Proceedings of the Eastern Asia Society for Transportation Studies, Vol. 5, pp. 1081 - 1093, 2005

# THE IMPACT OF ESTIMATION METHODS IN THE ACCURACY OF O-D MATRICES ESTIMATED FROM TRAFFIC COUNTS UNDER EQUILIBRIUM CONDITION

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**Abstract:** Many problems in transport planning and management tasks require an origin-destination (O-D) matrix to represent the travel pattern. However, O-D matrices obtained through a large scale survey such as home or road side interviews, tend to be costly, labour intensive and time disruptive to trip makers. Therefore, the alternative of using traffic counts to estimate O-D matrices is particularly attractive. The previous research concluded that estimation method is a significant factor in the accuracy of O-D matrices estimated form traffic counts. In this paper, four estimation methods have been analysed and tested to calibrate the transport demand models from traffic counts, namely: Non-Linear-Least-Squares (NLLS), Maximum-Likelihood (ML), Maximum-Entropy (ME) and Bayes-Inference (BI). The type of demand model used in this paper is gravity model (GR). The Bandung's Urban Traffic Movement survey has been used to test the developed method. Based on several statistical tests, the estimation methods are found to perform satisfactorily since each calibrated model reproduced the observed matrix fairly closely. The tests were carried out using two assignment techniques, all-or-nothing and equilibrium assignment.

**Key Words:** OD matrix, equilibrium assignment, traffic counts, maximum-entropy, impact, optimization

## 1. INTRODUCTION

Travel has become an integral part of our daily life. This activity generates its good share of problems to any community, including traffic congestion, delay, air pollution and visual intrusion. In order to alleviate these problems, it is necessary to understand the underlying travel pattern. The concept of an "O-D matrix" has been adopted by transport planners to represent the most important features of this travel pattern.An O-D matrix gives a very good indication of travel demand, and therefore, it plays a very important role in various transport studies, transport planning and management tasks.

The conventional methods to estimate O-D matrices requires very large surveys such as: home and roadside interviews; which are very expensive, lenghty, labour intensive, subject to large errors, and moreover, time disruptive to trip makers. All of these have led researchers to investigate alternative, less expensive methods for estimating O-D matrices.

The need for inexpensive methods, which require low-cost data, less time and less manpower generally called as 'unconventional method' is therefore obvious due to time and money constraint. Traffic counts, the embodiment and the reflection of the O-D matrix; provide direct information about the sum of all O-D pairs which use those links. Some reasons why traffic counts are so attractive as a data base: firstly, they are routinely collected by many authorities due to their multiple uses in many transport planning tasks. All of these make them easily available. Secondly, they can be obtained relatively inexpensive in terms of time and manpower, easier in terms of organization and management and also without disrupting the trip makers.

However, previous research (**Tamin *et al*, 2001**) concluded there are some factors that affecting the accuracy of O-D matrices estimated from traffic counts. These factors are as follows:

- The choice of the transport demand model itself to be used in representing the trip behaviour within the study area;
- **The estimation method used to calibrate the parameters of the transport model from traffic count information;**
- **The trip assignment techniques in determining the route choice;**
- The location and number of traffic count data;
- The level of errors in traffic counts; and finally
- The level of resolution of the zoning system and the network definition.

The objective of the research is to analyse the impact of the estimation methods used to calibrate the model in the accuracy of O-D matrices estimated from traffic counts data under equilibrium condition.

## 2. METHODS FOR ESTIMATING AN O-D MATRIX

Methods for estimating an O-D matrix can be classified into 2 main groups as shown in **Figure 1**. They are as follows: conventional and unconventional methods (**Tamin, 1988**).

Conventional methods rely heavily on extensive surveys, making them very expensive in terms of manpower and time, disruption to trip makers and most importantly the end products are sometimes short-lived and unreliable. Another important factor is the complications that arise when following each stage of the modelling process. Furthermore, in many case particularly in small towns and developing countries, planners are confronted with the task of undertaking studies under conditions of time and money constraints, which make the application of the conventional methods almost impossible. The introduction of inexpensive techniques for the estimation of O-D matrices will overcome the problem.

