Freight truck trip generation modelling at regional level

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Abstract

Freight truck trip generation is a crucial part of a 4-stage model, especially in regional freight model development. Data needed to construct trip generation equations are usually gathered at company level using the trip diary. Although this approach seems to be most suitable it may not cover all trips made by freight vehicles in analysed area. On the other hand, response rate may be unsatisfactory. Thus other methods of trip generation estimation should be explored. Based on results of roadside surveys O-D matrices for freight vehicles were estimated. In the next step, using large set of traffic measurements on national and regional roads, O-D matrices were calibrated. In order to calculate trip generations a step backwards was made. Additionally, the results of comprehensive travel studies and secondary data were used. Developed data sets were used to estimate trip generation equations, applying linear and nonlinear regression as well as artificial neural networks (ANN). The aim of this paper is to develop freight truck trip generation equations at regional level using different data sources, secondary data and indirect approaches.

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Selection and/or peer-review under responsibility of Scientific Committee

Keywords: trip generation, road freight transport

1. Introduction

Freight trip generation is the first step in the 4-stage model. Trip generation may refer to different areas (e.g. part of a city, commune, district) or particular objects (e.g. single generators). In road freight transport trip generation may be estimated either by the number of vehicles (vehicle based model) or the amount (tons, value) of commodity (commodity based model).

In commodity based models all modes of transport are considered. In particular, in road freight transport commodities are transferred to trucks using average payload factors. On the other hand, in vehicle based models mode split is conducted with trip generation, where trip generation rates or equations are defined for each type of

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vehicle. However, different vehicle classifications are used in freight models the most typical is division into light and heavy trucks. Light trucks usually have a gross vehicle weight (GVW) less than 3.5 tons while heavy trucks – more than 3.5 tons.

Trip generation may be calculated using different approaches. In majority of vehicle and commodity based models trip generation rates and multiple regression equations are used. This approach was used in many vehicle based models (Vehicle Allen (2000), Chen & Naylor (2009), List, Konieczny, Durnford & Papayanoulis (2002), QRFM (1996), Ruiter (1992)) as well as in commodity based models (Anater, Wall & White (2007), Baker & Bostrom (2008), Hwang (2005), Pendyala (2002), Shar, Anderson, Harris & Schroer (2005)). Different approach is used in I-O Models (e.g. QTFDS (2004), Jones & Sharma (2003)). In fact, in this type of models, OD matrix is directly calculated based on between economy sectors commodity flows. Large set of trip generation rates and equations is provided in NCHRP Synthesis 298 (2001) and QRFM (1996). Finally, in Holguín-Veras (2001) and QRFM II (2007), different approaches to trip generation estimation were presented.

Considering Polish freight studies, only few may be listed – those that were made in parallel with passenger movement analysis (KBR Poznań (2000), KBR Kraków (2007), Zipser et al. (2000)). However, freight transport was identified in mentioned studies no trip generation model was developed. Thus the results of comprehensive travel studies in Kraków and Poznań metropolitan areas will be used to develop trip generation models.

It may be stated that main explanatory variables in trip generation models are: number of inhabitants, number of employed persons (in total and in particular sectors of economy) and number of trucks garaging in particular TAZ (Traffic Analysis Zone). Moreover, main calculation methods used are multiple regression and trip generation rates. Artificial neural networks (ANN) were used only for analysis of single generators (Al-Deek, H. M., et al. (2005)).

Observing different approaches to freight modelling (vehicle/commodity based, I-O models) it may be seen that the choice of approach will depend on data availability and model application. Even the most sophisticated model will not provide good results when input data is uncertain or missing. Considering available data from Polish surveys, vehicle based model was chosen. Trucks were divided into two groups: light (GVW less than 3.5 t) and heavy (GVW more than 3.5 t). When it comes to spatial division it was assumed that the region is equivalent to province (there are 16 provinces in Poland) and TAZ is equivalent to commune.

2. Trip generation modelling

2.1. Estimation of empirical trip generations

As an input data for modelling purposes empirical trip generations has to be obtained. In this paper two sources of data were used: comprehensive travel study in Kraków metropolitan area (KBR Kraków (2007)) and comprehensive travel study in the city and district of Poznań (KBR Poznań (2000)).

Within the comprehensive travel study in Krakow metropolitan area questionnaires in firms using trucks were done. In 33 communes located in area of the survey 100 firms were inquired. In fact, the questionnaire was a trip diary that identifies trips origins, destinations and purposes. Extension of survey results to population gave confusing results. In some communes no truck trips were indentified. Hence, a different approach was introduced. Based on results of questionnaires, average number of daily trips made by light and heavy trucks was calculated. Only trips that have either origin or destination outside particular commune were considered. In average, light trucks carry out 1.91 trips daily, while heavy trucks – 2.34. In the next step the number of trucks registered in each commune was obtained. Then, the number of trucks in each commune was multiplied by average number of daily trips. Those were made for both types of trucks. Described procedure resulted in empirical trip generations. This method might be called the direct method.

