APPLICATION OF TRANSPORT DEMAND MODELS FOR INTER-REGIONAL VEHICLE MOVEMENTS IN WEST-JAVA (INDONESIA)

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Abstract: The objective of the study is to obtain the most appropriate transport demand models which can likely represent the behavior of inter-regional vehicle movements in terms of O-D matrices. The paper will report on a family of aggregate models containing a flexible Gravity-Opportunity (GO) model for modeling the trip making behavior in which standard forms of the Gravity (GR) and Intervening-Opportunity (IO) model can be obtained as special cases. Hence, the question of choice between gravity or intervening-opportunity approaches is decided empirically and statistically by restrictions on parameters which control the global functional form of the trip distribution mechanism. The approach has been tested using the 1992 National O-D Survey (Inter-Regional Vehicle Movements) in West-Java (Indonesia). The models were found to provide a reasonably good fit and the calibrated parameters can then be used for forecasting purposes.

1. GRAVITY (GR) MODEL

The Gravity (GR) model is developed by analogy with Newton's law of gravitation. Newton asserted that the force of attraction, F_{id}, between two bodies is proportional to the product of their masses, m_i and m_d, divided by the square of the distance between them (d_{id}^2).

In geography, 'force' is associated with the numbers of movements or trips between two regions; 'mass' is replaced by a variable such as population size and measures a region's capacity either to generate or to attract trips; and distance is either measured in physical terms or replaced by a more relevant variable such as travel cost or time. The analogous transport gravity model is:

$$T_{id} = k\frac{O_i O_d}{d_{id}^2} \qquad \text{k is a constant} \qquad (1)$$

This model has some sensible properties. It says that the number of trips from zone I to zone d is directly proportional to each of O_i and D_d and inversely proportional to the squareof the distance between them. Hence, if a particular O_i and a particular D_d are each doubled, then the number of trips between these zones would quadraple according to equation (1), when one would be expected that they would only double.

Therefore, the following constraint equations on T_{id} should always be required, such constraints are not satisfied by equation **(1)**:

$$\sum_d T_{id} = O_i \qquad \text{dan} \qquad \sum_i T_{id} = D_d \tag{2}$$

where O_i and D_d directly represent the total number of trips originating and terminating at $\underline{i}$ and $\underline{d}$ respectively. These constraint equations can be satisfied if sets of constants A_i and B_d associated with production zones and attraction zones respectively are introduced. They are sometimes called 'balancing factors'. The modified gravity model can then be expressed as:

$$T_{id} = O_i.D_d.A_i.B_d.f(C_{id}) \qquad \text{where:} \tag{3}$$

f_{id} = the deterrence function = $f(C_{id})$

A_i, B_d = the balancing factors which can be obtained by constraining equations **(2)**

Hence,
$$A_i = \frac{1}{\sum_d (B_d D_d f_{id})} \quad \text{and} \quad B_d = \frac{1}{\sum_i (A_i O_i f_{id})} \tag{4}$$

The equations for A_i and B_d are solved iteratively, and it can be easily checked that they ensure that T_{id} given in equation **(3)** satisfies the constraint equation **(2)**. This process is repeated until the values of A_i and B_d converge to certain unique values.

So far, there is no reason to think that distance plays the same role in transport. Hence, a general function of time, distance or generalized cost, normally called as 'deterrence function', is introduced. There are three types of deterrence functions being used in this study which are also shown in **Figure 1**, namely:

- $f(C_{id}) = C_{id}^{-\alpha}$ ('Power' function) (5)
- $f(C_{id}) = e^{-\beta C_{id}}$ ('Exponential' function) (6)
- $f(C_{id}) = C_{id}^{\alpha}.e^{-\beta C_{id}}$ ('Tanner' function) (7)

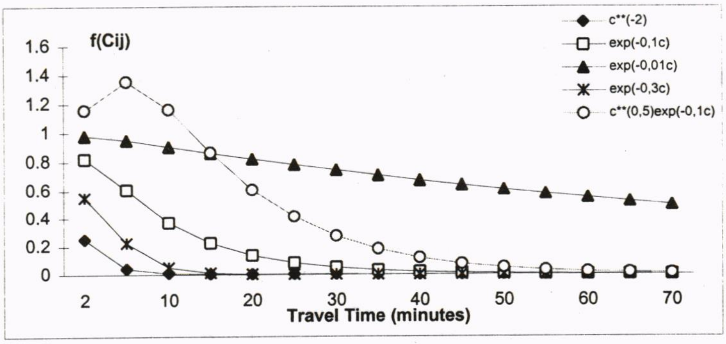

Figure 1: Types of Deterrence Functions

2. GRAVITY-OPPORTUNITY (GO) MODEL

2.1 Background

The underlying assumption of the model is that the trip maker considers each opportunity, as reached in turn, and has a definite probability that his needs will be satisfied. Consider now a single origin and its destinations, embedded in a two dimensional surface, allowing the full effects of contiguity to operate between all destinations, which are distance ordered from the origin.

