15.90	Waste/scrap	21.94
Basic chemicals	12.99	Coal-n.e.c.	18.59
Coal-n.e.c.	12.89	Mixed freight	16.06
Base metals	10.12	Gasoline	15.24
Gasoline	10.11	Fuel oils	11.70
Crude petroleum	7.29	Base metals	11.59
Fuel oils	7.19	Cereal grains	11.43

Note: Commodities are sorted by volume
n.e.c. = not elsewhere classified.
Highlighted commodities are also top commodities transported by truck

Table 3.3 Top 10 commodities by value in Utah for 2007 and 2040

Commodity	2007 (Billions of dollars)	Commodity	2040 (Billions of dollars)
Base metals	20.64	Precision instruments	123.04
Machinery	16.25	Pharmaceuticals	46.01
Mixed freight	14.46	Mixed freight	40.15
Misc. mfg. prods.	10.67	Misc. manufacture prods.	34.69
Pharmaceuticals	9.65	Base metals	34.24
Electronics	8.53	Machinery	33.35
Motorized vehicles	8.13	Electronics	27.08
Articles-based metal	7.51	Textiles/leather	18.75
Other foodstuffs	7.40	Motorized vehicles	18.04
Textiles/leather	7.00	Other foodstuffs	16.79

Note: Commodities are sorted by value
Highlighted commodities are also top commodities transported by truck

3.2 Utah Statewide Travel Model (USTM): Freight Component

3.2.1 USTM Overview

The USTM was conducted in 2008 by the Utah Department of Transportation (UDOT)'s consultant team (i.e., Wilbur Smith Associates (WSA) in cooperation with Resource Systems Group (RSG), Inc.). The main objective of the USTM is to forecast future traffic on Utah's state and interstate facilities based on roadway capacity and socio-economic projection to support strategic planning and investment management at the state level. The USTM framework is depicted in Figure 3.4. The consultant team have solicited inputs from local transportation planning models (i.e., metropolitan planning organization (MPO) models) and national models including long distance passenger and commodity-based truck freight demand models. The study area consists of 29 counties and four MPOs.

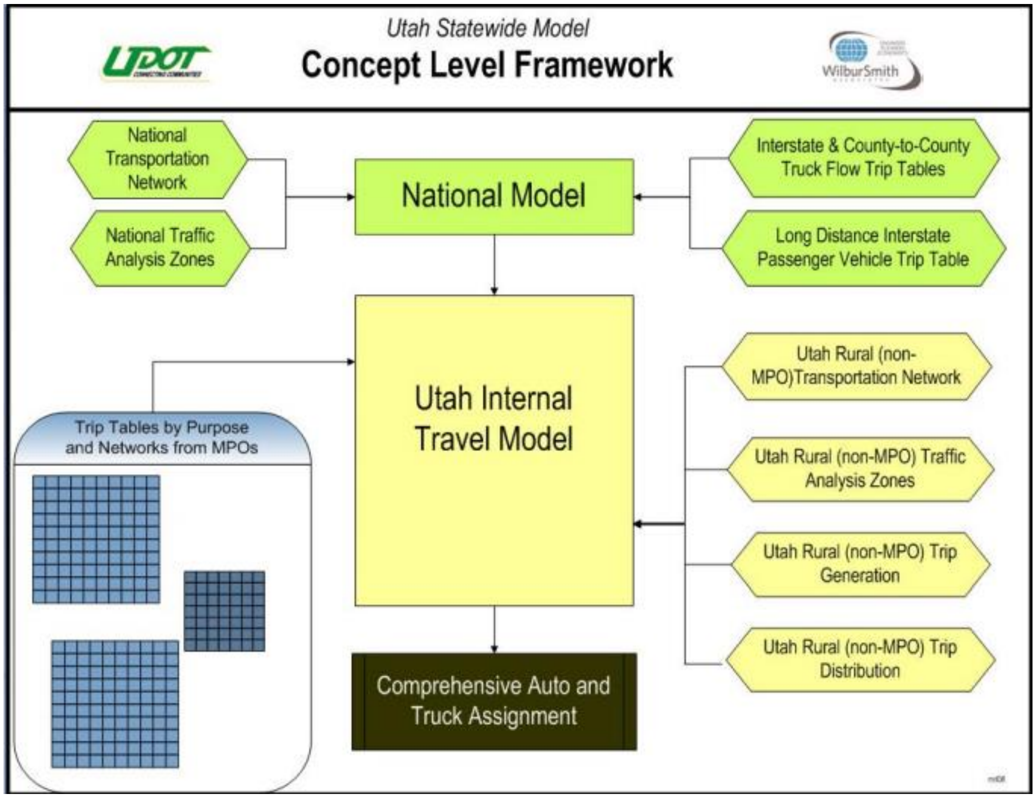


Figure 3.4 USTM framework

The MPOs in Utah consist of Cache, Dixie, Mountain Association of Government (MAG), and Wasatch Front Regional Council (WFRC). The internal TAZs outside the four MPOs and rural planning organizations (RPOs) were created by aggregating the census blocks based on road network details, census place boundaries that outline population centers, county boundaries, and major attraction areas (Wilbur Smith Associates in cooperation with Resource Systems Group, Inc. 2009). The USTM transportation network consists of 23,532 nodes and 31,630 links, excluding 8,098 centroid connectors and 3,464 internal and 27 external TAZs. The network link free-flow speeds and capacities are calculated based on the WFRC/MAG models as a function of the number of lanes, facility type, and area type. Link capacities are expressed in level of service (LOS) E in vehicle/hour/lane.

The trip generation models for all internal trips in Utah are estimated including trip ends within WFRC/MAG and Cache MPOs. The trip production flows are estimated using a two-way cross classification model, and the trip attraction flows are estimated using regression models. The external passenger movements adopted a national trip table from the Nationwide Personal Transportation Survey (NPTS). The external truck flows are estimated using the FAF database, while the internal truck flows are estimated from the calibrated regression models, similar to the QFRM trip rates. The details of freight models in USTM are explained in the next subsection. The trip distribution model uses a gravity model approach and the friction factors are calibrated for each trip purpose. The friction factors for truck purpose are calibrated based on travel distance. Traffic assignment in USTM is a simultaneous multi-class user equilibrium model. Different truck classes (i.e., commercial, single, multiple units) are converted to passenger cars using passenger car equivalent (PCE) factors. It should be noted that the high-occupant vehicle

(HOV) and single-occupant vehicle (SOV) trip tables are distinguished in the WFRC/MAG trip tables.

3.2.2 USTM Freight Model

The development of the USTM freight model makes use of the TRANSEARCH database to analyze the current and projected future freight movements in Utah's road infrastructure. The primary freight corridors or truck routes are depicted in Figure 3.5, and include I-15, I-70, I-80, U.S. 6, U.S. 89, U.S. 191, and U.S. 40. As can be seen, I-15 is the major north/south interstate and is also part of the North America Free Trade Act (NAFTA) CANAMEX corridor linking between Canada and Mexico through the United States. I-80 and I-70 are two of the primary interstates for east/west travel, both of which have heavy truck traffic volumes. The results from the USTM freight report indicated that Los Angeles is the origin of most freight trips passing through Utah. Other major origins and destinations are cities in California, New York, and the Midwest.

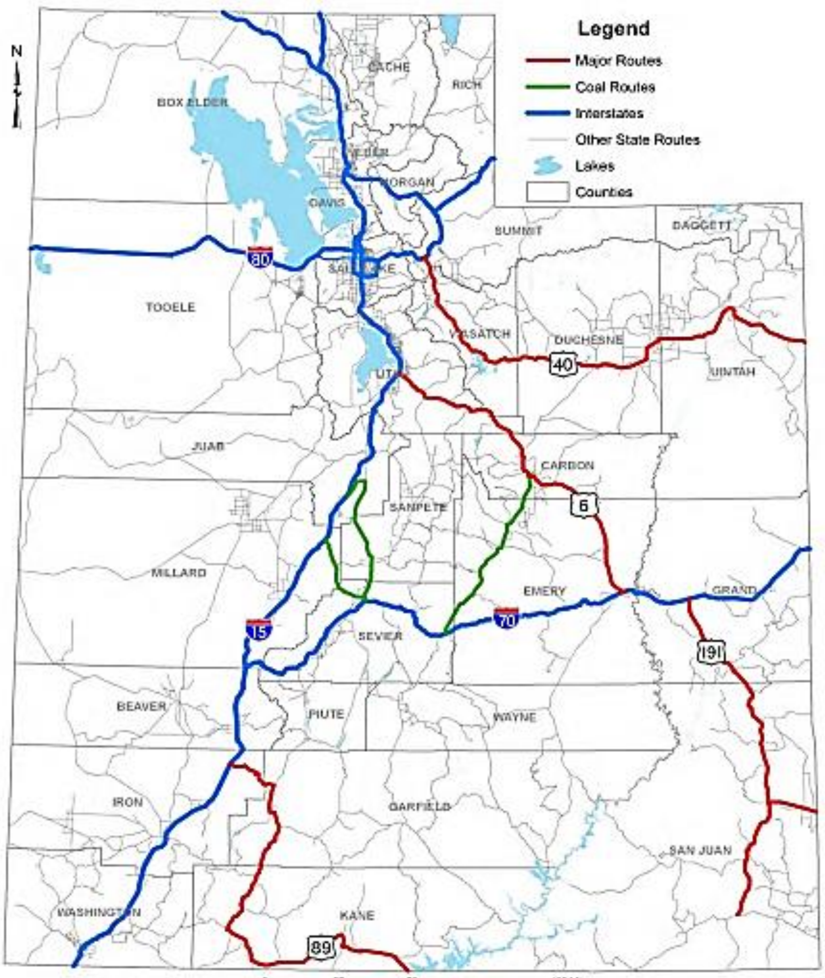


Figure 3.5 Utah major freight corridors
Source: USTM Utah Freight Planning Report (2010)

The internal trip generation models adopted trip rate parameters from QFRM to address three types of vehicles, including 1) Commercial (COMM), 2) Single Unit (SU), and 3) Multiple Unit (MU). The trip generation parameters were further calibrated in the feedback loop until the estimated statewide vehicle-mile of travel (VMT) and the observed VMT were within acceptable tolerance.

Table 3.4 summarizes the trip generation parameters from QFRM. Table 3.5 and Table 3.6 show the calibrated trip rates for urban and rural areas obtained from the final iteration in the USTM. The socio-economic data, including number of households, retail, basic, service, and agricultural employment, of each freight analysis zone are the major input data for calculating internal truck trips. The parameters in Table 3.5 and Table 3.6 are lower than the ones in Table 3.4. This indicates that the borrowed trip rates from QFRM could overestimate the internal truck trips in Utah, and suggests the need to calibrate these trip rates for their own states.

Table 3.4 Internal truck trip rates (QFRM)

	Trip Generation Parameters - QRFM				
Truck type	Households	Retail	Basic	Service	Agriculture
Commercial	0.251	0.888	0.938	0.437	1.11
Single-unit	0.099	0.253	0.242	0.068	0.289
Multi-unit	0.038	0.065	0.104	0.009	0.174

Table 3.5 Internal truck trip rate (Urban)

	Trip Generation Parameters - Urban				
Truck type	Households	Retail	Basic	Service	Agriculture
Commercial	0.03765	0.1332	0.1407	0.06555	0.1665
Single-unit	0.0495	0.1265	0.121	0.034	0.1445
Multi-unit	0.0152	0.026	0.0416	0.0036	0.0696

Table 3.6 Internal truck trip rate (Rural)

	Trip Generation Parameters - Rural				
Truck type	Households	Retail	Basic	Service	Agriculture
Commercial	0.0502	0.1776	0.1876	0.0874	0.222
Single-unit	0.05445	0.13915	0.1331	0.0374	0.15895
Multi-unit	0.0152	0.026	0.0416	0.0036	0.0696

4. A TWO-STAGE APPROACH FOR ESTIMATING TRUCK TRIP TABLE

This section describes the two-stage approach for estimating a statewide truck trip table. Figure 4.1 depicts a conceptual framework of the two-stage approach. The first stage uses a national commodity flow data from the Freight Analysis Framework Version 3 (FAF^3) database to develop a commodity-based truck trip table. The second stage uses the path flow estimator (PFE) concept to refine the truck trip table obtained from the first stage using the truck counts from the statewide truck count program. Details of these two stages are described in the following sections.

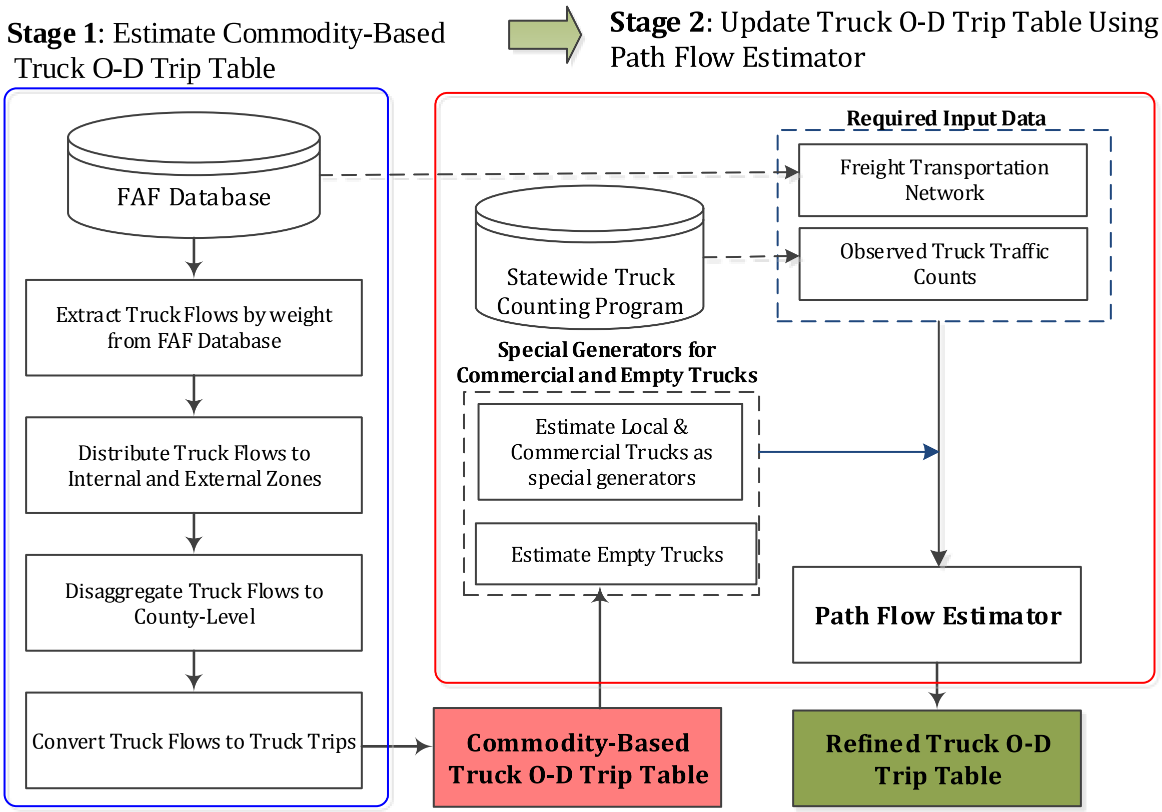


Figure 4.1 Conceptual framework of the two-stage approach

4.1 Stage 1: Develop a Commodity-Based Truck O-D Trip Table

Stage 1 is to develop a simplified procedure, depicted in Figure 4.2, for estimating truck O-D trip table from the FAF commodity flow database. It mainly consists of four steps: 1) extract truck flows by weight from FAF database, 2) distribute truck flows to internal and external zones, 3) disaggregate truck flows to the county level, and 4) convert truck flows to truck trips. The steps are briefly explained as follows:

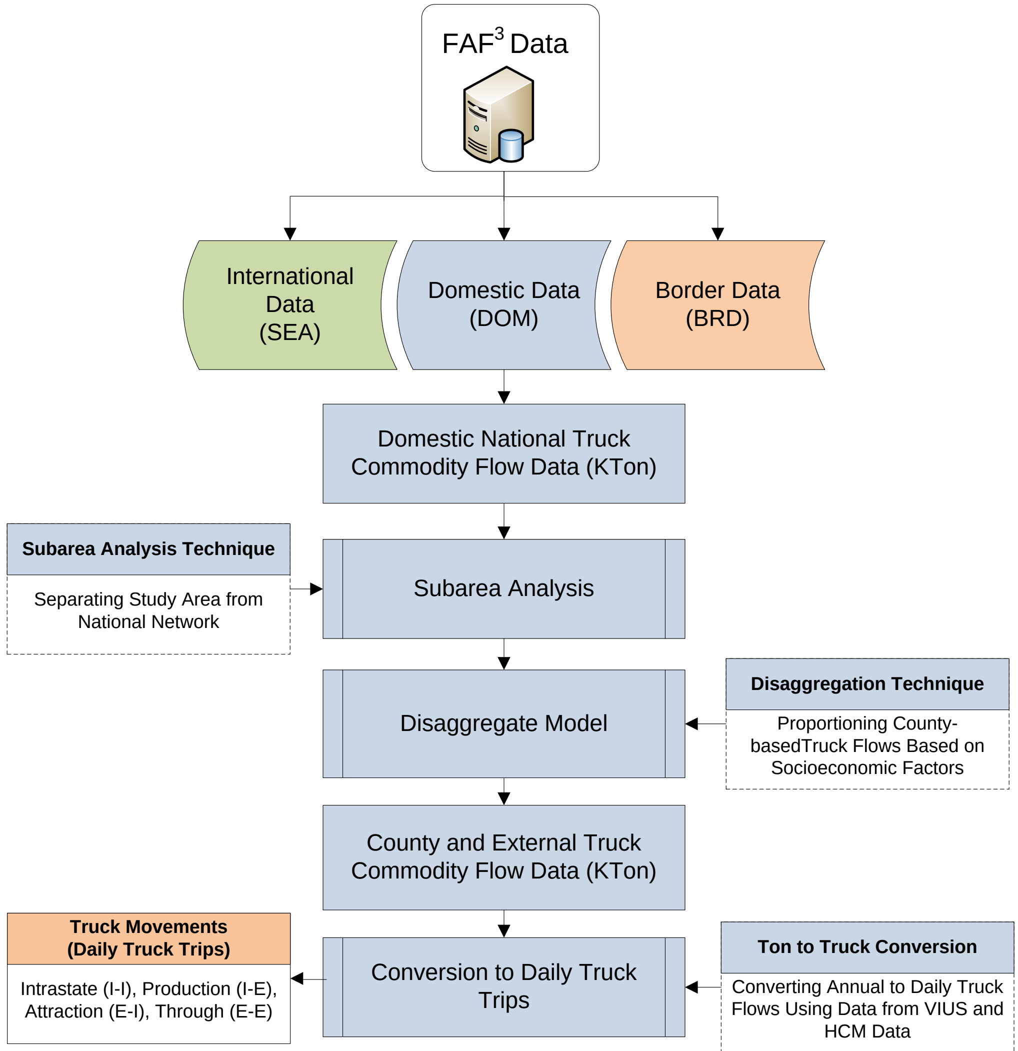


Figure 4.2 A simplified procedure for estimating the truck O-D trip table from commodity flows

(1) *Extract Truck Flows by Weight from FAF Database*

The first step is to extract truck flows from the FAF commodity flow database. It should be noted that the FAF3 commodity database can be publicly accessed from the Freight Management and Operations Database website[1]. It consists of three major databases: 1) DOM database: the commodity flows between domestic origins and domestic destinations, 2) BRD database: the commodity flows by land from Canada and Mexico to domestic destinations via ports of entry on the U.S. border and vice versa, and 3) SEA database: the commodity flows by water from overseas origins via ports of entry to domestic destinations and vice versa. The commodity flows are classified based on the Standard Classification of Transported Goods (SCTG). Details of the SCTG are found in Appendix A. The measurement units of the commodity flow database are in units of thousands of tons (KT) and millions of dollars (MDOL). The DOM truck flows were

[1] Available at: http://ops.fhwa.dot.gov/freight/freight_analysis/faf/index.htm

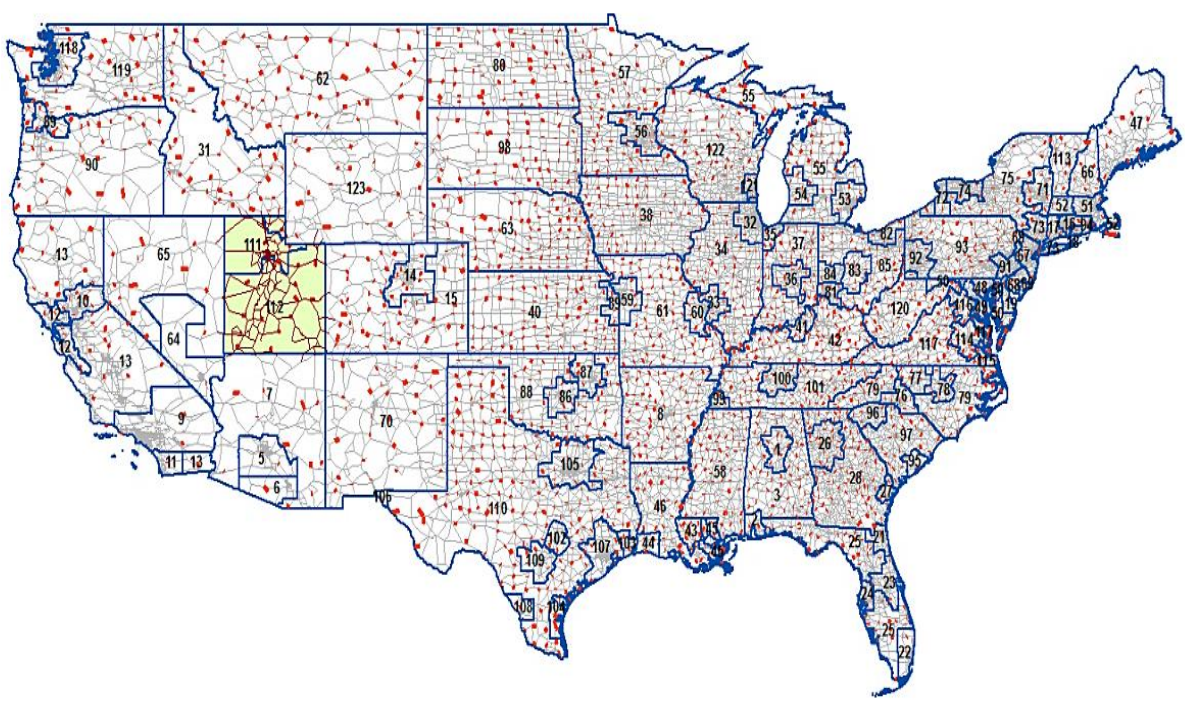
extracted from the FAF database and the outputs of this step are truck flows by weight in units of a thousand tons (kTon).

(2) *Distribute Truck Flows to Internal and External Zones*

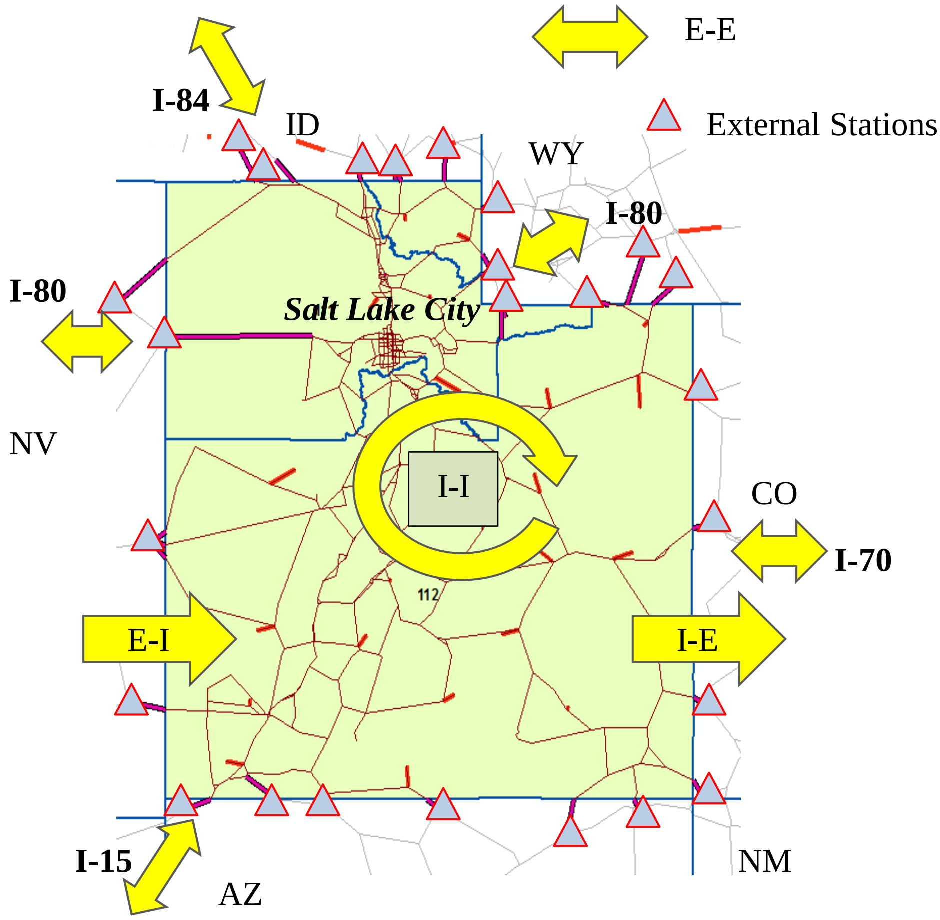
This step requires quantifying four types of truck flows, which are:

1) truck flows within Utah (Internal-Internal [I-I])
2) truck flows from Utah to other states (Internal-External [I-E]) or production flows
3) truck flows from other states to Utah (External-Internal [E-I]) or attraction flows
4) through truck flows ([E-E])

The results of I-I, I-E, and E-I truck flows are provided in Appendix B. Figure 4.3(a) depicts the FAF3 network that was originally obtained from the National Highway Planning Network (NHPN). As part of the NHPN, the Utah network for freight analysis consists of 2,430 links, 34 external stations in two FAF zones. It should be noted that the FAF database does not provide enough information to estimate the through truck flows (E-E). In order to estimate the through truck flows for the state of Utah from the DOM database, a pre-processing technique called Subarea Analysis was implemented in CUBE, a transportation planning software by Citilabs. This step distributes the commodity flows among 131 FAF zones.



(a) FAF network and 131 freight analysis zones (UT is highlighted)



(b) Four types of truck flows and external stations

Figure 4.3 FAF network, freight analysis zones, and four types of truck flows in Utah

(3) *Disaggregate Truck Flows to the County Level*

The next step is to disaggregate the truck flows from the state level to the county level using population and employment information of each county. Note that employment and population are the most common disaggregation factors, and this information can be obtained from state government organizations, e.g., Utah Governor's Office of Planning and Budget (GOPB) for population and Utah Department of Work Force Services for employment in this study (U.S. Bureau of Economic Analysis, Utah Department of Work Force Services 2000). The disaggregate factor of employment is used for truck trip production, while the disaggregate factor of population is used for truck trip attraction. These factors are calculated as follows:

$$O_c = \frac{Emp_c}{\sum_{c=1}^{C} Emp_c}, \quad (4.1)$$

$$D_c = \frac{Pop_c}{\sum_{c=1}^{C} Pop_c}, \tag{4.2}$$

where O_c is the disaggregation factor for truck production flows at county c; D_c is the disaggregation factor for truck attraction flows at county c; Emp_c is the employment rate of county c; Pop_c is the population rate of county c, and C is the number of counties in Utah.

(4) *Convert Truck Flows to Truck Trips*

The last step is to convert truck flows to truck trips using the truck payload equivalent factor (TPEF). Note that the TPEF is computed based on the truck weight data obtained from the Federal Vehicle Inventory and User Survey (VIUS) data (Office of Freight Management and Operations, FHWA 2007), Weigh-In-Motion (WIM), and Port of Entry (POE) stations in Utah. The result indicates that the TPEF for Utah is 41,196 lbs/vehicle or 20.6 tons/vehicle. This number is within a reasonable range compared with the empirical studies in other states (e.g., 16.07 tons/vehicle for Ohio (Cambridge Systematics 2002), 24.00 tons/vehicle for Wisconsin (Wisconsin Department of Transportation 1995), and 25.77 tons/vehicle for Texas (Cambridge Systematics 2004).

Note that the TPEF computed above is the mean payload for all commodities and truck types. The TPEF can be further analyzed to better capture the commodity and truck body types as suggested by the Oak Ridge National Laboratory (2011). The conversion equation is expressed as follows:

$$\sum_{j=1}^{J} Y_j = \sum_{i=1}^{I} X_i \sum_{j=1}^{J} \sum_{k=1}^{K} \frac{\beta_{ijk}}{\omega_{ijk}} \tag{4.3}$$

where Y_j is the number of trucks in group j (i.e., single unit, truck trailer, combination semitrailer, combination double, combination triple; $J = 5$); X_i is the tonnage of commodity i (i.e., classified using SCTG; $I = 43$); β_{ijk} is the fraction of commodity i moved by group j with body type k (i.e., dry van, flat bed, bulk, reefer, tank, logging, livestock, automobile, other; $K = 9$); and ω_{ijk} is the TPEF of group j with body type k transporting commodity i.

In the final step, the number of working days per year for truck operations from the Highway Capacity Manual (HCM) (Transportation Research Board 2000) (i.e., 300 workdays per year) is used to convert the annual truck flows to daily truck flows

4.2 Commercial and Empty Truck Demand Estimation

4.2.1 Commercial Truck Demand Estimation

It has been noted that estimating truck O-D trip table from the commodity flows often underestimates the local truck trips such as the light commercial and empty truck trips. In the USTM, the local truck flows are dominated by the intra-county flows at the county level. The results indicate that local truck movements are concentrated between Ogden and Provo, along the

I-15 corridor in Salt Lake City. Local traffic on U.S. 6 and U.S. 89 is projected to increase substantially by 2040, while traffic on I-80 shows a slight decrease. This shows the significant role of local truck traffic for estimating statewide freight movements. Thus, in this study, we adopt the commercial truck trip generation model to estimate the local and commercial trucks as follows:

$$O_r^{comm} = \lambda^{agriculture} y_r^{agriculture} + \lambda^{basic} y_r^{basic} + \lambda^{ratail} y_r^{retail} + \lambda^{office} y_r^{office} + \lambda^{household} y_r^{household}, \quad (4.4)$$

where O_r^{comm} is the production flows of origin *r* for commercial truck; $y_r^{agriculture}$, y_r^{basic}, y_r^{retail}, and y_r^{office} are the employment rates for agriculture, basic (e.g., manufacturing, transportation, wholesale, and utilities), retail, and office, respectively; and $y_r^{household}$ is the number of households in origin *r*. The calibrated coefficients ($\lambda^{agriculture}$, λ^{basic}, λ^{ratail}, λ^{office}, $\lambda^{household}$) were borrowed from the USTM (i.e., (0.166, 0.141, 0.133, 0.065, 0.038) for urban area, and (0.050, 0.222, 0.133, 0.065, 0.038) for rural area). Please refer to Table 3.5 and Table 3.6 for details. The attraction flows of destination *s* (D_s^{comm}) for commercial truck are assumed to be the same as the production flows.

4.2.2 Empty Truck Demand Estimation

The empty truck trips are estimated using the Holguín-Veras and Thorson (HV-T) model developed by Holguin-Veras *et al*. (2010). The empty truck trip model was developed using the destination choice probability functions expressed as a function of trip distance and the magnitude of opposing commodity flows. The probability functions for empty truck trips going from origin *r* to destination *s* and returning empty are summarized in Table 4.1. In this study, we selected the logit probability (model number 2 in Table 4.1) for estimating the total truck trips from *r* to *s* with consideration of both loaded and empty trips $E(z_{rs})$ as follows:

$$E(z_{rs}) = \frac{z_{rs}^{loaded}}{\omega_{rs}} \left(1 + \frac{z_{rs} e^{-\beta d_{rs}}}{\sum_l z_{rl} e^{-\beta d_{rl}}} \right), \quad (4.5)$$

where z_{rs}^{loaded} are the loaded truck trips between (*r*, *s*); ω_{rs} is the conversion factor or the average payload (tons/trip) for the loaded trips obtained from Eq. (4.3); z_{rs} are the commodity flows between (*r*, *s*); β is a parameter determined empirically from the observed data; and d_{rs} is the returning distance between (*r*, *s*).

Table 4.1 Destination choice probability functions for empty truck trips

Probability functions	Variables
$P(s)=\dfrac{z_{rs}}{\sum_l z_{rl}}$	HV-T 1: Commodity flows between origin *r* and destination *s*: z_{rs}
$P(s)=\dfrac{z_{rs}e^{-\beta d_{rs}}}{\sum_l z_{rl}e^{-\beta d_{rl}}}$	HV-T 2: Commodity flows between origin *r* and destination *s*: z_{rs}; distance between origin *r* and destination *s*: d_{rs}
$P(s)=\dfrac{z_{rs}d_{rs}^{-\beta}}{\sum_l z_{rl}d_{rl}^{-\beta}}$	HV-T 3: Commodity flows between origin *r* and destination *s*: z_{rs}; distance between origin *r* and destination *s*: d_{rs}
$P(s)=\dfrac{z_{rs}(d_{rs}+d_{hr})^{-\beta}}{\sum_l z_{rl}(d_{rl}+d_{hr})^{-\beta}}$	HV-T 4 (trip chain): Commodity flows between origin *r* and destination *s*: z_{rs}; distance between origin *h* and destination *r* : d_{hr}; distance between origin *r* and destination *s*: d_{rs}.

4.3 Stage 2: PFE Formulation, Optimality Conditions, and Solution Algorithm

4.3.1 Background and Formulation

This stage uses the optimization approach to refine the commodity-based truck O-D trip table obtained from the first stage. The basic idea is to use the concept of Path Flow Estimator (PFE) to estimate path flows that can reproduce the observed link counts and flows on other spatial levels. PFE is capable of estimating path flows and path travel times using only traffic counts from a subset of network links. PFE was originally developed by Bell and Shields (1995) and further enhanced by Chen *et al*. (2005). Hereafter, the following notation in Table 4.2 is considered.

