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THE DEVELOPMENT OF THE ROUTE GUIDANCE SYSTEM AND THE REAL-TIME INTEGRATED TRAFFIC INFORMATION SYSTEM (RITIS) FOR LARGE CITIES IN INDONESIA

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Abstract: The paper is written based on research on '**Dynamic Origin-Destination Matrices From Real-Time Traffic Count Information**'. The latest development in automatic traffic count data collection enables us to obtain the traffic count information in a real time or short-time-interval basis. For example, **ATCS** (**Area Traffic Control System**) already installed in several large cities in Indonesia, such as: DKI-Jakarta (since 1994), Bandung (since 1997), and Surabaya (since 1998) provided us the real-time or short-time-interval traffic count information for all signalised intersections. This traffic data is updated periodically in a short-time-interval basis (e.g. 5, 15, or 30 minutes time interval). This information is provided at the **Traffic Control Centre (TCC)** of ATCS project and can be directly and easily accessed at a very low cost through internet. This data is the main input for the short-time-interval **Origin-Destination (OD)** matrix estimation.

Before this type of traffic data is used in the OD matrix estimation process; firstly, these data have to be processed in the **Data Processing Interface (DPI)**. Having it processed; the traffic data will then be ready for estimating the short-time-interval OD matrices. The output of short-time-interval OD matrices together with several practical applications will be the main input for the **Real-Time Integrated Traffic Information System (RITIS)**. This information will be stored in a Website designed specifically and informatively for the purposes of user needs (numerical and graphical).

One of the most important information is the best routes from each origin zone to each destination zone which have already considered the effect of congestion. This information will be the main data for the development of the **Route Guidance System (RGS)** so that each driver can choose his best route through the road network. The best route information will be changed in a short-time-interval basis depending on the traffic condition. This short-time-interval traffic system information will become the public-domain information which can be directly and freely accessed through internet by the users (e.g. Planning Authorities, Traffic Authorities, Department of Public Works, Consultants, Police, drivers, radio stations, and TV stations, other related agencies, etc). Moreover, this approach can also be extended to provide the short-time-interval environmental information.

Keywords: Route Guidance, Intelligent Transport System**,** Urban Transport, OD Matrix, Real Time Traffic Information

1. INTRODUCTION

As reported by **Abidin (1998)**, some papers concluded that most of developed countries has faced of losing billions of dollar in transportation just due to the drivers have no enough prior information of what he thought the best routes. Beside that, the traffic congestion is blamed as the main factor which resulting in the loss of work productivity in USA around 100 billions of dollar per year. It is also said that in 1991 there has been 40.000 fatal injury in traffic accidents and more than 5 millions injured. More over, the traffic accident has also contributed as much as 70 billions of dollar per year. Some other qualitative disadvantageous are: delay, inefficient traffic movements, high fuel consumption due to congestion, air and noise pollution.

In order to alleviate these problems, it is necessary to understand the underlying travel pattern. As mentioned in **Tamin (1988)**, the notion of **Origin-Destination (OD)** matrix has been widely used and accepted by transport planners as an important tool to represent the travel pattern. When an OD matrix is assigned onto the network, a flow pattern is produced. By examining this flow pattern, one can identify the problems that exist in the network and some kind of solution may be devised. An OD matrix gives a very good indication of travel demand, and therefore, it plays a very important role in various types of transport studies, transport planning and management tasks.

The conventional method to estimate OD matrices usually requires very large surveys such as: home and roadside interviews; which are very expensive, lengthy, labor intensive, subject to large errors, and moreover, time disruptive to trip makers. As an illustration in **Tamin (2000.2003)**, to obtain the national OD matrix, the Department of Transportation, Republic of Indonesia could only carry out this such of survey five times within 25-years period (**1982**, **1988**, **1992,1998, 2002**).

Tamin et al (1998) mentioned that the Broad outline of the 2002 **Nation's Direction (GBHN)** of Indonesia stated that all policies in transport development should be directed to perform an efficient, safe, comfort, reliable, and environmentally-based **National Transportation System (Sistranas)**. The rapid changes in land use, population and employment, as well as vehicle ownership have resulted in the conventional methods are no longer suitable for developing countries. This is due to that the lengthy process (2-3 years) which will result in the information contained in the OD matrices do not reflect anymore the real situation.

Practically, it is frequently found that in solving the 2005 transportation problem, the 2002 OD matrix is still being used due to the lack of information of the most recent OD matrix information. Furthermore, during the monetary crisis, it is almost impossible to carry out this survey for the next 5-10 years. Moreover, for urban areas, the regional government of Jakarta can only afford to carry out this OD survey three times during the last 23 years as mentioned in **Tamin et al (1998)**, through very large and expensive transport projects such as: **Jakarta Metropolitan Area Transportation Study (JMATS)** in 1975, **Arterial Road System Development Study (ARSDS)** in 1987, **Transport Network Planning Regulation Study (TNPRS)** in 1992, and most recently **SISTRAMP** in 2003.

All of these require an answer. Therefore, the new approach to tackle all of these problems is urgently required. 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 OD matrix; provide direct information about the sum of all OD pairs which use those links. Some reasons why traffic counts are so attractive as a data base are: 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. Therefore, a key element of the approach is a system to update the transport demand model using low-cost traffic count information.

Previous research (**Tamin,2000,2003**) and several other researchers have been able to obtain the OD matrices by only using traffic counts information. Unfortunately, at that time, they still used the steady-state traffic count information obtained from the traffic count survey. Nowadays, the technology for automatic traffic data collection is very well advanced. The latest development in automatic data collection for traffic count enables us to obtain the short-time-interval traffic count information.

For example, as reported in **AWA Plessey (1997)**, **ATCS (Area Traffic Control System)** already installed in several large cities in Indonesia, such as: **Jakarta** (since 1994), **Bandung** (since 1997), and **Surabaya** (since 1998) provide us the short-time-interval traffic count information for all signalised intersections. Furthermore, the technology for transferring data is also readily available and at a very low cost through the use of telephone line. By using this information, the research is directed to develop a transport modeling system that enables us to produce the OD matrices in a short-time-interval basis.

