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THE ESTIMATION OF GRAVITY MODEL COMBINED WITH THE MULTI-NOMIAL LOGIT MODEL BASED ON TRAFFIC VOLUMES

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Abstract: Many problems in transportation require an Origin-Destination (O-D) matrix which is usually obtained from a large survey. This survey tends to be costly. Therefore, more use should be made of low-cost traffic data. This research aims to enhance the accuracy of the doubly constrained gravity model using negative exponential as deterrence function by applying transport demand models, described as a function of one or more parameters. The estimation methods have been developed, namely: Non-Linear-Least-Squares (NLLS) will be used as methods to estimate the parameters of transport demand models. The work concentrated on the estimation of Gravity (GR) model combined with the Multi-Nomial-Logit (MNL) model. General conclusions regarding the advantageous of the approach are given at the end of the paper.

BACKGROUND

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, see also Figure 1). Figure 1 shows the roadmap of the Transport Demand Model Estimation Research Agenda which have been conduct since 1988 by the Division of Transportation Engineering. 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 and Purwanti, 2002). In this case, the TDMC model is represented by a function of a model form and relevant parameters.

The idea of combining 'traditional' data sources (home or roadside interviews) with low cost data like traffic counts is not entirely new (see Tamin, 1988, see also 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 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.

OBJECTIVES

The level of accuracy of the estimated O-D matrices depends on some following factors:

a. the transport demand model itself in representing the trip making behaviour within the study area;
b. the estimation method used to calibrate the model from traffic counts;
c. trip assignment techniques used in determining the routes taken through the network;
d. location and number of traffic counts;
e. errors in traffic count information;
f. finally, the level of resolution of the zoning system and the network definition.

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). 1 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 congested road network in urban area because it never consider to the traffic jam effect and various of perception in considering of route selection .

However, 1 the previous research still in a burden condition of "All or Nothing" which is not realistic for some congested road networks 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 (congested road network).

Referring to the previous research, 5 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 .