As a result of dissatisfaction expressed by transport planners with conventional methods, other techniques for estimating O-D matrices which based on traffic counts have evolved over the years; these are generally called ‘unconventional methods’. The aim of unconventional methods is to provide a simpler approach to solve the same problem and at a lower cost. Ideally, this simpler approach would treat the four-stage sequential model as a single process. To achieve this economic goal, the data requirements for this new approach should be limited to simple zonal planning data and traffic counts on some links or other low-cost data.

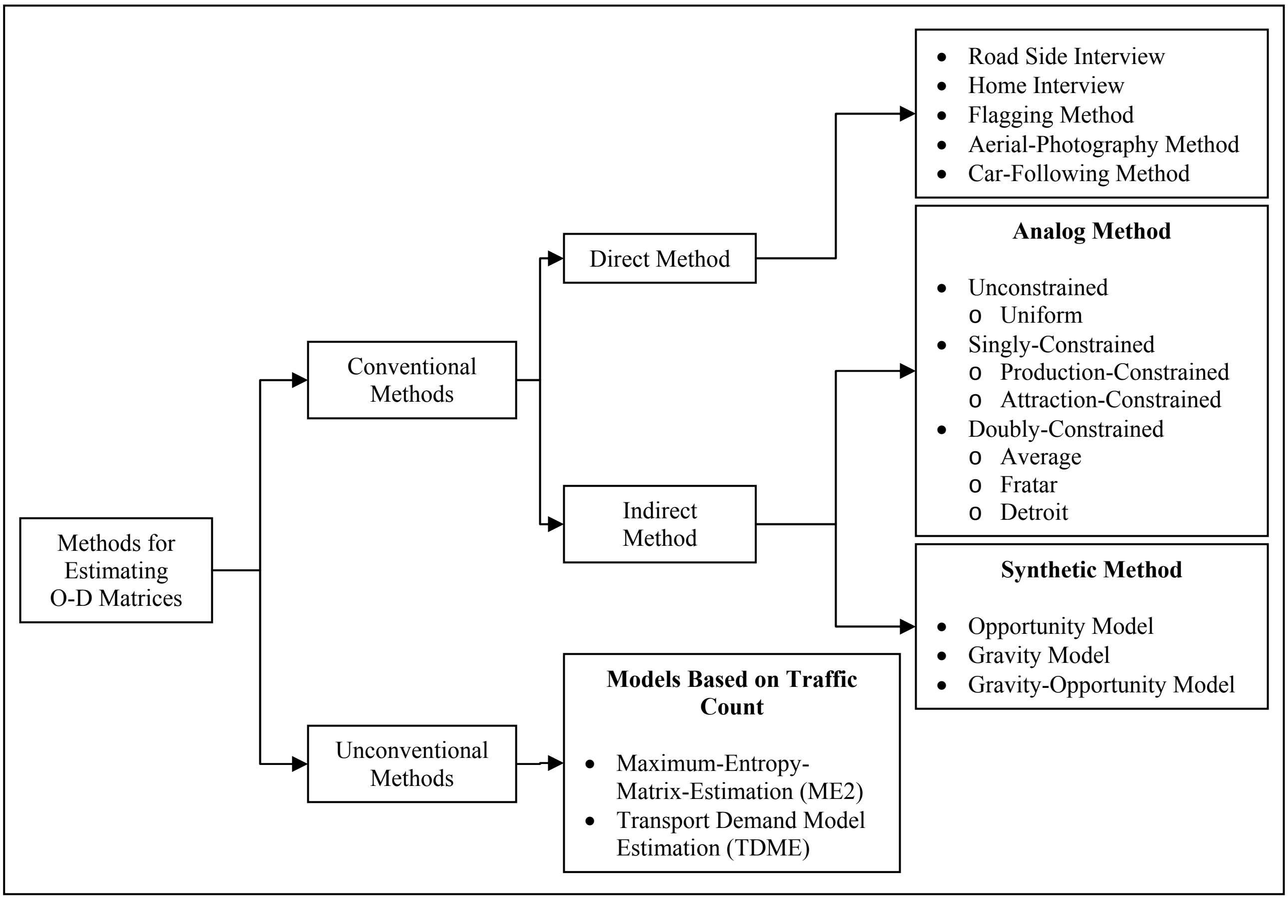


Figure 1. Methods for Estimating an O-D Matrix (**Tamin, 1988**)