Table 4.2 Notation for the PFE model

Notation	Description
Set of Variables	
M	: Set of network links with truck counts
U	: Set of network links without truck counts
A	: Set of all network links $A = M \cup U$
R	: Set of origins
S	: Set of destinations
RS	: Set of O-D pairs
K_{rs}	: Set of paths connecting origin *r* and destination *s*
$\bar{R}$	: Set of origins with commodity-based data
$\bar{S}$	: Set of destinations with commodity-based data
$\overline{RS}$	: Set of target (or prior) O-D pairs
Input Variables and Parameters	
v_a	: Observed truck volume on link *a*
C_a	: Capacity of link *a*
O_r	: Commodity-based truck trip production of origin *r*
D_s	: Commodity-based truck trip attraction of destination *s*
z_{rs}	: Commodity-based O-D flows between origin *r* and destination *s*
F	: Target total demand
ε_a	: Percentage measurement error allowed for truck count on link *a*
ε_r	: Percentage measurement error allowed for truck trip production of origin *r*
ε_s	: Percentage measurement error allowed for truck trip attraction of destination *s*
ε_{rs}	: Percentage measurement error allowed for the commodity-based O-D demands between origin *r* and destination *s*
ε	: Percentage measurement error allowed for the target total demand
θ	: Dispersion parameter in the logit model
$t_a(\cdot)$	: Truck travel time on link *a*
δ_{ka}^{rs}	: Path-link indicator, 1 if link a is on path *k* between O-D pair *rs* and 0 otherwise
f_k^{rs}	: Flow on path *k* connecting O-D pair *rs*
x_a	: Estimated truck traffic volume on link *a*
P_r	: Estimated truck trip production of origin *r*
A_s	: Estimated truck trip attraction of destination s
q_{rs}	: Estimated truck O-D flows between origin *r* and destination *s*
α_a, β_a	: Parameters for BPR link cost function

The core component of PFE is a logit-based path choice model in which the perception errors of path travel times are assumed to be independently and identically Gumbel variates. The logit model interacts with link cost functions to produce a stochastic user equilibrium (SUE) traffic pattern. It should be noted that the SUE traffic assignment procedure was also implemented to estimate the freight flows in the FAF version 3 (please refer to Chapter 5 of FAF3 report [FHWA 2009]). The aim of this stage is to adapt the PFE to take not only truck traffic counts but also the available freight planning data (i.e., truck production and attraction flows) to update the commodity-based truck O-D trip table. PFE requires traffic count data to estimate the statewide truck O-D trip table while the planning data are optional inputs in this process. However, the commodity-based truck O-D trip table obtained from the first stage can enhance the observability of the O-D estimation problem as well as preserving the spatial commodity flow pattern in the study area.

$$\text{Min } Z = \sum_{a \in A} \int_0^{x_a} t_a(\omega) dw + \frac{1}{\theta} \sum_{rs \in RS} \sum_{k \in K_{rs}} f_k^{rs} \ln f_k^{rs} \tag{4.6}$$

s.t.

$$(1-\varepsilon_a) \cdot v_a \le x_a \le (1+\varepsilon_a) \cdot v_a, \forall\, a \in \mathrm{M}, \tag{4.7}$$

$$x_a \le C_a, \forall\, a \in \mathrm{U}, \tag{4.8}$$

$$(1-\varepsilon_{rs}) \cdot z_{rs} \le q_{rs} \le (1+\varepsilon_{rs}) \cdot z_{rs}, \forall\, rs \in \overline{\mathrm{RS}}, \tag{4.9}$$

$$(1-\varepsilon_r) \cdot O_r \le P_r \le (1+\varepsilon_r) \cdot O_r, \forall r \in \bar{\mathrm{R}}, \tag{4.10}$$

$$(1-\varepsilon_s) \cdot D_s \le A_s \le (1+\varepsilon_s) \cdot D_s, \forall s \in \bar{\mathrm{S}}, \tag{4.11}$$

$$(1\text{-}\varepsilon\ ) \cdot F \ \le T \ \le (1+\varepsilon\ ) \cdot F, \tag{4.12}$$

$$f_k^{rs} \ge 0, \qquad \forall k \in \mathrm{K}_{\mathrm{rs}}, rs \in \mathrm{RS}, \tag{4.13}$$

where

$$x_a = \sum_{rs \in \mathrm{RS}} \sum_{k \in \mathrm{K}_{\mathrm{rs}}} f_k^{rs} \delta_{ka}^{rs}, \forall\, a \in \mathrm{A}, \tag{4.14}$$

$$q_{rs} = \sum_{k \in \mathrm{K}_{\mathrm{rs}}} f_k^{rs}, \forall\, rs \in \mathrm{RS}, \tag{4.15}$$

$$P_r = \sum_{s \in \mathrm{S}} \sum_{k \in \mathrm{K}_{\mathrm{rs}}} f_k^{rs}, \forall r \in \mathrm{R}, \tag{4.16}$$

$$A_s = \sum_{r \in \mathrm{R}} \sum_{k \in \mathrm{K}_{\mathrm{rs}}} f_k^{rs}, \forall s \in \mathrm{S}, \tag{4.17}$$

$$T = \sum_{rs \in \mathrm{RS}} \sum_{k \in K_{rs}} f_k^{rs}, \tag{4.18}$$

Objective function in Eq. (4.6) has two terms: a user equilibrium term and an entropy term. The entropy term seeks to spread trips onto multiple paths according to the dispersion parameter, while the user equilibrium term tends to cluster trips on the minimum cost paths. As opposed to the traditional logit-based SUE model, PFE finds path flows that minimize the SUE objective function while simultaneously reproducing truck traffic counts on all observed links in Eq. (4.7), commodity-based demands of certain O-D pairs in Eq. (4.9), truck production and attraction of certain origin and destination in Eqs. (4.10) and (4.11), and total demand in Eq. (4.12) within some predefined error bounds. These error bounds are essentially confidence levels of the observed data at different spatial levels used to constrain the path flow estimation. More reliable data will use a smaller error bound (or tolerance) to constrain the estimated flow within a narrower range, while less reliable data will use a larger tolerance to allow for a larger range of the estimated flow. For the unobserved links, the estimated flows cannot exceed their respective capacities, as indicated by Eq. (4.8). Eq. (4.13) constrains the path flows to be non-negativity, while Eqs. (4.14)-(4.18) are definitional constraints that sum up the estimated path flows to obtain the link flows, O-D flows, zonal production flows, zonal attraction flows, and total demand, respectively.

4.3.2 Optimality Conditions

The Lagrangian function of the above PFE formulation and its first partial derivatives with respect to the path-flow variables can be expressed as follows.

$$
\begin{aligned}
L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+}) = Z + \sum_{a\in \mathrm{M}} u_a^{-}\cdot\left(v_a\left(1-\varepsilon_a\right)-\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\delta_{ka}^{rs}\right)+ \\
\sum_{a\in \mathrm{M}} u_a^{+}\cdot\left(v_a\left(1+\varepsilon_a\right)-\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\delta_{ka}^{rs}\right)+\sum_{a\in \mathrm{U}} d_a\cdot\left(C_a-\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\delta_{ka}^{rs}\right)+ \\
\sum_{rs\in \mathrm{RS}} o_{rs}^{-}\cdot\left(z_{rs}\left(1-\varepsilon_{rs}\right)-\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\right)+\sum_{rs\in \mathrm{RS}} o_{rs}^{+}\cdot\left(z_{rs}\left(1+\varepsilon_{rs}\right)-\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\right)+ \\
\sum_{r\in \mathrm{R}} \rho_r^{-}\cdot\left(P_r\left(1-\varepsilon_r\right)-\sum_{s\in \mathrm{S}}\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\right)+\sum_{r\in \mathrm{R}} \rho_r^{+}\cdot\left(P_r\left(1+\varepsilon_r\right)-\sum_{s\in \mathrm{S}}\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\right)+ \\
\sum_{s\in \mathrm{S}} \eta_s^{-}\cdot\left(A_s\left(1-\varepsilon_s\right)-\sum_{r\in \mathrm{R}}\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\right)+\sum_{s\in \mathrm{S}} \eta_s^{+}\cdot\left(A_s\left(1+\varepsilon_s\right)-\sum_{r\in \mathrm{R}}\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\right)+ \\
\psi^{-}\left(T\left(1-\varepsilon\right)-\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\right)+\psi^{+}\left(T\left(1+\varepsilon\right)-\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K}_{rs}} f_k^{rs}\right)
\end{aligned}
\tag{4.19}
$$

where u_a^{-}, u_a^{+}, d_a, o_{rs}^{-}, o_{rs}^{+}, ρ_r^{-}, ρ_r^{+}, η_s^{-}, η_s^{+}, ψ^{-}, and ψ^{+} are the dual variables of constraints (4.7), (4.8), (4.9), (4.10), (4.11), and (4.12) respectively. The values of u_a^{+}, d_a, o_{rs}^{+}, ρ_r^{+}, η_s^{+}, and ψ^{+} are restricted to be non-positive, while the value of u_a^{-}, o_{rs}^{-}, ρ_r^{-}, η_s^{-}, and ψ^{-} must be nonnegative; u_a^{-} and u_a^{+} can be viewed as the corrections in the link cost function, which bring the estimated path flows into agreement with the observed link volumes; similarly, o_{rs}^{-}, o_{rs}^{+}, ρ_r^{-}, ρ_r^{+}, η_s^{-}, η_s^{+}, ψ^{-}, and ψ^{+} can be interpreted as corrections to the O-D travel times, zonal production attractiveness, zonal attraction attractiveness, and total demand attractiveness, respectively, that can be used to steer the estimated path flow pattern to within the O-D interval constraints specified by Eqs. (4.9), (4.10), (4.11), and (4.12). These dual variables are zero if the estimated link flows, O-D flows, zonal production flows, zonal attraction flows, and total demand are within an acceptable range defined by the measurement error bound, and non-zero if they are binding at one of the limits. d_a is related to the link queuing delay when the estimated link flow reaches its capacity (Bell and Iida 1997). Additionally, the following relation must hold.

$$
\begin{aligned}
& f_k^{rs}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial f_k^{rs}}=0,\ \forall\, k\in \mathrm{K}_{\mathrm{rs}}, rs\in \mathrm{RS} \\
& u_a^{-}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial u_a^{-}}=0,\ \forall\, a\in \mathrm{M} \\
& u_a^{+}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial u_a^{+}}=0,\ \forall\, a\in \mathrm{M} \\
& d_a\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial d_a}=0,\ \forall\, a\in \mathrm{U} \\
& o_{rs}^{-}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial o_{rs}^{-}}=0,\ \forall\ rs\in \overline{\mathrm{RS}} \\
& o_{rs}^{+}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial o_{rs}^{+}}=0,\ \forall\ rs\in \overline{\mathrm{RS}} \\
& \rho_r^{-}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial \rho_r^{-}}=0,\ \forall\ r\in \overline{\mathrm{R}} \\
& \rho_r^{+}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial \rho_r^{+}}=0,\ \forall\ r\in \overline{\mathrm{R}} \\
& \eta_s^{-}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial \eta_s^{-}}=0,\ \forall\ s\in \overline{\mathrm{S}} \\
& \eta_s^{+}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial \eta_s^{+}}=0,\ \forall\ s\in \overline{\mathrm{S}} \\
& \psi^{-}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial \psi^{-}}=0, \\
& \psi^{+}\,\frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial \psi^{+}}=0
\end{aligned}
\tag{4.20}
$$

$$
f_k^{rs}\begin{pmatrix}\dfrac{1}{\theta}\ln f_k^{rs}+\displaystyle\sum_{a\in \mathrm{A}} t_a(x_a)\,\delta_{ka}^{rs}-\left(\sum_{a\in \mathrm{M}} u_a^{-}\delta_{ka}^{rs}+\sum_{a\in \mathrm{M}} u_a^{+}\delta_{ka}^{rs}\right)-\sum_{a\in \mathrm{U}} d_a\delta_{ka}^{rs} \\ -\left(o_{rs}^{-}+o_{rs}^{+}\right)-\left(\rho_r^{-}+\rho_r^{+}\right)-\left(\eta_s^{-}+\eta_s^{+}\right)-\left(\psi^{-}+\psi^{+}\right)\end{pmatrix}=0,\forall\, k\in \mathrm{K}_{\mathrm{rs}}, rs\in \mathrm{RS} \tag{4.21}
$$

Since always $f_k^{rs}>0,\forall\, k\in \mathrm{K}_{\mathrm{rs}}, rs\in \mathrm{RS}$, in the logit-based SUE model,

$$
\begin{pmatrix}\dfrac{1}{\theta}\ln f_k^{rs}+\displaystyle\sum_{a\in \mathrm{A}} t_a(x_a)\,\delta_{ka}^{rs}-\left(\sum_{a\in \mathrm{M}} u_a^{-}\delta_{ka}^{rs}+\sum_{a\in \mathrm{M}} u_a^{+}\delta_{ka}^{rs}\right)-\sum_{a\in \mathrm{U}} d_a\delta_{ka}^{rs} \\ -\left(o_{rs}^{-}+o_{rs}^{+}\right)-\left(\rho_r^{-}+\rho_r^{+}\right)-\left(\eta_s^{-}+\eta_s^{+}\right)-\left(\psi^{-}+\psi^{+}\right)\end{pmatrix}=0 \tag{4.22}
$$

For u_a^- $\frac{L(\mathbf{f},\mathbf{u}^+,\mathbf{u}^-,\mathbf{d},\mathbf{o}^+,\mathbf{o}^-,\boldsymbol{\rho}^-,\boldsymbol{\rho}^+,\boldsymbol{\eta}^-,\boldsymbol{\eta}^+,\boldsymbol{\psi}^-,\boldsymbol{\psi}^+)}{\partial u_a^-}=0,\ \forall\, a\in \mathrm{M}:$

$$\begin{cases} v_a\left(1-\varepsilon_a\right)-\sum_{rs\in\mathrm{RS}}\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}\delta_{ka}^{rs}<0 \Rightarrow v_a\left(1-\varepsilon_a\right)<x_a, & if\ u_a^-=0 \\ v_a\left(1-\varepsilon_a\right)-\sum_{rs\in\mathrm{RS}}\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}\delta_{ka}^{rs}=0 \Rightarrow v_a\left(1-\varepsilon_a\right)=x_a, & if\ u_a^->0 \end{cases} \tag{4.23}$$

For u_a^+ $\frac{L(\mathbf{f},\mathbf{u}^+,\mathbf{u}^-,\mathbf{d},\mathbf{o}^+,\mathbf{o}^-,\boldsymbol{\rho}^-,\boldsymbol{\rho}^+,\boldsymbol{\eta}^-,\boldsymbol{\eta}^+,\boldsymbol{\psi}^-,\boldsymbol{\psi}^+)}{\partial u_a^+}=0,\ \forall\, a\in \mathrm{M}:$

$$\begin{cases} v_a\left(1+\varepsilon_a\right)-\sum_{rs\in\mathrm{RS}}\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}\delta_{ka}^{rs}>0 \Rightarrow v_a\left(1+\varepsilon_a\right)>x_a, & if\ u_a^+=0 \\ v_a\left(1+\varepsilon_a\right)-\sum_{rs\in\mathrm{RS}}\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}\delta_{ka}^{rs}=0 \Rightarrow v_a\left(1+\varepsilon_a\right)=x_a, & if\ u_a^+<0 \end{cases} \tag{4.24}$$

For d_a $\frac{L(\mathbf{f},\mathbf{u}^+,\mathbf{u}^-,\mathbf{d},\mathbf{o}^+,\mathbf{o}^-,\boldsymbol{\rho}^-,\boldsymbol{\rho}^+,\boldsymbol{\eta}^-,\boldsymbol{\eta}^+,\boldsymbol{\psi}^-,\boldsymbol{\psi}^+)}{\partial d_a}=0,\ \forall\, a\in \mathrm{U}:$

$$\begin{cases} C_a-\sum_{rs\in\mathrm{RS}}\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}\delta_{ka}^{rs}>0 \Rightarrow C_a>x_a, & if\ d_a=0 \\ C_a-\sum_{rs\in\mathrm{RS}}\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}\delta_{ka}^{rs}=0 \Rightarrow C_a=x_a, & if\ d_a<0 \end{cases} \tag{4.25}$$

For o_{rs}^- $\frac{L(\mathbf{f},\mathbf{u}^+,\mathbf{u}^-,\mathbf{d},\mathbf{o}^+,\mathbf{o}^-,\boldsymbol{\rho}^-,\boldsymbol{\rho}^+,\boldsymbol{\eta}^-,\boldsymbol{\eta}^+,\boldsymbol{\psi}^-,\boldsymbol{\psi}^+)}{\partial o_{rs}^-}=0,\ \forall\ rs\in \overline{\mathrm{RS}}:$

$$\begin{cases} z_{rs}\left(1-\varepsilon_{rs}\right)-\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}<0 \Rightarrow z_{rs}\left(1-\varepsilon_{rs}\right)<q_{rs}, & if\ o_{rs}^-=0 \\ z_{rs}\left(1-\varepsilon_{rs}\right)-\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}=0 \Rightarrow z_{rs}\left(1-\varepsilon_{rs}\right)=q_{rs}, & if\ o_{rs}^->0 \end{cases} \tag{4.26}$$

