MODELING TRUCK TRAFFIC IN TURKEY

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY
MUHAMMAD FAYYAZ

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
CIVIL ENGINEERING

JUNE 2015

Approval of the Thesis:

MODELING TRUCK TRAFFIC IN TURKEY

Submitted by **MUHAMMAD FAYYAZ** in partial fulfillment of the requirements for the degree of **Master of Science in Civil Engineering Department, Middle East Technical University** by,

Prof. Dr. Gülbin Dural Ünver
Dean, Graduate School **of Natural and Applied Sciences** ____________________

Prof. Dr. Ahmet Cevdet Yalçıner
Head of Department, **Civil Engineering** ____________________

Assoc. Prof. Dr. Hediye Tüydeş Yaman
Supervisor, **Civil Engineering Dept., METU** ____________________

Dr. Murat Ozen
Co-Supervisor, **Civil Engineering Dept., Mersin Univ.** ____________________

Examining Committee Members

Prof. Dr. Murat Güler
Civil Engineering Dept., METU ____________________

Assoc. Prof. Dr. Hediye Tüydeş Yaman
Civil Engineering Dept., METU ____________________

Assoc. Prof. Dr. Ela Babalık Sutcliffe
City and Regional Planning Dept., METU ____________________

Asst. Prof. Dr. Hikmet Bayırtepe
Civil Engineering Dept., Gazi University ____________________

Asst. Prof. Dr. Hande Isık Ozturk
Civil Engineering Dept., METU ____________________

Date: June 26, 2015

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

MODELING TRUCK TRAFFIC IN TURKEY

Fayyaz, Muhammad
M. S., Department of Civil Engineering
Supervisor: Assoc. Prof. Dr. Hediye Tüydeş Yaman
June 2015, 71 pages

The objective of this study is to contribute to intercity road freight modeling in Turkey in general, and particularly estimation of origin-destination (O-D) matrix for intercity truck traffic, using the available freight transport data. As commodity flow data is not available for Turkey, information collected through roadside axle surveys is the main data source of this study. Firstly, the survey matrix has beem estimated using roadside axle survey data from 2007-2011 period, and enlarged using link counts at the survey locations, which consequently. The data is used to estimate the observed produced and attracted (PA) trips for 81 provinces of Turkey. In trip generation, regression analysis is employed to derive truck trip production and attraction functions for 2011 using socioeconomic data (number of household, port existance and land square). Trip distribution is performed and the gravity model coefficients in the log-form are estimated regressing the data from 3959 available O-D flows in the survey data. Very low regression statistics for both distance and travel time based impedance functions and underestimation of truck traffic with the obtained models suggested that truck traffic distribution is controlled by parameters other than these two. Though underestimated, missing 2521 O-D flows are estimated using the developed gravity model, which suggested 11% additional trips (which

may be even more in reality). All the regression and statistical evaluations are performed in SPSS.

Keywords: *Trip Generation, Trip Distribution, Regression Analysis, Gravity Model, Roadside Axle Surveys*

ÖZ

TÜRKİYE'DE KAMYON TRAFİĞİNİN MODELLENMESİ

Fayyaz, Muhammad
Yüksek Lisans, İnşaat Mühendisliği Bölümü
Tez Yöneticisi: Doç. Dr. Hediye Tüydeş Yaman

June 2015, 71 sayfa

Bu çalışmanın amacı, mevcut yük taşımacılığı verilerini kullanarak, genel olarak Türkiye'deki şehirlerarası karayolu yük taşımacılığının ve özellikle de şehirlerarası kamyon trafiğinin başlangıç-bitiş (O-D) modellemesi konusunda katkıda bulunmaktır. Yük akış verileri Türkiye için mevcut olmadığından, bu çalışmanın temel veri kaynağı yol kenarında dingil ağırlığı anketleridir. Öncelikle, 2007-2011 dönemine ait yol kenarı anket verileri kullanılarak, anket tabanlı matriks elde edilmiş, ve anket noktalarındaki trafik sayımları da kullanılarak genişlemiştir. Bu matriks, Türkiye'nin 81 ili için gözlenen üretim ve çekim (PA) değerlerini elde etmek için kullanılmıştır. Yolculuk üretim modellemesi aşamasında, regresyon analizi ile sosyoekonomik veriler (hane sayısı, liman varlığı ve yüzölçümü) kullanılarak 2011 yılı için kamyon trafik üretim ve çekim fonksiyonları türetilmiştir. Yolculuk dağılımı aşamasında, log-formundaki çekim modeli katsayıları, mevcut 3959 O-D akış verileri ile regresyon edilerek tahmin edilmiştir. Gerek mesafeye ve gerekse seyahat süresine dayalı yapılan çekim modellerinin her ikisinde de istatistiki performansın çok düşük olması ve bu modellemelerle yapılan tahminlerin sürekli gözlemlenenlerden düşük olması, şehirlerarası kamyon trafiğinin bu iki etken dışında parametrelerce kontrol edildiğini göstermektedir. Düşük tahmin gücüne rağmen, elde edilen çekim modeler ile tahmin edilen ve anketlerde gözlemlenmeyen 2521 O-D akışı toplamda %11lik

bir talep artışı yaratmıştır (ki gerçekte bu daha fazla olabilir. Çalışmadaki bütün regresyon ve istatistiksel değerlendirmeler SPSS yapılmaktadır.

Anahtar Kelimeler: *Trip Üretimi, Seyahat dağılımı, Regresyon Analizi, Gravity Modeli, Yol Aks Anketleri*

To my parents

ACKNOWLEDGEMENTS

Foremost, I would like to express my sincere gratitude to my advisor Assoc. Prof. Dr. Hediye Tuydes Yaman for the continuous support of my MSc study and research, for her patience, motivation, enthusiasm, and immense knowledge. Her guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and mentor for my MSc study. Secondly, I would like to thank to Dr. Murat Ozen for his support and guidance about obtaining data and analyses.

Besides my advisor, I would like to thank the rest of my thesis committee: Prof. Dr. Murat Guler, Assoc. Prof. Dr. Ela Babalık Sutcliffe, Asst. Prof. Dr. Hikmet Bayirtepe, and Asst. Prof. Dr. Hande Isik Ozturk, for their insightful comments and hard questions.

I also would like to express my gratitude to the Turkish General Directorate of Highways, which provided the data used in this study; without it, we would not have known much about truck freight in Turkey.

I could not have finished this thesis without the support from my nearest and dearest. I am more than grateful to my family and I would especially like to thank my mother. Finally, I am very grateful to my dear friends, who have been there all the time during my study.

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CHAPTER 1

INTRODUCTION

The inland freight transportation industry in Turkey, as in other developing countries (World Trade Organization, 2010), is to a large extent road based. In 2009, 89% of the overall inland freight ton-km was carried by trucks (TurkStat, 2011) compared to an European average of 73% in 2010 (Road Freight Transport Va demecum, 2011). The annual road freight transportation for Turkey in a 10-year period of 2004-2013 has presented as ton-km and vehicle-km in Table 1.1. In this time period, the ton-km and vehicle-km increased steadily.

Table 1.1 Trucking ton-km and vehicle-km in Turkey (in million), (TGDH, 2013)

Year	Ton-km	Vehicle-km
2004	156,853	13,292
2005	166,831	14,378
2006	177,400	15,226
2007	181,330	16,097
2008	181,935	15,982
2009	176,455	16,366
2010	190,365	18,254
2011	203,072	19,722
2012	216,123	21,223
2013	224,048	22,209

1.1 Motivation

In general, the reasons for the dominancy of road transport are its flexibility and efficiency when considering short distances. In the future, it is quite clear that road transport will play a predominant role (White Paper on Transport, 2011) as it is the only mode to provide door-to-door delivery of goods to customers. It is important to model truck freight in order to be able to analyze the current situation and estimate the future ones.

Turkey is about to conduct a national transportation master plan study, and modeling truck freight is very important, and it is quite necessary to know what can be and how can be done, in this regard. The data availability is the main limitation in the analysis and developing of freight transport models. In developing countries, commodity flow data cannot be estimate very effectively, while most of the times traffic counts or roadside axle surveys regularly conducted, for various planning and design purposes of highways. For example, origin-destination (O-D) matrix for truck traffic can be estimated from transport statistics data (also called roadside surveys), which are more economical and can be easily modified with new data. A statewide truck trips estimation model can be develop, by combining different years of survey, to have a reliable model, which can forecast rational number of trips for horizon year too.

1.2 Research Objectives

The objective of this study is to contribute to intercity road freight modeling in Turkey in general, and particularly estimation of O-D matrix for intercity truck traffic, using the available freight transport data. To the most extent, estimation of O-D matrix depends on base-year O-D matrix, also called observed or survey O-D matrix (we will use survey matrix throughout the text). Afterwards trips are estimate for a horizon year, and distribute in trip distribution step, using different models i.e. growth factor model or gravity model etc.

In this study, an O-D matrix for truck traffic in Turkey has estimated. Firstly, a survey trip matrix has estimated, using the roadside axle survey data from year

2007 to 2011. Almost, 40% of the cells were empty. Nonetheless, the survey matrix is mostly sparse. In trip generation step, different trip production and attraction models have estimated. To solve the missing data problem, due to the sparsely survey matrix, gravity model-based regression approach has applied over the non-zero trips, in order to fit a regression line. The coefficients obtained from gravity model have used to estimate the missing O-D pairs.

Although these models can reliably estimate truck trips, they have based on socioeconomic and demographic structure of traffic analysis zones (TAZ), which were taken as the proviences in this study. In developing countries, due to rapid development, such characteristics change promptly, which substantially reduce forecasting ability of these models for long time, so regularly modification with current data is advisable to have a robust model for estimation.

1.3 Layout of the Thesis

Chapter 2 starts with the introduction of freight transport modelling. It describes the 4-step modelling approach. In addition, it explains the O-D estimation literature, the trip generation models, trip distribution models, and the truck freight data in Turkey. Chapter 3 briefly describes the methodology for the truck traffic modeling in Turkey. It explains the demographic and socio-economic variables; roadside axle survey data; existing state of truck traffic modeling in Turkey—and proposed methodology for truck traffic in Turkey and its contribution.

Chapter 4 shows the results of survey matrix, trip generation and trip distribution step. Firstly, it describes the trip produced and attracted trips from the survey matrix; secondly, it explains the multiple regression analysis results and the equations obtained for the estimation of produced and attracted trips, and comparison between the trip production and attraction from the survey matrix, and from regression analysis are showed. In addition, it explains the result of the trip distribution via gravity model. It shows the coefficients obtained from the log-linear regression form of the gravity model. Chapter 5 describes a main finding of the study, conclusion, and further directions for O-D estimation, in Turkey.

CHAPTER 2

LITERATURE REVIEW

In recent years, freight transport is becoming a major area for public policies, particularly related to emissions and traffic safety. Freight transport models developed in the early 1960 similar to passenger transport models, however their development and applications were much slower; maybe due to unavailability of data or no suitable economic theory (Tavasszy & de Jong, 2014a) . Figure 2.1 shows the four-step model, which can be used to model passenger as well as freight transport. The four-step model consists of the following steps (Ortuzar and Willumsen, 2011):

(a) Generation and attraction: the amount of trips/goods generated by and attracted to the defined zones (in number of trips or tons).

(b) Distribution: the number of trips or flows of goods transported between the defined zones (in number of trips or tons).

(c) Modal split: the number of trips or flows of goods allocate to transportation modes, which are motorways, railways, waterways and combined transportation, etc.

(d) Assignment: number of trips according to their mode is assign to shortest path while freight flows assign to transportation network after converting the flows in tons to vehicle units.

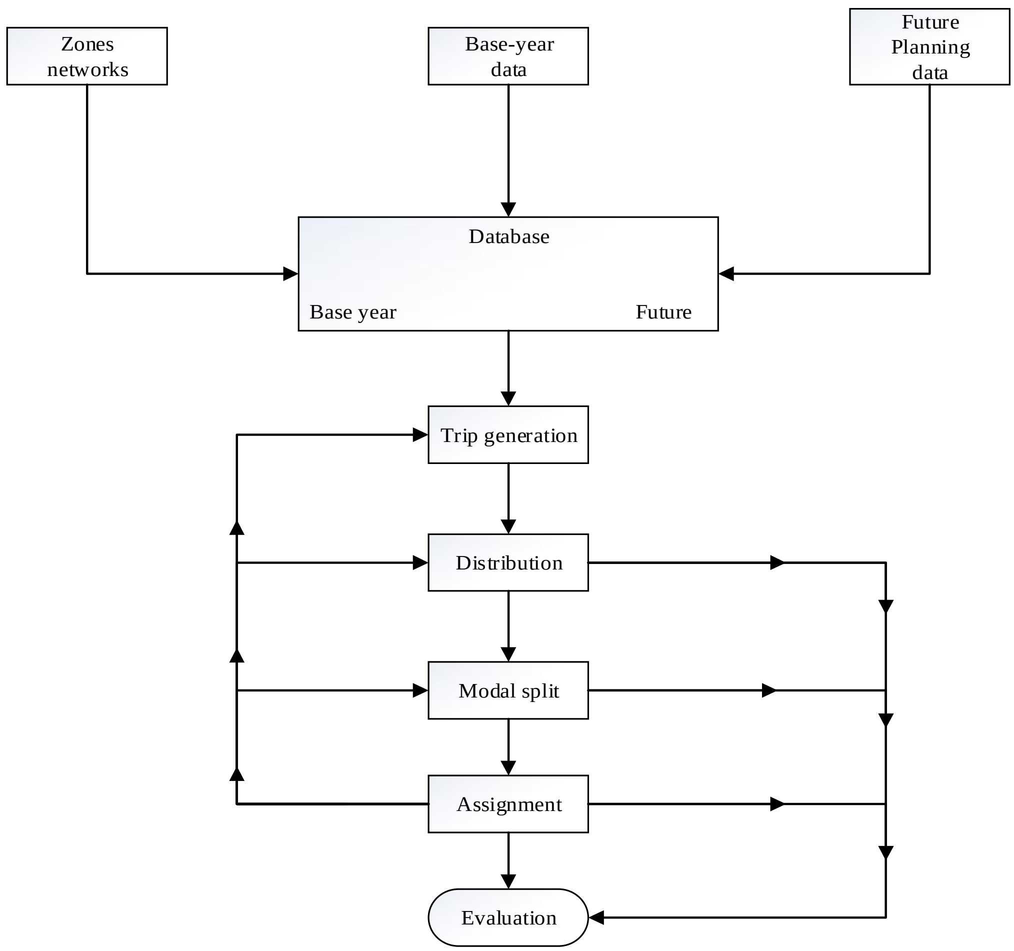


Figure 2.1 The four-stage transport model (Ortuzar and Willumsen, 2011).

2.1 O-D Estimation Literature

In transportation planning, the O-D matrix is main component. It is almost impossible to do survey of all the O-D trips due to large scale of these trips and limited resources, therefore, in the literature there are numerous methods and models to estimate or develop an O-D matrix (Shen & Aydin, 2014). These models and methods use to estimate O-D matrix using the survey matrix, and estimated trip production and attraction from the trip generation step.

There are various methods to model trip generation, and calculate the survey matrix, however most effective one is combination of home interviews and roadside surveys (Van Zuylen & Willumsen, 1980). Different methods includes road side interview of drivers (expensive in manpower and cause congestion), home interview (expensive in manpower and time consuming), flagging method (processing efforts require), aerial photography (not useful for statewide), car following (applicable only in cities) (Willumsen, 1978). On the other hand, due to high cost factors i.e. labor constraint and time consuming for aforementioned surveys, often planners opt for more cheap and composite strategy i.e. traffic counts from roadside survey.