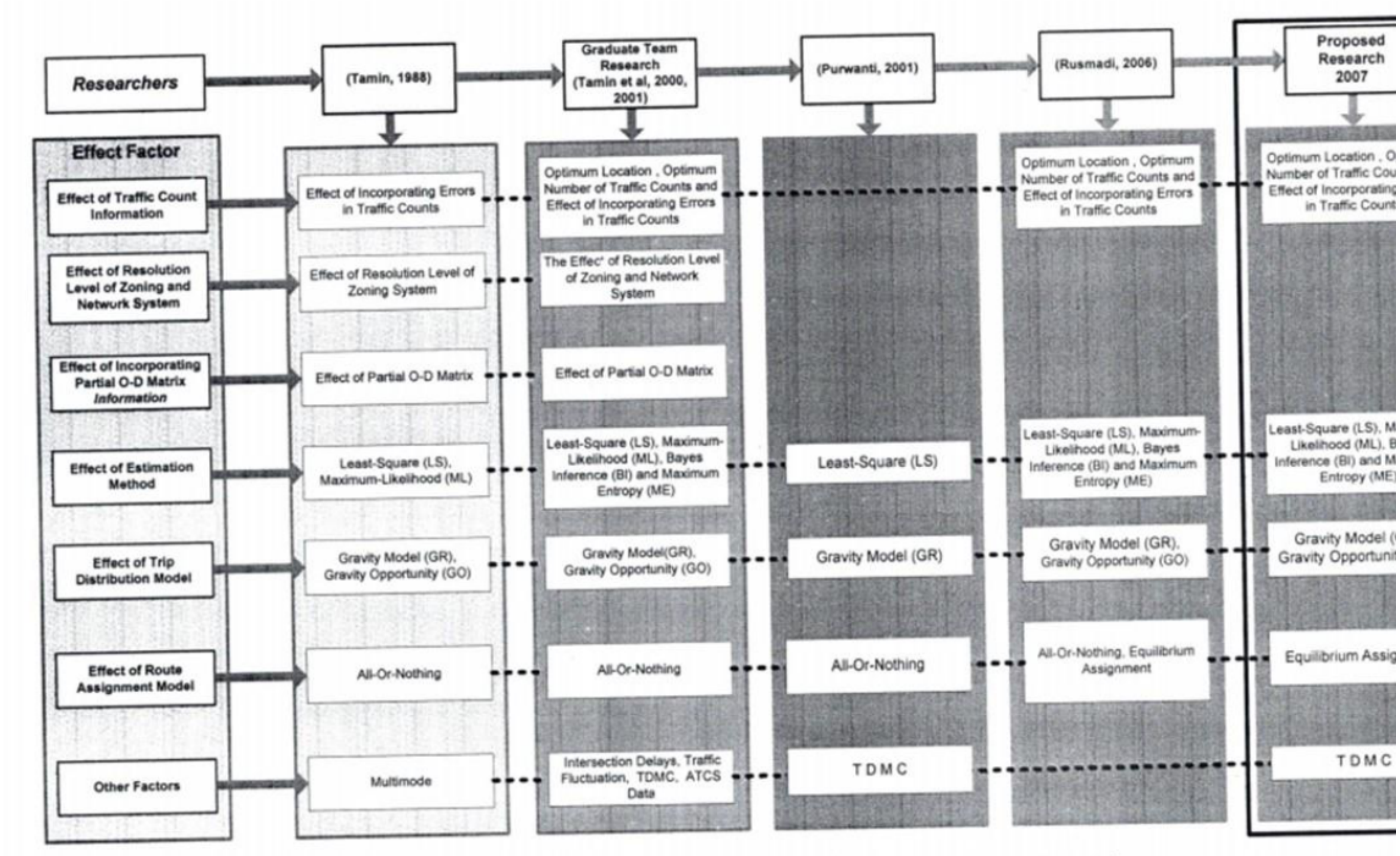


Figure 1 Roadmap On Transport Demand Model Estimation Research Agenda

LITERATURE REVIEW

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 that 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:

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

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

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

where: A_i^m and B_d^m = the balancing factors expressed as:

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

This process is repeated until the values for A_i^m and B_d^m are 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:

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

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:

$$V_l^k = \sum_d \sum_i \left[O_i^k . D_d^k . A_i^k . B_d^k . f_{id}^k . p_{id}^{lk} \frac{\exp(-\beta . C_{id}^k)}{\sum_m \exp(-\beta . C_{id}^m)} \right] \quad (6)$$

Equation (6) is a system of L simultaneous equations with only one (1) unknown parameter (β) need to be estimated.

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 4 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:

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

$\hat{V}_l^k$ = observed traffic flows for mode k $\qquad$ 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)

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

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).

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) .

$$\text{to maximize } \mathbf{L} = c.\prod_{l} p_l^{\hat{V}_l^k} \quad (9)$$

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

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

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

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

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

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:

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

2 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:

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

Equation (14) 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. Max,mum-Entropy Estimation Method (ME)

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

to maximise $$E_1 = -\sum_{l=1}^{L}\left[\sum_{i=1}^{N}\sum_{d=1}^{N} T_{id} \cdot p_{id}^{l} \cdot \log_e\left(\frac{\sum_{i=1}^{N}\sum_{d=1}^{N} T_{id} \cdot p_{id}^{l}}{\hat{V}_l}\right) - \left(\sum_{i=1}^{N}\sum_{d=1}^{N} T_{id} \cdot p_{id}^{l}\right) + \hat{V}_l\right] \quad (15)$$

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:

$$\frac{\partial E_1}{\partial \beta} = -\sum_{l}\left[\left(\sum_{i}\sum_{d} \frac{\partial T_{id}^{k}}{\partial \beta} \cdot p_{id}^{lk}\right) \cdot \log_e\left(\frac{\sum_{i}\sum_{d} T_{id}^{k} \cdot p_{id}^{lk}}{\hat{V}_l^{k}}\right)\right] = 0 \quad (16)$$