For o_{rs}^+ $\frac{L(\mathbf{f},\mathbf{u}^+,\mathbf{u}^-,\mathbf{d},\mathbf{o}^+,\mathbf{o}^-,\boldsymbol{\rho}^-,\boldsymbol{\rho}^+,\boldsymbol{\eta}^-,\boldsymbol{\eta}^+,\boldsymbol{\psi}^-,\boldsymbol{\psi}^+)}{\partial o_{rs}^+}=0,\ \forall\ rs\in \overline{\mathrm{RS}}:$

$$\begin{cases} z_{rs}\left(1+\varepsilon_{rs}\right)-\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}>0 \Rightarrow z_{rs}\left(1+\varepsilon_{rs}\right)>q_{rs}, & if\ o_{rs}^+=0 \\ z_{rs}\left(1+\varepsilon_{rs}\right)-\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}=0 \Rightarrow z_{rs}\left(1+\varepsilon_{rs}\right)=q_{rs}, & if\ o_{rs}^+<0 \end{cases} \tag{4.27}$$

For $\rho_r^- \ \dfrac{L(\mathbf{f},\mathbf{u}^+,\mathbf{u}^-,\mathbf{d},\mathbf{o}^+,\mathbf{o}^-,\boldsymbol{\rho}^-,\boldsymbol{\rho}^+,\boldsymbol{\eta}^-,\boldsymbol{\eta}^+,\boldsymbol{\psi}^-,\boldsymbol{\psi}^+)}{\partial\rho_r^-}=0,\ \forall\ r\in\overline{\mathrm{R}}:$

$$\begin{cases} P_r\left(1-\varepsilon_r\right)-\sum\limits_{s\in\mathrm{S}}\sum\limits_{k\in\mathrm{K_{rs}}} f_k^{rs}<0\ \Rightarrow P_r\left(1-\varepsilon_r\right)<O_r, & if\ \ \rho_r^-=0 \\ P_r\left(1-\varepsilon_r\right)-\sum\limits_{s\in\mathrm{S}}\sum\limits_{k\in\mathrm{K_{rs}}} f_k^{rs}=0\ \Rightarrow P_r\left(1-\varepsilon_r\right)=O_r, & if\ \ \rho_r^->0 \end{cases} \tag{4.28}$$

For $\rho_r^+ \ \dfrac{L(\mathbf{f},\mathbf{u}^+,\mathbf{u}^-,\mathbf{d},\mathbf{o}^+,\mathbf{o}^-,\boldsymbol{\rho}^-,\boldsymbol{\rho}^+,\boldsymbol{\eta}^-,\boldsymbol{\eta}^+,\boldsymbol{\psi}^-,\boldsymbol{\psi}^+)}{\partial\rho_r^+}=0,\ \forall\ r\in\overline{\mathrm{R}}:$

$$\begin{cases} P_r\left(1+\varepsilon_r\right)-\sum\limits_{s\in\mathrm{S}}\sum\limits_{k\in\mathrm{K_{rs}}} f_k^{rs}>0\ \Rightarrow P_r\left(1+\varepsilon_r\right)>O_r, & if\ \ \rho_r^+=0 \\ P_r\left(1+\varepsilon_r\right)-\sum\limits_{s\in\mathrm{S}}\sum\limits_{k\in\mathrm{K_{rs}}} f_k^{rs}=0\ \Rightarrow P_r\left(1+\varepsilon_r\right)=O_r, & if\ \ \rho_r^+<0 \end{cases} \tag{4.29}$$

For $\eta_s^- \ \dfrac{L(\mathbf{f},\mathbf{u}^+,\mathbf{u}^-,\mathbf{d},\mathbf{o}^+,\mathbf{o}^-,\boldsymbol{\rho}^-,\boldsymbol{\rho}^+,\boldsymbol{\eta}^-,\boldsymbol{\eta}^+,\boldsymbol{\psi}^-,\boldsymbol{\psi}^+)}{\partial\eta_s^+}=0,\ \forall\ s\in\bar{\mathrm{S}}:$

$$\begin{cases} A_r\left(1-\varepsilon_s\right)-\sum\limits_{r\in\mathrm{R}}\sum\limits_{k\in\mathrm{K_{rs}}} f_k^{rs}<0\ \Rightarrow A_s\left(1-\varepsilon_s\right)<D_s, & if\ \ \eta_s^-=0 \\ A_r\left(1-\varepsilon_s\right)-\sum\limits_{r\in\mathrm{R}}\sum\limits_{k\in\mathrm{K_{rs}}} f_k^{rs}=0\ \Rightarrow A_s\left(1-\varepsilon_s\right)=D_s, & if\ \ \eta_s^->0 \end{cases} \tag{4.30}$$

For $\eta_s^+ \ \dfrac{L(\mathbf{f},\mathbf{u}^+,\mathbf{u}^-,\mathbf{d},\mathbf{o}^+,\mathbf{o}^-,\boldsymbol{\rho}^-,\boldsymbol{\rho}^+,\boldsymbol{\eta}^-,\boldsymbol{\eta}^+,\boldsymbol{\psi}^-,\boldsymbol{\psi}^+)}{\partial\eta_s^+}=0,\ \forall\ s\in\bar{\mathrm{S}}:$

$$\begin{cases} A_r\left(1+\varepsilon_s\right)-\sum\limits_{r\in\mathrm{R}}\sum\limits_{k\in\mathrm{K_{rs}}} f_k^{rs}<0\ \Rightarrow A_s\left(1+\varepsilon_s\right)>D_s, & if\ \ \eta_s^-=0 \\ A_r\left(1+\varepsilon_s\right)-\sum\limits_{r\in\mathrm{R}}\sum\limits_{k\in\mathrm{K_{rs}}} f_k^{rs}=0\ \Rightarrow A_s\left(1+\varepsilon_s\right)=D_s, & if\ \ \eta_s^-<0 \end{cases} \tag{4.31}$$

For $\psi^- \ \dfrac{L(\mathbf{f},\mathbf{u}^+,\mathbf{u}^-,\mathbf{d},\mathbf{o}^+,\mathbf{o}^-,\boldsymbol{\rho}^-,\boldsymbol{\rho}^+,\boldsymbol{\eta}^-,\boldsymbol{\eta}^+,\boldsymbol{\psi}^-,\boldsymbol{\psi}^+)}{\partial\psi^-}=0:$

$$\begin{cases} F\left(1-\varepsilon\right)-\sum\limits_{rs\in\mathrm{RS}}\sum\limits_{k\in\mathrm{K_{rs}}} f_k^{rs}<0\ \Rightarrow F\left(1-\varepsilon\right)<T, & if\ \ \psi^-=0 \\ F\left(1-\varepsilon\right)-\sum\limits_{rs\in\mathrm{RS}}\sum\limits_{k\in\mathrm{K_{rs}}} f_k^{rs}=0\ \Rightarrow F\left(1-\varepsilon\right)=T, & if\ \ \psi^->0 \end{cases} \tag{4.32}$$

For $\psi^{+} \frac{L(\mathbf{f},\mathbf{u}^{+},\mathbf{u}^{-},\mathbf{d},\mathbf{o}^{+},\mathbf{o}^{-},\boldsymbol{\rho}^{-},\boldsymbol{\rho}^{+},\boldsymbol{\eta}^{-},\boldsymbol{\eta}^{+},\boldsymbol{\psi}^{-},\boldsymbol{\psi}^{+})}{\partial\psi^{+}}=0$:

$$\begin{cases} F\left(1+\varepsilon\right)-\sum_{rs\in\mathrm{RS}}\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}<0 \Rightarrow F\left(1+\varepsilon\right)>T, & if\ \psi^{-}=0 \\ F\left(1+\varepsilon\right)-\sum_{rs\in\mathrm{RS}}\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}=0 \Rightarrow F\left(1+\varepsilon\right)=T, & if\ \psi^{-}<0 \end{cases} \tag{4.33}$$

Let the generalized route cost

$$\tilde{c}_k^{rs}=c_k^{rs}-\sum_{a\in\mathrm{M}}\left(u_a^{-}+u_a^{+}\right)\delta_{ka}^{rs}-\sum_{a\in\mathrm{U}}d_a\delta_{ka}^{rs}-\left(o_{rs}^{+}+o_{rs}^{-}\right)-\left(\rho_r^{-}+\rho_r^{+}\right)-\left(\eta_s^{-}+\eta_s^{+}\right)-\left(\psi^{-}+\psi^{+}\right), \tag{4.34}$$

where ($c_k^{rs}=\sum_{a\in\mathrm{A}} t_a(x_a)\,\delta_{ka}^{rs}$). Rearrange the Equation (4.21) and obtain:

$$f_k^{rs}=\exp\left(-\theta\cdot\tilde{c}_k^{rs}\right),\forall\ k\in\mathrm{K_{rs}},\ rs\in\mathrm{RS} \tag{4.35}$$

Hence, the route choice probability function can be expressed as follows:

$$P_k^{rs}=\frac{f_k^{rs}}{\sum_{k\in\mathrm{K_{rs}}} f_k^{rs}}=\frac{\exp\left(-\theta\cdot\tilde{c}_k^{rs}\right)}{\sum_{k\in\mathrm{K_{rs}}}\exp\left(-\theta\cdot\tilde{c}_k^{rs}\right)},\forall\ k\in\mathrm{K_{rs}},\ rs\in\mathrm{RS} \tag{4.36}$$

Similar to the logit-based SUE model, path flows from PFE can be derived analytically as a function of path costs and dual variables associated with constraints (4.7)-(4.12) as follows:

$$f_k^{rs}=\exp\left(\theta\cdot\begin{pmatrix}-c_k^{rs}+\sum_{a\in\mathrm{M}}\left(u_a^{-}+u_a^{+}\right)\delta_{ka}^{rs}+\sum_{a\in\mathrm{U}}d_a\delta_{ka}^{rs}+ \\ \left(o_{rs}^{+}+o_{rs}^{-}\right)+\left(\rho_r^{-}+\rho_r^{+}\right)+\left(\eta_s^{-}+\eta_s^{+}\right)+\left(\psi^{-}+\psi^{+}\right)\end{pmatrix}\right)\forall\ k\in\mathrm{K_{rs}},\ rs\in\mathrm{RS} \tag{4.37}$$

4.3.3 Uniqueness Conditions

We proceed to the second-order condition to show the uniqueness of path-flow solution. Differentiating equation (4.21) by the path flow variable gives the following:

$$\frac{\partial^2 L}{\partial f_k^{rs} \partial f_l^{od}} = \begin{cases} \dfrac{\partial c_k^{rs}}{\partial f_k^{rs}} + \dfrac{1}{\theta f_k^{rs}} & if \;\; f_k^{rs} = f_l^{od} \\ 0 & otherwise \end{cases} \quad , \forall\, k \in \mathrm{K_{rs}}, l \in \mathrm{K_{rs}}, rs \in \mathrm{RS}, od \in \mathrm{RS} \tag{4.38}$$

Equation (4.35) indicates that all diagonal elements are positive (i.e., $\frac{\partial c_k^{rs}}{\partial f_k^{rs}} > 0$, $\theta > 0$, and $f_k^{rs} > 0$) and all off-diagonals are zero. In other words, the Hessian matrix with respect to O-D pair *rs* is

$$\frac{\partial^2 L}{\partial f_k^{rs} \partial f_l^{rs}} = \begin{bmatrix} \dfrac{\partial c_1^{rs}}{\partial f_1^{rs}} + \dfrac{1}{\theta f_1^{rs}} & 0 & 0 & \cdots \\ 0 & \dfrac{\partial c_2^{rs}}{\partial f_2^{rs}} + \dfrac{1}{\theta f_2^{rs}} & 0 & \cdots \\ 0 & 0 & \ddots & \\ \vdots & \vdots & & \dfrac{\partial c_k^{rs}}{\partial f_k^{rs}} + \dfrac{1}{\theta f_k^{rs}} \end{bmatrix} \tag{4.39}$$

Since the diagonal elements of the block matrix with respect to O-D pair *rs* are equal to $\frac{\partial c_k^{rs}}{\partial f_k^{rs}} + \frac{1}{\theta f_k^{rs}}$, the matrix ∇_{f}^2 is positive definite for all O-D pair *rs*. Hence, objective function (4.6) is strictly convex with respect to path flows; therefore, the path-flow solution is unique.

4.3.4 Solution Procedure

The overall solution procedure for solving the PFE formulation is provided in Figure 4.4.

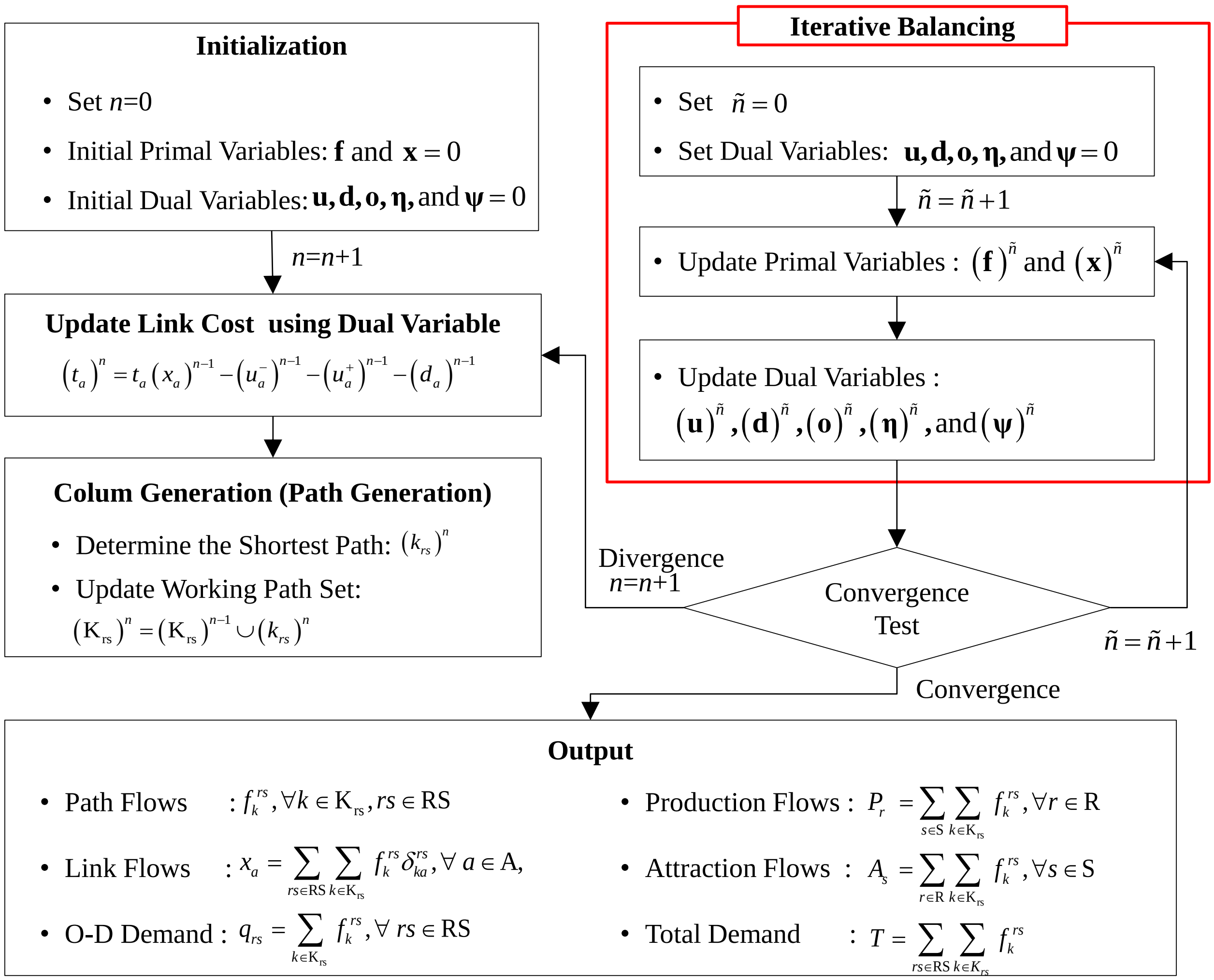


Figure 4.2 PFE solution procedure

(1) *Iterative balancing scheme*

The section describes the detailed steps of the iterative balancing scheme.