2. METHODS FOR ESTIMATING OD MATRICES

Methods for estimating OD matrices can be classified into **2 (two)** main groups as shown in **figure 1**. They are as follows: conventional and unconventional methods (**Tamin,2000,2003**). 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. The introduction of inexpensive techniques for the estimation of OD matrices will overcome the problem.

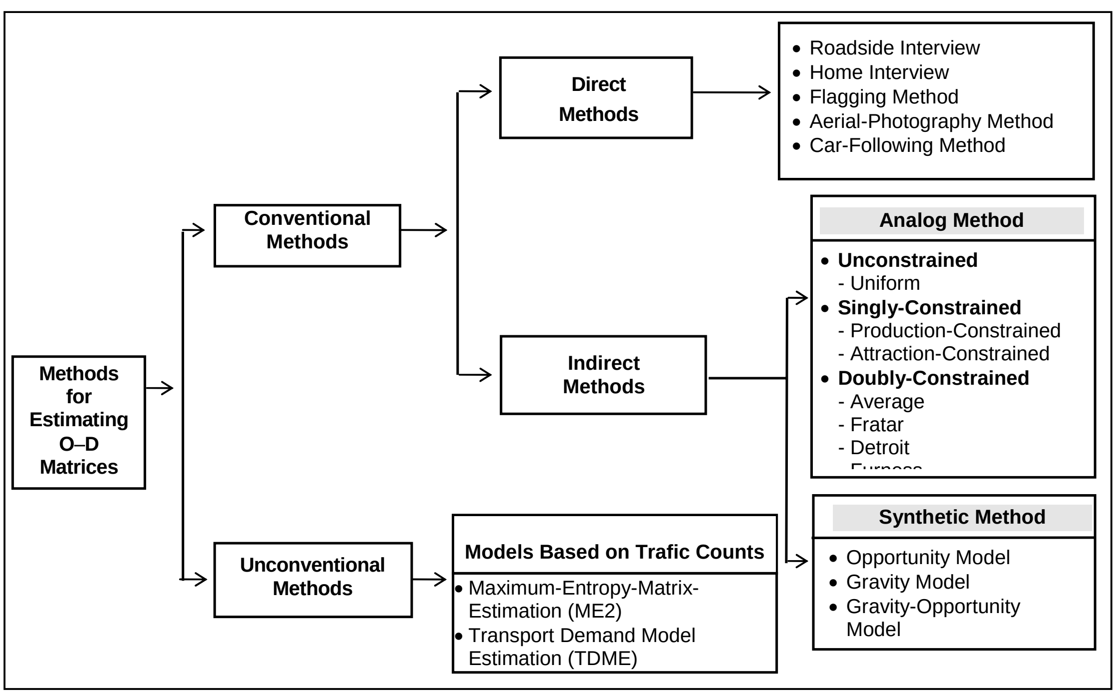

Figure 1: Methods for estimating OD matrices (Source: **Tamin,2000,2003**)

As a result of dissatisfaction expressed by transport planners with conventional methods, other techniques for estimating OD 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.

3. TRANSPORT DEMAND MODEL ESTIMATION BASED ON TRAFFIC COUNTS

3.1 General

Nguyen (1974), Willumsen (1981), and **Tamin(2000,2003)** provide a very good and comprehensive overview on the state of art in this research domain related to the OD matrix estimation based on traffic counts. They state the general problem in the following way. Let **P** denotes the sets of origins, **Q** denotes the set of destinations and **I=PxQ** denotes the set of origin-destination (OD) pairs. Most of the existing models to estimate an OD matrix $[T_{id}]$ from traffic counts may be written in the form:

$$\textbf{minimum or maximum} \quad S = f\left(\hat{V}_l, V_l\right) \tag{1}$$

$$\textbf{subject to} \quad \sum_i \sum_d T_{id} . p^l_{id} = \hat{V}_l \quad \text{for} \quad l \in L \tag{2}$$

$$T_{id} \geq 0 \tag{3}$$

where: T_{id} = number of trips travelling from origin **i** to destination **d**;

p^l_{id} = proportion of trips travelling from each origin **i** to each destination **d** that use link **l**, $0 \leq p^l_{id} \leq 1$;

$\hat{V}_l, V_l$ = observed and estimated volume on link **l**.

It can be seen that the value of p^l_{id} is defined by the route chosen by each user within the study area which can be estimated by applying suitable route choice technique. There are now available several route choice techniques ranging from the simplest one (**all-or-nothing**) to the most sophisticated one (**equilibrium**) (see **Van Vliet and Dow,1979**). To obtain the values of p^l_{id}, **Tamin (1990,1992,2000,2003)** have developed the procedure to estimate the values of p^l_{id} based on the predetermined trip assignment technique. Thus, theoretically, by knowing the information on $\hat{V}_l$ and p^l_{id}, the value of T_{id} can be estimated through mechanism of optimization equations (**1**)-(**3**).

3.2 Transport Demand Estimation Approach

The central idea is to develop estimation methods that can be used not only for estimating currently prevailing OD matrix in a short-time-interval basis and hence the OD flows but also for forecasting OD matrices and OD flows which will prevail in the future. One possible way to develop methods for estimating OD matrices from traffic counts is by modelling the trip making behaviour. The transport demand model estimation approach assumes that the travel pattern behaviour is well represented by a certain general transport model, e.g. a **gravity model**.

The main idea is to apply a system of transport models to represent the travel pattern (see **Tamin,2000,2003**). It should be noted here that the transport demand models are described as functions of some planning variables like population or employment and one or more parameters. Whatever the specification and the hypotheses underlying the models adopted, the main task 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 OD matrix, but also for predictive purposes. The latter requires the use of future values for the planning variables.

Consider a study area that is divided into **N** zones, each of which is represented by a centroid. All of these zones are inter-connected by a road network that consists of series of links and nodes. Furthermore, the OD matrix for this study area consists of N^2 trip cells. (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} ($0 \leq p_{id}^{lk} \leq 1$).

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:

$$V_l^k = \sum_i \sum_d T_{id}^k . p_{id}^{lk} \tag{4}$$

Given all the p_{id}^{lk} and all the observed traffic counts ($\hat{V}_l^k$), then there will be N^2 unknown T_{id}^k's to be 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 OD matrix [T_{id}^k]. (N^2–**N**) if intrazonal trips can be disregarded. In practice, the number of observed traffic counts is much less than the number of unknowns T_{id}^k's.