A different approach, called indirect method, was used in district of Poznań. The area of the survey covered 17 communes. Based on large set of roadside interviews initial O-D matrix was developed. In the next step elements
of O-D matrix were calibrated to minimize difference between measured and modeled traffic volumes on links. Last step was summing O-D matrix rows and columns to get productions and attractions for each commune.

2.2. Trip generation rates

Trip generation rates represent number of trips started and ended by trucks per unit of explanatory variable. Calculated trip generation rates for communes in regional freight transport are presented in Table 1. For both types of trucks the best results were obtained using the independent variable number of inhabitants (LM). The worst variable to be used is the number of employees in agriculture (LPR). For each case coefficient of determination ($R^2$) was calculated.

Table 1. Trip generation rates [trips/day]

| Explanatory variable | Light trucks | $R^2$ | Heavy trucks | $R^2$ |
|----------------------|--------------|-------|--------------|-------|
| Number of inhabitants (LM) | 0.102 | 0.94 | 0.042 | 0.88 |
| Number of companies (REG) | 1.03 | 0.88 | 0.442 | 0.85 |
| Number of companies (agriculture) (REGR) | 39.1 | 0.85 | 18.7 | 0.86 |
| Number of companies (industry) (REGP) | 3.73 | 0.84 | 1.54 | 0.83 |
| Number of companies (services) (REGU) | 1.51 | 0.89 | 0.63 | 0.83 |
| Number of companies (transport) (REGT) | 12.4 | 0.87 | 5.35 | 0.85 |
| Employment (total) (LP) | 0.490 | 0.82 | 0.228 | 0.83 |
| Employment (agriculture) (LPR) | 11.2 | 0.53 | 5.38 | 0.52 |
| Employment (industry) (LPP) | 0.863 | 0.70 | 0.395 | 0.70 |
| Employment (services) (LPU) | 1.04 | 0.87 | 0.469 | 0.83 |

2.3. Multiple regression

Multiple regression was used to find linear relationship between trip generation and available explanatory variables. Trip generation equations of two variables for communes (all or divided into types) were obtained (Table 2). In all cases, according to Wald statistics, employment in services (LPU) has the most significant influence on trip generation. Depending on the vehicle and commune type either employment in industry (LPP) or number of inhabitants (LM) was used as a second variable. However, for all models in Table 2 high values of $R^2$ were achieved, models for particular commune types are more suitable. Those models take into account differences between urban-rural and rural communes.

Table 2. Trip generation multiple regression equations [trips/day]

| Commune type      | Truck type | Equation | $R^2$ | Sample size |
|-------------------|------------|----------|-------|-------------|
| All               | Light      | $P=A=0.077\cdot LM + 0.303\cdot LPU$ | 0.93  | 50          |
|                   | Heavy      | $P=A=0.102\cdot LPP + 0.406\cdot LPU$ | 0.86  |             |
| Urban-rural       | Light      | $P=A=0.185\cdot LPP + 0.877\cdot LPU$ | 0.91  | 21          |
|                   | Heavy      | $P=A=0.085\cdot LPP + 0.367\cdot LPU$ | 0.85  |             |
| Rural             | Light      | $P=A=0.090\cdot LM + 0.416\cdot LPU$ | 0.93  | 29          |
|                   | Heavy      | $P=A=0.011\cdot LM + 0.612\cdot LPU$ | 0.93  |             |
2.4. Artificial neural networks

One of the purposes of this paper is to apply artificial neural networks (ANN) to trip generation modelling. Total number of communes in analyzed sample equals 50. Considering ANN requirements this is a small sample. Nevertheless, one can find application of ANN even for small samples (Al-Deek (2001)). In analyzed case sample of 50 communes was divided into three sets:

- 30 data points were used for training
- 10 data points were used for validation
- 10 data points were used for testing

In ANN analysis same variables as in multiple regression were used (see Table 2). Due to sample size no division into types of communes was considered. Four types of networks were tested: linear, multi-layer perceptron (MLP), radial based functions (RBF) and general regression (GRNN). For each neural network its structure (Table 3 and Table 4) were given according to pattern: number of independent variables : number of neurons in input layer – number of neurons in hidden layer – number of neurons in output layer : number of dependent variables. Similar to multiple regression, the most significant influence on trip generation has the employment in services (LPU). Influence of each variable is estimated by error quotient from sensitivity analysis. If the error quotient is higher, then the influence of independent variable on trip generation is stronger. On the other hand, if the value of error quotient is less than 1, variable may be removed from model without losing its reliability. Moreover, it is assumed that standard deviation quotient should be less than 0.7. Until standard deviation quotient is more than 0.7, the model should be rejected, even if correlation is very high (e.g. more than 0.9).