Step 1. *Initialization*

1.1 Set $\tilde{n}$ = 0,

1.2 Set dual variables: $(u_a^-)^{\tilde{n}}, (u_a^+)^{\tilde{n}}, (d_a)^{\tilde{n}}, (\rho_r^-)^{\tilde{n}}, (\rho_r^+)^{\tilde{n}}, (\eta_s^-)^{\tilde{n}}, (\eta_s^-)^{\tilde{n}}, (\psi^-)^{\tilde{n}}$ *and* $(\psi^+)^{\tilde{n}} = 0$,

Step 2. *Compute primal variables*

a. Compute path costs

$$\left(c_k^{rs}\right)^{\tilde{n}} = \sum_{a\in \mathrm{A}} t_a\left(\left(x_a\right)^{\tilde{n}}\right)\delta_{ka}^{rs}$$

b. Compute path flows

$$\left(f_k^{rs}\right)^{\tilde{n}} = \exp\left(\theta\cdot\left(\begin{array}{l} -\left(c_k^{rs}\right)^{\tilde{n}} + \sum_{a\in \mathrm{M}}\left(\left(u_a^{-}\right)^{\tilde{n}} + \left(u_a^{+}\right)^{\tilde{n}}\right)\delta_{ka}^{rs} + \sum_{a\in \mathrm{U}}\left(d_a\right)^{\tilde{n}}\delta_{ka}^{rs} + \left(o_{rs}^{+}\right)^{\tilde{n}} + \\ \left(o_{rs}^{-}\right)^{\tilde{n}} + \left(\rho_r^{-}\right)^{\tilde{n}} + \left(\rho_r^{+}\right)^{\tilde{n}} + \left(\eta_s^{-}\right)^{\tilde{n}} + \left(\eta_s^{+}\right)^{\tilde{n}} + \left(\psi^{-}\right)^{\tilde{n}} + \left(\psi^{+}\right)^{\tilde{n}} \end{array}\right)\right) \begin{array}{r}\forall\, k\in \mathrm{K}_{\mathrm{rs}} \\ rs\in \mathrm{RS}\end{array},$$

c. Compute link flows

$$\left(x_a\right)^{\tilde{n}} = \sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K}_{\mathrm{rs}}}\left(f_k^{rs}\right)^{\tilde{n}}\delta_{ka}^{rs}, \forall\, a\in \mathrm{A}$$

d. Compute zonal production and attraction flows

$$\left(P_r\right)^{\tilde{n}} = \sum_{s\in \mathrm{S}}\sum_{k\in \mathrm{K}_{\mathrm{rs}}}\left(f_k^{rs}\right)^{\tilde{n}},\ \forall r\in \mathrm{R}$$

$$\left(A_s\right)^{\tilde{n}} = \sum_{r\in \mathrm{R}}\sum_{k\in \mathrm{K}_{\mathrm{rs}}}\left(f_k^{rs}\right)^{\tilde{n}}, \forall s\in \mathrm{S}$$

e. Compute O-D flows

$$\left(q_{rs}\right)^{\tilde{n}} = \sum_{k\in \mathrm{K}_{\mathrm{rs}}}\left(f_k^{rs}\right)^{\tilde{n}}, \quad \forall\, rs\in \mathrm{RS}$$

f. Compute total demand

$$\left(T\right)^{\tilde{n}} = \sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K}_{\mathrm{rs}}}\left(f_k^{rs}\right)^{\tilde{n}}$$

Step 3. *Update dual variables*

a. For each measured link ($a\in \mathrm{M}$), update the dual variables

$$\left(u_a^{-}\right)^{\tilde{n}} = \mathrm{Max}\left\{0,\ \left(u_a^{-}\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{(1-\varepsilon_a)\cdot v_a}{\left(x_a\right)^{\tilde{n}}}\right)\right\}, \text{ and}$$

$$\left(u_a^{+}\right)^{\tilde{n}} = \mathrm{Min}\left\{0,\ \left(u_a^{+}\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{(1+\varepsilon_a)\cdot v_a}{\left(x_a\right)^{\tilde{n}}}\right)\right\}.$$

b. For each unmeasured link ($a \in \mathrm{U}$), update the dual variables

$$\left(d_a\right)^{\tilde{n}} = \mathrm{Min}\left\{0,\ \left(d_a\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{C_a}{\left(x_a\right)^{\tilde{n}}}\right)\right\}.$$

c. For each target O-D flow ($rs \in \overline{\mathrm{RS}}$), update the dual variables

$$\left(o_{rs}^{-}\right)^{\tilde{n}} = \mathrm{Max}\left\{0,\ \left(o_{rs}^{-}\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{(1-\varepsilon_{rs})\cdot z_{rs}}{\left(q_{rs}\right)^{\tilde{n}}}\right)\right\}, \text{ and}$$

$$\left(o_{rs}^{+}\right)^{\tilde{n}} = \mathrm{Min}\left\{0,\ \left(o_{rs}^{+}\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{(1+\varepsilon_{rs})\cdot z_{rs}}{\left(q_{rs}\right)^{\tilde{n}}}\right)\right\}.$$

d. For each zonal production flow ($r \in \overline{\mathrm{R}}$), update the dual variables

$$\left(\rho_{r}^{-}\right)^{\tilde{n}} = \mathrm{Max}\left\{0,\ \left(\rho_{r}^{-}\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{(1-\varepsilon_{r})\cdot O_{r}}{\left(P_{r}\right)^{\tilde{n}}}\right)\right\}, \text{ and}$$

$$\left(\rho_{r}^{+}\right)^{\tilde{n}} = \mathrm{Min}\left\{0,\ \left(\rho_{r}^{+}\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{(1+\varepsilon_{r})\cdot O_{r}}{\left(P_{r}\right)^{\tilde{n}}}\right)\right\}.$$

e. For each zonal attraction flow ($s \in \overline{\mathrm{S}}$), update the dual variables

$$\left(\eta_{s}^{-}\right)^{\tilde{n}} = \mathrm{Max}\left\{0,\ \left(\eta_{s}^{-}\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{(1-\varepsilon_{s})\cdot D_{s}}{\left(A_{s}\right)^{\tilde{n}}}\right)\right\}, \text{ and}$$

$$\left(\eta_{s}^{+}\right)^{\tilde{n}} = \mathrm{Min}\left\{0,\ \left(\eta_{s}^{+}\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{(1+\varepsilon_{s})\cdot D_{s}}{\left(A_{s}\right)^{\tilde{n}}}\right)\right\}.$$

f. For the total demand, update the dual variables

$$\left(\psi^{-}\right)^{\tilde{n}} = \mathrm{Max}\left\{0,\ \left(\psi^{-}\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{(1-\varepsilon)\cdot F}{\left(T\right)^{\tilde{n}}}\right)\right\}, \text{ and}$$

$$\left(\psi^{+}\right)^{\tilde{n}} = \mathrm{Min}\left\{0,\ \left(\psi^{+}\right)^{\tilde{n}-1} + \frac{1}{\theta}\ln\left(\frac{(1+\varepsilon)\cdot F}{\left(T\right)^{\tilde{n}}}\right)\right\}.$$

Step 4. *Convergence test*

$$\text{If}\quad \eta_0 \le \text{Max}\left\{\begin{array}{l} \left|\left(u_a^-\right)^{\tilde{n}}-\left(u_a^-\right)^{\tilde{n}-1}\right|,\left|\left(u_a^+\right)^{\tilde{n}}-\left(u_a^+\right)^{\tilde{n}-1}\right|,\left|\left(d_a\right)^{\tilde{n}}-\left(d_a\right)^{\tilde{n}-1}\right|,\left|\left(o_{rs}^-\right)^{n}-\left(o_{rs}^-\right)^{n-1}\right|, \\ \left|\left(o_{rs}^+\right)^{\tilde{n}}-\left(o_{rs}^+\right)^{\tilde{n}-1}\right|,\left|\left(\rho_r^-\right)^{\tilde{n}}-\left(\rho_r^-\right)^{\tilde{n}-1}\right|,\left|\left(\rho_r^+\right)^{\tilde{n}}-\left(\rho_r^+\right)^{\tilde{n}-1}\right|,\left|\left(\eta_s^-\right)^{\tilde{n}}-\left(\eta_s^-\right)^{\tilde{n}-1}\right|, \\ \left|\left(\eta_s^+\right)^{\tilde{n}}-\left(\eta_s^+\right)^{\tilde{n}-1}\right|,\left|\left(\psi^+\right)^{\tilde{n}}-\left(\psi^+\right)^{\tilde{n}-1}\right|,\left|\left(\psi^-\right)^{\tilde{n}}-\left(\psi^-\right)^{\tilde{n}-1}\right| \end{array}\right\} < \eta,$$

where η_0 is a convergence tolerance (e.g., 10^{-6}) and η is the upper limit of change in dual variables, then set all parameters of the next iteration equal to those of the current iteration, set $\tilde{n}=\tilde{n}+1$, and go to step 2.

$$\text{If}\quad \text{Max}\left\{\begin{array}{l} \left|\left(u_a^-\right)^{\tilde{n}}-\left(u_a^-\right)^{\tilde{n}-1}\right|,\left|\left(u_a^+\right)^{\tilde{n}}-\left(u_a^+\right)^{\tilde{n}-1}\right|,\left|\left(d_a\right)^{\tilde{n}}-\left(d_a\right)^{\tilde{n}-1}\right|,\left|\left(o_{rs}^-\right)^{n}-\left(o_{rs}^-\right)^{n-1}\right|, \\ \left|\left(o_{rs}^+\right)^{\tilde{n}}-\left(o_{rs}^+\right)^{\tilde{n}-1}\right|,\left|\left(\rho_r^-\right)^{\tilde{n}}-\left(\rho_r^-\right)^{\tilde{n}-1}\right|,\left|\left(\rho_r^+\right)^{\tilde{n}}-\left(\rho_r^+\right)^{\tilde{n}-1}\right|,\left|\left(\eta_s^-\right)^{\tilde{n}}-\left(\eta_s^-\right)^{\tilde{n}-1}\right|, \\ \left|\left(\eta_s^+\right)^{\tilde{n}}-\left(\eta_s^+\right)^{\tilde{n}-1}\right|,\left|\left(\psi^+\right)^{\tilde{n}}-\left(\psi^+\right)^{\tilde{n}-1}\right|,\left|\left(\psi^-\right)^{\tilde{n}}-\left(\psi^-\right)^{\tilde{n}-1}\right| \end{array}\right\} \ge \eta,$$

then set all parameters of the next outer iteration equal to those of the current iteration, set $n = n + 1$, and terminate the inner loop (iterative balancing).

In the above procedure, we just provide the adjustment equations for different types of constraint (e.g., observed links, unobserved links, observed intersections, target O-D flows, etc.). The detailed derivations of the adjustment equations can be found in Chen et al. (2009, 2010), and convergence of the iterative balancing scheme is discussed in details in Bell et al. (1997) and Bell and Iida (1997).

(2) *Column generation*

The above iterative balancing scheme assumes that a working path set is given. For large networks, it is not practical to enumerate a working path set in advance since the number of possible paths grows exponentially with respect to network size. To circumvent path enumeration, a column (or path) generation procedure can be augmented to the iterative balancing scheme. Basically, the algorithm introduces an outer loop (or iteration) to iteratively generate paths to the working path set as needed to replicate the observed interval constraints (e.g., link counts, turning movement counts, selected prior O-D flows, etc.), and to account for the capacity restraints for the unobserved links as well as the congestion effects, while the iterative balancing scheme iteratively adjusts the primal variables (e.g., path flows, link flows, intersection turning movement flows, O-D flows, etc.) and the dual variables in the inner loop for a given working path set from the outer loop. Note that the working path set is generated by a column generation scheme (or a shortest path algorithm) using the generalized link costs, which are based on not only the link costs but also the dual variables from the active side constraints. The dual variables force the column generation scheme to generate paths that satisfy the side constraints. For additional discussions on the issue of using the generalized link costs to generate paths, refer to Bell *et al*. (1997) and Chen *et al*. (2009, 2010).

(3) *Output derivation from path flows*

Using the path flow solution, various outputs can be derived as follows.

- Total demand: the sum of all path flows from all O-D pairs gives the total demand utilizing the network.
- Zonal production: the sum of all path flows emanating from a given origin gives the zonal production.
- Zonal attraction: the sum of all path flows terminating at a given destination gives the zonal attraction.
- O-D flow: the sum of all paths flows connecting that O-D pair gives the O-D flow.
- Link flow: the sum of all path flows passing through a given link gives the link flow.

5. NUMERICAL RESULTS

5.1 Utah Network

This section presents numerical results to demonstrate the features of the proposed approach as well as the applications to the Utah statewide freight transportation network. Utah's freight transportation network depicted in Figure 5.1 was extracted from the FAF3 network. The network consists of 385 nodes, 944 links, and 2,256 O-D pairs. The study area consists of 29 counties and 19 external stations (i.e., entry and exit points around the state borders). The Wasatch Front Regional Council (WFRC), the major truck generation area in the state highlighted in Figure 5.1, consists of three major counties: Salt Lake, Weber and Davis.

Truck traffic counts from 222 locations (about 23% of network links) were collected from the Utah Department of Transportation (UDOT) traffic map (UDOT traffic maps 2013). The observations are mainly located on the major interstate freeways of Utah, such as I-15, I-70, I-80, and I-84 (see the interstate freeways in Figure 5.1). These major interstate freeways are the major truck routes for Utah, especially I-15, which runs north-south and passes through Salt Lake City and many other cities. Note that the freight demand derived from the FAF3 database was based on the average annual daily truck traffic (AADTT), so link capacity values were required to replicate the daily equivalent capacity for a given link. To do so, we adopted the daily capacity conversion factors based on the functional class of the roadways. The capacity was then expanded by dividing the hourly capacity by the conversion factor and used for subsequent steps.

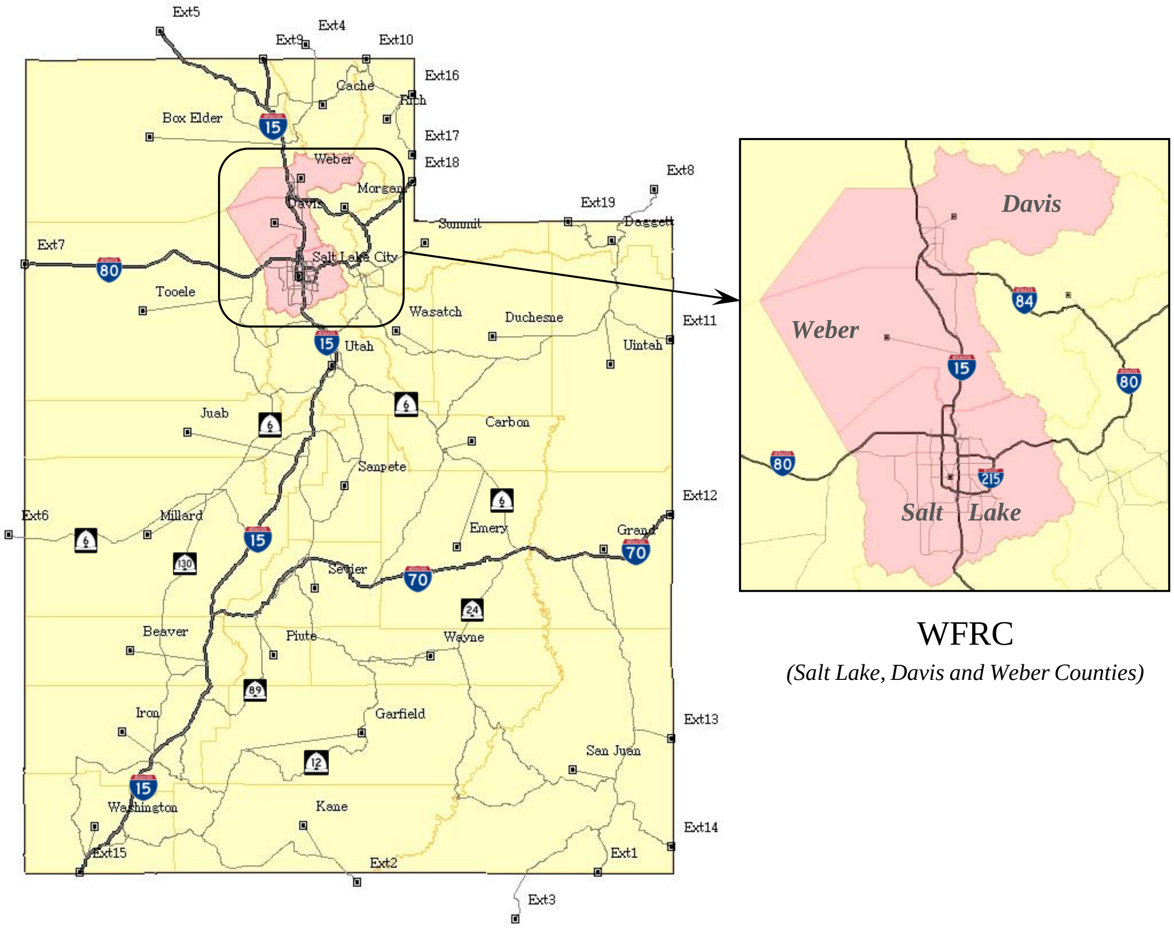


Figure 5.1 Utah statewide freight transportation network

5.2 Numerical Results

5.2.1 Commodity-based Truck O-D Trip Table

The estimation procedure described in Figure 4.1 was applied for the base year (2007) FAF commodity flow database. There are 29 internal zones or counties within Utah and 27 external stations. However, we found that only 19 external stations are used for truck traffic, hence the size of the trip table is 48×48 (i.e., 29 internal zones or counties within Utah and 19 external stations). Figure 5.2 depicts the truck O-D trip table for Utah (i.e., from all origins to all destinations). The total daily truck trips obtained from the first stage was 25,508 truck trips/day. Specifically, this total consists of 45.6% within Utah (I-I), 9.8% from Utah to other states (I-E), 11.0% from other states to Utah (E-I), and 33.6% through truck flows (E-E). We can observe the through truck flows (E-E) between I-80E and I-15N and between I-80E to I-80W are quite heavy. The highlighted bar series (in dark green) represent the production flows from the major counties along the Wasatch Front area such as Salt Lake, Cache, Weber, Davis, and Utah.