Equation **(16)** 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).**

METHODOLOGY

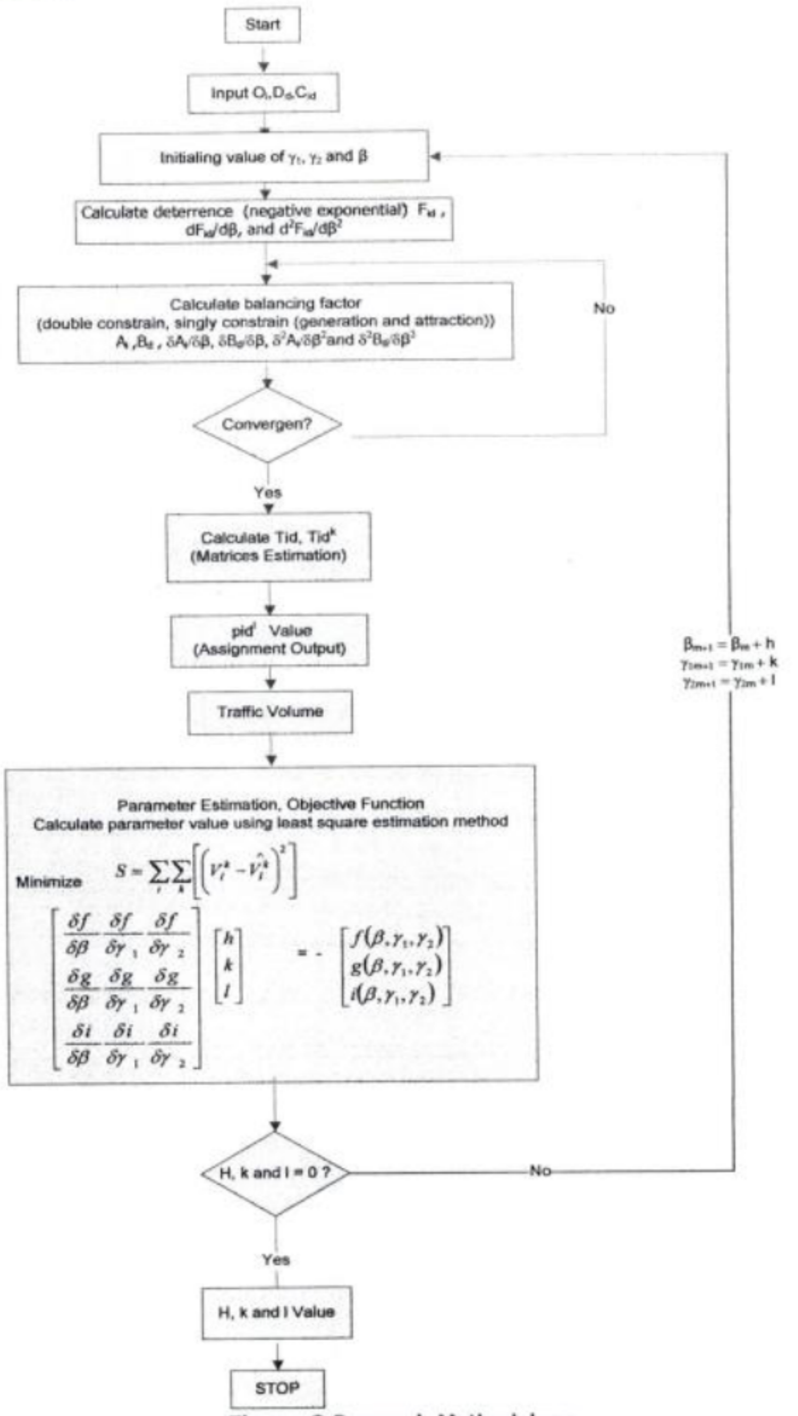


Figure 2 Research Methodology

$$f(\beta, \gamma_1, \gamma_2) = \frac{\delta S}{\delta \beta}$$

$$g(\beta, \gamma_1, \gamma_2) = \frac{\delta S}{\delta \gamma_1}$$

$$i(\beta, \gamma_1, \gamma_2) = \frac{\delta S}{\delta \gamma_2}$$

$$\frac{\delta f}{\delta \beta} = \frac{\delta^2 S}{\delta \beta^2}; \quad \frac{\delta f}{\delta \gamma_1} = \frac{\delta^2 S}{\delta \beta \delta \gamma_1}; \quad \frac{\delta f}{\delta \gamma_2} = \frac{\delta^2 S}{\delta \beta \delta \gamma_2}$$