Roadside axle surveys performed for truck trips and freight transportation as well. In developing countries, cardinal issue is of drastic changes in land use and demographic data, which implies to use cheap methods like traffic counts (Chen et. al 2005), which can easily be revised as well as while generate a reliable statewide truck-travel model, which can be used for various planning purposes (Park & Smith, 1997), and freight emissions estimation.

There are different models, which have applied to survey matrix, in order to estimate O-D matrix. These models are the gravity model (Casey 1955; Schneider 1959; Evans 1973; Ashtakala 1987) the entropy maximization model (Wilson 1970, 1974), the logit model (McFadden 1973, 1975; Ben-Akiva and Lerman 1985) and the flow-counting model (Cascetta 1984; Bell 1991). These models have calibrated then, using different procedures e.g. balancing factors (Furness 1965) and maximum likelihood (Spiess 1987). Table 2.1 provides a brief summary of the various O-D estimation models, in the literature.

2.2 Trip Generation Models

Freight transport become quite complex due to numerous activities involvement, a number of transport modes and geographical locations, and most importantly number of ways for the definition and measurement of freight. One of the features of the freight demand modelling is calculation of the freight generation (FG) (amount of payload produced) and the freight trip generation (FTG) (number of vehicle trips produced/attracted) (Holguín-Veras et al., 2011).

Table 2.1 Origin and destination estimation models in the literature (Guler, 2014)

Author	Model description
Bell (1983)	The estimation of an origin-destination matrix from traffic counts
Bell (1991)	The estimation of origin-destination matrices by constrained generalized least squares
Cascetta et al. (1993)	Dynamic estimators of origin-destination matrices using traffic counts
Cascetta and Russo (1997)	Calibrating aggregate travel demand models with traffic counts: estimators and statistical performance
Ashok and Ben-Akiva (2000)	Alternative approaches for real-time estimation and prediction of time-dependent origin–destination flows
Asakura et al. (2000)	Origin-destination matrices estimation model using automatic vehicle identification data and its application to the Han-Shin expressway network
Timms (2001)	A philosophical context for methods to estimate origin—destination trip matrices using link counts
Ashok and Ben-Akiva (2002)	Estimation and prediction of time-dependent origin-destination flows with a stochastic mapping to path flows and link flows
Celik (2004)	Modeling freight distribution using artificial neural networks
Chen et al. (2005)	Examining the quality of synthetic origin–destination trip table estimated by path flow estimator
Dixon and Rilett (2005)	Population origin–destination estimation using automatic vehicle identification and volume data
Castillo (2008)	Traffic estimation and optimal counting location without path enumeration using bayesian networks
Celik (2010)	Sample size needed for calibrating trip distribution and behavior of the gravity model
Sharma et al. (2011)	Approximation techniques for transportation network design problem under demand uncertainty
Silva and Agosto (2013)	A model to estimate the origin–destination matrix for soybean exportation in Brazil
Thomas and Tutert (2013)	An empirical model for trip distribution of commuters in The Netherlands: transferability in time and space reconsidered
Guler and Vitisoglu (2013)	Estimation of freight transportation
Guler (2014)	Model to Estimate Trip Distribution: Case Study of the Marmaray Project in Turkey

Freight generation (FG) and freight trip generation (FTG) are two separate activities and should be model individually. FG refers to cargo measured in tonnage or volume (m^3 etc.), while FTG refers to the number of trips generated or produced by carrying cargo. From the modelling perspective it can be seen that FG is the outcome of production and consumption, however, FTG is based on logistic decisions (Holguín-Veras et al., 2011). Variables, which affect the FG and FTG, are important to take into consideration, in order to have in-depth analysis of their relations. These can be further divided into freight attraction (FA), freight production (FP), freight trip attraction (FTA) and freight trip production, as in the case of passenger transport (Ortúzar and Willumsen, 2011).

According to Holguín-Veras et al., (2014) logistic decisions of supplier and receiver is the driving force behind number of trips generated; the supplier has to deliver the shipment in a way the receiver want, even if it lead to increase in the transport costs of the supplier, so to have no loss of the customer. On the other hand, whether a truck is empty or fully loaded, if it is running it leads to a trip, irrespective of the amount of cargo carried. Hence, supply chain modelling, in other words the reason after the business decisions is an important area to understand in order to have precisely accurate the FG/FTG.

Holguín-Veras et al., (2014) further mentioned that FG is a function of business size, i.e. if larger; the business is, higher will be the volume of cargo production and attracted. On the other hand, it is not necessary that larger FG will lead to increase in FTG, because it depends upon shipment size; using larger shipment size can decrease the number of FTG, or using higher vehicle size. Hence, we cannot infer that FG and
FTG are directly proportional to each other. Furthermore, the phenomenon of logistics decisions, the economic order quantity (EOQ) model is important to consider. According to EOQ equations, FG have a smaller effect over the increase of FTG, because shipment size increase lead to smaller increase in the FTG (Holguín-Veras et al., 2011). Most common methods to estimate FTG models are using ordinary least squares (OLS) models. However, the dependent variable i.e. number of trips should be estimated first, in order to apply regression analysis.

2.2.1 Estimation of Trip Matrix from Roadside Axle Surveys

In the beginning of 1980, trip matrix estimation from traffic counts had widely attracted various researchers. According to Willumsen (1978), number of trips from zone i to zone j are T_{ij}, and p_{ij}^{a} be proportion of trips moving on a link, each link total trips (V_a) can be calculated by:

$$V_a = \sum_{ij} T_{ij}\, p_{ij}^{a} \tag{2.1a}$$

$$0 \le p_{ij}^{a} \le 1 \tag{2.1b}$$

If a study area divides into N zones (centroids), trips made from all origins to all destinations to generate trip matrix of N^2 cells, while to disregard intra-zonal trips i.e. $T_{ij} = 0$ for $i = j$, trip matrix then consists of N^2-N cells. While number of individual link counts is lower than this, implies traffic counts lacking in determining exclusive O-D matrix [T_{ij}].

In order to overcome traffic counts lacking problem to estimate O-D matrix, trip maker behavior should be incorporated via assignment methods (Willumsen, 1978). In one approach, all-or-nothing assignment can be used i.e. route choice would be independent of flow levels over the link,(Van Zuylen & Willumsen, 1980). In another approach, if congestion effects include into the model, i.e. route choice would be function of flow levels over the link. It is difficult to have exact knowledge of route choice of drivers, developed an information minimization (IM) model in 1980 (Wang & Friedrich, 2009; Willumsen, 1978). Mathematically defined as:

$$T_{ij} = t_{ij} . \prod_{a} x_a^{\, p_{ij}^{a}} \tag{2.2a}$$

$$g_{ij} = \sum_{a} p_{ij}^{a} \tag{2.2b}$$

$$\sum_{ij} T_{ij}\, p_{ij}^{a} = V_a^{obs} \tag{2.2c}$$

where, T_{ij} = estimated O-D trips from i to j; t_{ij} = historical O-D trips from i to j; p_{ij}^{a} = proportion of O-D trips from i to j over link a; $X_a^{n+1} = X_a^{n} * \frac{V_a^{obs}}{V_a^{s}}$, adjustment factor for link *a* in iteration n+1 by using ratio of observed traffic flow for link *a* in *n* iterations.

By using this equation, most likely O-D matrix by iterative process can be estimate when all matrix constraints become fulfilled i.e. estimated matrix become equal to observed matrix. If route choice patterns are not explicitly available, there could be instability in estimated results. To overcome this effect, Van Zuylen (1981) modified the IM model by adding another factor x_0 , in order to eliminate difference between historical and actual trips. Mathematically:

$$T_{ij} = t_{ij} . x_0 \prod_a x_a{}^{p_{ij}^a} \tag{2.3a}$$

$$\sum_{ij} T_{ij} \cdot p_{ij}^a = V_a^{obs} \tag{2.3b}$$

while x_0 initial value can be calculated by:

$$x_0 = \frac{1}{\sum_{ij} t_{ij}} . \sum_{ij} T_{ij} \tag{2.4a}$$

$$x_0 = \frac{1}{\sum_a \sum_{ij} p_{ij}^a \quad t_{ij}} . \sum_a V_a^{obs} \tag{2.4b}$$

2.3 Trip Distribution Models

Trip distribution is the second step of the 4-step modelling, which distribute the produced and attracted trips to TAZ. As a result, the matrix obtained is O-D matrix. There are many models for trip distribution i.e. Fratar Model, Gravity model, and Input Output Model; however, the gravity model is most common in transportation planning. The basis for this model is the Newton's Law of Gravity, which states that the trips between an origin and a destination depend directly on the total trip productions and the total trip attractions, and that they depend inversely on the impedance (Guler, 2014). In transportation, this model has applied as a social interaction model, which used to estimate freight flows between production and consumptions regions (Ortuzar and Willumsen, 2011). The gravity model is of below form:

$$T_{ij} = kP_i^{\sim} A_j \; f(H_{ij}) \tag{2.5}$$

where T_{ij} = number of trips between origin i and destination j; P_i = number of trips produced at zone i; A_j = number of trips attracted to zone j; $f(H_{ij})$ = impedance between zone i and zone j, measured as a function of distance, time, or cost between origin i and destination j; k = proportionality constant, $\sim$, = production and attraction exponents, respectively (Shen & Aydin, 2014).

2.3.1 Log Form of Gravity Model

The general form of the gravity model is:

$$T_{ij} = kP_i^{\sim} A_j \; f(H_{ij}) \tag{2.6}$$

Using distance (d_{ij}) and time (t_{ij}) as impedance between zone i and zone j, respectively, and gravity model becomes:

$$T_{ij} = k \frac{P_i^{\sim} A_j}{d_{ij}^{ª}} \tag{2.7a}$$

$$T_{ij} = k \frac{P_i^{\sim} A_j}{t_{ij}^{ª}} \tag{2.7b}$$

where ª = impedance exponent. By taking the natural log (Ln), the transformation of the gravity model becomes:

$$Ln(T_{ij}) = Ln(k) + \sim Ln(P_i) + \quad Ln(A_j) - ª Ln(d_{ij}) \tag{2.8a}$$

$$Ln(T_{ij}) = Ln(k) + \sim Ln(P_i) + \quad Ln(A_j) - ª Ln(t_{ij}) \tag{2.8b}$$

Hence, using the above two equations, log-linear regression analysis apply to the survey matrix. $Ln(T_{ij})$ is dependent variable and $Ln(P_i)$, $Ln(A_j)$, $Ln(d_{ij})$, and $Ln(t_{ij})$ are independent variables; $Ln(k)$ is intercept constant. Using the coefficients obtain from regression analysis, the trips can be distributed among TAZs.

2.3.2 Gravity Model Friction-factor Method

Viton (1994) used the below from of the gravity model to distribution the production and attraction among zones:

$$T_{ij} = \frac{P_i A_j F_{ij}}{\sum_m A_m F_{im}} \tag{2.9}$$

where F_{ij} is called friction-factor or impedance-factor. The gravity model calibrate by adjusting the friction-factor. The procedure for calibration of the gravity model has shown in Figure 2.2. The stepwise procedure is:

1. Assume $F_{ij}=1$
2. Calculate the estimated trips by distributing the productions and attractions (from trip generation step) among the specified zones, using the above equation.
3. Check the values of the estimated trips and the observed (from survey matrix) trips.
4. Calculate the F_{ij} factor values according to the following formula:

$$F(adjusted) = F(previous) * \frac{Trips(observed)}{Trips(estimated)}$$

5. When the ratio of trips observed to trips calculated become close to one, then stop calibrating.
6. Now forecast the trips using the calibrated gravity model.

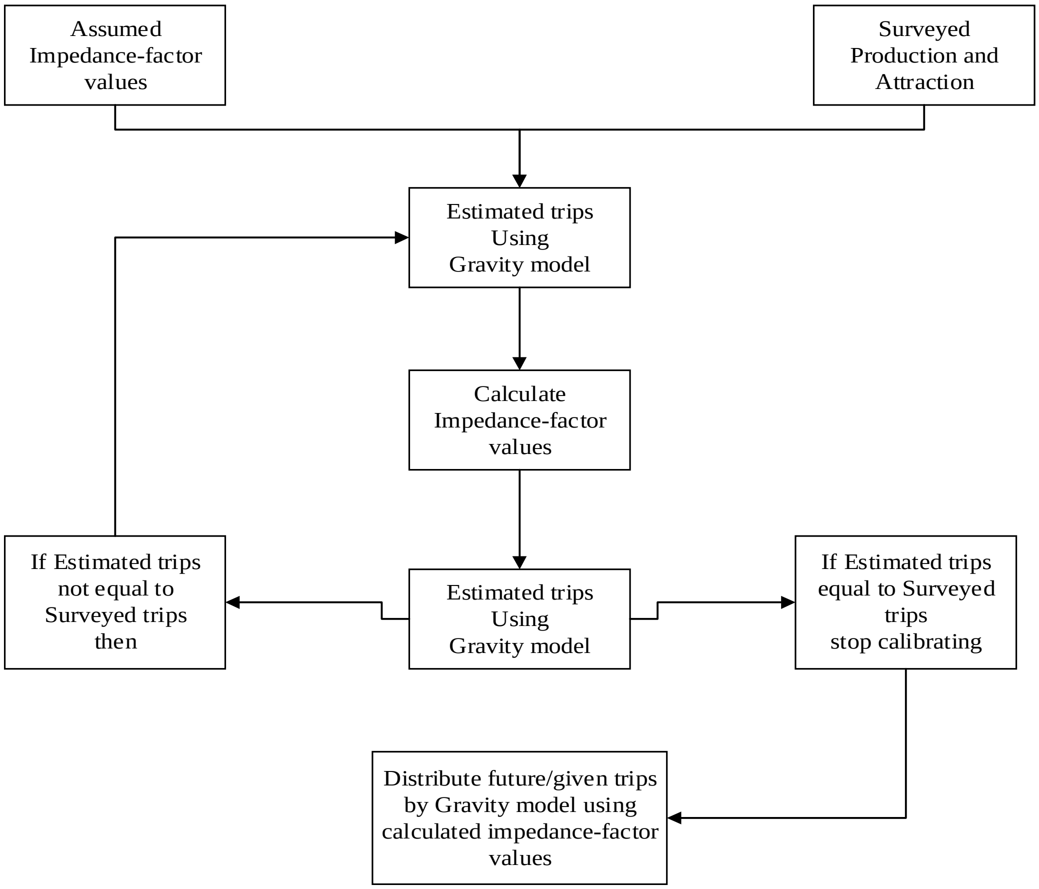


Figure 2.2 Flow chart showing the calibration of gravity model

2.4 Data Availability and Model Type in Freight Studies

Any freight transport model is govern by the data availability; hence, to know what the available data sources for freight transport modelling are necessary and important. Tavasszy & de Jong (2014b) presented a detailed discussion on data availability and model types, in which freight transport data was divided into several types. For example, trade statistics, published by international organizations e.g., EU or World Bank, consist of import/export to and from a country by some specific commodity classifications. National accounts data are usually published by national statistics offices and include description of the commodity flow in terms of monetary values e.g., input-output (I-O) tables. Transport statistics, for instance roadside surveys, include information about vehicle/truck origin and destination, which is used to generate O-D matrices. O-D and PC matrices can be similar if from producer to consumer only one mode of transport used, however, if it is a transport chain i.e. road to road, then sea, afterwards sea to rail and then rail to road; there will be four O-D flows while one PC flow. Such surveys usually perform by national statistics offices, which include information at O-D level, in units of tons and commodity is usually classify according to NSTR (Nomenclature uniforme des marchandises pour les Statistiques de Transport, Revisée) or NST-2000. Shipper surveys which collect data from firms through interviews and include information about a sample of goods (value and weight, producer and consumer and transport chain of goods) e.g. US Commodity Flow Survey, and may perform by statistical offices; however, the interval is not regular, and very difficult to access. Sometime if particular or more specific details required, stated preference data obtained from firms. Consignment bills and RFID (Radio Frequency Identification) are administrative documents for shipments and electronic tags, respectively. Traffic count data can be manual or automatic, and used for travel time calculation. Others types of data can be transport safety inspection data, network data, cost functions and terminal data. Table 2.2 shows the type of data and its use in freight transport modelling. It has shown that for the gravity models; trade statistics and transport statistics (roadside surveys) are required. However, for the PC matrices, which show the production and consumption of goods, trade statistics and national accounts data are necessary. Disaggregate models for freight generation and distribution are difficult to develop.