## 3. TRANSPORT DEMAND MODEL ESTIMATION FROM TRAFFIC COUNTS

The transport demand model estimation approach assumes that the travel pattern behaviour is well represented by a certain transport model, e.g. a gravity model. The main idea is to apply a transport model to represent the travel pattern. It should be noted here that the transport demand models are described as functions of some planning variables like population or employment and some parameters. Whatever the spesification and the hypothesis underlying the models, the main tasks is to estimate their parameters on the basis of traffic counts. Once, the parameters of the postulated transport demand models have been calibrated, they may be used not only for the estimation of the current O-D matrix, also for predictive purposes. The latter requires the use of future values for the planning variables.

Consider a study area which is divided into **N** zones, each of which is represented by a centroid. All of these zones are inter-connected by a road network which consists of series of links and nodes. Furthermore, the O-D matrix for this study area consists of $\mathbf{N^2}$ trip cells. ($\mathbf{N^2-N}$) trip cells if intrazonal trips can be disregarded. The most important stage is to identify the paths followed by the trips from each origin to each destination. The variable $p_{id}^{lk}$ is used to define the proportion of trips by mode ***k*** travelling from zone ***i*** to zone ***d*** through link ***l***. Thus the flow on each link is a result of:

- trip interchanges from zone ***i*** to zone ***d*** or combination of several types of movement travelling between zones within a study area (=$T_{id}$); and

- the proportion of trips by mode k travelling from zone ***i*** to zone ***d*** whose trips use link ***l*** which is defined by $p_{id}^{lk}$ (**0 ≤** $p_{id}^{lk}$ **≤ 1**).

The total volume of flow ($\hat{V}_l^k$) in a particular link ***l*** is the summation of the contributions of all trips interchanges by mode ***k*** between zones within the study area to that link. Mathematically, it can be expressed as follows:

$$V_l^k = \sum_i \sum_d T_{id}^k . p_{id}^{lk} \tag{1}$$

The value of $p_{id}^{lk}$ is determined by using trip assignment technique. The previous research (**Tamin *et al*, 2001**) used **all-or-nothing assignment** to obtain the value of $p_{id}^{lk}$. By using this method, the value of $p_{id}^{lk}$ is either 0 or 1. In this research, the uses of **equilibrium assignment** method which consider the congestion effect of route choice selection was introduced. Hence, the value of $p_{id}^{lk}$ obtained is between 0 and 1 (**0 ≤** $p_{id}^{lk}$ **≤ 1**).

Given all the $p_{id}^{lk}$ and all the observed traffic ounts ($\hat{V}_l^k$), then there will be ***N*²** unknown $T_{id}^k$ 's to estimated from a set of ***L*** simultaneous linear equations (**1**) where ***L*** is the total number of traffic (passenger) counts. In principle, ***N*²** independent and consistent traffic counts are required in order to determine uniquely the O-D matrix [$T_{id}^k$]. In practice, the number of observed traffic counts is much less than the number of unknown $T_{id}^k$ 's.

Assume that the interzonal movement within the study area can be represented by a certain transport demand model such as gravity (GR) model. Hence, the total number of trips Tid wth origin ini i and destination d for all trip purpose or commodities can be expressed as:

$$T_{id} = \sum_k T_{id}^k \tag{2}$$

$T_{id}^k$ is the number of trips for each trip purpose or commodity ***k*** travelling from zone ***i*** to zone ***d*** as expressed by equation (**3**) generally known as doubly-constrained gravity model (DCGR).

$$T_{id}^k = O_i^k . D_d^k . A_i^k . B_d^k . f_{id}^k \tag{3}$$

where:

$\boldsymbol{A_i}$ and $\boldsymbol{B_d}$ = the balancing factors expressed as:

$$A_i^k = \left[ \sum_d \left( B_d^k . D_d^k . f_{id}^k \right) \right]^{-1} \text{ and } B_d^k = \left[ \sum_i \left( A_i^k . O_i^k . f_{id}^k \right) \right]^{-1} \tag{4}$$