$$\frac{\delta g}{\delta \beta} = \frac{\delta^2 S}{\delta \beta \delta \gamma_1}; \quad \frac{\delta g}{\delta \gamma_1} = \frac{\delta^2 S}{\delta \gamma_1^2}; \quad \frac{\delta g}{\delta \gamma_2} = \frac{\delta^2 S}{\delta \gamma_1 \delta \gamma_2}$$

$$\frac{\delta i}{\delta \beta} = \frac{\delta^2 S}{\delta \beta \delta \gamma_2}; \quad \frac{\delta i}{\delta \gamma_1} = \frac{\delta^2 S}{\delta \gamma_1 \delta \gamma_2}; \quad \frac{\delta i}{\delta \gamma_2} = \frac{\delta^2 S}{\delta \gamma_2^2}$$

$$f(\beta, \gamma_1, \gamma_2) = \frac{\delta f}{\delta \beta}.h + \frac{\delta f}{\delta \gamma_1}.k + \frac{\delta f}{\delta \gamma_2} i$$

$$g(\beta, \gamma_1, \gamma_2) = \frac{\delta g}{\delta \beta}.h + \frac{\delta g}{\delta \gamma_1}.k + \frac{\delta g}{\delta \gamma_2} i$$

$$i(\beta, \gamma_1, \gamma_2) = \frac{\delta i}{\delta \beta}.h + \frac{\delta i}{\delta \gamma_1}.k + \frac{\delta i}{\delta \gamma_2} i$$

Application in Artificial Network

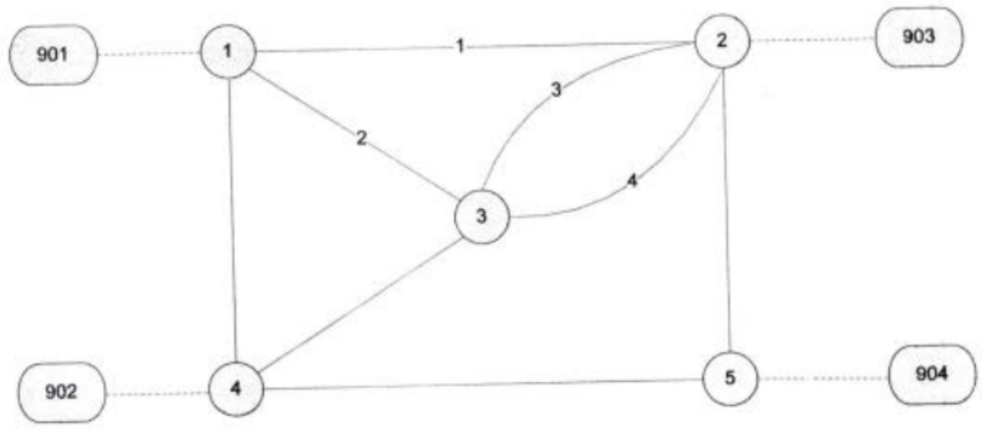


Figure 3 Artificial Network

1 Matrices C_{id}^1

From/to	1	2	3	4
1	15	20	30	60
2	35	15	50	55
3	60	45	20	45
4	35	50	45	15

2. Matrices C_{id}^2

From/to	1	2	3	4
1	5	10	20	50
2	25	5	40	45
3	50	35	10	35
4	25	40	35	5

3. Matrices C_{id}

Assumption to get C_{id} value

$$C_{id} = \frac{\left(C_{id}^1 + C_{id}^2\right)}{2}$$

From/to	1	2	3	4
1	10	15	25	55
2	30	10	45	50
3	55	40	15	40
4	30	45	40	10

Simplification process to get p_{id}^l value:

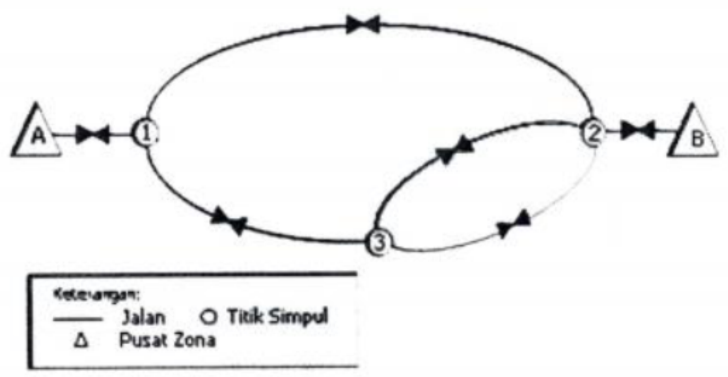


Figure 4 Artificial Network to get p_{id}^l value:

$$p_{id}^1 + p_{id}^2 = 1$$

$$p_{id}^1 + p_{id}^3 + p_{id}^4 = 1$$

T_{12} = 810

Cost Function in each route is:

Route 1 : C_{12} + 0.005 V_1

Route 2 : C_{12} + 0.02 V_2

Route 3 : C_{12} + 0.015 V_3

Using Repeated Assignment Method, Origin Destination Matrices is assigned in network system continuously. 3 Start with an all or nothing assignment, and then follow the rule developed by Frank-Wolfe to iterate toward the minimum value of the objective function. The new traffic volume is accounted as linear combination between V_n and $V_{(n-1)}$ in each assignment procedure. This algorithm as bellow:

1. Choice 1 set cost data
2. Build 1 set minimum cost, set n=n+ 1
3. Assign Origin Destination Matrices using all or nothing assignment to get Flow (Fi) value
4. calculate volume existing

$$V_l^{(n)} = (1-\phi).V_l^{(n-1)} + \phi.F_l$$

ϕ : Parameter (with value = 0-1)

$V_l^{(n)}$: Traffic flow in stage n

F_l : Traffic flow from all or nothing assignment with travel cost from stage (n-1)

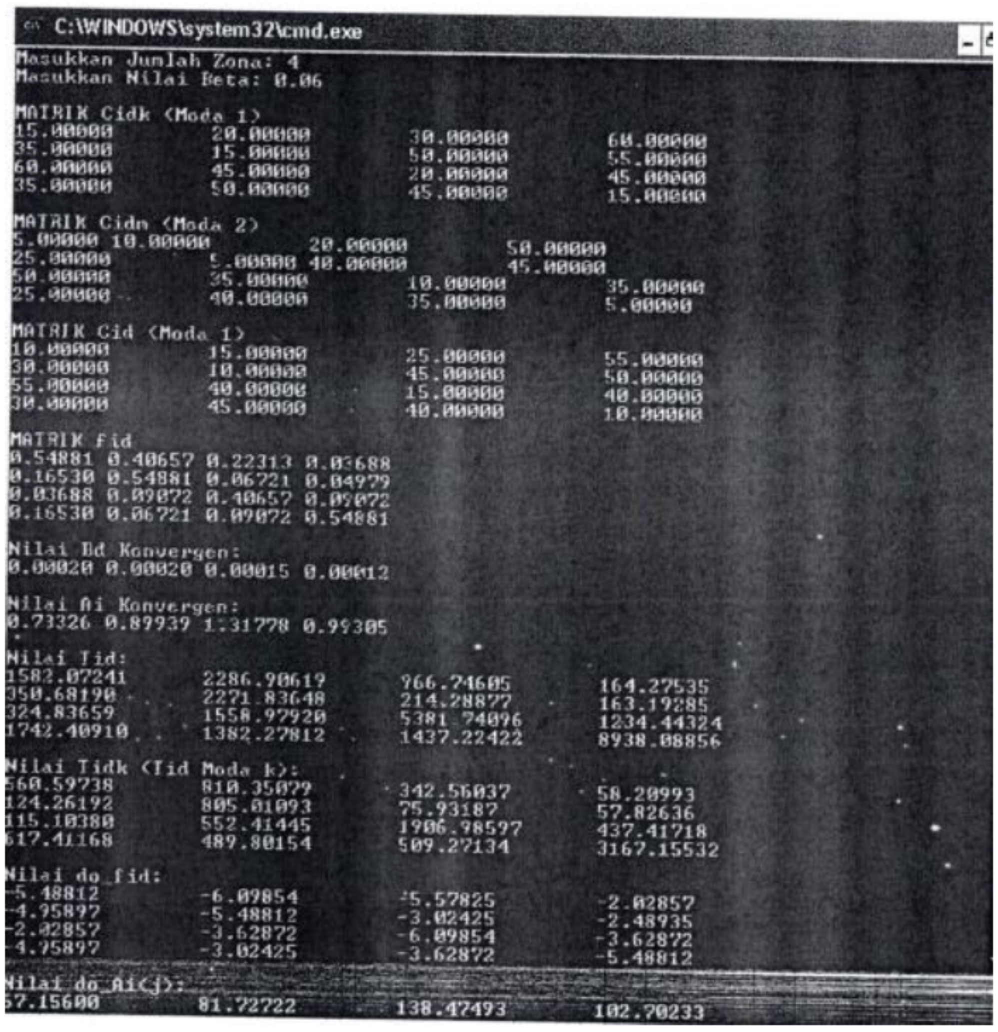
$V_l^{(n-1)}$: Traffic flow in stage (n-1)