Select one destination and induce change in its attributes. Such change is likely lead to a different, and lesser, effect on trips from the origin to those destinations nearer to it, compared with those which are more distant. The magnitude of this difference is a consequence of the intervening-opportunity effect of that destination, and it is an intuitively clear phenomenon that the gravity model fails to recognize.

Notational problems have hindered the adoption of the intervening-opportunity model since it requires destinations to be ranked in ascending order of distance away from origins. Whereas the gravity model is deficient in intervening-opportunity effects, the opportunity model constructed is equally deficient in omitting the trip impedance. It seems logical that an ideal model should contain both these distinct effects.

Wills (1978,1986) developed a flexible gravity-opportunity (GO) model for trip distribution in which standard forms of the gravity and intervening-opportunity model are obtained as special cases. Hence the question of choice between gravity or intervening-opportunity approaches is decided empirically and statistically by restrictions on parameters which control the global functional form of the trip distribution mechanism.

2.2 Definitions

2.2.1 An Ordered O-D Matrix. Let origins and destinations be numbered consecutively in the usual way, such that i=**1,2,..,I** are origins and d=**1,2,..,J** are destinations, and let T_{id} be the observed trips from origin i to destination d. Define now a transformation $d_j^{(i)}$ for each origin i such that:

$$\delta^{i}_{jd} = \begin{cases} 1 & \text{if destination } d \text{ is the } j^{th} \text{ position in ascending order of distance away from } i \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

and then the ordered O-D matrix can be obtained by the following transformation as:

$$Z_{ij} = \sum_d \left[\delta^{i}_{jd} . T_{id}\right] \tag{9}$$

Thus, Z_{ij} represents the trips from origin i to the j^{th} destination ranked by distance away from i. Note that j is always defined as a function of i, so it is perhaps more correctly designated as $j(i)$ but for notational simplicity we omit the i as being understood. While the ordering transformation δ_{jd}^{i} produces an ordered O-D matrix, its inverse δ_{jd}^{i-1} allows the observed O-D matrix to be recovered by:

$$T_{id} = \sum_{d}\left[\delta_{jd}^{i-1}.Z_{id}\right] \tag{10}$$

It should be noted that this part of transformations is applicable to any variable based on the O-D matrix, notably the trip cost matrix, the proportionality factor and the destination balancing factor, in addition to the O-D matrix.

2.2.2 Normalization. To achieve the logical consistency such that the sum (over destinations) of the estimated trips for each origin i is equal to the observed trips generated at i and similarly, for the sum (over origins) of the estimated trips for each destination j is equal to the observed trips generated at j, then the two following constraints are required.

$$O_i = \sum_{j} Z_{ij} \tag{11a}$$

$$D_j^i = \sum_{d}\left[\delta_{jd}^{i}.D_d\right] \quad \text{and} \quad D_d = \sum_{i}\left[\sum_{j}\left(\delta_{jd}^{i-1}.Z_{ij}\right)\right] \tag{11b}$$

2.2.3 Transformations. In order to provide a monotonic scaling of variables in such a manner as to generate families of specific functional forms, the Box-Cox transformations is used. The direct Box-Cox transformation of a variable y can be defined as:

$$y^{(\varepsilon)} = \begin{cases} \dfrac{(y^{\varepsilon}-1)}{\varepsilon} & \varepsilon \neq 0 \\ \log_e y & \varepsilon = 0 \end{cases} \tag{12}$$

and the inverse Box-Cox transformation as:

$$y^{1/\varepsilon} = \begin{cases} (y\varepsilon+1)^{1/\varepsilon} & \varepsilon \neq 0 \\ \exp y & \varepsilon = 0 \end{cases} \tag{13}$$

These transformations may be combined into a new function which we introduce as a convex combination in μ.

