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THE ESTIMATION OF COMBINED TRIP DISTRIBUTION-MODE CHOICE MODEL ESTIMATED FROM TRAFFIC COUNT UNDER EQUILIBRIUM CONDITION

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Abstract: The development of techniques for calibrating the trip distribution models from traffic volumes to obtain the O-D matrices is well advanced (see Tamin, 1988; Tamin and Willumsen, 1988; Tamin, 1992). Therefore, positive results on this development will be further developed by combining trip distribution and mode choice model (TDMC) and calibrating it using low cost traffic (passenger) volumes information (see Tamin 1997; Tamin and Purwanti, O 2002). As usual, the traffic (passenger) counts are expressed as a function of model form and relevant parameters. In this case , the TDMC model is represented by a function of a model formand relevant parameters. The previous research still in a burden condition of "All or Nothing" which is not realistic for some road network in urban area. So, the main objective of this research is the application of a combined trip distribution-mode choice model estimated from traffic count under equilibrium condition.

Key Words: *Combined Trip Distribution-Mode Choice Model, Traffic Count, Equilibrium Assignment*

1. INTRODUCTION

One can interpret link flows (or traffic counts) as resulting from a combination of two elements: **an O-D matrix** and **the route choice** pattern selected by drivers on the network. These two elements may be linearly related to traffic counts, see equation **(1)** below, but under normal circumstances there will never be enough traffic counts to identify a single O-D matrix as the only possible source of the observed flows. Traffic counts alone are not enough to estimate O-D matrices, something else is needed.

The idea of combining '**traditional**' data sources (home or roadside interviews) with low cost data like traffic counts is not entirely new (see **Van Zuylen and Willumsen, 1980** and **Tamin 1988, 1990**) in **figure 1**. The models can be used to combine, for example, roadside interview data with traffic (passenger) counts and this can be achieved with or without an explicit travel demand model (trip distribution model). For the purpose of public transport demand estimation, this idea can be extended to the development of a practical estimation approach to calibrate the combined **Trip Distribution and Mode Choice (TDMC)** model with traffic (passenger) counts and other simple zonal planning data.

This approach assumes that either trip distribution or mode choice model is represented by certain model forms. As usual, the traffic (passenger) counts are expressed as a function of the TDMC model. In this case, the TDMC model is represented by a function of a model form

Proceedings of the Eastern Asia Society for Transportation Studies, Vol.6, 2007

and relevant parameters. The parameters of the postulated model are then estimated, so that the errors between the estimated and observed traffic (passenger) counts are minimised.