2.5 Summary

In this chapter, as a background to upcoming modeling sections, a brief overview of the literature for the O-D estimation has been provided. After a general description of the 4-step modelling approach, methods employed in estimation of O-D matrix, more specifically the trip generation and trip distribution models, and their data requirements were discussed. If O-D estimation would be done based on a survey matrix, such as roadside surveys, it may provide a sparse matrix, based on the sampling rate and survey locations. But, such matr—it may be possible that the trucks are not observing there or it may be missed in the survey. There are numerous methods to estimate the complete O-D matrix. Trip generation referes to the estimation of trips produced and attracted, for the TAZs. In trip distribution step, the produced and attracted trips from the trip generation step, are distribute among the TAZs. There are various models i.e. growth factor model or gravity model, to distributed these produced and attracted trips.

Table 2.2 Type of data sources and their use in freight transport modeling (Tavasszy & de Jong, 2014b)

Data Sources	Use in Freight Transport Modelling
Trade statistics	Estimation of Production-Consumption (PC) matrices for the base year Aggregate gravity-type models for generation and distribution at the PC level
National account data	Estimation of PC matrices for the base year Aggregate I-O models and SCGE models for generation and distribution
Transport statistics (Roadside survey)	Estimation of Origin-Destination (O-D) matrices for the base year Estimation of gravity-type models for generation and distribution at the OD level Estimation of aggregate mode choice models Load factors (cargo weight to vehicle capacity) Empty running
Shipper surveys	Estimation of PC matrices for the base year Estimation of disaggregate mode choice models Estimation of transport chain choice models Estimation of disaggregate shipment size choice models Estimation of disaggregate joint models (mode-shipment; mode-supplier) Value-to-weight ratios
Stated preference surveys	Estimation of disaggregate mode choice models Estimation of transport chain choice models Estimation of disaggregate shipment size choice models Estimation of disaggregate joint models (mode-shipment; mode-supplier) Monetary value of service attributes (e.g. value of time)
Consignment bills and RFID data	Estimation of O-D matrices for the base year Estimation of disaggregate mode choice models Estimation of disaggregate shipment size choice models Estimation of disaggregate joint models (mode-shipment; mode-supplier)
Traffic count data	Estimation of O-D matrices for the base year Estimation of route choice models Calibration data
Traffic safety inspection data	Load factors
Network data with costs functions	Direct input for the estimation of aggregate and disaggregate mode choice models and joint models Direct input for the estimation of route choice models
Terminal data	Direct input for the estimation of transport chain choice models

CHAPTER 3

MODELING OF INTERCITY TRUCK TRAFFIC IN TURKEY

Trucking is the principal mode choice in Turkey; around 90 % of the overall inland freight ton-km carry out by trucks (TurkStat, 2011). The methodology developed in this study is limited only to truck traffic on intercity roads, and not to commodity flow. It is not easy to model freight-ton with in the capability of this model. Truck traffic mobility is simple, as survey sampling is based on truck trips. Since large share of the commodity is carry out by trucks, modal split analysis has not been conducted. Furthermore, network assignment for the truck traffic has also not been covered in this methodology. This methodology has been developed empirically using the two steps of the four-step model; trip generation and trip distribution, in order to estimate the number of truck trips among the 81 provinces of Turkey, as origin and destination pairs in the form of a complete O-D matrix.

The objectives of this study are two-fold. The first objective is to estimate the complete O-D matrix, in terms of truck traffic, for the 81 provinces of Turkey—by establishing a relationship between truck trips and the socio-economic characteristics of the provinces. The second objective is to reproduce the trip generation and trip distribution as an input for the last step of four-step model, i.e. network assignment. The model developed is unimodal (only trucks), for intercity roads of Turkey.

3.1 Introduction

Turkey is included in the Nomenclature of Territorial Units for Statistics (NUTS). According to this, the three NUTS levels are:

- NUTS-1: 12 Regions
- NUTS-2: 26 Sub-regions
- NUTS-3: 81 Provinces

Figure 3.1 and Figure 3.2 shows the NUTS-1 and NUTS-2 map of Turkey. Analysis have conducted at the provincial level, i.e. for the 81 provinces of Turkey, which can be seen in Figure 3.3. These provinces code and their names have shown in Table 3.1.

Table 3.1 Province code and name

Code	**Name**	**Code**	**Name**	**Code**	**Name**
1	Adana	**28**	Giresun	**55**	Samsun
2	Adiyaman	**29**	Gumushane	**56**	Siirt
3	Afyonkarahisar	**30**	Hakkari	**57**	Sinop
4	Agri	**31**	Hatay	**58**	Sivas
5	Amasya	**32**	Isparta	**59**	Tekirdag
6	Ankara	**33**	Mersin	**60**	Tokat
7	Antalya	**34**	Istanbul	**61**	Trabzon
8	Artvin	**35**	Izmir	**62**	Tunceli
9	Aydin	**36**	Kars	**63**	Sanlıurfa
10	Balikesir	**37**	Kastamonu	**64**	Usak
11	Bilecik	**38**	Kayseri	**65**	Van
12	Bingol	**39**	Kirklareli	**66**	Yozgat
13	Bitlis	**40**	Kirsehir	**67**	Zonguldak
14	Bolu	**41**	Kocaeli	**68**	Aksaray
15	Burdur	**42**	Konya	**69**	Bayburt
16	Bursa	**43**	Kutahya	**70**	Karaman
17	Canakkale	**44**	Malatya	**71**	Kirikkale
18	Cankiri	**45**	Manisa	**72**	Batman
19	Corum	**46**	Kahramanmaras	**73**	Sirnak
20	Denizli	**47**	Mardin	**74**	Bartin
21	Diyarbakir	**48**	Mugla	**75**	Ardahan
22	Edirne	**49**	Mus	**76**	Igdir
23	Elazıg	**50**	Nevsehir	**77**	Yalova
24	Erzincan	**51**	Nigde	**78**	Karabuk
25	Erzurum	**52**	Ordu	**79**	Kilis
26	Eskisehir	**53**	Rize	**80**	Osmaniye
27	Gaziantep	**54**	Sakarya	**81**	Duzce

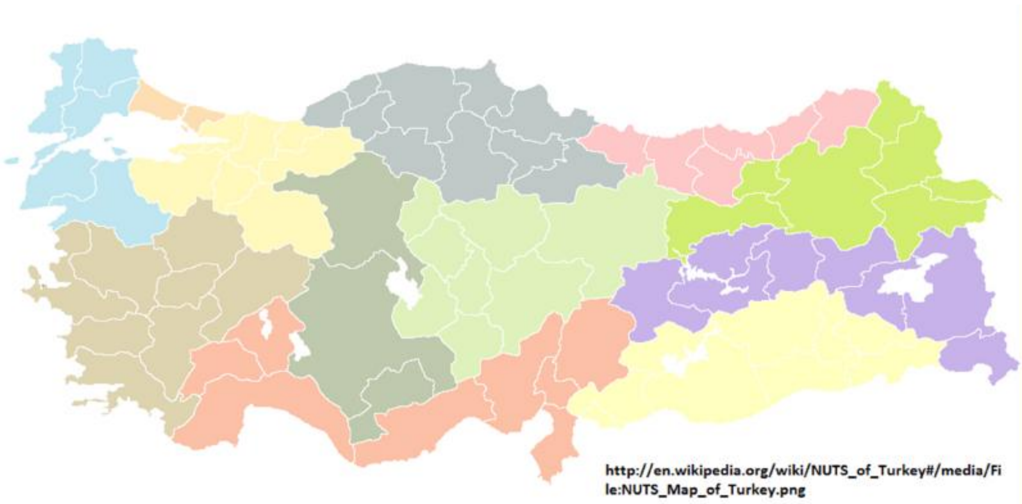
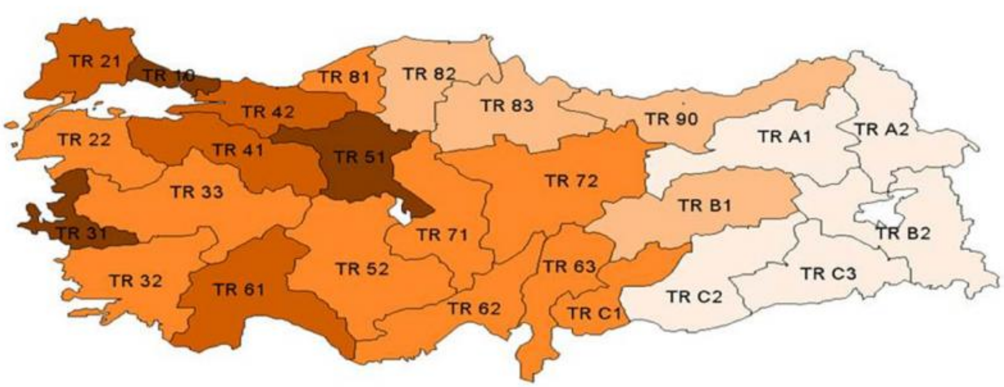


Figure 3.1 NUTS-1 map of Turkey



Source: https://ipa.sanayi.gov.tr/en/content/what-is-regional-competitiveness/113

Figure 3.2 NUTS-2 map of Turkey

Figure 3.3 Provinces of Turkey (NUTS-3)

3.2 Demographic and Socio-economic Variables

Demographic and socioeconomic variables play an important role in the number of truck trip produced and attracted to a particular TAZ. The direct way to estimate the number of truck trips is to establish a relationship with the employment, population, and land area at zone, district, or regional level (Kuzmyak, 2008). They can explain the trip produced and attracted to each province, by fitting multiple linear regression analysis. Hence, it is possible to estimate future year trip produced and attracted to a province, by using future demographic and socioeconomic data for that province. These variables are use as Independent variables in the regression analysis, which represents the social and economic activities, and demographic structures of the provinces. It is important to select these independent variables carefully, which explain the relationship between the truck trips and social and economic conditions of that TAZ. The demographic and socioeconomic variables i.e. population, number of households, vehicle ownership etc. are available at provincial level. These variables source is Turkish Statistics Institute called TurkSTAT. The variables and their acronyms, which are available at provincial level are shown in Table 3.2.

Table 3.2 Independent variables and their acronyms

1	POP	Population
2	POPSQ	Population Square
3	POP3	Cubic Population
4	LOGPOP	Logaritmic Transformation of Population
5	NHH	Number of Households
6	NHHSQ	Number of Households Square
7	NHH3	Cubic Number of Households
8	LOGNHH	Logaritmic Transformation of Number of Households
9	LS	Land Square
10	DENSITY	Density (Person per Square KM)
11	NHHPLS	Number of Households Per Land Square
12	EMP	Number of Employees
13	EMPSQ	Number of Employees Square
14	EMP3	Cubic Number of Employees
15	LOGEMP	Logaritmic Transformation of Number of Employees
16	EMPPLS	Number of Employees Per Land Square
17	EMPP1000PER	Number of Employees Per 1000 Persons
18	POPPEMP	Population Per Number of Employees
19	NHHPEMP	Number of Households Per Number of Employees
20	EMPP1000NHH	Number of Employees Per 1000 Households
21	EMPPPC	Number of Employees Per Passenger Car Ownership
22	EMPPTT	Number of Employees Per Total Truck Ownership
23	EPNTV	Number of Employees Per Total Vehicle Ownership
24	NTV	Number of Registered Total Vehicles
25	NTVP1000NHH	Number of Total Vehicles Per 1000 Households
26	PC	Number of Registered Passenger Car
27	TT	Number of Registered Total Truck
28	TTP1000PER	Number of Registered Total Truck Per 1000 Persons
29	TTP1000HH	Number of Registered Total Truck Per 1000 Households
30	TTSQ	Number of Registered Total Truck Square
31	TT3	Cubic Number of Registered Total Truck
32	PCP1000PER	Passenger Car Per 1000 Persons
33	PCP1000NHH	Passenger Car Per 1000 Households
34	ER	Employment Rate
35	UNER	Unemployment Rate
36	MBT	Minibus Number
37	BT	Bus Number
38	STT	Small Truck Number
39	IPE	Port Existence

For all provinces, independent variables obtained from TurkStat website (TurkStat, 2011). The major independent variables are within the low quality databases of Turkey, for year 2011. The pure data of population (POP), number of households (NHH), land square (LS), population density (DENSITY), number of employees (NEMP), total number of registered vehicles (NTV), and total registered truck numbers (TT) obtained from TurkStat. The total number of independent variables used in this study are thirty nine. Gross Domestic Produce (GDP) is not available, at provincial level, after year 2003—therefore, it is not possible to use this variable. Unal (2009) used trend extrapolation to estimate the GDP, for the year 2004. Furthermore, a dummy variable for the ports, called International Port Existence (IPE) included in the analysis.

Although these all independent variable, when use combine, can give high R-square value, but it is not possible to include all these variables, since there is usually a very high correlations among these independent variables; which may lead to multicollinearity. Variables that have high correlation (>0.80) with production and atraction values are summarized in Table 3.3.

In order to further reduce the number of independent variables, these thirty nine independent variables relating to trip production and attraction were factor analyzed using principal component analysis (PCA) with varimax rotation. Kaiser (1974) recommends KMO value of at least of .5, and that values between .5 and .7 are mediocre. After running the PCA in SPSS, the KMO value of .763, for these thirty nine independent variables indicate that the set of variables are suitable for factor analysis. The eigenvalues indicated to select six variables, which has shown in Table 3.4. The PCA analysis results have shown in Table 3.5. The LS and IPE variables have been revealed by the PCA analysis. Based on the PCA and correlations, the final selected independent variables and their units are available in Table 3.6.