3.3 Fundamental Basis

Using unconventional methods, it is assumed that a certain type of transport demand model such as gravity model can represent the trip-making behavior. The link flows can then be represented as a function of a model form and its relevant parameters. The parameters of the postulated model are then estimated so that the errors between the estimated and observed traffic counts are minimized.

Consider now that there are **K** trip purposes or commodities travelling between zones within the study area. Assume also that a certain transport demand model such as **gravity (GR)** model can represent the interzonal movement within the study area. Hence, the total number of trips T_{id} with origin in **i** and destination **d** for all trip purposes or commodities can be expressed as:

$$\mathbf{T_{id}} = \sum_{k} \mathbf{T_{id}^{k}} \tag{5}$$

$\mathbf{T_{id}^{k}}$ is the number of trips for each trip purpose or commodity **k** travelling from zone **i** to zone **d** as expressed by equation (**6**) generally known as a **doubly constrained gravity model (DCGR)**.

$$\mathbf{T_{id}^{k}} = \mathbf{O_i^k.D_d^k.A_i^k.B_d^k.f_{id}^k} \tag{6}$$

$\mathbf{A_i^k}$ and $\mathbf{B_d^k}$ = balancing factors expressed as:

$$\mathbf{A_i^k} = \left[\sum_{d}\left(\mathbf{B_d^k.D_d^k.f_{id}^k}\right)\right]^{-1} \text{and } \mathbf{B_d^k} = \left[\sum_{i}\left(\mathbf{A_i^k.O_i^k.f_{id}^k}\right)\right]^{-1} \tag{7}$$

$\mathbf{f_{id}^k}$ = the deterrence function = $\mathbf{exp}\left(-\boldsymbol{\beta}.\mathbf{C_{id}^k}\right)$ **(8)**

The readers who want to know more about the **Gravity-Opportunity (GO)** model are suggested to read **Tamin (1992)** and **Tamin and Soegondo (1989)**. By substituting equation (**6**) to (**4**), the fundamental equation for estimating the transport demand model based on traffic counts is:

$$\mathbf{V_l^k} = \sum_{i}\sum_{d}\left(\mathbf{O_i^k.D_d^k.A_i^k.B_d^k.f_{id}^k.p_{id}^{lk}}\right) \tag{9}$$

The fundamental equation (**9**) has been used by many literatures not only to estimate the OD matrices but also to calibrate the transport demand models from traffic count information (see **Tamin**[2,3,11,12]; **Tamin and Willumsen**[10], **Tamin and Soegondo**[13]). Theoretically, having known the values of $\mathbf{\hat{V}_l^k}$ and $\mathbf{p_{id}^{lk}}$, $\mathbf{T_{id}^k}$ can be estimated by following the optimization mechanism of equations (**1**)-(**3**). Equation (**9**) is a system of L simultaneous equations with only (**1**) unknown parameter β need to be estimated. The problem now is how to estimate the unknown parameter β so that the model reproduces the estimated traffic flows as close as possible to the observed traffic counts.

3.4 Estimation Methods

Tamin (2002,2003) explains several types of estimation methods that have been developed so far by many researchers are:

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

3.4.1 Least-Squares estimation method (LS)

Tamin (2000,2003) have developed several **Least-Squares (LS)** estimation methods of which its mathematical problem can be represented as equation (**10**).

$$\textbf{to minimize} \qquad \mathbf{S} = \sum_{l}\left[\left(\mathbf{\hat{V}_l^k} - \mathbf{V_l^k}\right)^2\right] \tag{10}$$

$\mathbf{\hat{V}_l^k}$ = observed traffic flows for mode **k** $\qquad$ $\mathbf{V_l^k}$ = 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 (**9**) to (**10**), the following set of equation is required in order to find an unknown parameter β which minimizes equation (**10**):

$$\frac{\delta S}{\delta \beta} = \sum_{l}\left[\left(2\sum_{i}\sum_{d} T_{id}^{k}.p_{id}^{lk} - \hat{V}_{l}^{k}\right).\left(\sum_{i}\sum_{d}\left(\frac{\partial T_{id}^{k}}{\partial \beta}.p_{id}^{lk}\right)\right)\right] = 0 \qquad \textbf{(11)}$$

Equation (**11**) 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 (**11**) (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 (2000,2003)** 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 behavior. Therefore, in general, the **NLLS** provides better results compared to the **LLS**.

3.4.2 Maximum-Likelihood estimation method (ML)

Tamin (2000,2003) have also developed an estimation method that tries to maximise the probability as expressed in equation (**12**). The framework of the ML estimation method is that the choice of the hypothesis **H** maximising equation (**12**) 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 this framework is expressed as:

to **maximize** $$L = c.\prod_{l} p_l^{\hat{V}_l^k} \qquad \textbf{(12)}$$

subject to: $$\sum_{l} V_l^k - \hat{V}_T^k = 0 \qquad \textbf{(13)}$$

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

By substituting equation (**9**) to (**12**), finally, the objective function of **ML** estimation method can then be expressed as equation (**14**) with respect to unknown parameters β and θ.

$$\textbf{max}.\ L_1 = \sum_{l}\left[\hat{V}_l^k.\log_e\left(\sum_{i}\sum_{d} T_{id}^{k}.p_{id}^{lk}\right) - \theta.\sum_{i}\sum_{d} T_{id}^{k}.p_{id}^{lk}\right] + \theta.\hat{V}_T^k - \hat{V}_T^k.\log_e \hat{V}_T^k + \log_e c \qquad \textbf{(14)}$$