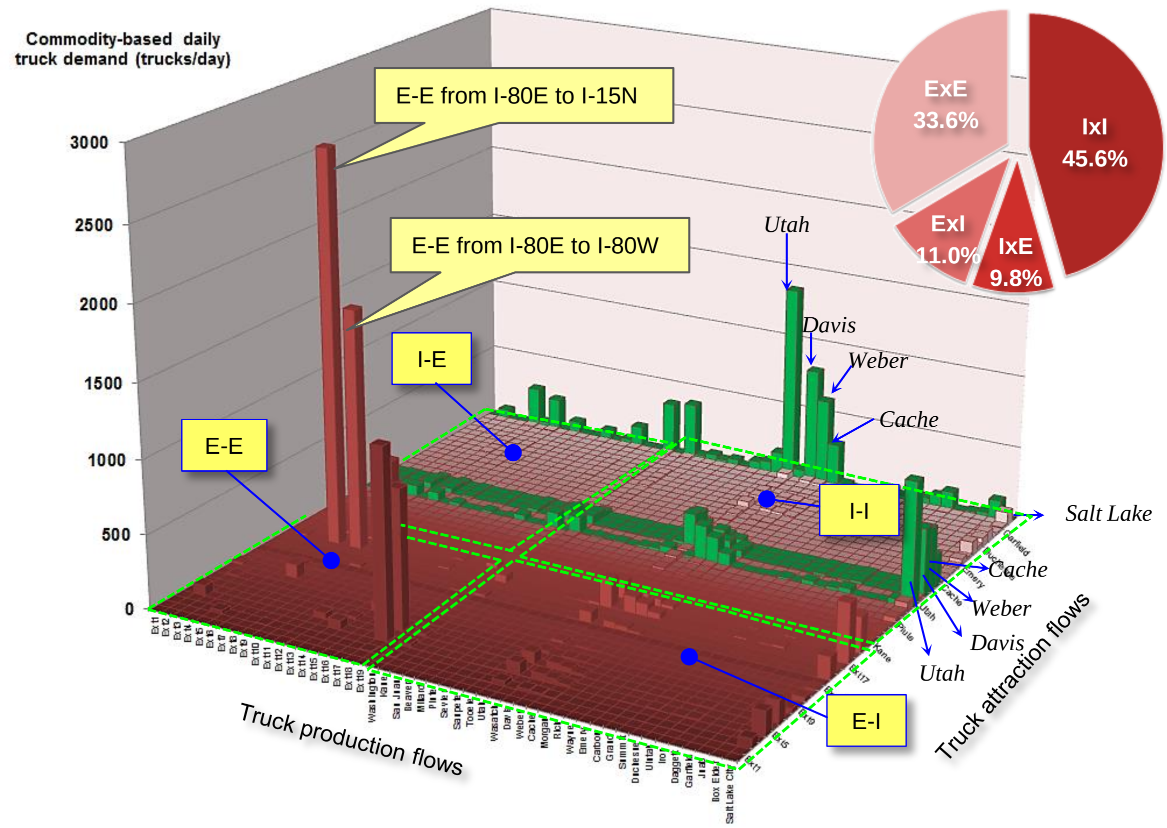


Figure 5.2 Commodity-based truck O-D trip table

Additionally, Table 5.1 summarizes the number of commercial truck trips estimated using the USTM commercial trips derived from Eq. 4.4, and Table 5.2 summarizes the number of empty truck trips estimated from Eq. 4.5. As can be seen, the daily empty truck trips account for approximately 40% of the commodity flows. If this component is not considered in the estimation, the total truck traffic and congestion in the study area could be significantly underestimated.

Table 5.1 Commercial truck trips by county (trucks/day)

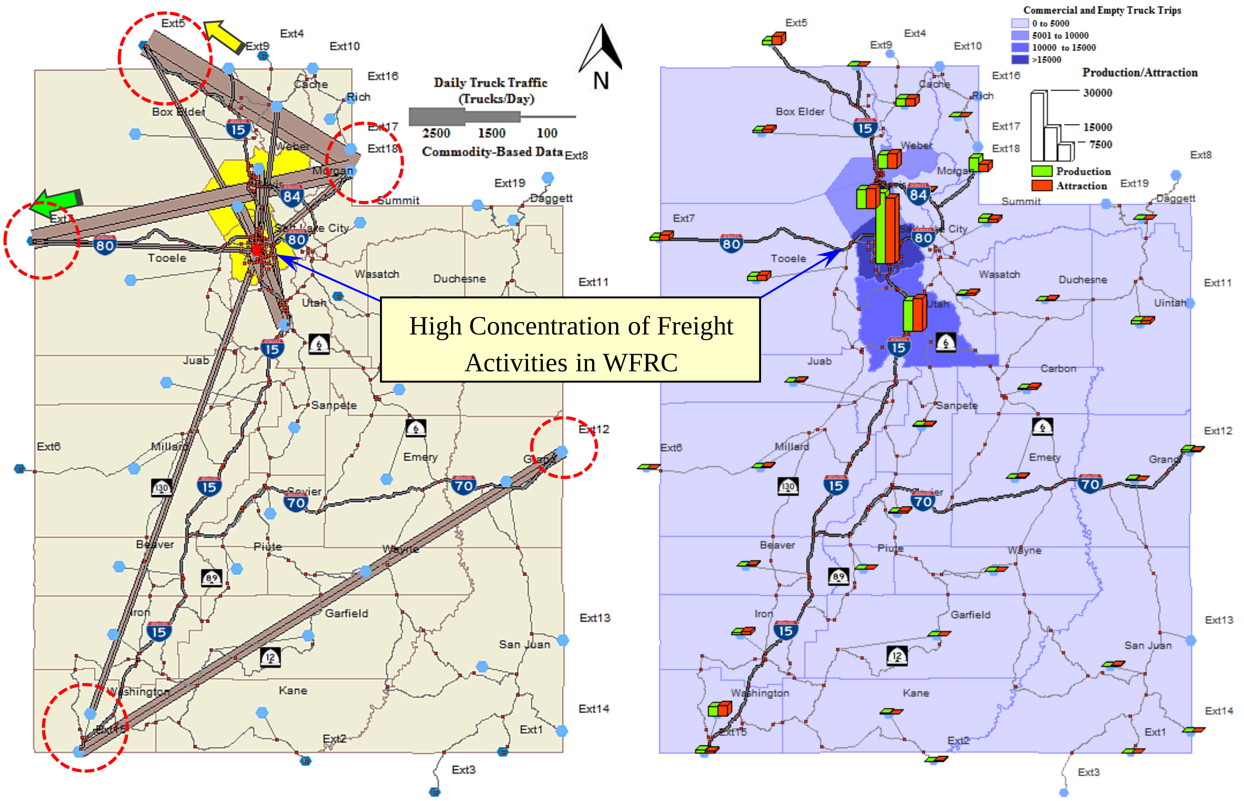
County	Commercial truck trips by sector (Trucks/day)					County total (Trucks/day)
	Household	Agriculture	Basic	Retail	Office	
Beaver	85	91	58	41	17	291
Box Elder	604	61	294	94	40	1,093
Cache	1,306	40	391	485	409	2,631
Carbon	300	216	216	1	44	777
Daggett	16	6	24	1	0	47
Davis	3,517	42	607	1,290	326	5,782
Duchesne	226	3	157	8	8	402
Emery	140	113	123	2	29	407
Garfield	73	5	41	18	2	139
Grand	146	24	111	5	13	300
Iron	565	38	386	7	65	1,061
Juab	116	6	102	3	40	267
Kane	109	27	51	3	71	261
Millard	158	79	204	13	4	459
Morgan	106	22	74	7	3	212
Piute	22	1	7	6	0	36
Rich	30	3	34	3	2	72
Salt Lake	12,883	52	6,803	492	1,048	21,278
San Juan	169	3	76	1	11	259
Sanpete	299	40	195	9	37	581
Sevier	267	11	217	13	26	534
Summit	488	8	598	7	38	1,140
Tooele	676	12	657	52	143	1,541
Uintah	397	11	836	6	63	1,313
Utah	5,287	157	2,466	1,454	160	9,523
Wasatch	274	3	313	3	38	631
Washington	1,742	8	906	11	551	3,219
Wayne	40	5	41	6	2	93
Weber	2,961	48	797	117	254	4,176
Total	**33,001**	**1,136**	**16,787**	**4,158**	**3,444**	**58,525**

Note: basic sectors include manufacturing, transportation, wholesale, and utilities

Table 5.2 Empty truck trips by county (trucks/day)

County	Empty production plows	Empty attraction flows	Empty total (Trucks/day)
Beaver	82	114	195
Box Elder	306	426	732
Cache	737	1,026	1,763
Carbon	218	303	521
Daggett	13	18	31
Davis	1,619	2,255	3,874
Duchesne	113	157	269
Emery	114	159	273
Garfield	39	54	93
Grand	84	117	201
Iron	297	414	711
Juab	75	104	179
Kane	73	102	175
Millard	128	179	307
Morgan	59	83	142
Piute	10	14	24
Rich	20	28	48
Salt Lake	5,958	8,298	14,256
San Juan	73	101	174
Sanpete	163	226	389
Sevier	149	208	358
Summit	319	444	764
Tooele	431	601	1,032
Uintah	368	512	880
Utah	2,666	3,714	6,380
Wasatch	177	246	423
Washington	901	1,255	2,157
Wayne	26	36	62
Weber	1,169	1,629	2,798
Total	**16,387**	**22,825**	**39,212**

Further, we used the desire lines to highlight selected O-D pairs with high truck flows (i.e., greater than 500 trucks/day) in Figure 5.3(a). The circles in the figure show the entering and exiting truck flows at major external stations along the interstate freeways. We can observe high entering and exiting freight flows at the external stations: between I-15 South and I-70, I-80 East and I-15 North, I-80 West and I-80 East via I-15 near Salt Lake City, and so on. These are the important interstate truck routes in Utah and are used for connecting the through trips from/to other states. The O-D flows were then aggregated to show the truck trip production and attraction flows at the county level as well as the external stations shown in Figure 5.3(b). As can be seen, truck trip production and attraction flows derived from the first stage are relatively concentrated around the WFRC area compared with other counties. Figure 5.3(b) reveals most commercial and empty truck trips are concentrated in the WFRC area and Utah County (shaded areas). This is to be expected because the major freight activities in Utah are mainly generated from these counties where warehousing and distribution centers are located. Overall, the truck flows within and through Utah are two major demand components as they account for almost 80% of total commodity flows transported in Utah.



(a) Commodity truck flows (desire lines)

(b) Total production/attraction flows

Figure 5.3 Estimated statewide commodity-based truck flows

The second stage used the path flow estimator (PFE) to refine the truck trip table obtained from the first stage using the truck counts from the statewide truck count program. Three different types of information, including truck counts, partial set of O-D flows, production and attraction flows (commodity and empty truck flows), were used to update the truck O-D trip table. Figure 5.4 depicts the scatter plots of observed and estimated link flows obtained from the two-stage approach and compares them with the one-stage approach (i.e., the commodity-based truck O-D trip table from stage one). Note that the one-stage approach assigns the commodity-based truck trips using an all-or-nothing (AON) traffic assignment procedure, which is a typical method used to preload trucks to the statewide network. Truck flows obtained from this method are usually assigned based on the shortest distance or travel time, and there is no consideration of congestion. As can be seen, the results obtained from this method are underestimated, especially in the WFRC area and the high freight activity locations in the study area (i.e., areas around Salt Lake City International Airport and perimeters of the Salt Lake County). Consequently, such issues often hinder statewide planning as it is incapable of capturing the freight movements under congestion and explaining the truck traffic variations in the urban areas mentioned above. On the other hand, the two-stage approach using PFE to refine the commodity-based truck O-D trip table with truck counts can provide a more reasonable match between the observed and estimated values. The majority of the observations are within an acceptable tolerance with a few points outside of the error bound.

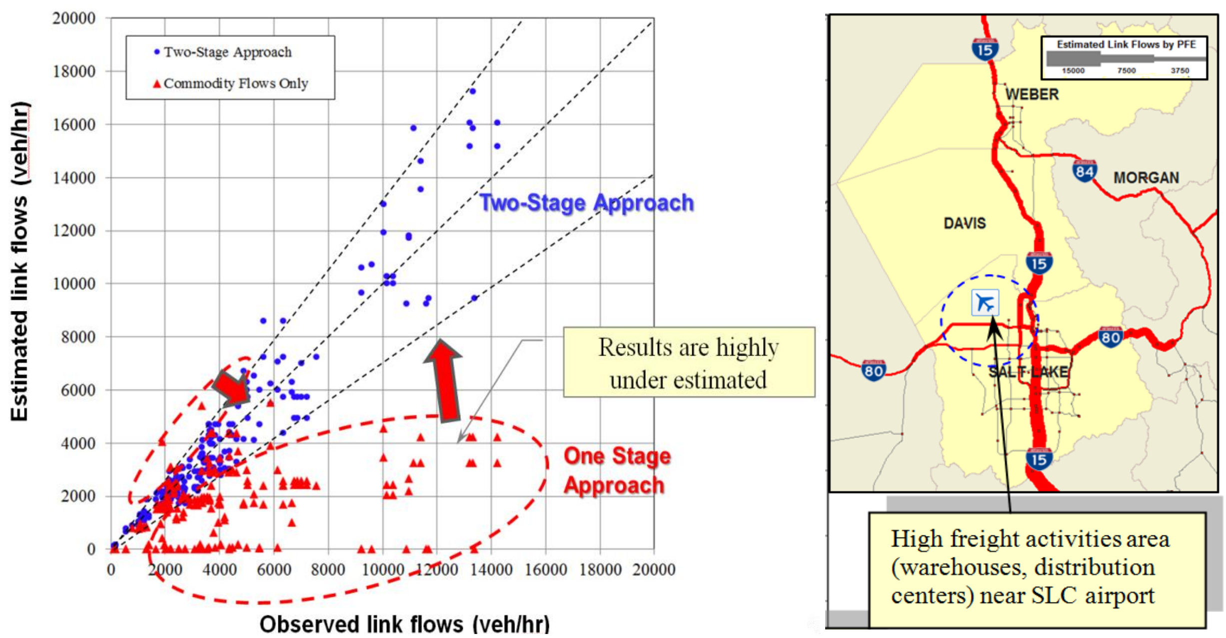
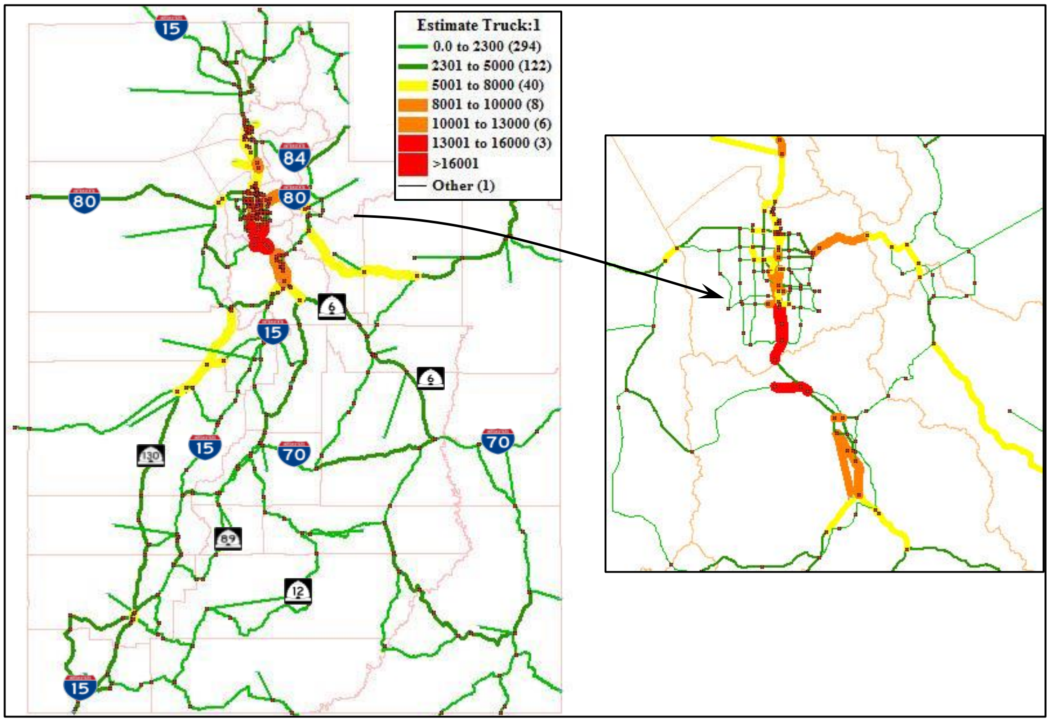


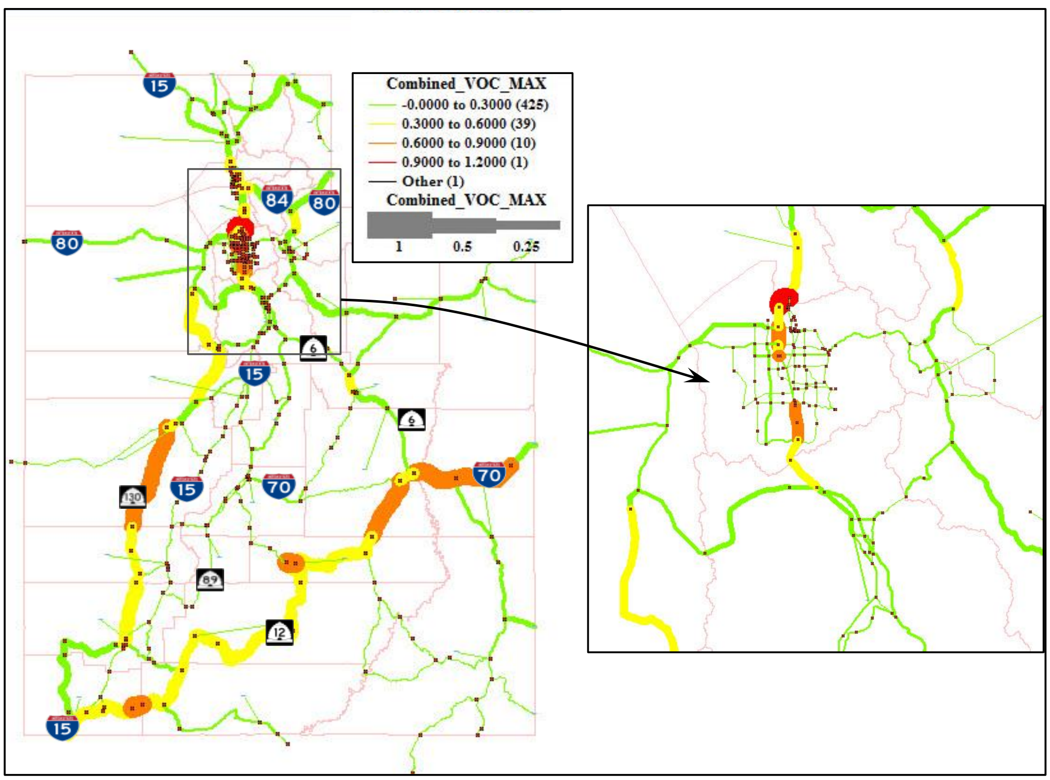
Figure 5.4 Comparison between one-stage and two-stage approaches

Figure 5.5(a) shows the complete truck flow pattern on the statewide network based on the two-stage approach. The figure reveals a high concentration of truck traffic on I-15 around Salt Lake County and I-80W in Summit County and Salt Lake County. To highlight the congested links,

Figure 5.5(b) shows the volume-to-capacity (V/C) ratios. As can be seen, many interstate and state routes (e.g., I-15, interchange to I-215, SR 130, SR 12, and SR 6) are quite congested.