$\boldsymbol{f_{id}^k}$ = the deterrence function (negative exponential $\mathbf{exp(-\beta . C_{id}^k)}$) (5)

By subtituting **equation (3)** to **equation (1)**, then **the fundamental equation** for the estimation of a transport demand model from traffic counts can be expressed as:

$$V_l^k = \sum_i \sum_d \left( O_i^k . D_d^k . A_i^k . B_d^k . f_{id}^k . p_{id}^{lk} \right) \tag{6}$$

The fundamental equation (**6**) has been used by many literatures not only to estimate the O-D matrices but also to calibrate the transport demand models from traffic count information (see **Tamin, 1988**; **Tamin and Willumsen, 1988**). Theoritically, having known the values of $\hat{V}_l^k$

and $p_{id}^{lk}$, $T_{id}^{k}$ can then be estimated. Equation (**6**) is a system of ***L*** simultaneous equations with only (**1**) unknown parameter $\beta$ need to be estimated. The problem now is how to estimate the unknown parameter $\beta$ so that the model reproduces the estimated traffic flows as close as possible to the observed traffic counts.

## 4. ESTIMATION METHODS

**Tamin (1999)** explains several types of estimation methods which have been developed so far by many researchers are:

- Least-Square estimation method (LLS or NLLS)
- Maximum-Likelihood estimation method (ML)
- Bayes-Inference estimation method (BI)
- Maximum-Entropy estimation method (ME)

### 4.1 Least-Square Estimation Method (LS)

Tamin (1988,1999) have developed several Least-Square (LS) estimation methods of which its mathematical problem can be represented as equation (7).

**to minimize** $$S = \sum_{l}\left[\left(\hat{V}_l^k - V_l^k\right)^2\right] \quad (7)$$

$\hat{V}_l^k$ = observed traffic flows for mode ***k*** $\quad V_l^k$ = estimated traffic flows for mode ***k***

The main idea behind this estimation method is that we try to calibrate the unknown parameters of the postulated model so that to minimize the deviations or differences between the traffic flows estimated by the calibrated model and the observed flows. Having substituted equation (**6**) to (**7**), the following equation is required in order to find an unknown parameter β which minimize equation (**7**):

$$\frac{\delta S}{\delta \beta} = \sum_{l}\left[\left(2\sum_{i}\sum_{d} T_{id}^{k}.p_{id}^{lk} - \hat{V}_l^k\right).\left(\sum_{i}\sum_{d}\left(\frac{\delta T_{id}^{k}}{\delta \beta}.p_{id}^{lk}\right)\right)\right] = 0 \quad (8)$$

Equation (**8**) is an equation which has only one (**1**) unknown parameter β need to be estimated. Then it is possible to determine uniquely all the parameters, provided that **L>1**. Newton-Raphson's method combined with the Gauss-Jordan Matrix Elimination technique can then be used to solve equation (**8**) (see **Batty, 1976; Wilson and Bennet, 1985**).

The LS estimation method can be classified into two: Linear-Least-Squares (LLS) and Non-Linear-Least-Squares (NLLS) estimation methods. **Tamin (1988)** has concluded that the NLLS estimation method requires longer processing time for the same amount of parameters. This may due to that the NLLS estimation method contains a more complicated algebra compared to the LLS so that it requires longer time to process. However, the NLLS estimation method allows us to use the more realistic transport demand model in representing the trip-making behaviour. Therefore, in general, the NLLS provides better result compared to the LLS.

### 4.2 Maximum-Likelihood Estimation Method (ML)

**Tamin (1988,1999)** have also developed an estimation method which tries to maximise the probability as expressed in equation (**9**). The framework of the ML estimation method is that the choice of the hypothesis **H** maximising equation (**9**) subject to a particular constraint, will yield a distribution of $V_l^k$ giving the best possible fit to the survey data ($\hat{V}_l^k$). The objective function for the framework is expressed as:

**to maximize** $$L = c.\prod_l p_l^{\hat{V}_l^k} \qquad (9)$$

subject to: $$\sum_l V_l^k - \hat{V}_T^k = 0 \qquad (10)$$

where: $\hat{V}_T^k$ = total observed traffic flows **c** = constant $p_l = \dfrac{V_l^k}{\hat{V}_T^k}$

by substituting equation (**6**) to (**9**), finally, the objective function of ML estimation method can then be expressed as equation (**11**) with respect to unknown parameters β and θ.