The purpose of an additional parameter θ, which appears in equation (**14**), is that to ensure the constraint equation (**13**) should always be satisfied. In order to determine uniquely parameter β of the **GR** model together with an additional parameter θ, which maximizes equation (**14**), the following two sets of equations are then required. They are as follows:

$$\frac{\delta \mathbf{L_1}}{\delta \boldsymbol{\beta}} = \sum_{l} \left[\hat{\mathbf{V}}_l^k \cdot \frac{\sum_i \sum_d \frac{\delta \mathbf{T}_{id}^k}{\delta \boldsymbol{\beta}} \cdot \mathbf{p}_{id}^{lk}}{\sum_i \sum_d \mathbf{T}_{id}^k \cdot \mathbf{p}_{id}^{lk}} \right] - \left(\boldsymbol{\theta} \cdot \sum_i \sum_d \frac{\delta \mathbf{T}_{id}^k}{\delta \boldsymbol{\beta}} \cdot \mathbf{p}_{id}^{lk} \right) = \mathbf{0} \qquad \textbf{(15a)}$$

$$\frac{\delta \mathbf{L_1}}{\delta \boldsymbol{\theta}} = -\boldsymbol{\theta} \cdot \left[\sum_i \sum_d \mathbf{T}_{id}^k \cdot \mathbf{p}_{id}^{lk} - \hat{\mathbf{V}}_T^k \right] = \mathbf{0} \qquad \textbf{(15b)}$$

Equation (**15ab**) is in effect a system of two (**2**) simultaneous equations which has two (**2**) unknown parameters β and θ need to be estimated. Again, the **Newton-Raphson's** method combined with the **Gauss-Jordan Matrix Elimination** technique can then be used to solve equation (**15ab**).

3.4.3 Bayes-Inference estimation method (BI)

Tamin (2000,2003) has developed the **B̲ayes-I̲nference (BI)** estimation method in which the main idea is to combine 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. In other words, prior beliefs are modified by observations to produce 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 $$\mathbf{BI}\ (\boldsymbol{\tau}_l^k \mathbf{V}_l^k) = \sum_l \left(\hat{\mathbf{V}}_l^k \log_e \mathbf{V}_l^k \right) \qquad \textbf{(16)}$$

By substituting equation (**9**) to (**16**), the objective function can then be rewritten as:

to maximize $$\mathbf{BI} = \sum_l \left[\hat{\mathbf{V}}_l^k \cdot \log_e \left(\sum_i \sum_d \mathbf{T}_{id}^k \cdot \mathbf{p}_{id}^{lk} \right) \right] \qquad \textbf{(17)}$$

In order to determine uniquely parameter β of the **GR** model, which maximizes equation (**17**), the following two sets of equations are then required. They are as follows:

$$\frac{\partial \mathbf{BI}}{\partial \boldsymbol{\beta}} = \sum_l \left[\left(\frac{\hat{\mathbf{V}}_l^k}{\sum_i \sum_d \left(\mathbf{T}_{id}^k \cdot \mathbf{p}_{id}^{lk} \right)} \right) \cdot \left(\sum_i \sum_d \left(\frac{\partial \mathbf{T}_{id}^k}{\partial \boldsymbol{\beta}} \cdot \mathbf{p}_{id}^{lk} \right) \right) = \mathbf{0} \right] \qquad \textbf{(18)}$$

Equation (**18**) is an equation which has one (**1**) unknown parameter β need to be estimated. Again, the **Newton-Raphson's** method combined with the **Gauss-Jordan Matrix Elimination** technique can then be used to solve equation (**18**).

3.4.4 Maximum-Entropy estimation method (ME)

Tamin (2000,2003) has developed the **maximum-entropy** approach to calibrate the unknown 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{ $\mathbf{V}_l^k$ } associated with the meso state $\mathbf{V}_l^k$ is given by:

$$\mathbf{W}\left[\mathbf{V_l^k}\right] = \frac{\mathbf{V_T^k!}}{\prod_l \mathbf{V_l^k!}} \tag{19}$$

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 **[$\mathbf{V_l^k}$]** which maximize **W** in equation (**19**). For convenience, we seek to maximize a monotonic function of **W**, namely **log*e*W**, as both problems have the same maximum. Therefore:

$$\log_e \mathbf{W} = \log_e \frac{\mathbf{V_T^k!}}{\prod_l \mathbf{V_l^k!}} = \log_e \mathbf{V_T^k!} - \sum_l \log_e \mathbf{V_l^k!} \tag{20}$$

Using **Stirling's approximation** for **log$_e$X! ≈ Xlog$_e$X–X**, equation (**20**) can be simplified as:

$$\log_e \mathbf{W} = \log_e \mathbf{V_T^k!} - \sum_l \left(\mathbf{V_l^k} \log_e \mathbf{V_l^k} - \mathbf{V_l^k}\right) \tag{21}$$

Using the term $\log_e \mathbf{V_T^k!}$ 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**.

$$\log_e \mathbf{W'} = -\sum_l \left(\mathbf{V_l^k} \log_e \mathbf{V_l^k} - \mathbf{V_l^k}\right) \tag{22}$$

By maximising equation (**22**), 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 $\mathbf{V_l^k}$). 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 ($\mathbf{\hat{V}_l^k}$). The revised objective function becomes:

$$\log_e \mathbf{W''} = -\sum_l \left(\mathbf{V_l^k} \log_e \left(\frac{\mathbf{V_l^k}}{\mathbf{\hat{V}_l^k}}\right) - \mathbf{V_l^k} + \mathbf{\hat{V}_l^k}\right) \tag{23}$$

Equation (**23**) is an interesting function in which each element in the summation takes the value zero if $\mathbf{V_l^k} = \mathbf{\hat{V}_l^k}$ and otherwise is a positive value which increases with the difference between $\mathbf{V_l^k}$ and $\mathbf{\hat{V}_l^k}$. The greater the differences, the smaller the value of **log*e* W''**. Therefore, **log*e* W''** is a good measure of the difference between $\mathbf{V_l^k}$ and $\mathbf{\hat{V}_l^k}$. Mathematically, the objective function of the **ME** estimation method can be expressed as:

$$\textbf{to maximise} \quad \mathbf{E_1} = \log_e \mathbf{W''} = -\sum_l \left(\mathbf{V_l^k} \log_e \left(\frac{\mathbf{V_l^k}}{\mathbf{\hat{V}_l^k}}\right) - \mathbf{V_l^k} + \mathbf{\hat{V}_l^k}\right) \tag{24}$$

In order to determine uniquely parameter β of the **GR** model that maximizes the equation (**24**), the following equation is then required. They are as follows:

$$\boldsymbol{\delta}\mathbf{E_1} = -\sum_l \left[\left(\sum_i \sum_d \frac{\partial \mathbf{T_{id}^k}}{\partial \boldsymbol{\beta}} . \mathbf{p_{id}^{lk}}\right) . \log_e \left(\frac{\sum_i \sum_d \mathbf{T_{id}^k} . \mathbf{p_{id}^{lk}}}{\mathbf{\hat{V}_l^k}}\right)\right] = \mathbf{0} \tag{25}$$

Equation (**25**) is an equation which has only one (**1**) unknown parameter β need to be estimated. Again, the **Newton–Raphson's** method combined with the **Gauss–Jordan Matrix Elimination** technique can then be used to solve equation (**25**).