$$y^{(\varepsilon,\mu)} = \mu\,.\,y^{(\varepsilon)} + (1-\mu)\,.\,y^{(1/\varepsilon)} \qquad \text{with } 0 \leq \mu \leq 1 \tag{14}$$

2.3 Specification of the Opportunity Function

A key step in the integration of both models is the specification of an opportunity function which has as arguments destination-attribute variables such as population, income or some other measures of opportunities and generalized cost or trip impedance variables relating origin and destination. The opportunity function U_{ip} relates i and the p^{th} destination away from i and is defined generally as:

$$U_{ip} = \exp[(1-\varepsilon).\alpha.D_p.^{i(\Omega)} - \beta.C_{ip}^{\ (\Phi)} \tag{15}$$

U_{ip} is defined here as a combined vector of intervening-opportunity factors and impedances. The term **(1-ε)** ensures that, when ε**=1** then the gravity model is obtained and the destination intervening-opportunity effect is removed. These impedances weight the intervening-opportunity by their location to origin and destination, generally the closer the intervening-opportunity to an origin the greater the impact on travel between ***i*** and ***j***. **Table 1** shows the specification of the opportunity function depending on the value of parameters Ω and Φ.

Table 1: Specification of the Opportunity Function

Ω	Φ	Intervening-Opportunity	Impedance	U_{ip}
Ω	Φ	$\exp[\,(1-\varepsilon)\,.\,\alpha\,.\mathrm{D}_{\mathrm{p}}^{\mathrm{i}(\Omega)}]$	$\exp[-\beta\,.C_{ip}^{(\Phi)}]$	$\exp[\,(1-\varepsilon)\,.\,\alpha\,.\mathrm{D}_{\mathrm{p}}^{\mathrm{i}(\Omega)}-\beta\,.C_{ip}^{(\Phi)}]$
1	1	$\exp[\,(1-\varepsilon)\,.\,\alpha\,.\mathrm{D}_{\mathrm{p}}^{\mathrm{i}}]$	$\exp[-\beta\,.C_{ip}]$	$\exp[\,(1-\varepsilon)\,.\alpha\,.D_p^i-\beta\,.C_{ip}]$
0	0	$D_{pi}^{\alpha\,(1-\varepsilon)}$	$C_{ip}^{-\beta}$	$D_{pi}^{\alpha(1-\varepsilon)}\,.\,\mathrm{C}_{\mathrm{ip}}^{-\beta}$
1	0	$\exp[\,(1-\varepsilon)\,.\,\alpha\,.\mathrm{D}_{\mathrm{p}}^{\mathrm{i}}]$	$C_{ip}^{-\beta}$	$\exp[\,(1-\varepsilon)\,.\alpha\,.\mathrm{D}_{\mathrm{p}}^{\mathrm{i}}-\beta\,.\log_e C_{ip}]$
0	1	$D_{pi}^{\alpha\,(1-\varepsilon)}$	$\exp[-\beta\,.C_{ip}]$	$\exp[\,(1-\varepsilon)\,.\,\alpha.\,\log_e D_p^i-\beta\,.C_{ip}]$

Source: Wills (1986)

2.4 Structure of the Proportionality Factor

The opportunity function is incorporated into a general proportionality factor F_{ij} which is defined by the difference in functions of the cumulative opportunities from ***i*** to the j^{th} destination away from ***i***, and from ***i*** to the **(*j*-1)**th destination away from ***i***, and can be defined as:

$$F_{ij}=X_{ij}-X_{ij-1} \tag{16}$$

The most general form of the cumulative opportunities to be considered here defines X_{ij} and X_{ij-1} as:

$$X_{ij}=(\sum_{p}^{j}U_{ip})^{(\varepsilon,\mu)} \quad \text{and} \quad X_{ij-1}=(\sum_{p}^{j-1}U_{ip})^{(\varepsilon,\mu)} \tag{17}$$

where (ε,μ) transformation is defined by equations **(12)**-**(14)**. Subsitution of equation **(17)** into equation **(14)** leads to the general proportionality factor form as:

$$F_{ij}=(\sum_{p}^{j}U_{ip})^{(\varepsilon,\mu)}-(\sum_{p}^{j-1}U_{ip})^{(\varepsilon,\mu)} \tag{18}$$

The general proportionality factor is subjected to a convex combination of direct and inverse Box-Cox transformations. The form given by equation **(18)** generates two branches of special cases: the direct-opportunity (DO) model, with μ**=1**, and the inverse-opportunity