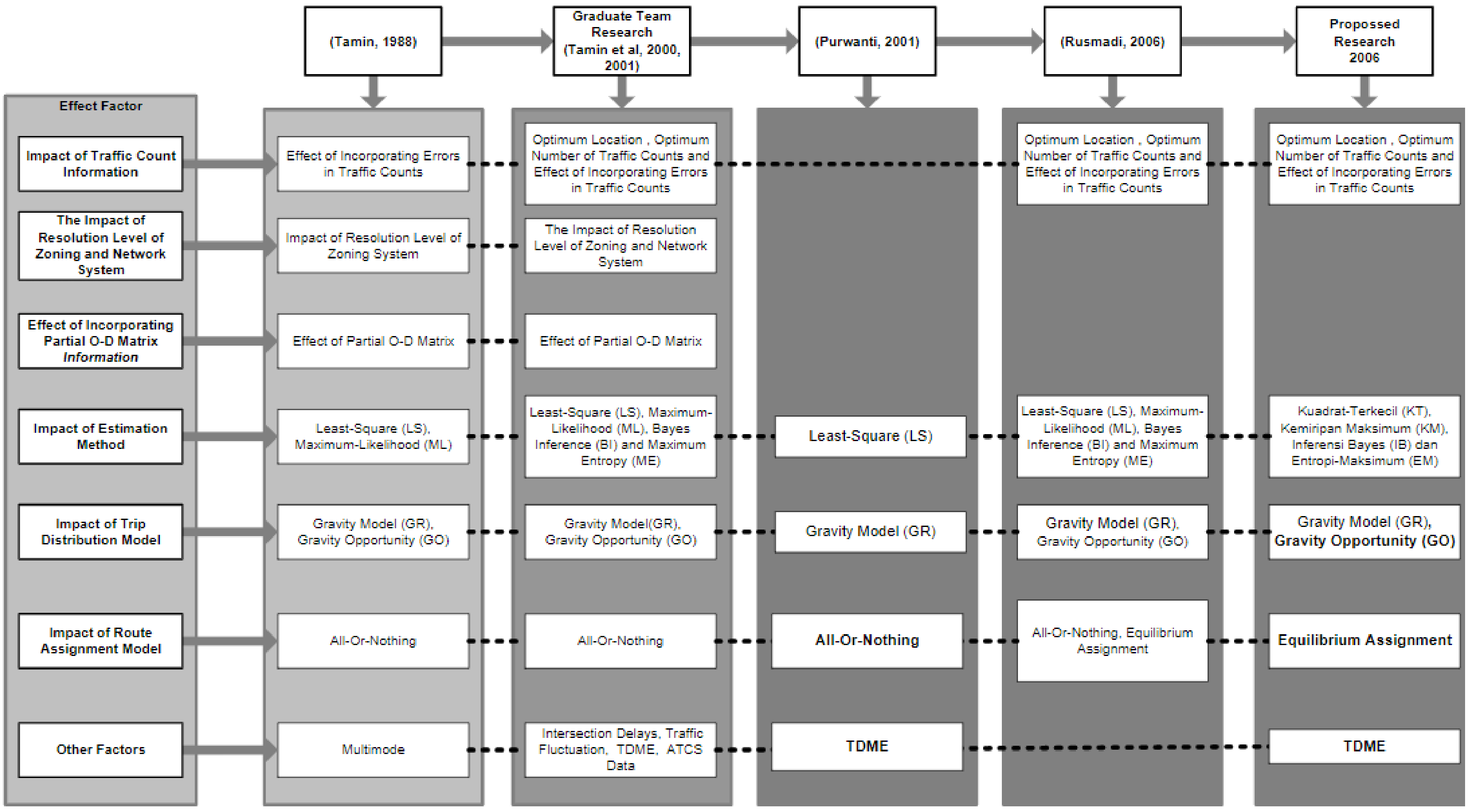

Figure 1 Roadmap on transport demand model estimation research agenda

Tamin (1997) developed aggregate model which was combined with logit model selection that was calibrated by traffic flow data (for passenger). **Tamin and Purwanti O. (2002)** developed combination of Trip Distribution-Mode Choice, parameter of model was calibrated from traffic flow data or passenger and some simple planning data.
Estimation methods of this kind have been proposed by **Low (1972)** using linear-least-squares, **Robillard (1975)** and **Högberg (1976)** using non-linear-least-squares estimation techniques. Other relevant methods have been proposed by **Holm etal (1976)** and **Tamin (1988, 1992)**. There has been, however, little validation of these techniques and there is a scope for exploring more advanced and flexible model forms.

Route Choice is a major element which has to be considered carefully by travellers as an attempt to minimize their travel time. The main objective of the route choice model is to predict the correct throughput of traffic on each road (flow distribution). The previous research still in a burden condition of "All or Nothing" which was assumption that driver who select a route try to minimize its expense, not depend on traffic flow level, so all driver will select the same route.
This method is not realistic for some road network in urban area because it never consider to the traffic jam effect and various of perception in considering of route selection.

Referring to the previous research, the main objective of the research development is develop and demonstrate the application of a combined trip distribution-mode choice model estimated from traffic count under equilibrium condition.

2. RESEARCH PLAN

2.1 Outline

2.1.1 Model Formulation

a. Proportion of trip interchanges on a particular link

One can interpret link flows (or traffic counts) as resulting from a combination of two elements: **an O-D matrix** and **the route choice** pattern selected by drivers on the network. These two elements may be linearly related to traffic counts, see equation **(1),** the total volume of flow in tha particular link l (V_l) can be expressed as follows:

$$V_l = \sum_i \sum_d T_{id} \cdot p_{id}^l \qquad (1)$$

In this reserch , the use of equilibrium assignment method which consider the congestion effect cause the value of p_{id}^l obtained is between 0-1.

b. Trip Distribution-Mode Choice Model

The analogous transport gravity model is:

$$T_{id} = k \frac{O_i O_d}{d_{id}^2} \qquad \text{k is a constant} \qquad (2)$$

Proceedings of the Eastern Asia Society for Transportation Studies, Vol.6, 2007

Suppose now there are **M** modes travelling between zones, the modified gravity model (**Doubly-Constrained Gravity Model**) can then be expressed as:

$$\mathbf{T_{id}} = \sum_{m}\left(\mathbf{O_i^m}.\mathbf{D_d^m}.\mathbf{A_i^m}.\mathbf{B_d^m}.\mathbf{f_{id}^m}\right) \tag{3}$$

where: $\mathbf{A_i^m}$ and $\mathbf{B_d^m}$ = the balancing factors expressed as:

$$\mathbf{A_i^m} = \left[\sum_{d}\left(\mathbf{B_d^m}.\mathbf{D_d^m}.\mathbf{f_{id}^m}\right)\right]^{-1} \text{ and } \mathbf{B_d^m} = \left[\sum_{i}\left(\mathbf{A_i^m}.\mathbf{O_i^m}.\mathbf{f_{id}^m}\right)\right]^{-1} \tag{4}$$