Table 3.3 Strongly correlated variables (for 2011 values)

Variables	Production	Attraction	POP	LOGPOP	NHH	LOGNHH	EMP
Production	**1.00**	**0.98**	**0.88**	**0.83**	**0.89**	**0.85**	**0.89**
Attraction	**0.98**	**1.00**	**0.85**	**0.83**	**0.86**	**0.85**	**0.86**
POP	**0.88**	**0.85**	**1.00**	0.71	**0.99**	0.71	**1.00**
LOGPOP	**0.83**	**0.83**	0.71	**1.00**	0.70	**0.96**	0.72
NHH	**0.89**	**0.86**	**0.99**	0.70	**1.00**	0.72	**1.00**
LOGNHH	**0.85**	**0.85**	0.71	**0.96**	0.72	**1.00**	0.73
EMP	**0.89**	**0.86**	**1.00**	0.72	**1.00**	0.73	**1.00**
LOGEMP	**0.86**	**0.85**	0.73	**0.98**	0.73	**0.98**	0.74
NTV	**0.89**	**0.87**	**0.98**	0.72	**0.99**	0.75	**0.98**
PC	**0.87**	**0.84**	**0.98**	0.66	**0.99**	0.69	**0.98**
TT	**0.89**	**0.86**	**0.98**	0.71	**0.98**	0.72	**0.98**
MBT	**0.85**	**0.82**	**0.97**	0.73	**0.97**	0.74	**0.97**
BT	**0.86**	**0.83**	**0.98**	0.63	**0.99**	0.66	**0.99**
STT	**0.89**	**0.87**	**0.99**	0.69	**1.00**	0.71	**0.99**

Variables	LOGEMP	NTV	PC	TT	MBT	BT	STT
Production	**0.86**	**0.89**	**0.87**	**0.89**	**0.85**	**0.86**	**0.89**
Attraction	**0.85**	**0.87**	**0.84**	**0.86**	**0.82**	**0.83**	**0.87**
POP	0.73	**0.98**	**0.98**	**0.98**	**0.97**	**0.98**	**0.99**
LOGPOP	**0.98**	0.72	0.66	0.71	0.73	0.63	0.69
NHH	0.73	**0.99**	**0.99**	**0.98**	**0.97**	**0.99**	**1.00**
LOGNHH	**0.98**	0.75	0.69	0.72	0.74	0.66	0.71
EMP	0.74	**0.98**	**0.98**	**0.98**	**0.97**	**0.99**	**0.99**
LOGEMP	**1.00**	0.75	0.69	0.73	0.76	0.67	0.72
NTV	0.75	**1.00**	**0.99**	**0.98**	**0.96**	**0.97**	**0.99**
PC	0.69	**0.99**	**1.00**	**0.98**	**0.96**	**0.98**	**0.98**
TT	0.73	**0.98**	**0.98**	**1.00**	**0.95**	**0.96**	**0.97**
MBT	0.76	**0.96**	**0.96**	**0.95**	**1.00**	**0.94**	**0.96**
BT	0.67	**0.97**	**0.98**	**0.96**	**0.94**	**1.00**	**0.99**
STT	0.72	**0.99**	**0.98**	**0.97**	**0.96**	**0.99**	**1.00**

Table 3.4 PCA eigenvalues

Component	**Initial Eigenvalues**		
	Total	**% of Variance**	**Cumulative %**
1	20.8	56.215	56.215
2	6.196	16.745	72.96
3	2.799	7.564	80.524
4	2.431	6.571	87.095
5	1.819	4.916	92.011
6	1.009	2.728	94.739

Extraction Method: Principal Component Analysis.

Table 3.5 PCA analysis for independent variables

Component Matrix[a]						
	Component					
	1	2	3	4	5	6
BT	**.987**					
NHH	**.987**					
EMP	**.986**					
STT	**.985**					
POP	**.984**					
PC	**.972**					
NTV	**.972**					
TT	**.964**		.172			
MBT	**.962**			-.107		
TTSQ	**.961**	.201				
NHHSQ	**.957**	.224	-.118			
EMPSQ	**.955**	.229	-.120			
POPSQ	**.953**	.235	-.118	.103		
NHHPLS	**.951**	.185	-.139			
DENSITY	**.946**	.215	-.111			
EMPPLS	**.945**	.199	-.135			-.108
TT3	**.936**	.254	-.142	.131		
NHH3	**.926**	.268	-.160	.138		
EMP3	**.923**	.270	-.163	.140		
POP3	**.922**	.272	-.163	.141		
LOGNHH	**.700**	-.427	.362	-.346	.165	-.126
LOGEMP	**.689**	-.303	.408	-.366	.277	-.128
LOGPOP	**.678**	-.244	.511	-.379	.158	-.118
EPNTV	-.266	**.874**		-.177	.157	
PCP1000PER	.398	**-.841**	-.185			.113
EMPPPC	-.275	**.831**	.264	.108	.177	
PCP1000NHH	.448	**-.826**				.132
NTVP1000NHH	.234	**-.815**		.144		
EMPP1000NHH	-.277	**.776**	.131		.483	
NHHPEMP	.276	**-.722**			-.515	
EMPP1000PER		-.286	**-.660**	.147	.650	
POPPEMP		.311	**.655**	-.112	-.654	
LS	.122	-.245	.494	-.408	**.308**	.438
TTP1000PER		-.283	.386	**.826**	.230	
TTP1000HH		.136	.615	**.726**	.152	
EMPPTT	-.182	.522	-.445	**-.614**		
IPE	.459					**-.804**

Extraction Method: Principal Component Analysis.
a. 6 components extracted.

Table 3.6 Variables and their explanation

Variable	Explanation	Unit
POP	Population	Millions
NEMP	Number of employees	Hundreds
NHH	Number of Households	Hundreds
IPE	International Port Existence	Dummy variable
LS	Land square	Km sq.

3.3 Roadside Axle Survey Data

The Turkish General Directorate of Highways (TGDH) who perform roadside axle surveys two to three times, annually, has provided the data used for this study. TGDH has been collecting this data electronically since 1996, while the data used for this study ranges from year 2007 to 2011. The interviews are conduct on intercity roads at around 40 strategic locations, annually. Trucks stop at random to prevent any systematic bias. Unal (2009) discussed in very detail the complete procedure for how the survey is conducted.

The data include information about truck type (rigid or articulated), production year, commodity type and weight, empty weight, load carrying capacity, as well as origin and destination of the trip, which has summarized in Table 3.7.

Table 3.7 Roadside axle survey data structure

Location	Vehicle	Trip	Commodity
Date Time Location Direction Hourly volume	Truck type Axle type Body type License number Production year Empty weight Load carrying capacity	Origin Destination Payload	Commodity Type

One of the limitations in the data is that the survey conduct on state roads, which include mainly intercity truck transports. As a result, the analysis is not representative for intra-city transports, which will behave differently. Secondly, information about trip chains, truck tours, warehouses, as well as loading and unloading at transitional hubs is not included in this data set. Nevertheless, it has some distinctive aspects and features. For instance, in case of a developing country, the data set represents a relative unique disaggregated data set. Such kind of data is available in most EU countries, yet hard to obtain due to privacy reasons. However, in case of developing countries such statistics are almost never available due to lack of surveys and resources.

Table 3.8 shows the descriptive statistics of the roadside axle surveys from 2007 to 2011. A total number of 53,383 trucks surveyed at 246 different locations across whole Turkey. The average trips distance is around 500 km.

Table 3.8 Descriptive statistics of the roadside axle surveys, 2007-2011

Truck	Year	Surveyed Trucks		Vehicle-Km (%)	Ton-Km (%)	Trip Distance (Km)	Payload (Ton)
		Number	%				
All Trucks	2007	11,572	21.7	21.6	22.4	543	12.6
	2008	8,104	15.2	14.7	14.1	524	12.1
	2009	12,086	22.6	19.5	20.1	492	11.9
	2010	11,289	21.1	22.4	23.3	458	11.5
	2011	10,332	19.4	21.8	20.2	445	11.4
	Total	53,383	100.0	100.0	100.0	492.4	12.2

3.4 Existing State of Truck Traffic Modeling in Turkey

Three studies, which are very relevant with truck traffic modeling in Turkey, are presented here. These studies are 1) modeling of freight transportation on Turkish highways by Unal (2009), 2) estimation of road freight transportation emissions in

Turkey by Ozen (2013), and 3) estimation of freight transportation by Guler and Vitosoglu (2013).

3.4.1 Trip Generation and Distribution by Unal (2009)

Unal (2009) estimated the O-D matrix using the roadside axle surveys from 1998 to 2004. The survey data was aggregated, which were consists of 42,164 surveyed trucks in order to obtain observed city level sample 81x81 O-D matrices. The three main steps were development of the base matrix; trip generation; and trip distribution analysis for intercity truck transportation in Turkey.

Unal (2009) enlarged the base matrix for the year 2004, however, the enlargement procedure has not been described there. In trip generation step, the equations were developed for the truck trips and the tonnage of goods, using fifty six independent variables. Unal (2009) had obtained the below equations, from regression analysis, using 2004 variables statistics:

Freight Trip Production:

Number of Produced Trips = 70,498.06 + 0.98*(Number of Employees)
+ 302,163.4 (if International Port Exist) (3.1a)

Freight Trip Production = 1,542,173 + 1.294*(GDP Million TL)
(Tons of Moved Goods) + 3,928,667 (if International Port Exist) (3.1b)

Freight Trip Attraction:

Number of Attracted Trips = -25,454 + 0.287*Population
+ 672.976 *Passenger Car Own. per 1000 Household (3.2a)

Freight Trip Attraction = -333,701 + 3.556*(Population) + 6317.94* (Passenger Car
(Tons of Moved Goods) Ownership per 1000 Households) (3.2b)

In the trip distribution step, to distribute the trips among the 81 provinces from the trip generation step—Unal (2009) applied TRANPLAN travel demand software—to estimate the coefficients of the gravity model. As a result, the following form of gravity model equation had obtained:

$$T_{ij} = 0.498 \frac{P_i^{0.641} A_j^{0.628}}{d_{ij}^{0.894}} \quad (3.3)$$

3.4.2 Trip Distribution and Network Assignment by Ozen (2013)

Ozen (2013) modified the equations of Unal (2009) gravity model with 2007-2009 values in order to evaluate the network assignment step and compared the link flow values obtained from network assignment step with values provided by Turkish General Directorate of Highways. Ozen (2013) obtained the following value for the gravity model equation:

$$T_{ij} = 0.0996 \frac{P_i^{0.641} A_j^{0.628}}{d_{ij}^{0.894}} \quad (3.4)$$

Table 3.9 shows that around 76-83% of the trucks were on either time-based shortest path (TbSP) or distance-based shortest path (DbSP). It can be further seen that around 20% of the trucks were was neither on TbSP nor on DbSP; which suggests that there are some other factors that affects truck assignment. Ozen (2013) discussed in detail those factors.

Table 3.9 Evaluation of network assignment principles of surveyed trucks (Ozen, 2013)

	2007		**2008**		**2009**	
Number of Surveyed Intercity Trucks	11572		8104		12086	
Survey location on	**Number of Trips**	**(%)**	**Number of Trips**	**(%)**	**Number of Trips**	**(%)**
Both TbSP and DbSP	7814	(67.5%)	5857	(72.3%)	8123	(67.2%)
Only TbSP	853	(7.4%)	785	(9.7%)	863	(7.1%)
Only DbSP	248	(2.1%)	99	(1.2%)	230	(1.9%)
Either TbSP or DbSP	8915	(77.0%)	6741	(83.2%)	9216	(76.2%)
Neither TbSP nor DbSP*	2657	(23.0%)	1363	(16.8%)	2870	(23.8%)

*Cannot be validated by TbSP or DbSP assignment

3.4.3 Trip Distribution by Guler and Vitosoglu (2013)

Guler and Vitosoglu (2013) calculated the intercity freight transportation matrices (O-D estimation) for the year 2009 using gravity model, for seven commodity groups moved among 81 provinces of Turkey. They used the GDP and inter-zonal distances in the gravity model calculation:

$$\log\left[att_{ij}^{f}\right] = \log\left(k_f\right) + \sim \log\left(GDP_{fi}\right) + \quad \log\left(GDP_j\right) - \text{¥} \log\left(d_{ij}\right) \tag{3.5}$$

where $\left[att_{ij}^{f}\right]$ = number of trucks carrying freight type f between provinces of i and j; k_f = coefficient of the gravity model; $\sim$, ,¥= calibration constants; GDP_{fi} = sectored gross domestic product by province for freight type f and province (zone) i; GDP_j = total gross domestic product by province (zone) j; d_{ij} = distance between province i and province j.

The intercity O-D freight transportation matrices were estimated for the year 2009 using below gravity model form , for nine commodity groups. The coefficient of the gravity model for the nine commodity groups are shown in Table 3.10.

$$T_{ij} = k_f \frac{(GDP_i)^{\tilde{}} \times (GDP_j)}{d_{ij}^{a}} \tag{3.6}$$

Table 3.10 Gravity model coefficients for nine commodity groups (Guler and Vitosoglu, 2013)

Freights	Independent variables	Coefficients	P	Freights	Independent variables	Coefficients	P
Total freight	GDP_i	0·547	0·00	8th freight type	GDP_{8i}	0·161	0·00
$R^2 = 0·699$	GDP_j	0·524	0·00	(forest products)	GDP_j	0·251	0·00
	d_{ij}	1·021	0·00	$R^2 = 0·359$	d_{ij}	0·385	0·00
	k	5·838	0·00		k_8	1·851	0·00
1st freight type	GDP_{1i}	0·269	0·00	9th freight type	GDP_{9i}	0·220	0·00
(empty trucks)	GDP_j	0·290	0·00	(others)	GDP_j	0·329	0·00
$R^2 = 0·651$	d_{ij}	1·086	0·00	$R^2 = 0·601$	d_{ij}	0·616	0·00
	k_1	1·543	0·00		k_9	2·537	0·00
2nd freight type	GDP_{2i}	0·308	0·00	(4+3) freight types	$GDP_{(4+3)i}$	0·200	0·00
(agricultural products)	GDP_j	0·305	0·00	$R^2 = 0·605$	GDP_j	0·326	0·00
$R^2 = 0·457$	d_{ij}	0·571	0·00		d_{ij}	0·850	0·00
	k_2	3·185	0·00		k_2	1·657	0·00
3rd freight type	GDP_{3i}	0·087	0·00	(9+6) freight types	$GDP_{(9+6)i}$	0·283	0·00
(ores)	GDP_j	0·272	0·00	$R^2 = 0·639$	GDP_j	0·404	0·00
$R^2 = 0·330$	d_{ij}	0·434	0·00		d_{ij}	0·691	0·00
	k_3	1·347	0·00		$k_{(9+6)}$	3·312	0·00
4th freight type	GDP_{4i}	0·171	0·00	(8+7+5+2) freight types	$GDP_{(8+7+5+2)i}$	0·455	0·00
(construction materials)	GDP_j	0·272	0·00	$R^2 = 0·534$	GDP_j	0·407	0·00
$R^2 = 0·577$	d_{ij}	0·808	0·00		d_{ij}	0·648	0·00
	k_4	1·127	0·00		$k_{(8+7+5+2)}$	5·023	0·00
5th freight type	GDP_{5i}	0·230	0·00	(2+8) freight type	$GDP_{(2+8)i}$	0·345	0·00
(animal products)	GDP_j	0·217	0·00	$R^2 = 0·493$	GDP_j	0·356	0·00
$R^2 = 0·384$	d_{ij}	0·439	0·00		d_{ij}	0·599	0·00
	k_5	2·125	0·00		$k_{(2+8)}$	3·823	0·00
6th freight type	GDP_{6i}	0·238	0·00	(5+7) freight types	$GDP_{(5+7)i}$	0·242	0·00
(manufactured materials)	GDP_j	0·326	0·00	$R^2 = 0·375$	GDP_j	0·253	0·00
$R^2 = 0·557$	d_{ij}	0·598	0·00		d_{ij}	0·446	0·00
	k_6	2·651	0·00		$k_{(5+7)}$	2·532	0·00
7th freight type	GDP_{7i}	0·053	0·26				
(livestock)	GDP_j	0·148	0·00				
$R^2 = 0·198$	d_{ij}	0·273	0·00				
	k_7	0·619	0·11				

3.5 Proposed Methodology for Truck Traffic in Turkey

A methodology has been developed for the estimation of the O-D matrix. This proposed methodology firstly describes the survey matrix estimation processes in details; secondly, it explains the trip generation procedure for the 81 provinces of Turkey; lastly, it explains the estimation of the unobserved O-D pairs by gravity model, among the 81 provinces of Turkey.

3.5.1 Survey Matrix Estimation

TGDH conducts roadside surveys yearly, across different location in Turkey, which include information mainly about freight movement (tons-km) and Equivalent Single Axle Load (ESAL) for pavement design, in addition to origin and destination of freight also taken into account in these surveys. In order to obtain a consistent survey matrix, it is necessary that the trips cover all the TAZs. However, yearly survey hardly grasps all the trips made between all provinces of Turkey, i.e. it only consist of 10,000 to 12,000 trucks; implies it can't be taken as representative for each link of state roads. Therefore, if the yealy survey data for a number of years aggregated, the survey matrix obtain may cover majority of truck traffic. Hence, for the estimation of survey matrix for Turkey, the roadside axle survey data from 2007 to 2011 have combined together.