$$\textbf{max}.\, L_1 = \sum_l \left[ \hat{V}_l^k.log_e\left( \sum_i \sum_d T_{id}^k.p_{id}^l \right) - \theta.\sum_i \sum_d T_{id}^k.p_{id}^{lk} \right] + \theta.\hat{V}_T^k - \hat{V}_T^k.log_e \hat{V}_T^k + log_e c \qquad (11)$$

The purpose of an additional parameter θ, which appears in equation (**11**), is that to ensure the constraint equation (**10**) should always be satisfied. In order to determine uniquely parameter β of the GR model together with an additional parameter θ, which maximizes equation (**11**), the following two sets of equations are then required. They are as follows:

$$\frac{\delta L_1}{\delta \beta} = \sum_l \left[ \hat{V}_l^k . \frac{\sum_i \sum_d \left( \frac{\delta T_{id}^k}{\delta \beta} .p_{id}^{lk} \right)}{\sum_i \sum_d \left( T_{id}^k.p_{id}^{lk} \right)} - \theta.\sum_i \sum_d \left( \frac{\delta T_{id}^k}{\delta \beta} .p_{id}^{lk} \right) \right] = 0 \qquad (12a)$$

$$\frac{\delta L_1}{\delta \theta} = -\theta.\left[ \sum_i \sum_d T_{id}^k.p_{id}^{lk} - \hat{V}_T^k \right] = 0 \qquad (12b)$$

Equation (**12ab**) is in effect a system of two (**2**) simultaneous equations which has two (**2**) unknown parameters β and θ need to be estimated.

### 4.3 Bayes-Inference Estimation Method (BI)

The main idea behind the Bayes-Inference estimation method is by combining the prior beliefs and observations will produce posterior beliefs. If one has 100% confidence in one's prior belief then no random observations, however remarkable, will change one's opinions and the posterior will be identical to the prior beliefs. If, on the other hand, one has little confidence in the prior beliefs, the observations will then play the dominant role in determining the posterior beliefs; the stronger the prior beliefs, the less influence the observations will have to produce the posterior beliefs. The objective function of the Bayes-Inference (BI) estimation method can be expressed as:

**to maximize** $$BI\left(\tau_l^k V_l^k\right) = \sum_l \left( \hat{V}_l^k log_e V_l^k \right) \qquad (13)$$

By substituting equation (**6**) to (**13**), the objective function can then be rewritten as :

**to maximize**
$$BI = \sum_l \left[ \hat{V}_l^k . \log_e \left( \sum_i \sum_d T_{id}^k . p_{id}^{lk} \right) \right] \qquad (14)$$

In order to determine uniquely parameter β of the GR model, which maximizes equation (**14**), the following equation is then required, as follow:

$$\frac{\delta BI}{\delta \beta} = \sum_l \left[ \left( \frac{\hat{V}_l^k}{\sum_i \sum_d \left( T_{id}^k . p_{id}^{lk} \right)} \right) \cdot \left( \sum_i \sum_d \left( \frac{\delta T_{id}^k}{\delta \beta} . p_{id}^{lk} \right) \right) \right] = 0 \qquad (15)$$

Equation (**15**) is an equation which has one (**1**) unknown parameter β need to be estimated.

### 4.4 Maximum-Entropy Estimation Method (ME)

**Tamin (1998)** has developed the maximum-entropy approach to calibrate the inknown parameters of gravity model. Now, this approach is used to develop procedure to calibrate the unknown parameters of the transport demand model based on traffic count information. The basic of the method is to accept that all micro states consistent with our information about macro states are equally likely to occur. **Wilson (1970)** explains that the number of micro states $W\{V_l^k\}$ associated with the meso state $V_l^k$ is given by:

$$W\left[V_l^k\right] = \frac{V_T^k!}{\prod_l V_l^k!} \qquad (16)$$

As it is assumed that all micro states are equally likely, the most probable meso state would be the one that can be generated in a greater number of ways. Therefore, what is needed is a technique to identify the values $\left[V_l^k\right]$ which maximize ***W*** in equation (**16**). For convenience, we seek to maximize a monotonic function of ***W***, namely $\log_e W$, as both problems have the same maximum. Therefore:

$$\log_e W = \log_e \frac{V_T^k!}{\prod_l V_l^k!} = \log_e V_T^k! - \sum_l \log_e V_l^k! \qquad (17)$$