3.4.5 Test case with real steady state traffic counts data

The real data set of urban traffic movement in Bandung in terms of steady state traffic count information was used to validate the proposed estimation methods. Bandung is a capital of West Java Province and its population is around 6.4 millions in 1998 and expected to increase to 13.8 millions in 2020. The total area of Bandung is around 325,096 hectares and is divided into **66** kecamatans and **590** kelurahans.

The study area was divided into **146** zones of which **140** are internal zones and **6** are external. The road network of the study area consisted of **653** nodes and **1,811** road links. There are **95** observed 'steady-state' traffic counts ($\hat{\mathbf{V}}_\mathbf{l}$), traffic generation and attraction ($\mathbf{O_i}$ and $\mathbf{D_d}$) for each zone, and observed OD matrix for comparison purpose. The units used in equation (**9**) are as follows:

$\hat{\mathbf{V}}_\mathbf{l}$ = traffic counts in vehicles/hour

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

The most important thing in 'transport demand model estimation from traffic counts' is to know how good the calibrated transport models are in reproducing the observed OD matrix. There are two ways of doing this task:

a. the accuracy of the estimated OD matrices compared to the observed one;
b. if the estimated OD matrix is assigned onto the network then the corresponding traffic flows in each link should be as close as possible with the observed link flow obtained from ATCS control center.

In order to establish the strategy for validity and sensitivity tests, it is necessary to introduce at this stage the main issues affecting the accuracy of the estimated OD matrix produced by the calibrated models. These are as follows:

- the choice of the transport demand model itself to be used in representing the trip making behaviour within the study area or, perhaps, a system of the real world;
- the estimation method used to calibrate the parameters of the transport model from traffic count information;
- location and number of traffic count information;
- the level of errors in traffic counts; and
- the level of resolution of the zoning system and the network definition.

The validity and sensitivity tests can then be established from these **5 (five)** main issues. Two transport demand models, namely **gravity (GR)** and **gravity-opportunity (GO)** models, and four estimation methods (**NLLS, ML, BI, ME**) have been used in the validity tests. The four estimation methods mentioned above have been discussed in detail in section 3.4. The value of $\mathbf{R^2}$ statistic as expressed in equation (**26**)–(**27**) is used to compare the observed and estimated OD matrices to ascertain how close they are (see **Tamin,2000,2003**).

$$\mathbf{R^2} = \mathbf{1} - \frac{\sum_{\mathbf{i}}\sum_{\mathbf{d}}\left(\hat{\mathbf{T}}_{\mathbf{id}} - \mathbf{T}_{\mathbf{id}}\right)^2}{\sum_{\mathbf{i}}\sum_{\mathbf{d}}\left(\hat{\mathbf{T}}_{\mathbf{id}} - \mathbf{T}_{\mathbf{1}}\right)^2} \qquad \textbf{(26)}$$

$$\mathbf{T_1} = \frac{\mathbf{1}}{\mathbf{N.(N-1)}}.\sum_{\mathbf{i}}\sum_{\mathbf{d}}\mathbf{T}_{\mathbf{id}} \qquad \text{for } \mathbf{i \neq d} \qquad \textbf{(27)}$$

3.4.6 Optimum number of traffic counts

Equation (**4**) is the fundamental equation developed for estimating the OD matrices from traffic counts information. In this model, the parameters $\mathbf{p^l_{id}}$ are estimated using traffic assgnment technique. Given all the $\mathbf{p^l_{id}}$ and all the observed traffic counts ($\hat{\mathbf{V}}_l$), then there will be $\mathbf{N^2}$ buah $\mathbf{T_{id}}$'s to be estimated from a set of **L** simultaneous linear equations (**1**) where **L** is the total number of traffic counts. In principle, $\mathbf{N^2}$ independent and consistent traffic counts are required in order to determine uniquely the OD matrix $\mathbf{[T_{id}]}$; $\mathbf{[N^2–N]}$ if intrazonal trips can be disregarded. In practice, the number of observed traffic counts is much less than the number of unknowns $\mathbf{T_{id}}$'s. Therefore, it is impossible to determine uniquely the solution (**Tamin et al 2001**).

3.4.7 The determination of the optimum number of traffic counts

As mentioned above, the determination of the optimum number of traffic count will be conducted under **1 (one)** condition representing the sensitivity between the number of traffic counts and the link rank to the accuracy of the estimated OD matrices, namely: random condition. In this condition, several combinations of traffic counts will be created based on random selection. Each combination of traffic counts will then be used to estimate the OD matrices. **Figure 2** show the relationship between the level of accuracy of the estimated matrices compared to the initial one and the number of selected traffic counts under random condition.