Yearly survey matrices have obtained, using the O-D data in the surveys and the survey location. The yearly suveys matrices were added up to form an intermediary total matrix. The intermediary total matrix has been enlarged to form the survey matrix. In summary, the survey matrix consists of 61,312 truck trips surveyed at 246 different locations across whole Turkey. The various steps involved in the estimation of the survey matrix have been shown in Figure 3.4.

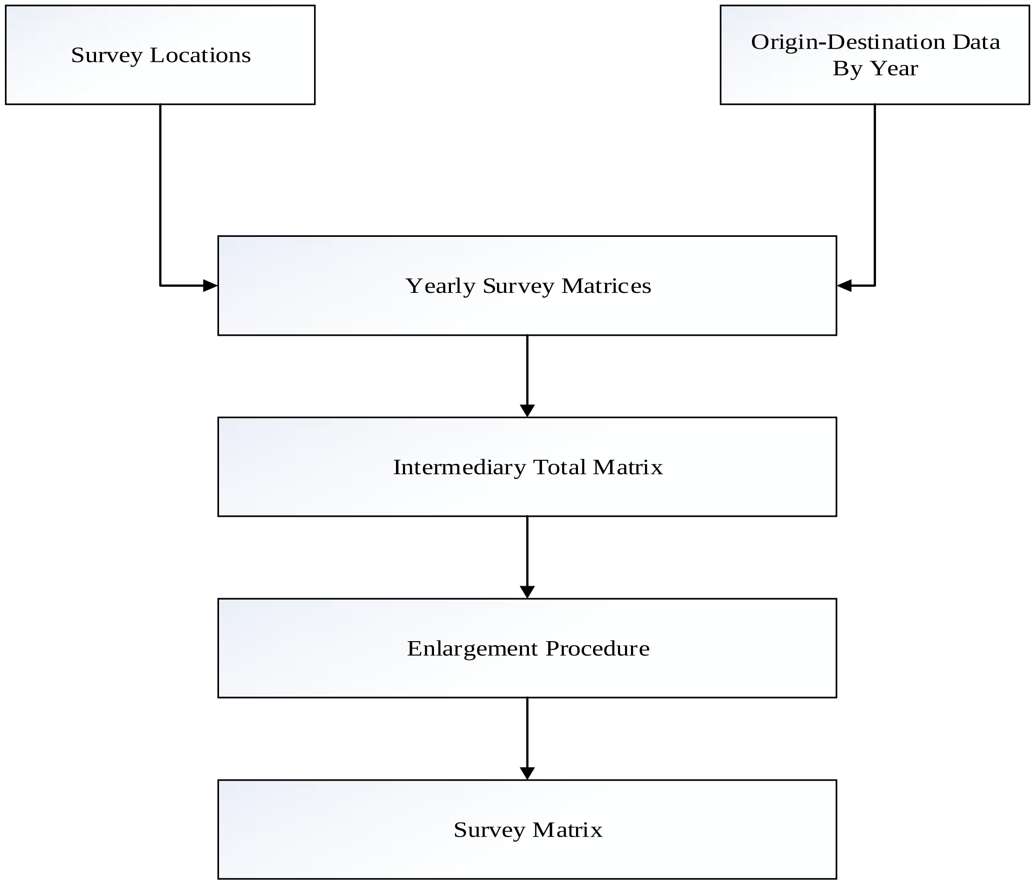


Figure 3.4 Survey matrix estimation flowchart

Yearly Survey Matrices

The number of survey locations from 2007 to 2011 has shown in Figure 3.5. In total from 2007 to 2011, the survey locations are 246 across the whole Turkey. Therefore, for each survey location, a matrix has estimated using MATLAB. Hence for each survey location, separate survey matrices have obtained, called axle survey matrix yearly $\left[T_{S,y}\right]$. The mathematical form of the matrix is:

$$\left[T_{S,y}\right]=\begin{pmatrix} t_{11} & \cdots & t_{1,81} \\ \vdots & \ddots & \vdots \\ t_{81,1} & \cdots & t_{81,81} \end{pmatrix} \quad (3.7)$$

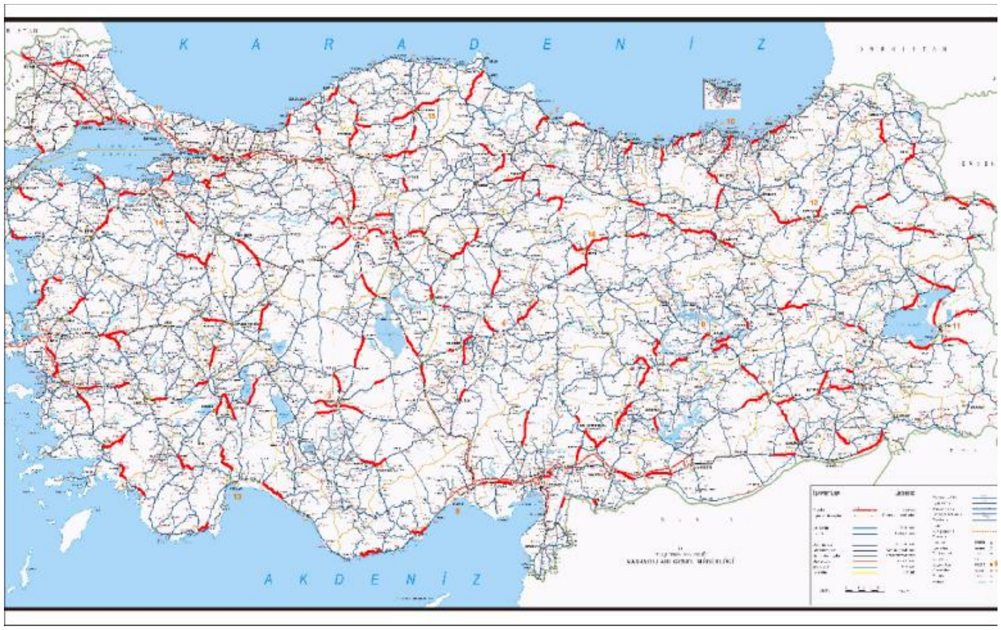


Figure 3.5 Location of all survey sections (in red) from 2007-2011

Intermediary Total Matrix

As it has mentioned earlier that in order to obtain a consistent data, survey data from 2007 to 2011 have combined. For 246 locations, these matrices have added to get, one intermediary total matrix [T_{IT}]:

$$[T_{IT}] = \sum_{y=1}^{5} [T_{S,y}] \tag{3.8}$$

Enlargement of the Survey Matrix

In order to enlarge intermediary total matrix [T_{IT}] to survey matrix, enlargement coefficient, C_N , were calculated, by dividing annual average daily truck traffic (AADTT) in total for both directions for section N (N=246) over total number of trucks and trailers in both directions for section N, N_T. These have calculated using the below equations:

$$C_N = \frac{AADTT_N}{N_T} \tag{3.9a}$$

$$N_T = \sum_{ij} t_{ij}^{IT} \tag{3.9b}$$

AADTT is the total truck traffic volume divided by 365 days. Truck traffic counting is done throughout Turkey, once every year. The counting sample survey includes a partial day, 7-day, 24-hour, and continuous truck classification counts. TGDH publish yearly AADTT values for different road sections. These values have obtained for year 2007 to 2011. N_T, which is the total number of trucks and trailers surveyed in the combined roadside axle survey, can be calculated by the summation of the cells in the intermediary total matrix [T_{IT}]. Thus, survey matrix $\left[T_{ST}\right]$ has calculated by multiplying enlargement coefficient, C_N, with intermediary total matrix [T_{IT}].

$$\left[T_{ST}\right] = C_N \left[T_{IT}\right] \tag{3.10}$$

3.5.2 Trip Generation

Trip generation refers to the estimation of produced and attracted (PA) trips for the TAZs. The PA trips estimated usually for a particular period to time through regression analysis using demographic and socio-economic data of that period. The regression analysis establish a relationship between the truck trips, and the socio-economic development—in the form of mathematical equations. In multiple linear regression analysis, the dependent variable is the number of trips (produced or attracted) from the survey, and independent variables are socio-economic data.

Figure 3.6 describes the methodology for the trip generation. The below equation shows the general form of the multiple linear regression.

$$\hat{Y} = \ _o + \ _1X_1 + \ _2X_2 + ... + \ _nX_n \qquad (3.11)$$

The selection of the independent variables have finalized by PCA and correlations among them. The main variables used are population, number of household, number of employees, land square, and port existence.

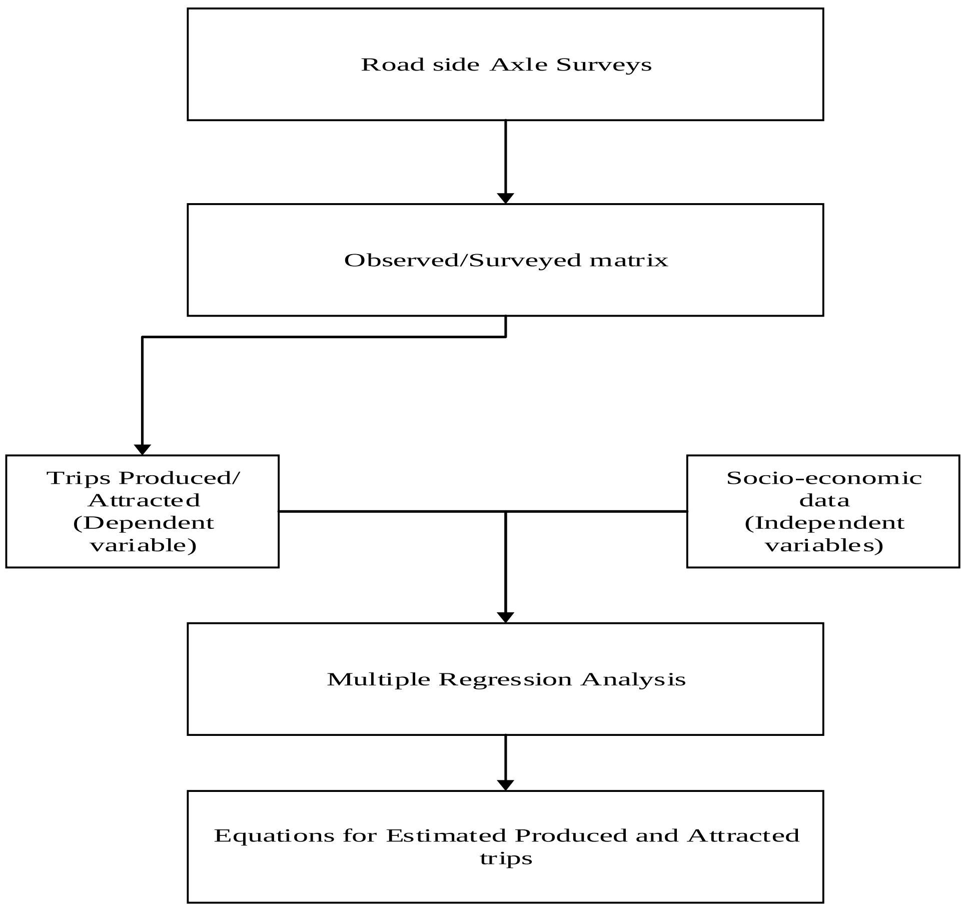


Figure 3.6 Framework for trip generation step

3.5.3 Trip Distribution

As mentioned earlier, the survey matrix is composed of 40 % empty cells. In order to have a complete O-D matrix, these empty cells values have to be estimated. Figure 3.5 shows a portion of survey O-D matrix. The gravity model has used to find the empty cell value. Gravity model has advantages over other models because it takes into account the actual impedance (in the form of distance or time etc.), while other models like growth factor model assume uniform growth which is generally unrealistic (Ortuzar and Willumsen, 2011).

Code	1	2	3	4	5	6	7	8	9
1	0	47	76	134	31	298	192	174	53
2	68	0	--	--	9	6	10	--	--
3	19	--	0	8	--	64	733	5	66
4	87	7	28	0	22	160	29	17	7
5	42	--	10	18	0	98	17	28	4
6	351	21	104	202	56	0	555	364	132
7	111	--	392	51	21	145	0	65	81
8	44	--	--	2	--	389	38	0	--
9	9	26	152	2	3	59	252	--	0

Figure 3.7 Snapshot of survey O-D matrix

Usually, the trips produced or attracted to a TAZ, from trip generation or survey matrix, are not equal. However, in order to apply gravity model, these trips produced and attracted should be equal (Ortuzar and Willumsen, 2011). This problem has solved by augmenting the survey matrix. An imaginary TAZ, having code 82, has added to the survey matrix—to make the production equal to attraction for each province. The distance, from all other 81 provinces to the imaginary TAZ, has selected in such a way that gravity model does not send flow to this TAZ—unless it is absolutely necessary.

In gravity model equations 2.7a and 2.7b using distance and time impedance, respectively; the gravity model the coefficients were estimated firstly. The estimated produced and attracted trips for the 81 provinces of Turkey have distributed using gravity model equations 2.8a and 2.8b. The coefficients have estimated using log form of the gravity model equations 2.9a and 2.9b. The flow chart, describing these steps, has shown in Figure 3.8.

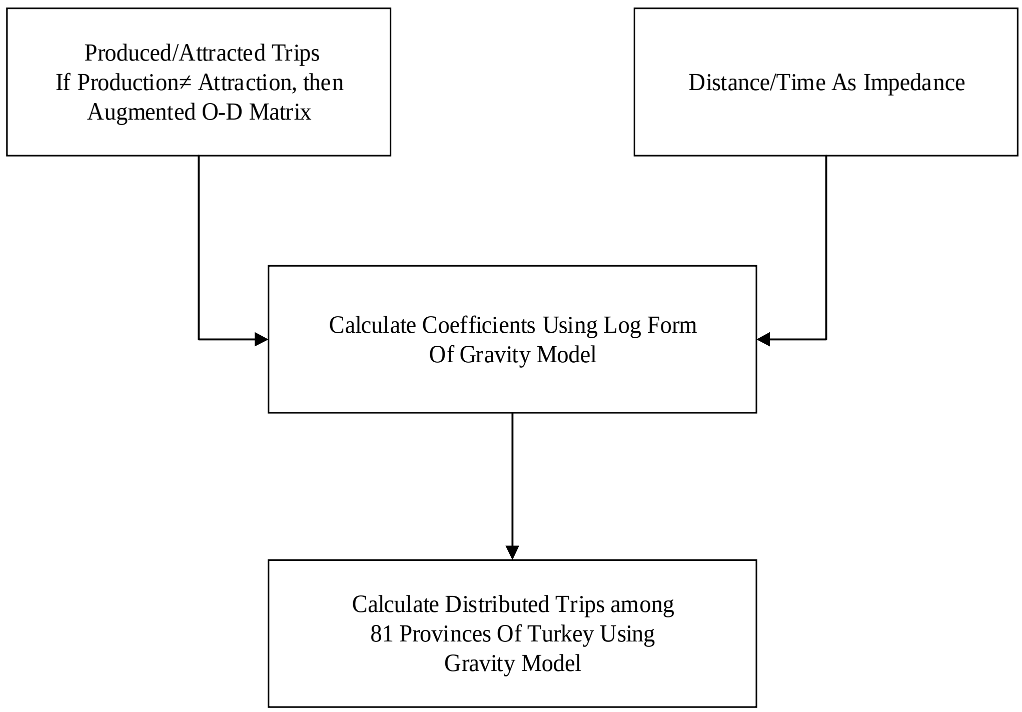


Figure 3.8 Trip distribution by gravity model flow chart

The inputs and the outputs of the gravity model are as follows:

Inputs:

1. The trips from the survey matrix among the 81 provinces.
2. The estimated produced and attracted trips from the trips generation steps, for the 81 provinces.
3. The shortest distance and time among the 81 provinces

Outputs:

1. k : proportionality constant
2. ~ : production exponent
3. : attraction exponent

4. ^{a} : impedence i.e. distance and time exponent.