Using Stirling's approximation for $\log_e X! \approx X \log_e X - X$, equation (**17**) can then be simplified as:

$$\log_e W = \log_e V_T^k! - \sum_l \left( V_l^k \log_e V_l^k - V_l^k \right) \qquad (18)$$

Using the term $\log_e V_T^k!$ is a constant; therefore it can be omitted from the optimization problem. The rest of the equation is often referred to as **the entropy function**.

$$\log_e W = -\sum_l \left( V_l^k \log_e V_l^k - V_l^k \right) \qquad (19)$$

By maximising equation (**19**), subject to constraints corresponding to our knowledge about the macro states, enables us to generate models to estimate the most likely meso states (in this case the most likely $V_l^k$). The key to this model generation method is, therefore, the identification of suitable micro-, meso- and macro-state descriptions, together with the macro-level constraints that must be met by the solution to the optimisation problem. In some cases, there may be additional information in the form of prior or old values of the meso states, for example observed traffic counts ($\hat{V}_l^k$). The revised objective function becomes:

$$\log_e W' = -\sum_l \left( V_l^k \log_e \left( \frac{V_l^k}{\hat{V}_l^k} \right) - V_l^k + \hat{V}_l^k \right) \tag{20}$$

Equation (**20**) is an interesting function in which each element in the summation takes the value zero if $V_l^k = \hat{V}_l^k$ and otherwise is a positive value which increase with the difference between $V_l^k$ and $\hat{V}_l^k$. The greater the difference, the smaller the value of $\log_e W'$. Therefore, $\log_e W'$ is a good measure of difference between $V_l^k$ and $\hat{V}_l^k$. Mathematically, the objective function of the ME estimation method can be expressed as:

**to maximise** $$E_1 = \log_e W' = -\sum_l \left( V_l^k \log_e \left( \frac{V_l^k}{\hat{V}_l^k} \right) - V_l^k + \hat{V}_l^k \right) \tag{21}$$

In order to determine uniquely parameter β of the GR model which maximizes the equation (**21**), the following equation is then required, as follow:

$$\frac{\delta E_l}{\delta \beta} = -\sum_l \left[ \left( \sum_i \sum_d \frac{\delta T_{id}^k}{\delta \beta} . p_{id}^{lk} \right) . log_e \left( \frac{\sum_i \sum_d T_{id}^k . p_{id}^{lk}}{\hat{V}_l^k} \right) \right] = 0 \tag{22}$$

Equation (**22**) is an equation which has only one (**1**) unknown parameter β need to be estimated.

## 5. TEST CASE WITH BANDUNG TRAFFIC DATA

The real data set of urban traffic movement in Bandung, Indonesia in terms of traffic count information was used to validate the proposed estimation methods. Bandung is a capital city of West Java Province. The total area of Bandung is around 325,096 Ha and is divided into 66 kecamatans and 590 kelurahans. The study area was divided into 125 zones of which 100 are internal zones and 25 are external zones. The road network of the study area consisted of 964 nodes and 1,238 road links (total 2,725 one way road links). **Figure 2**. shows the zoning system and network definition in the study area. There are 95 observed traffic counts ($\hat{V}_l$), traffic generation and attraction ($\boldsymbol{O_i}$ and $\boldsymbol{D_d}$) for each zone, and an observed O-D matrix for comparison purpose. The units used in equation (**6**) are as follows:

$\hat{V}_l$ = traffic counts in vehicles/hour

$\boldsymbol{O_i}$, $\boldsymbol{D_d}$ = trip generation/attraction for each zone in vehicles/hour