(a) Statewide Truck Traffic (AADTT)



(b) Volume/Capacity

Figure 5.5 Statewide truck traffic and volume/capacity analysis

5.2.2 Effect of spatial constraints

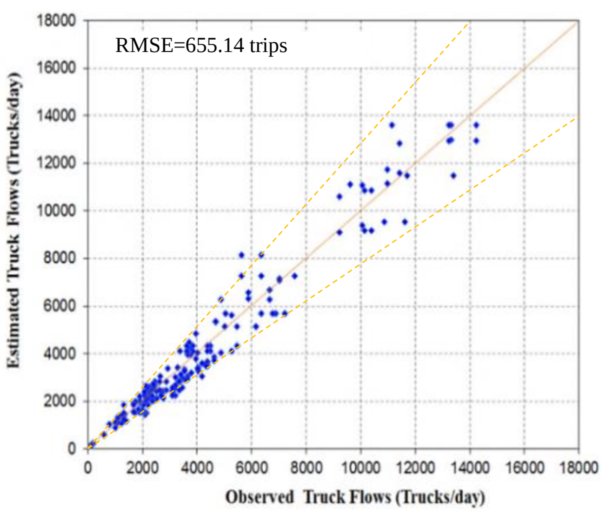
In this section, two cases are considered for assessing the effect of including spatial constraints in the PFE:

- Case 1: PFE with truck counts only
- Case 2: PFE with truck counts with zonal production and attraction flow constraints derived from the first stage

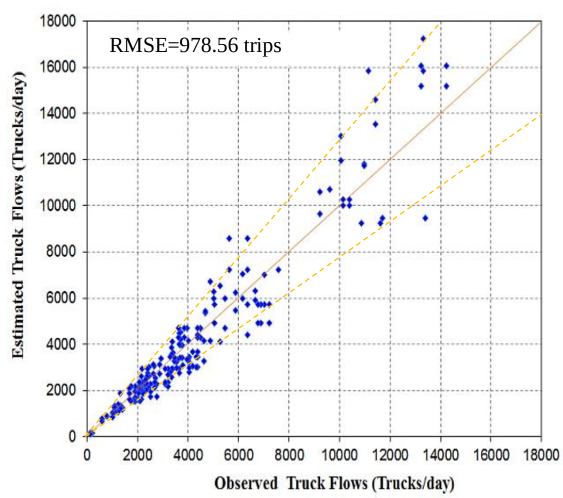
Accuracy of the estimates can be measured by the root mean square error (RMSE) as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}\left(x_{est}^{n} - x_{obs}^{n}\right)^{2}} \quad (4.39)$$

where N is the number of observations, x_{est}^{n} and x_{obs}^{n} are the estimated and observed truck flows, respectively. Figure 5.6(a) a and Figure 5.6(b) depict the scatter plots of observed and estimated link flows and estimated trip production for these two cases.



(a) Truck count only (case 1)



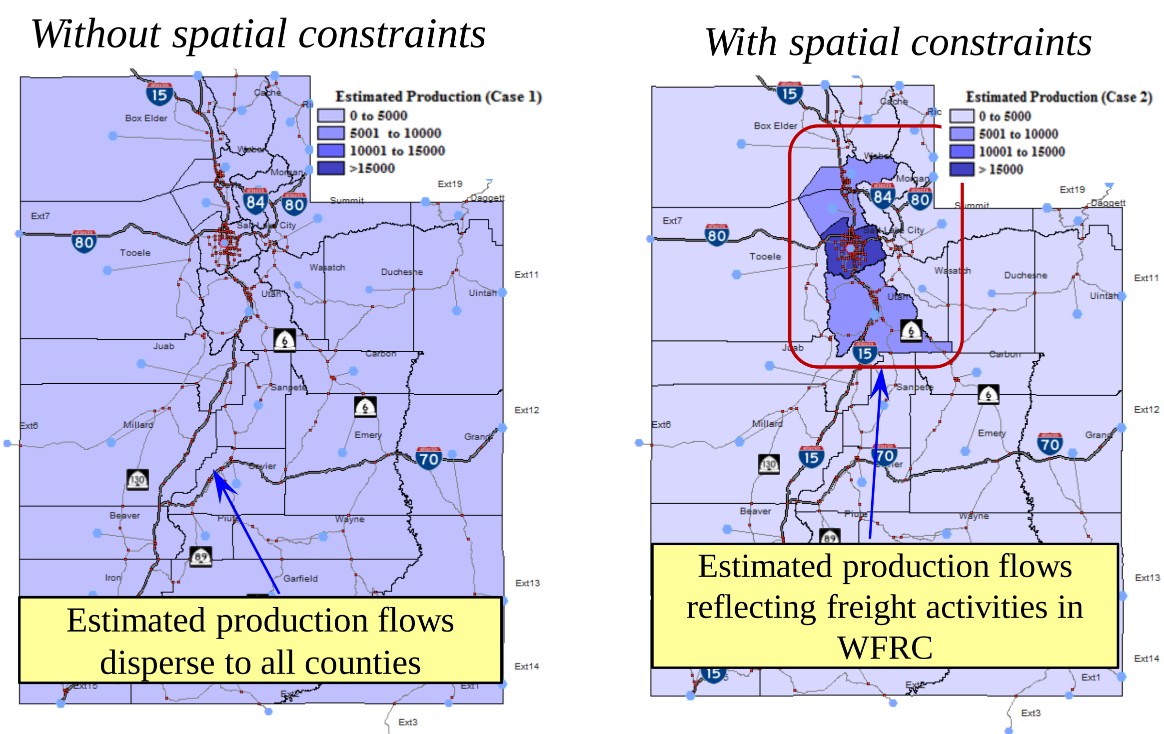
(b) Truck count only + commodity base data (case 2)

Figure 5.6 Comparisons of observed and estimated statewide truck flows

The results show the truck trip table estimated by PFE produces a fairly good match for both cases (i.e., case 1: RMSE=655.14 trucks/day, case 2: RMSE=978.56 trucks/day). It should be noted that the RMSE indicates the aggregated quality of O-D estimates. A smaller value indicates a higher quality of the estimation process. Between the two cases, including spatial constraints into the estimation slightly deteriorates the matching of truck counts as indicated by the higher RMSE. This is compensated by the better estimates of zonal production and attraction flows. The estimated total demand of case 1 is approximately 38% less than the total demand estimated from the first stage. This highlights the importance of including the spatial constraints into the PFE model, which can better capture the total demand in case 2 (i.e., slightly over 6%). However, we still observe that case 2 underestimates some link flows, especially those links with high truck flows on I-15 near Salt Lake City.

This is because those links are located closed to areas with a higher level of freight activities near the Salt Lake City International Airport. This is the concentrated area with high truck traffic accessing to/from the shipping companies and intermodal facilities such as rail-truck and air-truck modes. Resolving this issue requires adding special generators of truck trips from surveys of high freight density areas such as warehouses and freight distribution centers. From the modeling point of view, these special generators can be implemented in the PFE framework as they are handled by the zonal production and attraction constraints (in Eqs. 4.8, and 4.9) similar to the commercial and empty truck trips.

Figure 5.7(a) and Figure 5.7(b) depict the truck production flows for case 1 and case 2, respectively. From these two figures, we can observe the trip productions in case 2 are more distributed when the spatial constraints are considered in the estimation process. By adding zonal production and attraction flows as constraints in case 2, it can improve the observability of the trip generation pattern. Thus, this emphasizes the importance of using a two-stage approach to capture both the commodity flows and truck counts in the field, so that the statewide truck flow pattern can better reflect the reality.



(a) Estimated trip production (case 1)

(b) Estimated trip production (case 2)

Figure 5.7 Comparisons of estimated production flows

5.2.3 Truck Corridor Analysis

This section provides the truck corridor analysis. In Utah, I-15 is a primary corridor for both passenger and freight movements. The truck corridor serves as a backbone route for truck movements of agricultural energy (i.e., oil, gas, and coal) products in southern Utah and onward to major cities in the state such as Provo, Salt Lake City, and Ogden. Additionaly, the I-15 corridor also helps to connect the through truck traffic as part of the CANAMEX corridor. Figure 5.(a) depicts the daily truck traffic flows on the I-15 corridor. Figure 5.8(b) and Figure 5.8(c) show additional details of the truck flow profile starting from the northern border (from Idaho) to the southen border (to Arizona) and the corresponding daily truck V/C ratios.

As expected, the heavily used truck links are in the WFRC area, especially the links near Salt Lake City and its pheripheral urbanized areas such as Weber County, Davis County, and Utah County. The most congested link carries daily truck traffic of 16,058 trucks/day with an AADT of 34,634 passenger cars/day, or about 30% of this segment being truck traffic. Additionally, in this area the daily truck flow to capacity ratios range between 0.3 and 0.5. The most congested link is about 0.52, which indicates that truck traffic highly contributes to the congestion on this particular link in the urban areas. Figure 5.8(d) depicts the daily truck vehicle mile traveled (TVMT) for this corridor. The daily TVMT is calculated based on the truck travel distance and the daily truck flows estimated from the two-stage approach. As can be seen, the TVMT in Salt Lake county is lower than those of Davis and Utah counties. The major reason is that higher truck flows can travel a longer distance in those counties, while a similar amount of truck flows can travel a shorter distance within Salt Lake county. This suggests that these links could have higher congestion, which could lead to stop-and-go traffic conditions around this area.

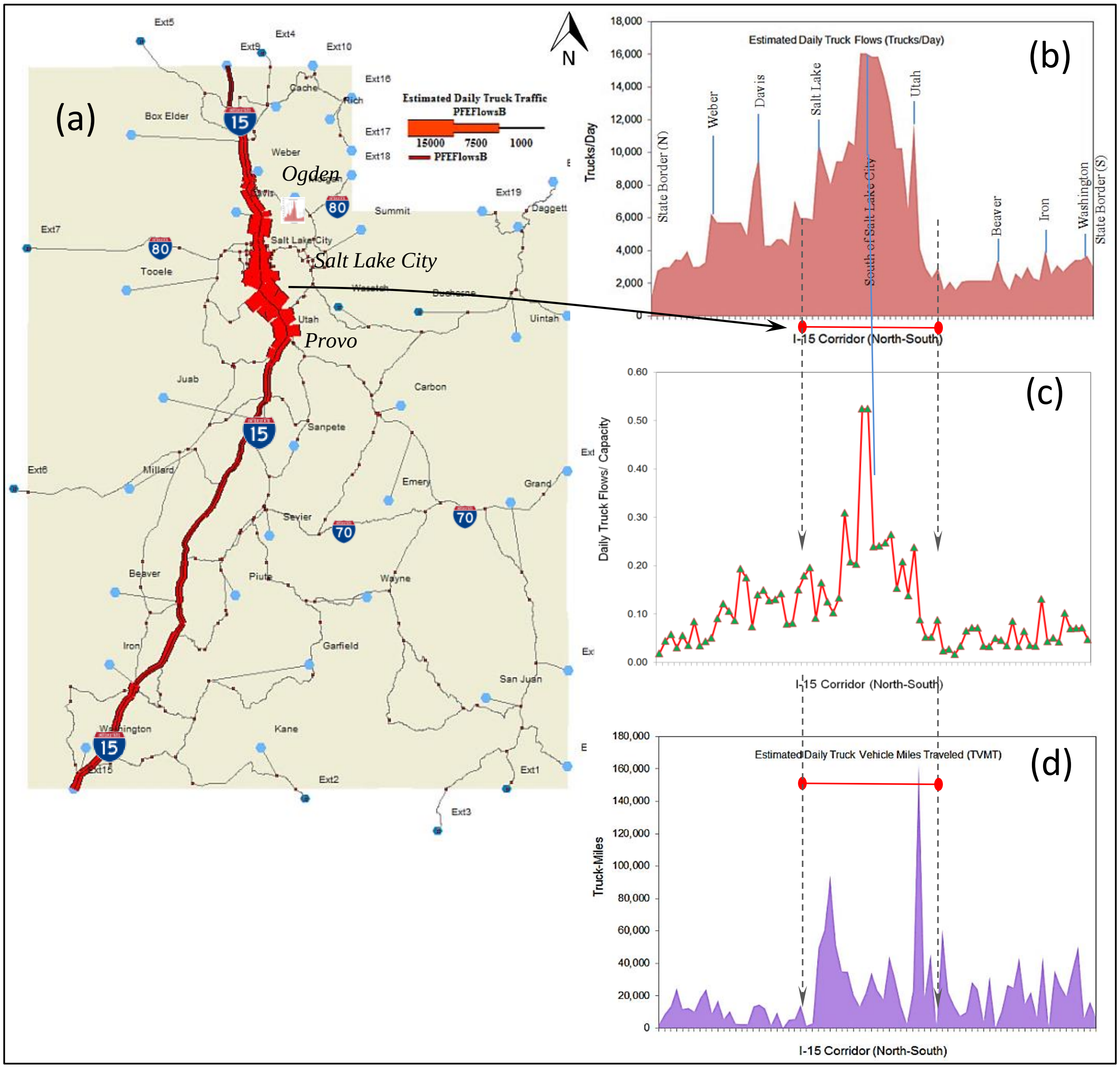


Figure 5.8 Estimated truck flows and truck vehicle miles traveled on I-15 corridor, Utah

6. CONCLUSIONS

This study has developed a two-stage approach for estimating truck O-D trip table using both commodity flows and truck counts data. The model is supported by two sequential stages: Stage one estimates the commodity-based truck O-D trip tables primarily derived from the commodity flow database, while stage two uses the path flow estimator (PFE) to refine the truck trip table to better match the observed truck counts.

In the first stage, we have developed a simplified procedure to estimate a commodity-based truck trip table using the commodity flows from the newly released FAF^3. The FAF^3 provides commodity flow estimates based on tonnage and value by commodity type, mode, origin, and destination for 2007, and forecasts through 2040. It is publicly accessible from the Freight Management and Operations Database from the FHWA website. This stage considers intrastate, interstate, and through truck flows. Four tasks are needed to accomplish this: 1) extract a state-specific commodity flows by from FAF^3, 2) conduct subarea analysis to estimate through truck flows, 3) disaggregate the state-specific to county-specific commodity flows, and 4) convert the commodity flows into truck trips.

The second stage adopts the PFE to refine the truck trip table obtained from the first stage using the up-to-date truck counts. The basic idea is to find a set of path flows that can reproduce the observed truck counts from the statewide truck count program collected from permanent count station locations within the state and state borders, while preserving the spatial distribution of the O-D commodity flow pattern obtained from the first stage. To enhance the observability of the truck O-D trip table, additional planning data, such as production and attraction flows, are included in the PFE estimation. Validation of the results of the PFE is assessed by the accuracy of the assignment estimates measured by the root mean square error (RMSE) between the estimated and observed truck counts.