Using the coefficients values obtained from the gravity model, the estimated produced and attracted trips from the trip generation step, have used to distribute the trips among the 81 provinces of Turkey. The complete O-D matrix has obtained by including the missing values estimated by the gravity model. The survey matrix is usually sparse, and some portion of it consists of empty cells (Ortuzar and Willumsen, 2011). Almost, 40 % of the survey matrix is empty, in this study. This problem occurs due to high number of O-D pairs, and large regions. Once the coefficients have calculated, these missing trips have also estimated.

3.6 Contribution of the Proposed Methodology

The methodology developed in this study is unique in the sense that for the first time it has applied to truck trips in Turkey. Unal (2009) also estimated the O-D matrix for the Turkey, however, the methodology described there is one way or another lacking in the empirical modeling. Unal (2009) combined the roadside axle survey data from 1998 to 2004 for the survey matrix (observed) but didn't mention the methodology for the aggregation of these surveys. Furthermore, enlargement procedure usually applied to observed matrix to form a consistent survey matrix. However, Unal (2009) didn't apply any enlargement procedure.

The methodology applied in this study, has clear and sound empirical background, for the estimation of the survey matrix. This methodology apply Willumsen (1978) procedure for the estimation of the survey matrix from the roadside axle surveys (traffic counts), which has solid background.

In trip generation step, Unal (2009) used GDP as independent variable in socio-economic data. However, from 2004 onward, TurkSTAT is no longer publishing GDP at provincial level. The roadside axle survey data used by Unal (2009) are from 1998 to 2004. Therefore, Unal (2009) used trend extrapolation for 2004 year GDP. Nonetheless, in this study independend variables have finalized using PCA and correlations among each other.

Unal (2009) distributed the produced and attracted trips from the trip generation step, using TRANPLAN travel demand software. However, there is no description of unobserved or missing trips in that study. In this study, the missing trips have estimated by fitting the regression of the log form of the gravity model—on the available O-D trips. The complete O-D matrix has developed by combining the available trips and the estimated missing trips.

3.7 Summary

In Turkey, truck freight modeling has contributions from Unal (2009) which estimated the O-D matrix using the roadside axle surveys from 1998 to 2004 by developing the base matrix (survey); trip generation; and trip distribution models. Ozen (2013) modified the equations of Unal (2009) gravity model with 2007-2009 values in order to evaluate the network assignment step and compared the link flow values obtained from network assignment step with values provided by Turkish General Directorate of Highways (TGDH). Guler and Vitosoglu (2013) calculated the intercity freight transportation matrices (O-D estimation) for the year 2009 using gravity model with GDP only, for seven commodity groups moved among 81 provinces of Turkey. The proposed methodology for the estimation of the O-D matrix for truck traffic on the intercity roads in Turkey starts with the determination of observed O-D matrix from roadside axle surveys from 2007 to 2011. Roadside axle survey data were obtained from TGDH, from 2007 to 2011. This data includes information about the origin and destination of truck trips. A total number of 53,383 trucks surveyed at 246 different locations across whole Turkey, from 2007 to 2011. The average trips distance is around 500 km. The data include only intercity trips. Proposed methodology has some advantages over the previous studies: It has sound empirical background for the estimation of the survey matrix and the combination of roadside axle survey data. The demographic and socio-economic variables have selected using PCA and correlations among them. The equations developed for the trip production and attraction are up-to-date. In addition, the missing or unobserved O-D trips have addressed using the log form of the gravity model.

CHAPTER 4

MODEL RESULTS FOR TRUCK TRAFFIC IN TURKEY

The results, of the proposed model in chapter 3, are presented here. Firstly, the survey matrix results are explained; secondly, trip generation results have shown; lastly, trip distribution results have described.

4.1 Survey Matrix Estimation Results

The survey matrix has dimensions of 81 by 81, at provincial level, which contains 6561 cell entries, out of these 2521 entries are empty, which corresponds to 40 %. These empty cells may be unobserved in survey which are called missing O-D pairs, or there may be possibility of actually no truck trips between that origin and destination province. Missing data occurs because most of the time it is not possible to survey all the trucks, at all locations. In addition, during the survey the TGDH does not stop some highly loaded trucks. It should be noted that the survey performs on inter-city roads, and hence the intra-city trips are excluded from analysis..

Out of 246 survey locations—in nineteen locations twice and in two locations thrice—surveys have conducted in different years, i.e. exact match locations. To normalize these effects, average has taken at those locations. For example, at section number 010-20,2, survey was performed in 2007 as well as 2009, with AADTT: 2347 and 2177 respectively, so average value of these two location was considered. In addition to these exact match locations, 17 locations were those, where close surveys have performed. For example at two close survey locations, i.e. 230-06,3 and 230-06,4, their location and AADTT studied in MapInfo, to decide whether these are duplication or separate links, and found 4 out of 17 locations were duplication, while 13 location were not repeating. Table 4.1 and Table 4.2 show the produced and attracted trips to these zones from survey matrix, respectively.

Table 4.1 Provincial trip productions (P_i) (from survey matrix)

Code	P_i	Code	P_i	Code	P_i
1	10021	**28**	2038	**55**	6873
2	1333	**29**	654	**56**	522
3	3701	**30**	257	**57**	509
4	3875	**31**	6188	**58**	2527
5	2126	**32**	2938	**59**	4951
6	16278	**33**	8745	**60**	2005
7	9341	**34**	25790	**61**	6452
8	2734	**35**	16474	**62**	380
9	3249	**36**	1374	**63**	2764
10	7225	**37**	2069	**64**	1317
11	1925	**38**	8488	**65**	3923
12	1006	**39**	2004	**66**	1661
13	1656	**40**	878	**67**	3954
14	2320	**41**	13265	**68**	1286
15	3099	**42**	6575	**69**	398
16	11441	**43**	3124	**70**	1258
17	1913	**44**	3240	**71**	3852
18	864	**45**	5631	**72**	2608
19	2497	**46**	3364	**73**	2863
20	4953	**47**	3100	**74**	1078
21	3816	**48**	2523	**75**	358
22	4478	**49**	1420	**76**	1534
23	3741	**50**	2291	**77**	576
24	1000	**51**	1310	**78**	1908
25	4021	**52**	2022	**79**	352
26	4522	**53**	2113	**80**	1278
27	5698	**54**	5821	**81**	2027
$\sum P_i$ = **311,740 trips per day**					

Table 4.2 Provincial trip attractions (A_j) (from survey matrix)

Code	A_j	Code	A_j	Code	A_j
1	7841	**28**	1908	**55**	6814
2	1753	**29**	674	**56**	1076
3	3664	**30**	488	**57**	1204
4	3786	**31**	5086	**58**	3511
5	1699	**32**	3190	**59**	4552
6	14504	**33**	7861	**60**	2024
7	10510	**34**	23377	**61**	7347
8	4768	**35**	16930	**62**	783
9	3416	**36**	1556	**63**	2561
10	7603	**37**	2119	**64**	1111
11	1997	**38**	8969	**65**	4996
12	1364	**39**	2041	**66**	1941
13	1663	**40**	1341	**67**	4087
14	2066	**41**	8627	**68**	1665
15	3274	**42**	6836	**69**	543
16	13103	**43**	2579	**70**	819
17	2435	**44**	3417	**71**	2865
18	883	**45**	4775	**72**	2350
19	3149	**46**	2998	**73**	5064
20	4746	**47**	2530	**74**	1230
21	4341	**48**	2866	**75**	319
22	4261	**49**	1542	**76**	1120
23	3339	**50**	2314	**77**	549
24	1294	**51**	1313	**78**	1692
25	4582	**52**	1864	**79**	302
26	4949	**53**	2144	**80**	1083
27	6147	**54**	6018	**81**	1633
$\sum A_j$ = **311,740 trips per day**					

From Table 4.1 and Table 4.2, it can be seen that the production and attraction are not equal for respective provinces, e.g. the number of trips produced from Istanbul are not equal to the number of trips attracted to Istanbul. Why these production and attraction values are not equal for each province?

The major problem in truck traffic forecasting is the trip chain behavior, which is lacking in the survey data. The roadside axle survey data does not take into account the vehicle tours, because the drivers do not mention it in stated preferences. Most of the times, truck drivers or companies try to minimize the transportation costs, which lead to independent trips and not to consider the backhaul route. It is prudent to assume that trucks make a substantial amount of trip chains (González-Calderón, Holguín-Veras, & Ban, 2012). Keeping this in mind, it implies that the production and attraction of a province cannot be equal. However, the total sum of production and attraction should be equal, which is true in this case.

4.2 Trip Generation Results

Trip generation models for truck trips have developed for 81 provinces of Turkey. Multiple regression analysis has applied to determine the relationship between demographic and socioeconomic variables of the 81 provinces of Turkey and truck trips. The dependent variable, i.e. the number of trips produced or attracted obtained from the survey matrix.

4.2.1 Trip Generation (PA) Models

To obtain trip production and attractions equations, multiple regression analysis have carried out. In total six models have developed for both trip production and trip attraction. The IPE has included in every model. The three main variables used in separate models are POP, NEMP, and NHH. In addition, LS has included in three out of the six models. Table 4.3 and Table 4.4 show the result for the trip production and trip attraction, respectively. All of the models and independent variables were significant. The inclusion of LS improves the model fit.

Table 4.3 Trip production regression results

	Model P1	Model P2	Model P3	Model P4	Model P5	**Model P6**
R^2	0.798	0.816	0.814	0.830	0.813	**0.831**
F	153.92	114.08	170.12	125.61	169.82	**127.95**
Variables						
Constant (t)	1741.36 (7.20)	931.31 (2.50)	1664.75 (7.12)	894.92 (2.50)	1825.77 (7.95)	**984.33** **(2.77)**
POP (t)	1982.57 (13.81)	1884.83 (13.26)				
NHH (t)					0.733 (14.59)	**0.689** **(14.17)**
NEMP (t)			0.468 (14.60)	0.446 (14.02)		
IPE (t)	2817.92 (3.59)	3192.35 (4.17)	2556.85 (3.37)	2927.77 (3.95)	2646.40 (3.49)	**3026.41** **(4.14)**
LS (t)		0.089 (2.78)		0.085 (2.76)		**0.092** **(3.01)**

Table 4.4 Trip attraction regression results

	Model A1	Model A2	Model A3	Model A4	Model A5	**Model A6**
R^2	0.756	0.791	0.774	0.806	0.774	**0.810**
F	121.08	97.09	133.74	106.88	133.63	**109.45**
Variable						
Constant (t)	1938.28 (7.85)	908.33 (2.50)	1864.24 (7.79)	874.55 (2.46)	2013.79 (8.57)	**955.85** **(2.72)**
POP (t)	1839.20 (12.555)	1714.94 (12.16)				
NEMP (t)			0.435 (13.27)	0.407 (12.87)		
NHH (t)					0.682 (13.26)	**0.638** **(13.06)**
IPE (t)	2163.14 (2.70)	2639.22 (3.48)	1910.23 (2.46)	2387.26 (3.24)	1933.09 (2.57)	**2470.88** **(3.40)**
LS (t)		0.113 (3.57)		0.109 (3.58)		**0.115** **(3.82)**

After six comparative analyses between population and number of households, the best model is same, for estimated production and attraction, which has the independent variables of NHH, IPE and LS. For this model, the truck trip production and attraction equations are below:

Truck Trip Production (Model P6);

Number of Produced Trips = f (NHH, IPE (Dummy), LS)

Number of Produced Trips = 984.33 + 0.689*NHH +3026.41*IPE + 0.092*LS

The best-fit production equation in terms of number of trucks is a function of number of households, land square and international port existence. Port existence can cause increase in number of truck trips produced, because of import. The regression is statistically significant, i.e. the value of R-square is 0.831. F-test or also called Analysis of Variance (ANOVA) test result has shown in Table 4.24 and F-value is 127.95 with highly significant p-value.

Truck Trip Attraction (Model A6);

Number of Attracted Trips = f (NHH, IPE (Dummy), LS)

Number of Attracted Trips = 955.85 + 0.639 *NHH +2466.622*IPE + .115*LS

The best-fit attraction equation in terms of number of trucks is a function of number of households, land square and international port existence. Port existence can cause increase in number of truck trips attracted, because of export. The regression is statistically significant, i.e. the value of R-square is 0.810. F-value is 109.45 with highly significant p-value.

Using the above model, the trip produced and attracted have estimated, for the 81 provinces, for 2011. These estimated produced and attracted trips have presented in Table 4.5 and Table 4.6, respectively. Istanbul (9.72%) is the center of highest truck trip production. Izmir (4.35%), Ankara (4.28%), Mersin (2.75%) and Konya (2.73%) are the other main production centers. Similarly, Kocaeli (2.33%), Bursa (2.30%), Samsun (2.28%), and Antalya (2.27%) have high trip production potentials. Likewise, Istanbul (8.61%) is also the main center of truck trip attraction, in Turkey. Ankara (4.11%), Izmir (3.97%), and Konya (2.93%) are the other main truck trips attraction centers.

Table 4.5 Estimated trip production ($\hat{P}_i$) from regression analysis for 2011

Code	$\hat{P}_i$	Code	$\hat{P}_i$	Code	$\hat{P}_i$
1	5886	**28**	2478	**55**	7126
2	2497	**29**	1811	**56**	1801
3	3629	**30**	1885	**57**	1955
4	2627	**31**	6927	**58**	4770
5	2142	**32**	2671	**59**	3237
6	13378	**33**	8590	**60**	2996
7	7105	**34**	30354	**61**	5870
8	1995	**35**	13602	**62**	1845
9	3883	**36**	2312	**63**	4694
10	4997	**37**	2931	**64**	2182
11	1795	**38**	4804	**65**	4058
12	2094	**39**	2303	**66**	3118
13	2169	**40**	2017	**67**	2493
14	2303	**41**	7279	**68**	2362
15	2209	**42**	8519	**69**	1448
16	7187	**43**	3270	**70**	2273
17	6090	**44**	3343	**71**	1953
18	2042	**45**	4987	**72**	1970
19	3236	**46**	3963	**73**	2036
20	4080	**47**	2631	**74**	1539
21	4201	**48**	4064	**75**	1622
22	2412	**49**	2161	**76**	1549
23	2779	**50**	2023	**77**	1488
24	2473	**51**	2286	**78**	1818
25	4459	**52**	2900	**79**	1305
26	4068	**53**	1941	**80**	2064
27	4170	**54**	2996	**81**	1844
$\sum \hat{P}_i$ **= 312373 trips per day**					

Table 4.6 Estimated trip attraction ($\hat{A}_j$) from regression analysis for 2011

Code	$\hat{A}_j$	Code	$\hat{A}_j$	Code	$\hat{A}_j$
1	5669	28	2483	55	6430
2	2529	29	1898	56	1855
3	3758	30	1989	57	1998
4	2781	31	6134	58	5239
5	2154	32	2725	59	3116
6	12501	33	7913	60	3045
7	6960	34	26194	61	5184
8	2088	35	12078	62	1973
9	3728	36	2454	63	4841
10	4912	37	3101	64	2177
11	1807	38	4852	65	4364
12	2207	39	2314	66	3296
13	2292	40	2078	67	2368
14	2388	41	6354	68	2426
15	2265	42	8901	69	1489
16	6667	43	3352	70	2384
17	5564	44	3418	71	1951
18	2134	45	4868	72	1970
19	3349	46	4036	73	2118
20	4039	47	2688	74	1506
21	4266	48	4066	75	1689
22	2401	49	2257	76	1568
23	2831	50	2042	77	1417
24	2657	51	2339	78	1819
25	4854	52	2813	79	1282
26	4104	53	1917	80	1998
27	3936	54	2857	81	1785
$\sum \hat{A}_j$ **= 304251 trips per day**					

4.2.2 Model Fit Performance

Figure 4.1 shows the produced and attracted trips from the survey matrix versus the estimated produced and attracted trips (solid black line) from the regression analysis. From the figure, it is obvious that the regression line fits very well between the survey and estimated production and attraction.