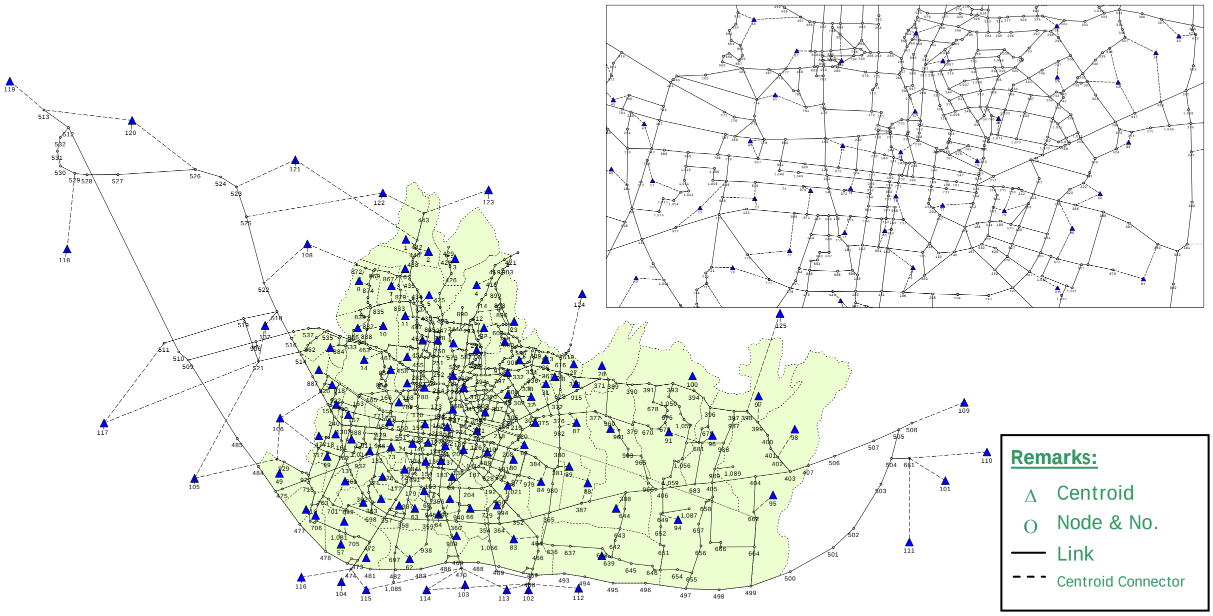


Figure 2. Zoning and Network System in Bandung

The road network system in Indonesia can be grouped according to their hierarchy of the function, status and class. Hierarchy of the function can divide the road as arterial, collector and local roads. By status, the road can be divided into national, provincial and kabupaten roads. By class, the road can be grouped into class I, II and III. In this paper, the road network classified by road function such as: arterial, collector and local roads and consists of 2,279 links representing the modelled road network.

The development of good model estimation techniques to ensure that the fitted parameters result in flows as close as possible to the observations is not enough to show the value of a new technique. We also need an indication of how accurate the reluting models are and this requires a comparison between estimated and observed O-D matrices using appropriate statistical indicators of this fit. For this purpose, the value of $R^2$ statistic as expressed in equation (**23**) is used to compare the observed and estimated O-D matrices to ascertain how close they are.

$$R^2 = 1 - \frac{\sum_i \sum_d \left(\hat{T}_{id} - T_{id}\right)^2}{\sum_i \sum_d \left(\hat{T}_{id} - T_1\right)^2} \qquad T_1 = \frac{1}{N.(N-1)}.\sum_i \sum_d T_{id} \qquad \text{for } i \neq d \tag{23}$$

where:

$\hat{T}_{id}$ = observed O-D matrix

$T_{id}$ = estimated O-D matrix

N = number of zones in study area

## 6. THE RESULT OF ANALYSIS

Using the 4 (four) estimation methods to calibrate the Gravity (GR) model from traffic counts data, the value of β which optimized the objective function S for each method can be estimated. **Table 1** shows the value of β and S as a result of O-D matrix estimation from traffic count data, for each estimation method.