This process is repeated until the values of $\mathbf{A_i^m}$ and $\mathbf{B_d^m}$ converge to certain unique values.

c. Multi-Nomial-Logit model (MNL) as a mode choice model

The most general and simplest mode choice model (Multi-Nomial Logit Model) was used in this study. It can be expressed as:

$$\mathbf{T_{id}^k} = \mathbf{T_{id}} \cdot \frac{\mathbf{exp}\left(-\beta.\mathbf{C_{id}^k}\right)}{\sum_{m}\mathbf{exp}\left(-\beta.\mathbf{C_{id}^m}\right)} \tag{5}$$

By substituting equations (2)-(5) to equation (1), then '**the fundamental equation**' for the estimation of a combined transport demand model from traffic counts is:

$$V_l^k = \sum_{d}\sum_{i}\left[O_i^k.D_d^k.A_i^k.B_d^k.f_{id}^k.p_{id}^{lk}\frac{\exp\left(-\beta.C_{id}^k\right)}{\sum_{m}\exp\left(-\beta.C_{id}^m\right)}\right] \tag{6}$$

Equation **(6)** is a system of **L** simultaneous equations with only one **(1)** unknown parameter ***(β)***need to be estimated. There are four methods to estimate the unknown parameter so that the model reproduces the estimated traffic (passenger) counts as close as possible to the observed ones (see Tamin 2000).

2.1.2 Estimation Methods

There are four estimation methods to estimate the unknown parameter so that the model reproduces the estimated traffic (passenger) counts as close as possible to the observed ones (see **Tamin, 2000**).

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

1. Non-Linear-Least-Squares Estimation Method (NLLS)

The main idea of this method is to estimate the unknown parameter which minimises the sum of the squared differences between the estimated and observed traffic counts. The problem now is:

Proceedings of the Eastern Asia Society for Transportation Studies, Vol.6, 2007

$$\text{to minimise} \quad S = \sum_l \left[V_l^{\wedge k} - V_l^k \right]^2 \tag{7}$$

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

Having substituted (6) to (7), the following set of equation is required in order to find a set of unknown parameter β which minimises eq. (8):

$$\frac{\delta S}{\delta \beta} = \sum_l \left[\left(2 \sum_i \sum_d T_{id}^k . p_{id}^{lk} - V_l^k \right) \left(\frac{\sum_i \sum_d \delta T_{id}^k}{\delta \beta . p_{id}^{lk}} \right) \right] = 0 \tag{8}$$

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).

2. Maximum-Likelihood Estimation Method (ML)

Tamin (**1988, 2000**) have also developed an estimation method which tries to maximise the probability as expressed in equation (9).

$$\text{to maximize} \quad \mathbf{L} = c.\prod_l p_l^{\hat{V}_l^k} \tag{9}$$

$$\text{subject to:} \quad \sum_l V_l^k - \hat{V}_T^k = 0 \tag{10}$$

The main idea of this method is to estimate the unknown parameter which maximise **L**.

$$\text{Max} \quad \mathbf{L}_1 = \sum_l \left[\hat{V}_l^k . \log_e \left(\sum_i \sum_d T_{id}^k . p_{id}^{lk} \right) - \theta . \sum_i \sum_d T_{id}^k . p_{id}^{lk} \right] + \theta . \hat{V}_T^k - \hat{V}_T^k . \log_e \hat{V}_T^k + \log_e c \tag{11}$$

$$\frac{\delta L_1}{\delta \beta} = f\beta = \sum_l \left[V_l^m \frac{\sum_i \sum_d \frac{\delta T_{id}^m}{\delta \beta . p_{id}^{lm}}}{\sum_i \sum_d T_{id}^m . p_{id}^{lm}} \right] - \theta . \sum_i \sum_d \frac{\delta T_{id}^m . p_{id}^{lm}}{\delta \beta . p_{id}^{lm}} = 0 \tag{12a}$$

$$\frac{\delta L_1}{\delta \theta} = f\theta = -\theta \left[\sum_i \sum_d T_{id}^m . p_{id}^{lm} - V_T^m \right] = 0 \tag{12b}$$

Equation (12ab) is in effect a system of 2 (two) simultaneous equations which has 2 (two) parameters β and θ need to be estimated. Again, the Newton's method combined with the Gauss-Jordan Matrix Elimination technique can then be used to solve for equation (12ab).