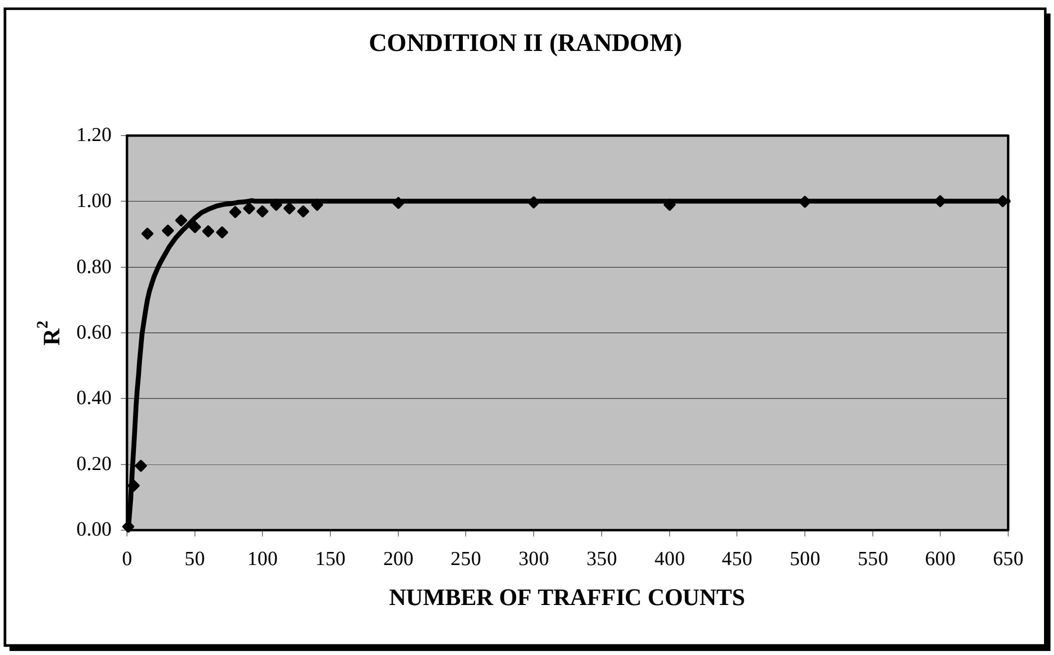

Figure 2: Number of traffic counts and the value of $\mathbf{R^2}$ (random condition)

It can be seen from **figure 2** that the use of **90** links has reproduced the relatively high accuracy of estimated OD matrices compared to the initial one (in terms of $\mathbf{R^2}$). The use of **90** links has relatively the same accuracy with the use of **646** links. It can be concluded that the optimum number of traffic counts is **90** links (**14%** of **646** selected links or **3.6%** of **2485** available links).

3.4.8 Important findings

Table 1 shows the values of $\mathbf{R^2}$ statistic of the observed OD matrix compared with the estimated OD matrices obtained from traffic counts.

Table 1: The value of R^2 for the comparison of the observed and estimated OD matrices

Model	Estimation Methods				GR/GO[1]
	NLLS	ML	BI	ME	
GR	0.944	0.936	0.935	0.939	0.950
GO	0.946	0.943	0.942	0.945	0.956

Note: [1)] obtained using the observed OD matrix information

Some final conclusions can then be drawn from **table 1**. They are as follows:

- in terms of OD matrix level, it was found that the **GO** model always produced the best estimated matrices. However, these are only marginally better than those obtained by the **GR** model. Taking into account the results of using other criteria, it can be concluded that the best overall estimation methods are the combination of **GO** model with **NLLS** estimation method and the worst is **GR** model estimated by **BI** estimation method.
- with evidence so far, it was found that the estimated models and therefore OD matrices are only slightly less accurate than those obtained directly from the full OD surveys. This finding concludes that the transport demand model estimation approach is found encouraging in term of data collection and transport model estimation costs.

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.

Table 2: Performance ranking of model estimation methods for specified criteria

Model and estimation methods		Criteria				
		Accuracy[*)]	Computer time	Sensitivity to errors in traffic counts	Sensitivity to zoning level and network resolution	Sensitivity to number of traffic counts
GR	**NLLS**	6	8	8	7	4
	ML	2	6	7	8	3
	BI	1	6	6	5	1
	ME	3	5	5	6	2
GO	**NLLS**	8	4	NA	NA	8
	ML	5	2	NA	NA	7
	BI	4	3	NA	NA	5
	ME	7	2	NA	NA	6

Note: [*)] concluded from table 1 **Source**: Analysis

Small differences of $\mathbf{R^2}$ on **table 1** will then be regarded as reasonable differences to determine the superiority/inferiority among the estimation methods. The values of $\mathbf{R^2}$ are transferred to the ranking scale ranging from **1** to **8** to see the performance of estimation methods based on the above criteria. This approach is used to homogenise several types of quantitative scaling systems between each criteria into a **1–8** scaling system. Scale **1** shows the **worst** performance, while scale **8** shows the **best** performance.

It can be seen from **table 2** that in terms of accuracy and sensitivity to number of traffic counts criteria, the **GO** model together with **NLLS** estimation performs the best. While, in terms of computer time, sensitivity to errors in traffic counts, sensitivity to zoning level and network resolution, the **GR** model with **NLLS** estimation 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.

4. AREA TRAFFIC CONTROL SYSTEM (ATCS)

4.1 Introduction

The **Area Traffic Control System (ATCS)** which have been installed in three large cities (Jakarta, Bandung, and Surabaya) enable us to obtain the real-time or short-time-interval traffic count information automatically for all signalized intersections. **DLGT (1996)** and **AWA Plessey (1997)** reports that the ATCS has been fully operated in Bandung since 1997. The technologies for transferring data via internet and telephone line are also available and at a very low cost that enables us to obtain the traffic count information in a short-time-interval basis. Basically, the objective of ATCS is to achieve the optimum traffic performance through minimization of intersection delay and creating continuous traffic flow called as green wave along the coordinated intersections. To achieve the above condition, the loop detectors record the traffic flow passing through the approaches. Then, the traffic data will be used for traffic signal arrangement interactively. The traffic data would be saved in the data base system at the ATCS control center through telecommunication network.

This traffic data is updated periodically in a short-time-interval basis. The data base system can be accessed very easily at a very low cost through the internet facility. This data would be as a main input data for short-time-interval OD matrix estimation. As an illustration as reported in **AWA Plessey (1997)**, Bandung has **117** intersections under ATCS and divided into two areas: the **northern area** consists of **59** intersections and the **southern area** consists of **58** intersections. The traffic data obtained from ATCS is traffic data in the approach of intersection. It is demanded to convert the data into link traffic data as required by the estimation process. This can be done through conversion factor.

4.2 The development of Data Processing Center (DPC)

As we know that the short-time-interval data traffic count will be used as the main data. For final process, the traffic count files are required to estimate the OD matrices. These files are taken periodically from ATCS. All the traffic data of every sensor in each intersection is sent to the ATCS server and saved into a file which have to be ordered first. In ordering the file, some variables should be specified such as: location of intersection, and the saving period (date, hour, minute).