5. Calculate new travel cost base on flow $V_l^{(n)}$. The procedure is stopped when the flow for two successive iteration are quasi-equal.If not, go on tage (2).

The new travel cost is accounted after each combination of flow ($V_l^{(n)}$) is assigned. The process is repeated until convergence.

ϕ = 1/ sum of repeated = 1/n

Next, for real network system, p_{kd}^{l} value is expected as output of assignment from EMME/2 software programs. The implementation in software can see on this figure, using C++ as bellow:



```
C:\WINDOWS\system32\cmd.exe
Masukkan Jumlah Zona: 4
Masukkan Nilai Beta: 0.06

MATRIK Cidk (Moda 1)
15.00000        20.00000        30.00000        60.00000
35.00000        15.00000        50.00000        55.00000
60.00000        45.00000        20.00000        45.00000
35.00000        50.00000        45.00000        15.00000

MATRIK Cidn (Moda 2)
5.00000 10.00000        20.00000        50.00000
25.00000        5.00000 40.00000        45.00000
50.00000        35.00000        10.00000        35.00000
25.00000        40.00000        35.00000        5.00000

MATRIK Cid (Moda 1)
10.00000        15.00000        25.00000        55.00000
30.00000        10.00000        45.00000        50.00000
55.00000        40.00000        15.00000        40.00000
30.00000        45.00000        40.00000        10.00000

MATRIK fid
0.54881 0.40657 0.22313 0.03688
0.16530 0.54881 0.06721 0.04979
0.03688 0.09072 0.40657 0.09072
0.16530 0.06721 0.09072 0.54881

Nilai Bd Konvergen:
0.00020 0.00020 0.00015 0.00012

Nilai Ai Konvergen:
0.73326 0.89939 1.31778 0.99305

Nilai Tid:
1582.07241      2286.90619      966.74605       164.27535
350.68190       2271.83648      214.28877       163.19285
324.83659       1558.97920      5381.74096      1234.44324
1742.40910      1382.27812      1437.22422      8938.08856

Nilai Tidk (Tid Moda k):
560.59738       810.35079       342.56037       58.20993
124.26192       805.01093       75.93187        57.82636
115.10380       552.41445       1906.98597      437.41718
617.41168       489.80154       509.27134       3167.15532

Nilai do_fid:
-5.48812        -6.09854        -5.57825        -2.02857
-4.95897        -5.48812        -3.02425        -2.48935
-2.02857        -3.62872        -6.09854        -3.62872
-4.75897        -3.02425        -3.62872        -5.48812

Nilai do_Ai(j):
57.15600        81.72722        138.47493       102.70233
```