Table 3. Results of ANN analysis for light trucks

| Error quotient for independent variable calculated in sensitivity analysis | Standard deviation quotient | Correlation | Average absolute error | Network type and structure |
|---|---|---|---|---|
| LM | LPU | 1.64 | 1.28 | 0.44 | 0.90 | 324 | Linear 2:2-1:1 |
| 1.38 | 1.36 | 0.46 | 0.90 | 331 | MLP 2:2-2:1:1 |
| 1.07 | 1.23 | 0.49 | 0.90 | 347 | RBF 2:2-10-1:1 |
| 1.35 | 1.61 | 0.47 | 0.91 | 355 | GRNN 2:2-26-2-1:1 |

Table 4. Results of ANN analysis for heavy trucks

| Error quotient for independent variable calculated in sensitivity analysis | Standard deviation quotient | Correlation | Average absolute error | Network type and structure |
|---|---|---|---|---|
| LPP | LPU | 1.14 | 1.34 | 0.65 | 0.79 | 271 | Linear 2:2-1:1 |
| 1.15 | 1.32 | 0.66 | 0.80 | 299 | MLP 2:2-1-1:1 |
| 1.13 | 1.37 | 0.64 | 0.80 | 268 | RBF 2:2-3-1:1 |
| 1.20 | 1.34 | 0.67 | 0.81 | 320 | GRNN 2:2-26-2-1:1 |
3. Model verification

Model verification was based on 7 communes located close to Kraków. In set A two communes were considered, chosen from 33 communes investigated during the comprehensive travel study in Kraków metropolitan area (KBR Kraków (2007)), while in set B five communes were considered which were not located in mentioned area. To obtain trip generations of communes used to model verification traffic measurements were conducted. The idea of measurements was to identify inbound and outbound traffic for each commune. Light and heavy trucks traffic volumes were measured on all road inlets and outlets in each commune. Additionally registration numbers were recorded to identify through traffic. By subtracting through traffic from total inbound and outbound traffic volume appropriately trip attraction and trip generation was calculated. Measurements were done for morning peak hour and then recalculated to daily volumes by peak hour factor.

| Model                                              | Average absolute error | Average absolute error |
|----------------------------------------------------|------------------------|------------------------|
|                                                    | Set A                  | Set B                  |
| Trip generation rates, number of companies in total| 32 %                   | 57 %                   |
| Trip generation rates, number of companies in industry| 38 %                   | 47 %                   |
| Multiple regression, no division into commune types| 53 %                   | 75 %                   |
| Multiple regression, division into commune types    | 41 %                   | 107 %                  |
| ANN Linear                                         | 38 %                   | 203 %                  |
| ANN MLP                                            | 26 %                   | 356 %                  |
| ANN RBF                                            | 35 %                   | 290 %                  |
| ANN GRNN                                           | 26 %                   | 391 %                  |

Analyzing achieved results, trip generation rates models based on number of companies in total (REG) or in industry (REGP) gave the lowest error when comparing with measured trip generations and may be considered as a general models. It is confusing that in multiple regression analysis worse results were obtained than in trip generation rates analysis. Artificial neural networks analysis provided satisfactory results for Set A, while for Set B errors are extremely high. Nevertheless the lowest values of average absolute error are still around 30 %. The average absolute errors obtained in ANN analysis are lower than errors from multiple regression. Thus it may be stated that multiple regression gives worse results than ANN but with less calculation effort and easier model interpretation as well as further application. At the same time for Set A errors obtained in ANN are comparable to errors obtained in trip generation rates, while for Set B differences are enormous.

4. Summary

In this paper, it was shown that empirical values of trip generations for modelling purposes can be obtained not necessary from questionaires in transport companies. Of course, this gives general overview on truck usage, but still does not give information about all trucks if is conducted on small area. Thus, wider truck survey like TIUS (Truck Inventory and Usage Survey) made in USA should be conducted in Polish condition. This kind of survey should answer questions about garaging places as well as daily truck trips. On the other hand, for specified area, trip generations may be calculated using calibrated O-D matrix.

In model development different methods were used: trip generation rates, multiple regression and artificial neural networks. Although the easiest to apply are the trip generation rates, it may not reflect commune characteristic. Often in data bases only few independent variables characterizing commune are available. In this
case trip generation rates are very suitable. Multiple regression and ANN are more complex and depending on the number of explanatory variables may give better results. However in model verification, especially for Set B, ANN and multiple regression models resulted with higher errors.

Artificial neural networks has both advantages and disadvantages. The main advantage of ANN is possibility to disclose unobvious relation between dependent and independent variables. On the other hand, there is a risk of ANN usage of “black box”. On the part of disadvantages two may be listed. Firstly, in ANN analysis it is not possible to formulate equations similar to regression equations. Usually to use neural network for prediction same software which was used for ANN development has to be applied. Secondly, ANN needs a large sample size, which is very often difficult to obtain in transportation analysis. Nevertheless ANN are suitable in trip generation modelling, what was shown in this paper.

Presented models are vehicle based and consider two types of trucks: light and heavy. Bearing in mind limited input data for travel models in Poland it may be used as initial values. Later on, in O-D matrix calibration process, can be corrected to achieve satisfactory conformity of modeled and measured traffic volumes.

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