(IO) model, with μ=**0**. The DO model is significant because it contains the important special case of the logarithmic-opportunity (LO) model, with ε=**0**. That is:

$$F_{ij} = \log_e(\sum_p^{j} U_{ip}) - \log_e(\sum_p^{j-1} U_{ip}) \tag{19}$$

The IO model is particularly important becasue it contains the exponential-opportunity (EO) model, again with ε=**0**. That is:

$$F_{ij} = \exp(\sum_p^{j} U_{ip}) - \exp(\sum_p^{j-1} U_{ip}) \tag{20}$$

We can also consider blends of the LO and EO models, without going to the full GO model, by taking a convex combination of equations (**19**) and (**20**) with the mixture depending on values of μ. This blended form, the blended-opportunity (BO) model, is given in equation (**21**) as:

$$F_{ij} = \mu[\log_e(\sum_p^{j} U_{ip}) - \log_e(\sum_p^{j-1} U_{ip})] + (1-\mu)[\exp(\sum_p^{j} U_{ip}) - \exp(\sum_p^{j-1} U_{ip})] \tag{21}$$

Finally, we observe that if ε=**1**, for $\mathbf{0} \le \mu \le \mathbf{1}$, the gravity (GR) model is revealed as:

$$F_{ij} = (\sum_p^{j} U_{ip}) - (\sum_p^{j-1} U_{ip}) = U_{ij} \tag{22}$$

showing that the standard GR model can be obtained as a special case of the GO model. As mentioned, different values of the parameters controlling these transformations generate contrasting families of models, notably the exponential-opportunity (EO) model, the logarithmic-opportunity (LO) model and the gravity (GR) model, see **Table 2**. All models are shown to be embedded in a transformed triangular region over which likelihood function, response surface or simultaneous confidence interval contours may be plotted as shown in **Figure 2**.

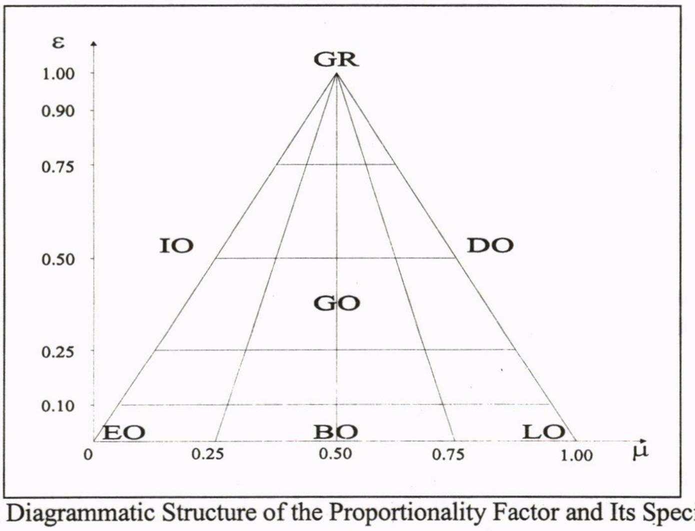

Figure 2: Diagrammatic Structure of the Proportionality Factor and Its Special Cases (**Source**: Wills, 1986)

Table 2: The Specification of Proportional Factor

Form	μ	ε	*Cummulative Opportunities* (X_{ij})	Proportional Factor (F_{ij})
GO	$0 \le \mu \le 1$	$0 \le \varepsilon \le 1$	$(\sum_p^j U_{ip})^{(\varepsilon,\mu)}$	$(\sum_p^j U_{ip})^{(\varepsilon,\mu)} - (\sum_p^{j-p} U_{ip})^{(\varepsilon,\mu)}$
LO	1	0	$\log_e(\sum_p^j U_{ip})$	$\log_e(\sum_p^j U_{ip}) - \log_e(\sum_p^{j-p} U_{ip})$
DO	1	$0 \le \varepsilon \le 1$	$(\sum_p^j U_{ip})^{(\varepsilon)}$	$(\sum_p^j U_{ip})^{(\varepsilon)} - (\sum_p^{j-p} U_{ip})^{(\varepsilon)}$
GR	$0 \le \mu \le 1$	1	$(\sum_p^j U_{ip})$	U_{ip}
IO	0	$0 \le \varepsilon \le 1$	$(\sum_p^j U_{ip})^{(1/\varepsilon)}$	$(\sum_p^j U_{ip})^{(1/\varepsilon)} - (\sum_p^{j-p} U_{ip})^{(1/\varepsilon)}$
EO	0	0	$\exp(\sum_p^j U_{ip})$	$\exp(\sum_p^j U_{ip}) - \exp(\sum_p^{j-p} U_{ip})$
BO	$0 \le \mu \le 1$	0	$\mu \log_e(\sum_p^j U_{ip}) + (1-\mu)\exp(\sum_p^j U_{ip})$	$\mu\left[\log_e(\sum_p^j U_{ip}) - \log_e(\sum_p^{j-p} U_{ip})\right] +$ $(1-\mu)\left[\exp(\sum_p^j U_{ip}) - \exp(\sum_p^{j-p} U_{ip})\right]$