Table 1. The Result of Estimation Process

| Estimation Method | β parameter | Objective Function S |
|---|---|---|
| NLLS | 0.0025 | 9.28 |
| ML | 0.0095 | 267 |
| BI | 0.0015 | 375 |
| ME | 0.0075 | - 7.55 |

Several important findings can be concluded as given in **Table 2**, which shows the performance ranking of model's estimation method according to specified criteria. The purpose of this table is to provide guidance to choose the best overall model's estimation method regarding its behaviour to several criteria such as: accuracy, computer time, sensitivity to errors in traffic counts, sensitivity to zoning level and network solution, and sensitivity to number of traffic counts. The scale ranging from 1 to 4 will be used to see the performance of estimation methods based on the above criteria. Scale **1** shows the worst performance, while scale **4** shows the best performance.

Table 2. Performance Ranking of Model Estimation Methods for Specified Criteria

| Estimation Methods | Criteria | | | | |
|---|---|---|---|---|---|
| | Accuracy | Computer time | Sensitivity to erros in traffic counts | Sensitivity to zoning level and network resolution | Sensitivity to number of traffic counts |
| NLLS | 4 | 1 | 4 | 3 | 4 |
| ML | 2 | 1 | 3 | 4 | 3 |
| BI | 1 | 1 | 2 | 1 | 1 |
| ME | 3 | 1 | 1 | 2 | 2 |

It can be seen from **Table 2** that in terms of accuracy, sensitivity to errors in traffic counts and sensitivity to number of traffic counts criteria, the NLLS estimation method performs the best. While, in terms of sensitivity to zoning level and network resolution, the ML estimation method performs the best. In general, it can be concluded that the NLLS estimation method shows the best ranking performance based on several types of criteria.

**Table 3** shows the values of $R^2$ statistics of the observed O-D matrix compared with the estimated O-D matrices obtained from traffic counts.

Table 3. The Value of $R^2$ for The Comparison of
The Observed and Estimated O-D Matrices

| Estimation Method | | | |
|---|---|---|---|
| NLLS | ML | BI | ME |
| 0.944 | 0.936 | 0.935 | 0.939 |

Some conclusions can also be drawn from **Table 3**. They are as follows:

- Taking into account the results of using other criteria, it can be concluded that the best overall estimation methods are the combination of GR model with NLLS estimation method
- With evidence so far, it was found that the estimated models and therefore O-D matrices are only slightly less accurate than those obtained directly from the full O-D surveys. This finding concludes that the transport demand model estimation approach is found encouraging in term of data collection and transport model estimation costs.

In terms of trip assignment technique used, **Table 4** shows the comparison result of using all-or-nothing assignment and equilibrium assignment.

Table 4: The Value of $R^2$ for Each Assignment Method

| **Assignment Method** | $R^2$ |
|---|---|
| Equilibrium Assignment | 0,863 |
| All-Or-Nothing Assignment | 0,519 |

It can be seen from **Table 4**, that equilibrium assignment gives better result than those of all-or-nothing assignment, in the process of O-D matrices estimation using traffic count data by applying several estimation methods.

## 7. CONCLUSIONS

The paper explains the impact of estimation methods developed to calibrate the parameters of transport demand model from traffic counts information. Some conclusions can be drawn from the result obtained:

- The number of observed traffic counts required are at least as many as the number of parameters. The more traffic counts you have, the more accurate the estimated O-D matrix. From several application, it can be concluded that the optimal number of traffic counts required is between 25 – 30 % of total number of links in the network
- In general, it can be concluded that the GR model with NLLS estimation method shows the best ranking performance based on several types of criteria
- The calibrated model can then be used to forecast the future O-D matrices
- The results are encouraging since the estimated O-D matrices obtained using traffic count information are only marginally worse than those obtained by full O-D survey.
- Equilibrium assignment gives better result than those of all-or nothing assignment in the process of O-D matrices estimation using traffic count data by applying several estimation methods, especially in urban area.
- The level of accuracy of the estimated O-D matrices depends on some following factors:
    - The choice of the transport demand model itself to be used in representing the trip behaviour within the study area;
    - The estimation method used to calibrate the parameters of the transport model from traffic count information;
    - The trip assignment techniques in determining the route choice;
    - The location and number of traffic count data;
    - The level of errors in traffic counts; and finally
    - The level of resolution of the zoning system and the network definition.

- Further research is underway to analyse the impact of other factors of the O-D matrices estimation from traffic count estimation.

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