Figure 4.2 shows two curves for the produced and attracted number of trips from survey matrix and regression analysis, for 81 provinces, respectively. The comparison shows that the regression model fit well. From the result, it can be seen that the developed provinces and those provinces having ports, have most trip production and attraction. These figures show that the daily productions and attractions are not normally distributed. Istanbul, Ankara, Izmir, Konya and Mersin is the main production and attraction centers in Turkey

4.3 Trip Distribution Results

This section explains the result of the trip distribution via gravity model. Using equations 2.8a and 2.8b, gravity model coefficients have estimated by regression analysis. The log-linear regression form of the gravity model has applied to 3959 available O-D pairs with their respective production and attraction values, using SPSS software. The result of the regression analysis for the log form of the gravity model has shown in Table 4.7. The R-square value is 0.347 using distance impedance and 0.350 using travel time impedance, which is not very high. This shows that the model has not fitted very well. However, it is best so far as there is no other way to estimated the missing trips. In addition, the production, and impedance variables i.e. distance and time both are highly significant.

The production and the impedance i.e. distance and time all are highly significant. In Table 4.7, the coefficients shows the values of the parameters ~, , ª and k. The negative sign of the impedance variables show that the trips decrease, if the distance or the travel-time among the provinces increases.

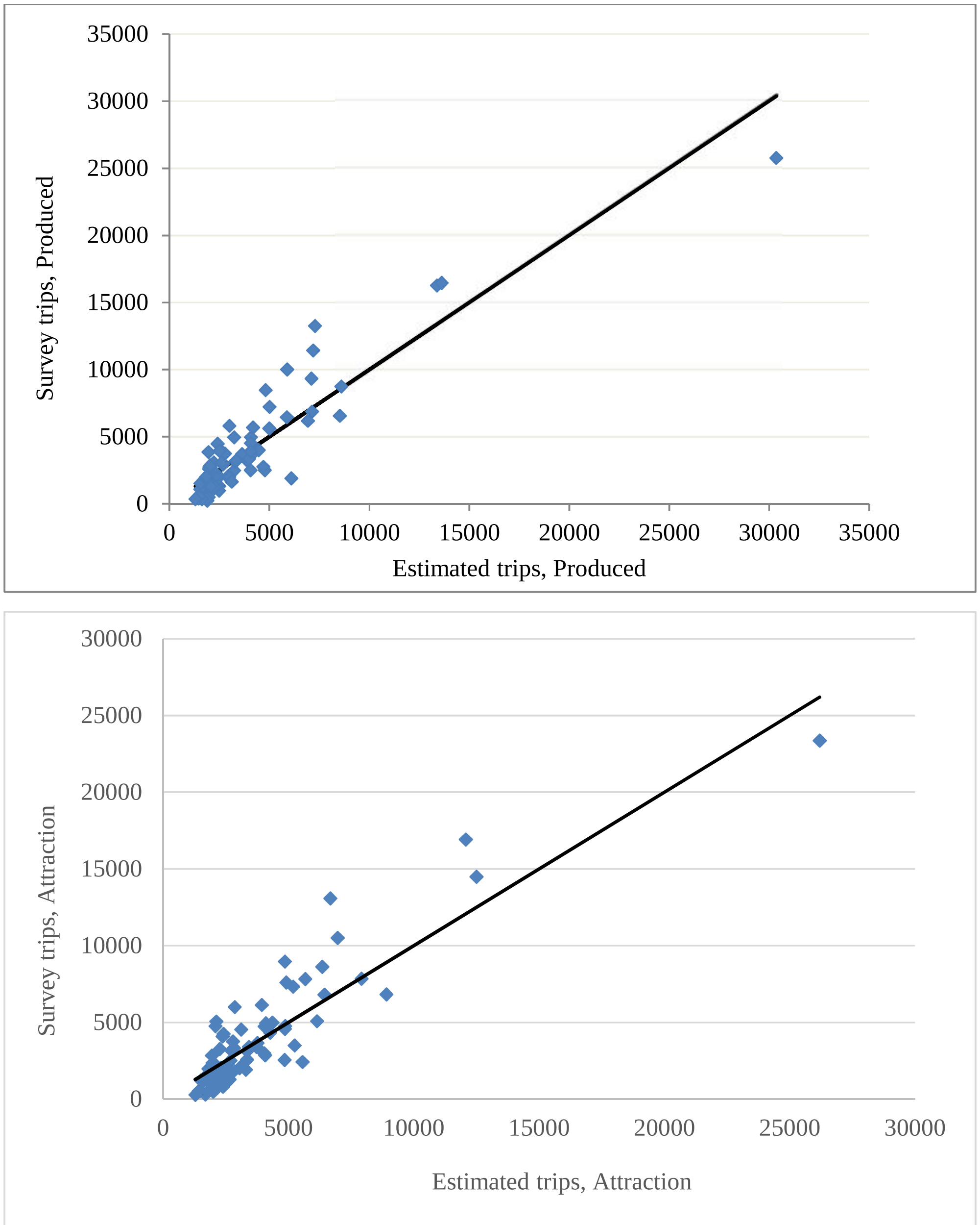
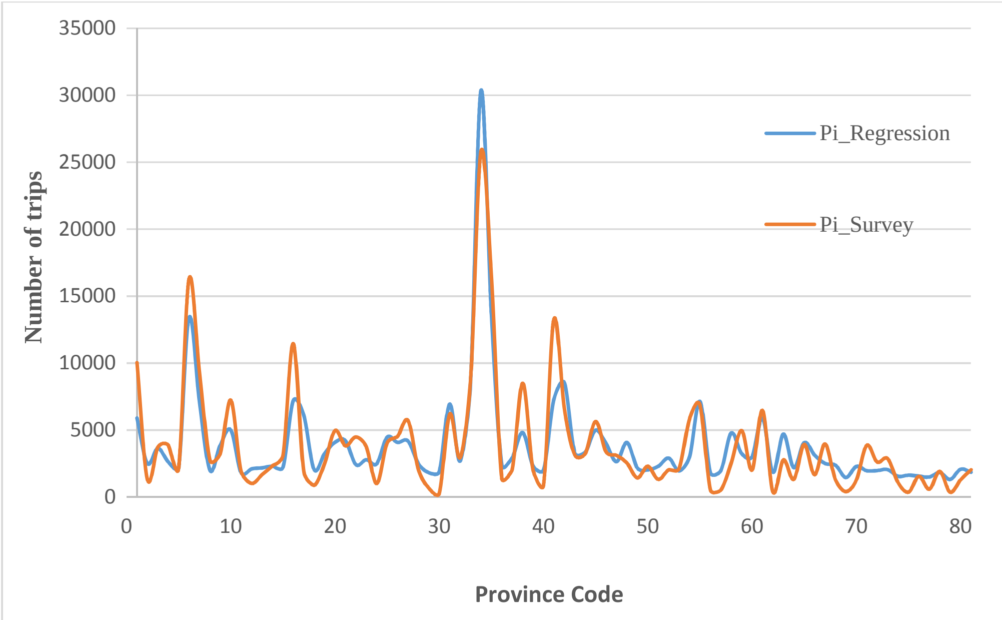


Figure 4.1 Scattered plot of survey and estimated trips (solid black line) for production and attraction



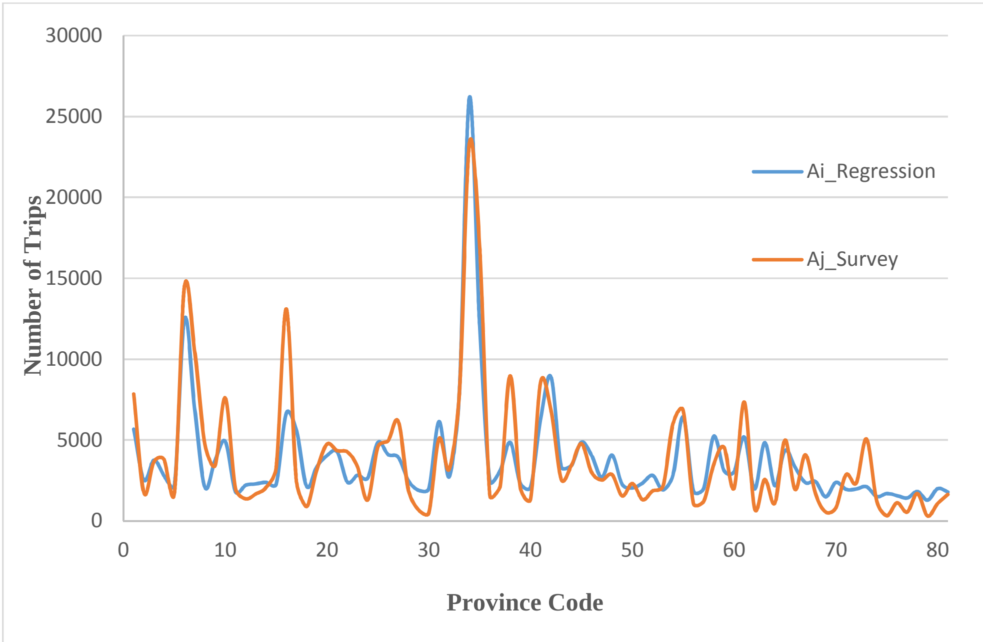


Figure 4.2 Provincial estimated production and attraction from regression (2011) versus survey production and attraction

Table 4.7 Regression analysis result from log-linear form of the gravity model

	Variables	Coefficients	*t*-statistics	*P* value
Impedance Distance **R^2=0.347**	$Ln(k)$	3.167	13.219	0.000
	$Ln(P_i)$	0.625	7.150	0.000
	$Ln(A_j)$	0.110	1.187	0.235
	$Ln(d_{ij})$	-0.926	-33.502	0.000
Impedance Travel-time **R^2=0.350**	$Ln(k)$	-0.730	-3.928	0.000
	$Ln(P_i)$	0.635	7.285	0.000
	$Ln(A_j)$	0.102	1.109	0.297
	$Ln(d_{ij})$	-0.929	-33.844	0.000

The estimated produced and attracted trips from the trips generation step have distributed among the 81 provinces of Turkey, using the equations below:

$$T_{ij} = e^{3.167} \frac{P_i^{0.625} A_j^{0.110}}{d_{ij}^{0.926}} \tag{5.1a}$$

$$T_{ij} = \frac{1}{e^{3.167}} \frac{P_i^{0.635} A_j^{0.102}}{t_{ij}^{0.929}} \tag{5.1b}$$

Figure 5.1 and 5.2 shows the comparison for the trips from the survey matrix and estimated by gravity model versus time and distance, respectively. The trips from the survey matrix are very disperse, compare to the trips estimated by the gravity model. Both impedance formulations i.e. distance and time, underestimated the observed trips. Nonetheless, this formulation suggested 11% additional trips (which may be even more in reality).

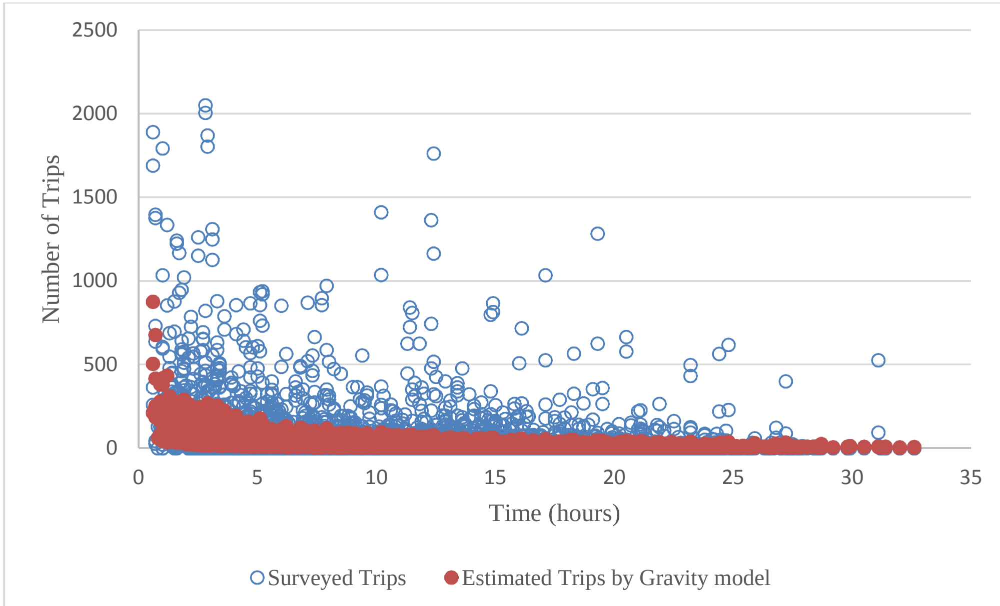


Figure 4.3 Survey trips and estimated by gravity model vs. time (in hours)

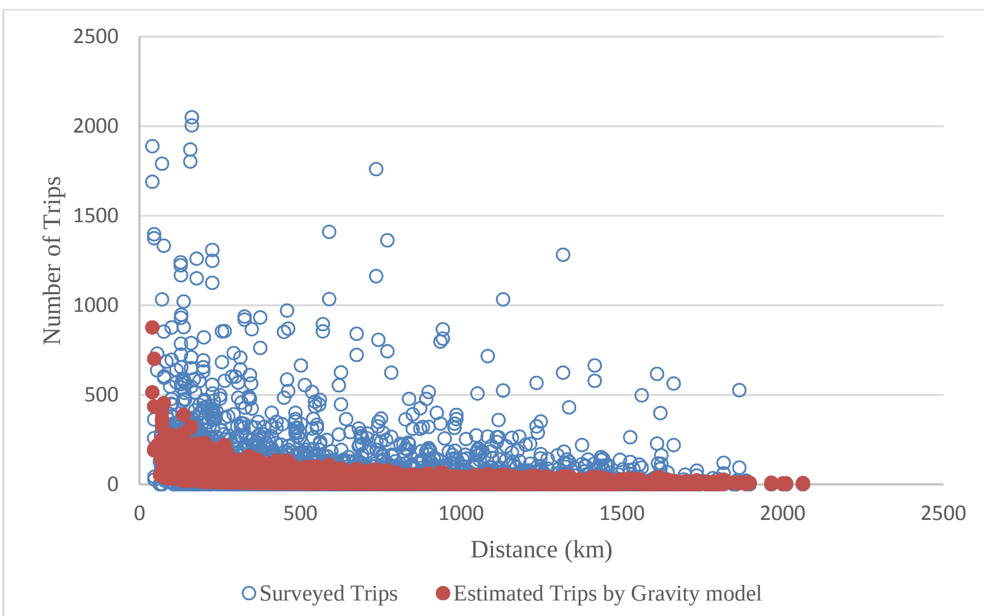


Figure 4.4 Survey trips and estimated by gravity model vs. distance (in km)

As it has mentioned before, for trip distribution it is necessary to have production and attraction equal for each respective TAZ. The above analysis has done using the unequal production and attraction. By adding the imaginary TAZ, code 82, it has been made possible to have equal production and attraction, from the survey matrix. Table 4.8 shows the equal production and attraction for 81 provinces of Turkey. Using these production and attraction values, in gravity model, the trips distributed among these provinces have estimated again.