5. THE CONCEPT IN DEVELOPING THE REALTIME INTEGRATED TRAFFIC INFORMATION SYSTEM (RITIS)

5.1 Basic configuration

- In general, the basic configuration of the system is summarized in **figure 3**. Collecting automatically the traffic count information obtained from the **Traffic Control Center (TCC)** of ATCS in a short-time-interval basis develops this information system.

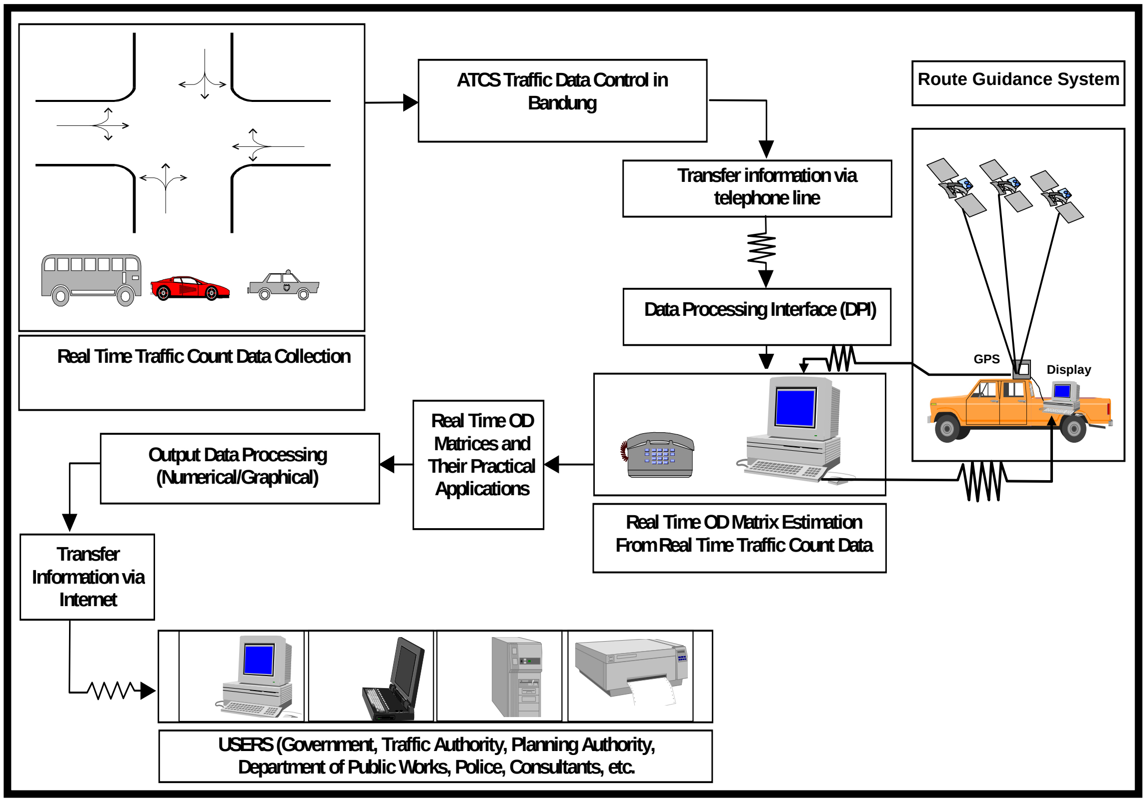

Figure 3: The basic configuration of Real-Time Integrated Traffic Information System (RITIS)

However, some important processes are required such as data transferring, data processing, and output processing, as follows:

- **Data transferring**: Traffic counts at signalised intersections were detected via wire detectors and automatically connected to the **Traffic Control Center (TCC)** of ATCS. This traffic data is updated periodically in a short-time-interval basis. The traffic data information is then provided at the TCC and can be directly and easily accessed at a very low cost via telephone line.
- **Data processing:** This data is a main input for short-time-interval OD matrix estimation. Before the traffic data is used in the estimation process; firstly, those data has to be processed in the **Data Processing Center (DPC)**. The process includes: error treatment due to transfer process, data formatting, data base preparation of zoning and network system, etc. Moreover, the traffic data obtained from ATCS is traffic at the approach of intersection. It is demanded to convert the data into link traffic data as required by the estimation process. This can be done through conversion factor. Having it processed, the traffic data will then be ready to be used for estimating the short-time-interval OD matrices.
- **Output processing**: The estimated short-time-interval OD matrices and their practical applications are stored in a **Real Time Integrated Traffic Information System (RITIS)** so that the users can directly and easily access the information through the internet facility. The RITIS is designed specifically and informatively for the purposes of user needs.
- **Route Information processing**: The driver can contact the **Data Processing Center (DPC)** to inform his location and his destination zone in which his location will be

determined by GPS. The DPC will then processed the best route by considering latest traffic condition and send the best route information back to the vehicle.

All of these processes will be designed in the forms of **Route Guidance System (RGS)** and the **Real Time Integrated Transportation Information System (RITIS)**.

6. THE POTENTIAL OF RITIS IN SOLVING URBAN TRANSPORTATION PROBLEMS

As mentioned above that some techniques and methods have been developed in very recent years which enable us to obtain the OD matrices by using only easily available and low-cost traffic count information. Unfortunately, at that time, the models still used the steady-state traffic count information obtained from the traffic count survey. The latest development in automatic data collection for traffic count enables us to obtain the short-time-interval traffic count information. For example, **ATCS (Area Traffic Control System)** already installed in Bandung since 1997 provides us the real-time or short-time-interval traffic count information for all signalized intersections. Furthermore, the technology for transferring data is also readily available and at a very low cost through the use of internet or telephone line facility.

The use of short-time-interval traffic count information enables us to analyze the dynamic phenomena of OD matrices in a short-time-interval basis. The developed model will give high added value through high efficiencies in terms of time and cost especially to be used to solve the dynamic urban transportation problem. In other words, we can obtain the accurate and low-cost OD matrix information regularly within a very short period such as in every 30 minutes.