Figure 5 Output Program (layer I)

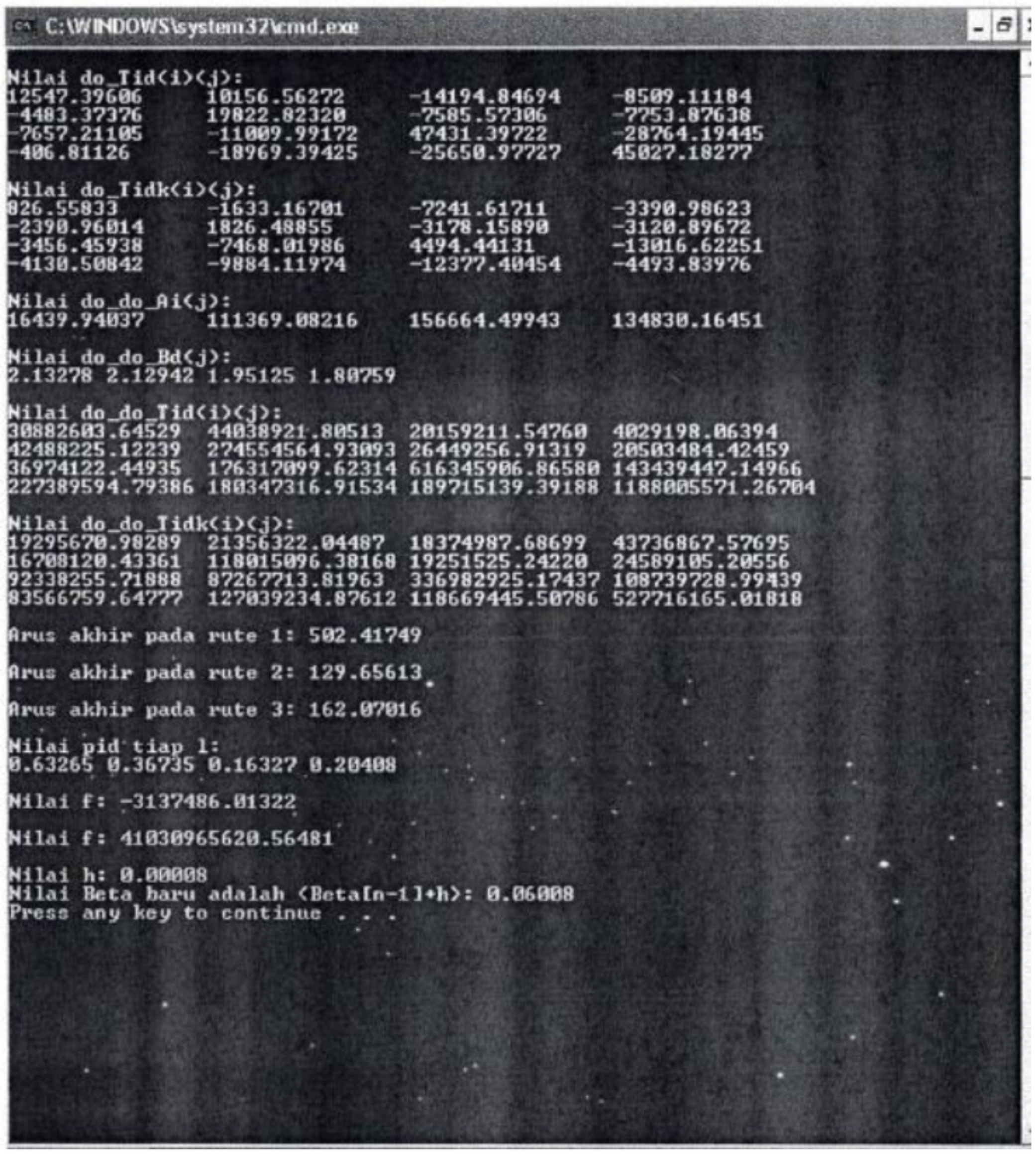


Figure 6 Output Program (layer 2)

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