The flexibility of aggregating path flows at different spatial levels in the PFE allows us to makes use of various existing data (e.g., truck counts, production and attraction commodity flows, truck VMT at the state level, etc.) and commodity-based data with commercial and empty truck trips for estimating the statewide truck trip table. The proposed approach can be also used to conduct the truck corridor analysis to determine the congested links and potential bottlenecks. Although the results using Utah as a case study are satisfactory, accurate and consistent truck counts are required in the PFE to produce reliable results. Extending the PFE to handle inconsistent traffic counts at the statewide level should be explored (see Chen *et al*. 2009, 2010). Constraints such as trip length frequency distribution is needed to model different types of statewide truck traffic (i.e., short haul, long haul, and empty truck trips) in the PFE. Hence, further work should consider multiclass and multimode (e.g., commercial, single- and multiple-unit trucks, and passenger cars) (see, for example, Yang and Huang 2004; Marcotte and Wynter 2004; Wong *et al*. 2005), so that it can better reflect the actual congestion of the statewide network. In addition, truck surveys at freight companies and distribution centers for each county and state border (e.g., Weigh-in-motion, Port of Entry stations) should be conducted to understand the freight movements in the statewide network. The current truck O-D trip table is estimated from the commodity flow data from FAF and truck counts collected by the Utah Department of Transportation. It should be updated using the newly developed Utah Statewide Travel Model to improve the accuracy and quality of the truck O-D trip table.

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APPENDIX A.
COMMODITY CODES BASED ON THE STANDARD CLASSIFICATION OF TRANSPORTED GOODS (SCTG)

Table A.1 Commodity codes based on the SCTG

SCTG	BTS/Census Full Commodity Name
1	Live Animals and Fish
2	Cereal Grains (including seed)
3	Other Agricultural Products, except for Animal Feed
4	Animal Feed and Products of Animal Origin, n.e.c.[2]
5	Meat, Fish, and Seafood, and Their Preparations
6	Milled Grain Products and Preparations, and Bakery Products
7	Other Prepared Foodstuffs, and Fats and Oils
8	Alcoholic Beverages
9	Tobacco Products
10	Monumental or Building Stone
11	Natural Sands
12	Gravel and Crushed Stone
13	Non-Metallic Minerals, n.e.c.
14	Metallic Ores and Concentrates
15	Coal
16	Crude Petroleum Oil
17	Gasoline and Aviation Turbine Fuel
18	Fuel Oils
19	Coal and Petroleum Products, n.e.c.
20	Basic Chemicals
21	Pharmaceutical Products
22	Fertilizers
23	Chemical Products and Preparations, n.e.c.
24	Plastics and Rubber
25	Logs and Other Wood in the Rough
26	Wood Products
27	Pulp, Newsprint, Paper, and Paperboard
28	Paper or Paperboard Articles
29	Printed Products

[2] n.e.c. = not elsewhere classified

Table A.1 Commodity codes based on the SCTG (Continued)

SCTG	BTS/Census Full Commodity Name
30	Textiles, Leather, and Articles of Textiles or Leather
31	Non-Metallic Mineral Products
32	Base Metal in Primary or Semi-Finished Forms and in Finished Basic Shapes
33	Articles of Base Metal
34	Machinery
35	Electronic and Other Electrical Equipment and Components, and Office Equipment
36	Motorized and Other Vehicles (including parts)
37	Transportation Equipment, n.e.c.
38	Precision Instruments and Apparatus
39	Furniture, Mattresses and Mattress Supports, Lamps, Lighting Fittings, and Illuminated Signs
40	Miscellaneous Manufactured Products
41	Waste and Scrap
42	Mixed Freight
43	Commodity unknown

APPENDIX B.
DISAGGREGATED PRODUCTION-ATTRACTION OF UTAH

Table B.1 Disaggregated Production-Attraction within Utah (I-I) (1x1)

	Utah (KT)	
From	2007	2040
Utah	93,302.06	158,537.40

Table B.2 Disaggregated Production-Attraction from Utah to Other States (I-E) (1x48)

Utah	Destination								
	Year	AL	AK	AZ	AR	CA	CO	CT	DE
	2007	14	4	750	44	2,575	1,314	15	1
	2040	30	4	1,646	68	3,444	2,042	41	2

Utah	Destination								
	Year	DC	FL	GA	ID	IL	IN	IA	KS
	2007	0	27	86	2,372	160	149	61	68
	2040	0	50	141	3,690	351	238	243	165

Utah	Destination								
	Year	KY	LA	ME	MD	MA	MI	MN	MS
	2007	46	15	1	7	27	62	111	21
	2040	82	27	2	18	77	45	278	54

Utah	Destination								
	Year	MO	MT	NE	NV	NH	NJ	NM	NY
	2007	101	920	58	2,231	1	49	145	58
	2040	249	1,628	149	3,858	2	149	186	110

Utah	Destination								
	Year	NC	ND	OH	OK	OR	PA	RI	SC
	2007	84	36	115	61	290	103	2	42
	2040	161	76	226	151	491	217	3	94

Utah	Destination									
	Year	SD	TN	TX	VT	VE	WA	WV	WI	WY
	2007	67	44	340	16	28	729	2	210	1,849
	2040	198	74	707	37	64	1,309	3	348	3,595

Table B.3 Disaggregated Production-Attraction from Other States to Utah (E-I) (48x1)

	Origin								
Utah	Year	AL	AK	AZ	AR	CA	CO	CT	DE
	2007	68	2	1,101	134	3,514	1,168	28	2
	2040	138	2	1,574	241	12,375	2,238	54	6

	Origin								
Utah	Year	DC	FL	GA	ID	IL	IN	IA	KS
	2007	0	83	206	1,568	324	242	185	98
	2040	0	166	290	3,927	561	669	195	103

	Origin								
Utah	Year	KY	LA	ME	MD	MA	MI	MN	MS
	2007	61	93	9	15	40	130	116	60
	2040	144	144	9	16	70	445	140	97

	Origin								
Utah	Year	MO	MT	NE	NV	NH	NJ	NM	NY
	2007	384	562	148	1,928	6	93	78	122
	2040	533	720	238	3,272	12	133	219	176

	Origin								
Utah	Year	NC	ND	OH	OK	OR	PA	RI	SC
	2007	112	11	259	654	573	224	4	73
	2040	200	21	473	674	1321	212	5	187

	Origin									
Utah	Year	SD	TN	TX	VT	VE	WA	WV	WI	WY
	2007	68	145	573	8	117	585	5	187	1,618
	2040	156	372	1,283	9	179	1,014	8	234	2,597

APPENDIX C.
DERIVATIONS OF THE ADJUSTMENT EQUATIONS

This appendix provides the full derivations of the adjustment equations for the link-capacity constraints, the lower limit and upper limit of link-flow constraints, O-D demand, zonal production flow constraints, zonal attraction flow constraints and total demand constraint for the PFE model.

Handling link-capacity constraint

Consider the link-capacity constraint (4.8). If flow on link a exceeds its link-capacity (i.e., $x_a > C_a$), dual variable d_a is adjusted to reduce the flow on link *a* back to its link-capacity. The adjustment value (λ) is the root of the following equation, which is obtained by replacing the analytical expressions.

$$\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K_{rs}}} f_k^{rs}\delta_{ka}^{rs} = \sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K_{rs}}} \exp\left(\theta\cdot\begin{pmatrix} -c_k^{rs} + \sum_{a\in \mathrm{M}}\left(u_a^- + u_a^+\right)\delta_{ka}^{rs} + \sum_{a\in \mathrm{U}} d_a\delta_{ka}^{rs} + \lambda \\ \left(o_{rs}^+ + o_{rs}^-\right) + \left(\rho_r^- + \rho_r^+\right) + \left(\eta_s^- + \eta_s^+\right) + \left(\psi^- + \psi^+\right)\end{pmatrix}\right)\delta_{ka}^{rs} = C_a \qquad \text{(C1)}$$

which is equivalent to:

$$\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K_{rs}}} f_k^{rs}\delta_{ka}^{rs}\exp\left(\theta\cdot\lambda\delta_{ka}^{rs}\right) = C_a \;\Rightarrow x_a\cdot\exp\left(\theta\cdot\lambda\delta_{ka}^{rs}\right) = C_a \qquad \text{(C2)}$$

In Eq. (C2), it should be noted that only the paths passing through link *a* are involved in the computation of link-flow (e.g., δ_{ka}^{rs}=1). The exponential term is common to all the relevant paths and therefore can be moved outside the summation. After re-arranging Eq. (C2), the adjustment factor for the dual variable of the link-capacity constraint (4.8) can be written as follows:

$$\lambda = \frac{1}{\theta}\ln\left(\frac{C_a}{x_a}\right) \qquad \text{(C3)}$$

Handling observed link flow constraint

Likewise, the adjust factor involving observed link flow constraint (4.7) can be derived as follows.

$$\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K_{rs}}} \exp\left(\theta\cdot\begin{pmatrix} -c_k^{rs} + \sum_{a\in \mathrm{M}}\left(u_a^- + u_a^+\right)\delta_{ka}^{rs} + \sum_{a\in \mathrm{U}} d_a\delta_{ka}^{rs} + \lambda \\ \left(o_{rs}^+ + o_{rs}^-\right) + \left(\rho_r^- + \rho_r^+\right) + \left(\eta_s^- + \eta_s^+\right) + \left(\psi^- + \psi^+\right)\end{pmatrix}\right)\delta_{ka}^{rs} = \begin{cases}(1-\varepsilon_a)\cdot v_a \\ (1+\varepsilon_a)\cdot v_a\end{cases} \qquad \text{(C4)}$$

which is equivalent to:

$$\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K_{rs}}} f_k^{rs}\delta_{ka}^{rs}\exp\left(\theta\cdot\lambda\delta_{ka}^{rs}\right) = \begin{cases}(1-\varepsilon_a)\cdot v_a \\ (1+\varepsilon_a)\cdot v_a\end{cases} \Rightarrow x_a\cdot\exp\left(\theta\cdot\lambda\delta_{ka}^{rs}\right) = \begin{cases}(1-\varepsilon_a)\cdot v_a \\ (1+\varepsilon_a)\cdot v_a\end{cases} \qquad \text{(C5)}$$

Hence, $\lambda = \frac{1}{\theta}\ln\left(\frac{(1-\varepsilon_a)\cdot v_a}{x_a}\right)$ for u_a^- and $\lambda = \frac{1}{\theta}\ln\left(\frac{(1+\varepsilon_a)\cdot v_a}{x_a}\right)$ for u_a^+ (C6)

Handling prior O-D demand, zonal production and attraction flow and total demand constraints

Likewise, the adjust factor involving prior O-D demand, zonal production and attractions flows, total demand constraints (4.9), (4.10), (4.11) and (4.12), respectively, can be derived as follows.

Prior O-D demand

$$\sum_{k\in \mathrm{K_{rs}}} \exp\left(\theta\cdot\left(\begin{matrix}-c_k^{rs}+\sum_{a\in \mathrm{M}}\left(u_a^-+u_a^+\right)\delta_{ka}^{rs}+\sum_{a\in \mathrm{U}} d_a\delta_{ka}^{rs}+\lambda \\ \left(o_{rs}^+ + o_{rs}^-\right)+\left(\rho_r^-+\rho_r^+\right)+\left(\eta_s^-+\eta_s^+\right)+\left(\psi^-+\psi^+\right)\end{matrix}\right)\right)=\begin{cases}(1-\varepsilon_{rs})\cdot z_{rs}\\(1+\varepsilon_{rs})\cdot z_{rs}\end{cases} \tag{C7}$$

which is equivalent to:

$$\sum_{k\in \mathrm{K_{rs}}} f_k^{rs}\exp\left(\theta\cdot\lambda\right)=\begin{cases}(1-\varepsilon_{rs})\cdot z_{rs}\\(1+\varepsilon_{rs})\cdot z_{rs}\end{cases} \Rightarrow q_{rs}\cdot\exp\left(\theta\cdot\lambda\right)=\begin{cases}(1-\varepsilon_{rs})\cdot z_{rs}\\(1+\varepsilon_{rs})\cdot z_{rs}\end{cases} \tag{C8}$$

Hence, $\lambda=\frac{1}{\theta}\ln\left(\frac{(1-\varepsilon_{rs})\cdot z_{rs}}{q_{rs}}\right)$ for o_{rs}^- and $\lambda=\frac{1}{\theta}\ln\left(\frac{(1+\varepsilon_{rs})\cdot z_{rs}}{q_{rs}}\right)$ for o_{rs}^+ (C9)

Zonal production flow

$$\sum_{s\in \mathrm{S}}\sum_{k\in \mathrm{K_{rs}}} \exp\left(\theta\cdot\left(\begin{matrix}-c_k^{rs}+\sum_{a\in \mathrm{M}}\left(u_a^-+u_a^+\right)\delta_{ka}^{rs}+\sum_{a\in \mathrm{U}} d_a\delta_{ka}^{rs}+\lambda \\ \left(o_{rs}^+ + o_{rs}^-\right)+\left(\rho_r^-+\rho_r^+\right)+\left(\eta_s^-+\eta_s^+\right)+\left(\psi^-+\psi^+\right)\end{matrix}\right)\right)=\begin{cases}(1-\varepsilon_r)\cdot O_r\\(1+\varepsilon_r)\cdot O_r\end{cases} \tag{C10}$$

which is equivalent to:

$$\sum_{s\in \mathrm{S}}\sum_{k\in \mathrm{K_{rs}}} f_k^{rs}\exp\left(\theta\cdot\lambda\right)=\begin{cases}(1-\varepsilon_r)\cdot O_r\\(1+\varepsilon_r)\cdot O_r\end{cases} \Rightarrow P_r\cdot\exp\left(\theta\cdot\lambda\right)=\begin{cases}(1-\varepsilon_r)\cdot O_{rs}\\(1+\varepsilon_r)\cdot O_{rs}\end{cases} \tag{C11}$$

Hence, $\lambda=\frac{1}{\theta}\ln\left(\frac{(1-\varepsilon_r)\cdot O_r}{P_r}\right)$ for ρ_r^- and $\lambda=\frac{1}{\theta}\ln\left(\frac{(1+\varepsilon_r)\cdot O_r}{P_r}\right)$ for ρ_r^+ (C12)

Zonal attraction flow

$$\sum_{r\in \mathrm{R}}\sum_{k\in \mathrm{K_{rs}}} \exp\left(\theta\cdot\left(\begin{matrix}-c_k^{rs}+\sum_{a\in \mathrm{M}}\left(u_a^-+u_a^+\right)\delta_{ka}^{rs}+\sum_{a\in \mathrm{U}} d_a\delta_{ka}^{rs}+\lambda \\ \left(o_{rs}^+ + o_{rs}^-\right)+\left(\rho_r^-+\rho_r^+\right)+\left(\eta_s^-+\eta_s^+\right)+\left(\psi^-+\psi^+\right)\end{matrix}\right)\right)=\begin{cases}(1-\varepsilon_s)\cdot D_s\\(1+\varepsilon_s)\cdot D_s\end{cases} \tag{C13}$$

which is equivalent to:

$$\sum_{r\in \mathrm{R}}\sum_{k\in \mathrm{K_{rs}}} f_k^{rs}\exp\left(\theta\cdot\lambda\right)=\begin{cases}(1-\varepsilon_s)\cdot D_s\\(1+\varepsilon_s)\cdot D_s\end{cases} \Rightarrow A_s\cdot\exp\left(\theta\cdot\lambda\right)=\begin{cases}(1-\varepsilon_s)\cdot D_s\\(1+\varepsilon_s)\cdot D_s\end{cases} \tag{C14}$$

Hence, $\lambda=\frac{1}{\theta}\ln\left(\frac{(1-\varepsilon_s)\cdot D_s}{A_s}\right)$ for η_s^- and $\lambda=\frac{1}{\theta}\ln\left(\frac{(1+\varepsilon_s)\cdot D_s}{A_s}\right)$ for η_s^+ (C15)

Total Demand

$$\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K_{rs}}}\exp\left(\theta\cdot\begin{pmatrix}-c_k^{rs}+\sum_{a\in \mathrm{M}}\left(u_a^{-}+u_a^{+}\right)\delta_{ka}^{rs}+\sum_{a\in \mathrm{U}}d_a\delta_{ka}^{rs}+\lambda\\ \left(o_{rs}^{+}+o_{rs}^{-}\right)+\left(\rho_r^{-}+\rho_r^{+}\right)+\left(\eta_s^{-}+\eta_s^{+}\right)+\left(\psi^{-}+\psi^{+}\right)\end{pmatrix}\right)=\begin{cases}(1-\varepsilon)\cdot F\\(1+\varepsilon)\cdot F\end{cases} \tag{C16}$$

which is equivalent to:

$$\sum_{rs\in \mathrm{RS}}\sum_{k\in \mathrm{K_{rs}}} f_k^{rs}\exp\left(\theta\cdot\lambda\right)=\begin{cases}(1-\varepsilon)\cdot F\\(1+\varepsilon)\cdot F\end{cases}\Rightarrow T\cdot\exp\left(\theta\cdot\lambda\right)=\begin{cases}(1-\varepsilon)\cdot F\\(1+\varepsilon)\cdot F\end{cases} \tag{C17}$$

Hence, $\lambda=\frac{1}{\theta}\ln\left(\frac{(1-\varepsilon)\cdot F}{T}\right)$ for ψ^{-} and $\lambda=\frac{1}{\theta}\ln\left(\frac{(1+\varepsilon)\cdot F}{T}\right)$ for ψ^{+} (C18)