Several things have been studied in order to increase the accuracy of the estimated OD matrices. They are as follows:

a. development of the **Data Processing Interface (DPI)** and to study the best procedure for collecting short-time-interval traffic count data from ATCS Control Center;
b. the conversion factor to convert the intersection-based traffic data into link-based traffic data;
c. better knowledge and obtaining more advanced transport demand models which will represent more accurately some specific travel demand pattern;
d. the optimum time-slice of O–D matrices;
e. the optimum location and number of traffic count data and its impact to the accuracy of the estimated OD matrices;
f. explanation on some unanswered questions relating to the impact of level of detail of zoning system and network definition on the OD matrices' accuracy;
g. more advanced route choice techniques (capacity-restrained or equilibrium) to take into account the effect of congestion especially in urban areas in relation to dynamic OD matrix estimation from traffic counts;
h. the impact of the intersection delay to route choice and its effect to the accuracy of the estimated OD matrices;
i. the evolution of short-time-interval OD matrices due to traffic flow fluctuation;

The output of short-time-interval OD matrices together with their practical applications will be stored in a **Real Time Integrated Traffic Information System (RITIS)** designed specifically for the purposes of user needs (numerical and graphical). All users (Planning Authorities, Traffic Authorities, Department of Public Works, Consultants, Police, and other related agencies) can directly and easily access this information at a very low cost through internet facility.

Several transport analysis can be conducted and several applications can be carried out by using the **RITIS**, some of them are:

- to predict short-time-interval (30 minutes) O–D matrices based on fluctuated traffic, hence to provide the evolution of link flows as sources in identifying an appropriate road management scheme;
- to provide short-time-interval information on the performance of the network, both numerical and graphical e.g. link flows, link speeds, VCR values for all links, route guidance, locations of bottleneck, and many other short-time-interval practical information;
- to assess merits of the new introduction of new transport policy on the road network performance before it is implemented;
- to analyze the effect of ATCS implementation on road traffic circulation;
- several important applications which will solve the dynamic urban transport problems.

This short-time-interval traffic information will become the public-domain information that can be directly and freely accessed via internet by the users (e.g. road users, traffic police, traffic planners, traffic authority, radio stations and TV stations, etc). Moreover, this approach can also be extended to provide the short-time-interval environmental information. This method have been tested and validated in Bandung and it shows remarkably good results for Bandung condition. Several further applications can also be developed such as: the route guidance system for private vehicle and taxi, bus operating system, fleet management, etc.

7. CONCLUSIONS

The paper explains the concept of developing the **Real Time Integrated Traffic Information System (RITIS)** and the **Route Guidance System (RGS)** by utilizing the short-time-interval traffic count information. A novel of unifying approach to describe the estimation of OD matrices from traffic count information has given. The significance of the model is, both theoretical and practical values; by understanding thoroughly the use of short-time-interval traffic count information in obtaining the short-time-interval OD matrices is a breakthrough giving high added value for applications in developing countries due to its effectiveness and efficient uses in many transport planning, engineering, management and policy tasks.

The result of previous research, which utilised the steady-state traffic count information, was found very useful in developing the modified model based on short-time-interval traffic count information. By using these traffic count information, the short-time-interval OD matrix can also be estimated. The OD matrices together with their applications will be stored and provided in the **RITIS** designed specifically for the purposes of users (numerically and graphically) so that it can be directly accessed and used by the users via internet at a very low cost.

One of the most important information is the best routes from each origin zone to each destination zone which have already considered the effect of congestion. This information will be the main data for the development of the **Route Guidance System (RGS)** so that each driver can choose his best route through the road network. The best route information will be changed in a short-time-interval basis depending on the traffic condition. Moreover, this approach can also be extended to provide the short-time-interval environmental information.

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REFERENCES

Abidin (1998) The Potential and Prospect of GPS for Transportation Sector in Indonesia, **Proceedings of 1st Symposium of Indonesian Inter-University Transport Studies Forum (IIUTSF)**, 3 Desember 1998, Bandung (in Indonesian).

AWA Plessey (1997) **Bandung Area Traffic Control System**: After Traffic Study, Bandung.

Batty, M. (1976) Urban Modelling: Algorithm, Calibrations and Predictions. **Cambridge University Press**, Cambridge.

DLGT (1996) **Bandung Area Traffic Control System**, Final System Design, AWA Traffic System.

Nguyen, S. (1974) An Algorithm for the Traffic Assignment Problem, **Transportation Science**, **Vol 8**, **No 3**, 203–216.

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

Tamin, O.Z. (1990) Public Transport Demand Estimation by Calibrating a Trip Distribution-Modal Choice from Traffic Counts. **Proceedings of the 5th CODATU Conference**, Sao Paulo (Brazil).

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

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

Tamin, O.Z. (2003) **Transport Planning and Modelling: Example and Application**, 1st Edition. ITB Press, Bandung.

Tamin, O.Z. and Willumsen, L.G. (1988) Freight Demand Model Estimation from Traffic Counts. **Proceedings of the 16th PTRC Summer Annual Conference**, Bath (UK).

Tamin, O.Z. and Soegondo, T. (1989) Freight Demand Modelling from Traffic Counts: A Case Study in Bali. **Proceedings of the 5th World Conference on Transport Research**, Yokohama (Japan).

Tamin, O.Z., Hidayat, H., Sjafruddin, A. (1998) The Concept of Developing the Real Time O-D Matrices Based on ATCS Data, **Proceedings of 1st Symposium of Indonesian Inter-University Transport Studies Forum (IIUTSF)**, Desember 1998, Bandung (in Indonesian).

Tamin, O.Z., Soedirdjo, T.L., and Suyono, R.S. (2001) The Impact of Location and Number of Traffic Counts in the Accuracy of O-D Matrices Estimated From Traffic Counts: A Case Study in Bandung (Indonesia), to be published in **the 4th Journal of the Eastern Asia Society for Transportation Studies (EASTS)**.

Van Vliet, D. and Dow, P.D. (1979) Capacity Restrained Road Assignment, **Traffic Engineering and Control**, **Vol 20, No 6**, 226–235.

Wilson, A.G. (1970) **Entropy in Urban and Region Modeling**, Pion Ltd, London.

Wilson, A.G. and Bennet, R.J. (1985) **Mathematical Methods in Human Geography and Planning,** John Wiley and Sons Ltd.