3. Bayes-Inference Estimation Method (BI)

The objective function of the Bayes-Inference (BI) estimation method can be expressed as:

$$\text{to maximize} \quad \text{BI} = \sum_l \left[\hat{V}_l^k . \log_e \left(\sum_i \sum_d T_{id}^k . p_{id}^{lk} \right) \right] \tag{13}$$

In order to determine uniquely parameter β of the Gravity (GR) model, which maximizes equation (13), the following two sets of equations are then required. They are as follows:

$$\frac{\partial \mathrm{BI}}{\partial \beta} = \sum_l \left[\left(\frac{\hat{V}_l^k}{\sum_i \sum_d \left(T_{id}^k \cdot p_{id}^{lk} \right)} \right) \cdot \left(\sum_i \sum_d \left(\frac{\partial T_{id}^k}{\partial \beta} \cdot p_{id}^{lk} \right) \right) = 0 \right] \qquad (14)$$

Equation (14) 2 is an equation which has one (1) unknown parameter β need to be estimated. The Newton's method combined with the Gauss-Jordan Matrix Elimination technique can then be used to solve for equation (14).

4. Maximum-Entropy Estimation Method (ME)

Mathematically, the objective function of the ME estimation method can be expressed as:

to maximise $$\mathrm{E}_1 = -\sum_{l=1}^{\mathrm{L}} \left[\sum_{i=1}^{\mathrm{N}} \sum_{d=1}^{\mathrm{N}} T_{id} \cdot p_{id}^l \cdot \log_e \left(\frac{\sum_{i=1}^{\mathrm{N}} \sum_{d=1}^{\mathrm{N}} T_{id} \cdot p_{id}^l}{\hat{V}_l} \right) - \left(\sum_{i=1}^{\mathrm{N}} \sum_{d=1}^{\mathrm{N}} T_{id} \cdot p_{id}^l \right) + \hat{V}_l \right] \qquad (15)$$

In order to determine uniquely parameter β of the GR model which maximizes the equation (15), the following equation is then required. They are as follows:

$$\frac{\partial E_1}{\partial \beta} = -\sum_l \left[\left(\sum_i \sum_d \frac{\partial T_{id}^k}{\partial \beta} \cdot p_{id}^{lk} \right) \cdot \log_e \left(\frac{\sum_i \sum_d T_{id}^k \cdot p_{id}^{lk}}{\hat{V}_l^k} \right) \right] = 0 \qquad (16)$$

Equation (16) 4 is an equation which has only one (1) unknown parameter β need to be estimated. Newton–Raphson's method combined with the Gauss–Jordan Matrix Elimination technique can then be used to solve equation (16).

3. OUTPUT TARGET

The use of all or nothing assignment for estimating the transport demand model can no longer be used for congested road networks. The research will develop the methodology and algorithms to cooperate the effect of equilibrium assignment. Therefore, the major contribution of this research is to enrich the knowledge on transport demand model estimation by cooperating the congestion effect using the application of the equilibrium assignment.