Table 4.8 Equal production and attraction for each province

Code	$P_i = A_j$	Code	$P_i = A_j$	Code	$P_i = A_j$	Code	$P_i = A_j$
1	10021	**22**	4478	**43**	3124	**64**	1317
2	1754	**23**	3741	**44**	3417	**65**	4996
3	3701	**24**	1294	**45**	5631	**66**	1941
4	3875	**25**	4582	**46**	3364	**67**	4086
5	2126	**26**	4949	**47**	3100	**68**	1665
6	16278	**27**	6146	**48**	2866	**69**	543
7	10510	**28**	2038	**49**	1542	**70**	1258
8	4768	**29**	674	**50**	2314	**71**	3852
9	3416	**30**	489	**51**	1312	**72**	2608
10	7604	**31**	6188	**52**	2022	**73**	5064
11	1997	**32**	3190	**53**	2144	**74**	1230
12	1364	**33**	8745	**54**	6018	**75**	358
13	1663	**34**	25790	**55**	6873	**76**	1534
14	2320	**35**	16931	**56**	1076	**77**	576
15	3274	**36**	1556	**57**	1203	**78**	1908
16	13103	**37**	2119	**58**	3511	**79**	352
17	2435	**38**	8969	**59**	4951	**80**	1278
18	883	**39**	2041	**60**	2024	**81**	2027
19	3150	**40**	1341	**61**	7347	**82 (undefined)**	21133
20	4953	**41**	13265	**62**	783		
21	4341	**42**	6836	**63**	2764		

Table 4.9 shows the results of the log-form of the gravity model, using augmented production and attraction. As the production and attraction are exactly equal, which leads to multicollinearity problem, production values have automatically removed by the software. The distributed trip were calculated again, using the below equation, and found to be exactly the same as estimated from the previous equations.

$$T_{ij} = e^{0.307} \frac{A_j^{0.762}}{d_{ij}^{0.510}} \quad (5.2)$$

Table 4.9 Regression results using augmented production and attraction

	Variables	Coefficients	*t*-statistics	*P* value
Impedance Distance	$Ln(k)$	0.307	1.264	0.206
	$Ln(P_i)$	.	.	.
R^2=0.234	$Ln(A_j)$	0.762	31.641	0.000
	$Ln(d_{ij})$	-0.926	-19.367	0.000

4.3.1 Determination of Trips for Missing O-D Pairs

The survey matrix at provincial level, of dimensions 81 by 81, contains 6561 cell entries, out of this 2521 entries (40%) are missing. As the axleload surveys were performs on inter-city roads, the intra-city trips (the diagonals of the matrix) are excluded naturally. Missing data occurs because most of the time it is not possible to survey all the trucks, at all locations. In addition, during the survey the TGDH does not stop some highly loaded trucks. By applying log-form of the gravity model; empty cells in the survey matrix could be estimated. For example, in the survey matrix the daily trips from province Adiyaman (Code 2) to Afyonkarahisar (Code 3) is an empty cell. However, using the gravity model, the trips have estimated from Adiyaman to Afyonkarahisar, which are 9 trips. Figure 4.5 shows a snapshot of estimated missing O-D pairs.

Code	1	2	3	4	5	6	7	8	9
1	0	47	76	134	31	298	192	174	53
2	68	0	9	12	9	6	10	11	7
3	19	16	0	8	25	64	733	5	66
4	87	7	28	0	22	160	29	17	7
5	42	16	10	18	0	98	17	28	4
6	351	21	104	202	56	0	555	364	132
7	111	30	392	51	21	145	0	65	81
8	44	15	11	2	18	389	38	0	9
9	9	26	152	2	3	59	252	10	0

Figure 4.5 Estimated values for the Missing O-D pairs (in red)

4.3.2 Complete O-D Matrix

The complete O-D matrix has been obtained, by including the missing data into the survey matrix to form a complete O-D matrix. In that matrix, there is no empty cell, except intra-city trips. The production and attraction have calculated again, from the complete O-D matrix. This process suggested an increase of 11% in the total truck trips which may be larger in reality. Table 4.10 and Table 4.11 show the provincial production and attraction from the complete O-D matrix, respectively, using distance impedance. The total production ($\sum \tilde{P}_i$), from the complete O-D matrix is 346,651 trips per day. However, the production from the survey matrix was 311,740. Table 4.8 also shows the difference between the production from survey matrix for each province and production from the complete O-D matrix.

Similarly, total attraction ($\sum \tilde{A}_j$), from the complete O-D matrix is 346,651 trips per day. However, the total estimated attraction from trips generation step is 311,740. Table 4.9 also shows the difference between the estimated attraction ($\tilde{A}_j$) of each province from trip generation and attraction from the complete O-D matrix.

As it can be seen, that the $\tilde{P}_i$ is higher than the P_i. The same is true for the attraction. It is because of the inclusion of the missing trips, which values have calculated by gravity model.

Table 4.10 Provincial distributed production ($\tilde{P}_i$) using distance impedance, and its difference from survey production ($\tilde{P}_i - P_i$)

Code	$\tilde{P}_i$	$\tilde{P}_i - P_i$	Code	$\tilde{P}_i$	$\tilde{P}_i - P_i$	Code	$\tilde{P}_i$	$\tilde{P}_i - P_i$
1	10181	160	**28**	2531	493	**55**	7127	254
2	1875	542	**29**	1084	430	**56**	864	343
3	4346	644	**30**	455	199	**57**	822	313
4	4276	401	**31**	6612	424	**58**	2865	337
5	2703	577	**32**	3710	772	**59**	5295	344
6	16278	0	**33**	9019	274	**60**	2376	371
7	9595	254	**34**	25833	42	**61**	6718	267
8	3352	617	**35**	16619	145	**62**	724	343
9	3669	421	**36**	1619	245	**63**	3266	503
10	7611	387	**37**	2482	413	**64**	1866	549
11	2437	512	**38**	8687	200	**65**	4162	239
12	1491	485	**39**	2569	564	**66**	2294	633
13	2193	536	**40**	1404	525	**67**	4471	517
14	2766	446	**41**	13696	431	**68**	1817	531
15	3814	715	**42**	6826	251	**69**	762	364
16	11489	48	**43**	3657	533	**70**	1650	392
17	2335	423	**44**	3805	566	**71**	4444	592
18	1295	431	**45**	6141	509	**72**	3171	563
19	2847	350	**46**	4014	650	**73**	3438	575
20	5598	645	**47**	3819	719	**74**	1478	400
21	4262	446	**48**	2927	404	**75**	635	277
22	5064	587	**49**	1801	381	**76**	1888	354
23	4117	376	**50**	2859	568	**77**	1016	441
24	1414	414	**51**	1849	539	**78**	2390	482
25	4391	370	**52**	2424	402	**79**	724	372
26	4745	223	**53**	2727	614	**80**	1921	643
27	6186	488	**54**	6385	564	**81**	2586	559
$\sum \tilde{P}_i$ =346,651 trips per day								

4.11 Provincial distributed production ($\tilde{A}_j$) using distance impedance, and its difference from survey production ($\tilde{A}_j$ - A_j)

Code	$\tilde{A}_j$	$\tilde{A}_j$ - A_j	Code	$\tilde{A}_j$	$\tilde{A}_j$ - A_j	Code	$\tilde{A}_j$	$\tilde{A}_j$ - A_j
1	7869	27	**28**	2501	593	**55**	7059	245
2	2266	513	**29**	1424	750	**56**	1594	518
3	3987	323	**30**	961	473	**57**	1916	712
4	3996	210	**31**	5334	248	**58**	3810	299
5	2219	520	**32**	3674	484	**59**	4857	304
6	14536	32	**33**	7985	125	**60**	2420	395
7	10647	138	**34**	23381	4	**61**	7491	144
8	5036	268	**35**	16950	20	**62**	1534	751
9	3792	377	**36**	1925	369	**63**	2955	394
10	7757	154	**37**	2682	564	**64**	1700	589
11	2636	639	**38**	9065	96	**65**	5129	134
12	2085	721	**39**	2537	496	**66**	2532	591
13	2191	528	**40**	1879	538	**67**	4393	307
14	2443	377	**41**	8770	142	**68**	2473	809
15	3960	686	**42**	6940	104	**69**	1499	957
16	13123	19	**43**	3059	479	**70**	1469	651
17	2815	380	**44**	3726	309	**71**	3321	456
18	1615	732	**45**	5042	267	**72**	2729	379
19	3458	308	**46**	3324	326	**73**	5401	336
20	5026	281	**47**	2964	433	**74**	1864	635
21	4536	195	**48**	3154	287	**75**	1003	684
22	4534	273	**49**	2065	523	**76**	1414	294
23	3610	271	**50**	2899	585	**77**	1903	1354
24	1721	427	**51**	2057	744	**78**	2351	659
25	4884	302	**52**	2333	469	**79**	1561	1259
26	5242	293	**53**	2620	476	**80**	1960	877
27	6323	176	**54**	6228	209	**81**	2530	897
$\sum \tilde{A}_j$ =346,651 trips per day								

4.4 Summary

This chapter shows the results of survey matrix, trip generation step, and trip distribution step. The survey matrix has dimensions of 81 by 81, at provincial level, which contains 6561 cell entries, out of these 2521 entries are empty, which corresponds to 40 %. These empty cells may be unobserved in survey which are called missing O-D pairs, or there may be possibility of actually no truck trips between that origin and destination province. Missing data occurs because most of the time it is not possible to survey all the trucks, at all locations.

Trip generation models for truck trips have developed for 81 provinces of Turkey. Multiple regression analysis has applied to determine the relationship between demographic and socioeconomic variables of the 81 provinces of Turkey, and number of trips produced or attracted. The dependent variable, i.e. the number of trips produced or attracted obtained from the survey matrix.

In trip distribution step, the gravity model coefficients have estimated by regression analysis. The log linear regression form of the gravity model has applied to 3959 available O-D pairs with their respective production and attraction values, using SPSS software. Although the value of the R-square is not very high, nevertheless, it is best so far as there is no other way to estimated the missing trips. In addition, the production, and impedance variables i.e. distance and time both are highly significant.

CHAPTER 5

CONCLUSION AND FURTHER RECOMMENDATIONS

Trucking is the principal mode choice in Turkey; around 90 % of the overall inland freight ton-km carry out by trucks (TurkStat, 2011). Turkey is about to conduct a national transportation master plan study, and modeling truck freight is very important, and it is quite necessary to know what can be and how can be done, in this regard. The data availability is the main limitation in the analysis and developing of freight transport models. In developing countries, commodity flow data cannot be estimate very effectively, while most of the times traffic counts or roadside axle surveys regularly conducted, for various planning and design purposes of highways. For example, origin-destination (O-D) matrix for truck traffic can be estimated from transport statistics data (also called roadside surveys), which are more economical and can be easily modified with new data. A statewide truck trips estimation model can be develop, by combining different years of survey, to have a reliable model, which can forecast rational number of trips for horizon year too. Though capture limited O-D pairs, truck freight modeling using roadside surveys is economical.

5.1 Major Findings

The survey matrix has been estimated by combining data from 2007 to 2011; every year observations have been assumed statistically independent. It has dimensions of 81 by 81, at provincial level, which contains 6561 cell entries. Out of 246 survey locations—in nineteen locations twice and in two locations thrice—surveys have conducted in different years, i.e. exact match locations. Average value was taken for those links, where surveys had repeated in different years, while links which were close to each other, their AADT and location in MapInfo were studied in detail, to decide whether they are duplicated links or not. To normalize these effects, average has taken at those locations. 2521 entries were empty, which corresponds to 40 %. These empty cells may be unobserved in survey which are called missing O-D pairs, or there may be possibility of actually no truck trips between that origin and destination province. Missing data occurs because most of the time it is not possible to survey all the trucks, at all locations.

Trip generation analysis are performed to estimate produced and attracted trips. Socioeconomic and demographic variables, for 81 provinces of Turkey, are used as independent variables in regression analysis. Though TURKSTAT has many variables, some of them are not available at provincial level, other have strong collinearity; very few are stastically significant in the models. The missing trips in the survey matrix have calculated using the log form of the gravity model. Distance and travel time as impedance produced similar results. Both impedance formulations underestimated the observed trips. However, this formulation suggested 11% additional trips (which may be even more in reality).

The best model is same, for estimated production and attraction, which has the independent variables of number of household, port existance and land sqaure. The best-fit production equation is a function of number of households, land square and international port existence. Port existence can cause increase in number of truck trips produced, because of import. The regression is statistically significant, i.e. the value of R-square is 0.831. F-test or also called Analysis of Variance (ANOVA) test result shows F-value is 127.95 with highly significant p-value. The best-fit attraction equation is a function of number of households, land square and international port existence. Port existence can cause increase in number of truck trips attracted, because of export. The regression is statistically significant, i.e. the value of R-square is 0.810. F-value is 109.45 with highly significant p-value. Estimated trip productions and attractions revealed that Istanbul (9.72%) is the center of highest truck trip production. Izmir (4.35%), Ankara (4.28%), Mersin (2.75%) and Konya (2.73%) are the other main production centers. Likewise, Istanbul (8.61%) is also the main center of truck trip attraction, in Turkey. Ankara (4.11%), Izmir (3.97%), and Konya (2.93%) are the other main truck trips attraction centers.

Trip distribution analysis are conducted via gravity model. Using log form of the gravity model, coefficients have estimated by regression analysis. The log-linear regression form of the gravity model has applied to 3959 available O-D pairs with their respective production and attraction values, using SPSS software. The R-square value is 0.347 using distance impedance and 0.350 using travel time impedance, which is not very high. This shows that the model has not fitted very well. However, it is best so far as there is no other way to estimated the missing trips. In addition, the production, and impedance variables i.e. distance and time both are highly significant. The negative sign of the impedance variables show that the trips decrease, if the distance or the travel-time among the provinces increases. The trips from the survey matrix are very disperse, compare to the trips estimated by the gravity model. Both impedance formulations i.e. distance and time, underestimated the observed trips. Nonetheless, this formulation suggested 11% additional trips (which may be even more in reality). Using the coefficient obtained from the gravity model, the missing cells have estimated.

5.2 Conclusions

Trip matrix from roadside surveys are more economical and can be easily modify with new data. In developing countries, commodity flow data cannot be estimate very effectively, while most of the times traffic counts or roadside axle surveys regularly conducted, for various planning and design purposes of highways. A statewide truck trips estimation model can be develop, by combining different years of survey, to have a reliable model, which can forecast rational number of trips for horizon year too.Multiple regression analysis has performed in SPSS, i.e. to describe which variable are effective in trip production and trip attraction. Multicollinearity among all variable had calculated, to avoid correlated variables in models. Different trip production and attraction models have estimated and best model has selected based on R-square value.

Although these models can reliably estimate future-year truck trips, they based on socioeconomic and demographic structure of TAZs. In developing countries, due to rapid development, such characteristics change promptly too, which substantially reduce forecasting ability of these models for long time, so regularly modification with current data is advisable to have a robust model for estimation.

In trip distribution step, the coefficients of the gravity model have calculated by regression analysis, using log form of the gravity model. Then the estimated produced and attracted trips from trip generation step have distributed among the 81 provinces of Turkey, using gravity model.

5.3 Further Recommendations

In the survey matrix, at provincial level, 40% of the cells are empty. Because of this large share of empty cells in the survey matrix, if the calculated produced and attracted trips are distribute through gravity model friction-factor method: the value of the distributed trips, for those cells that are empty in the survey matrix, will also be none or empty. It is because of the fact that in the calculation of friction-factor, observed trips from the survey matrix are take into account for calibration. Hence, this method will not be effective or robust for the distribution of trips, at provincial level. It is worthwhile to check if we can improve estimation of missing O-D pair developing models at different NUTS levels (regional and sub-regional) and establishing a relationship between economic development and truck traffic demand.If the relationship among these three different zones of Turkey can be determine, it will be possible to eatablish a way from aggregated modeling to disaggregate modeling. one way is to look into the city development indix for Turkey. There can be other resons too, which should be the focus of future study.

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