Proceedings of the Eastern Asia Society for Transportation Studies, Vol.6, 2007

4. METHODOLOGY

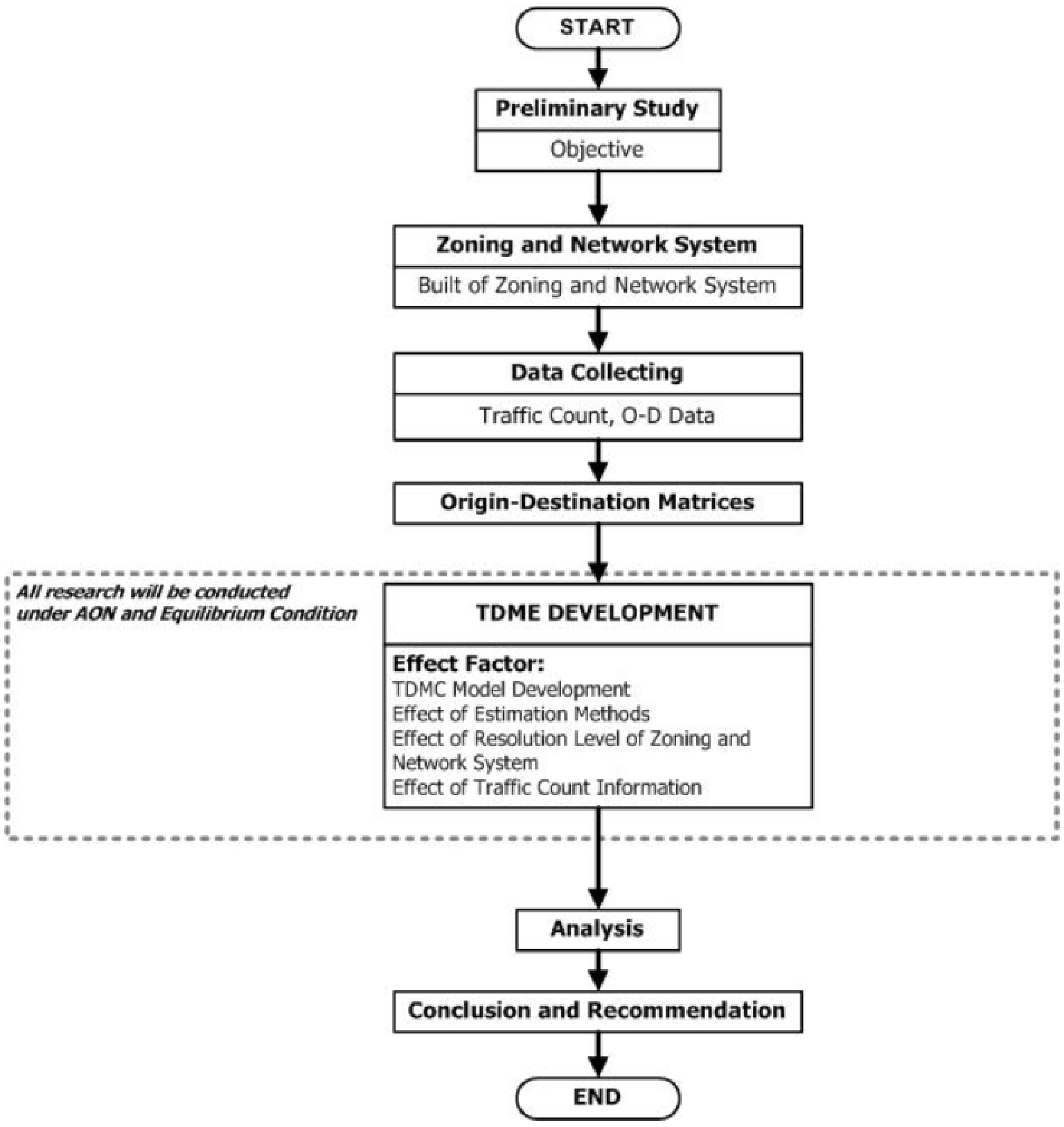

Figure 2 Research methodology

REFERENCES

Suyuti, R. And Tamin, O.Z. (2005), The Impact of Estimation Methods in the Accuracy of O-D Matrices Estimated From Traffic Counts Under Equilibrium Condition, **Proceedings of The Eastern Asia Society for Transportation Studies, Vol. 5**, 1081-1093.

Tamin, O.Z. (1985), **The Estimation of Matrices for Freight Movement From Traffic Counts Using a Non-Linear Regression Approach**, MSc Thesis of the University of London, Imperial College and University College London.

Tamin, O.Z. (1988), **The Estimation of Transport Demand Model From Traffic Counts**, PhD Dissertation of the University of London, University College London.

Tamin, O.Z. and Willumsen, L.G. (1989), Transport Demand Model Estimation From Traffic Counts, **Journal of Transportation**, 16, 3-26.

Tamin, O.Z. (1992). *Application of Transport Demand Models for Inter-Regional Vehilce Movements in East Java (Indonesia)*. **Proceedings of the 6th World Conference on Transport Research (WCTR)**, Lyon, France.

Tamin, O.Z. (2000), **Transport Planning and Modelling**, 2nd Edition. ITB Press, Bandung.

Tamin, O.Z., et al (2001), **Dynamic Origin-Destination (O-D) Matrices Estimation From Real Time Traffic Count Information**, Graduate Team Research, University Research for Graduate Education (URGE) Project

Tamin, O.Z., Sjafruddin A, and Purwanti, O. (2002), Public Transport Demand Estimation by Calibrating The Combined Trip Distribution-Mode Choice (TDMC) Model from Passenger Counts: A Case Study in Bandung, Indonesia, **the 4th Proceedings of the Eastern Asia Society for Transportation Studies (EASTS)**.