Source: Wills (1986)

Having all the assumptions, the proposed GO model is therefore:

$$T_{id} = \sum_{k}\left[b_k . O_i^k . D_d^k . A_i^k . B_d^k . f_{id}^k\right] \quad \text{where:} \tag{23}$$

A_i and B_d are defined as equations (**4**)

- $$f_{id}^k = \sum_j \left[\delta_{jd}^{i-1} . \mathrm{F}_{ij}^k\right] \tag{24}$$

- $$F_{ij}^k = \left(\sum_p^j U_{ip}^k\right)^{(\varepsilon,\mu)} - \left(\sum_p^{j-1} U_{ip}^k\right)^{(\varepsilon,\mu)} \tag{25}$$

- $$U_{ip}^k = \exp\left[(1-\varepsilon).\alpha_k . D_{pk}^{i(\Omega)} - \beta_k . C_{ip}^{(\Phi)}\right] \tag{26}$$

- $$D_{jk}^i = \sum_{d}\left[\delta_{jd}^{i} - D_d^k\right] \tag{27}$$

- the (Ω,Φ) parameters were chosen, in advance, externally to the main calibration process, see **Table 1**.

- the (ε,μ) transformation is defined by equations (**12**)-(**14**), see also **Table 2**.

3. APPLICATIONS

3.1 West-Java Inter-Regional Vehicle Movement Data Set

In order to validate the new transport model, a real data set of inter-regional vehicle movements corresponding to West-Java was used. West-Java was one of the 27 provinces in Indonesia as part of Java island. A real data set of inter-regional vehicle movements was available, obtained from roadside interview survey as one of regional surveys of the National Origin-Destination Transportation Study carried out in 1992. The data set comprises the following:

- The 1992 O-D matrix, a 24 hour average annual daily traffic (AADT) matrix, compiled from roadside interview data collected in 1992,
- The study area was coded into 21 internal zones and 2 external zones.

3.2 Estimation Methods

3.2.1 Non-Linear-Least-Squares Estimation Method (NLLS)

The main idea in the calibration procedure is to estimate the unknown parameters by minimizing the sum of the squared differences between the estimated and observed O-D matrix. That is to minimize the following equation:

to minimize $$S = \sum_i \sum_d \left[\frac{1}{\dot{T}} \left(T_{id} - \hat{T}_{id} \right)^2 \right] \tag{28}$$

where: $\dot{T} = 1$ for NLLS and $\dot{T} = \hat{T}_{id}$ for WNLLS

The following set of equation (**29**) is required in order to find a set of unknown parameter (α,β) of the GO model which minimises equation (**28**).

$$\begin{aligned} \frac{\partial S}{\partial \alpha} = f_\alpha = \sum_i \sum_d \left[\frac{1}{\dot{T}} \left\{ 2\left(T_{id} - \hat{T}_{id} \right) \frac{\partial T_{id}}{\partial \alpha} \right\} \right] = 0 \\ \frac{\partial S}{\partial \beta} = f_\beta = \sum_i \sum_d \left[\frac{1}{\dot{T}} \left\{ 2\left(T_{id} - \hat{T}_{id} \right) \frac{\partial T_{id}}{\partial \beta} \right\} \right] = 0 \end{aligned} \tag{29}$$

For GO model, equation (**29**) is a equation which has two unkown parameters (α,β) need to be estimated. Newton's method combined with the Gauss-Jordan Matrix Ellimination technique can then be used to solve equation (**29**).

3.2.2 Maximum-Likelihood Estimation Method (ML)

Let assume that p_{id} be the probability of having an estimated independent trip interchange for each particular origin $\underline{i}$ and destination $\underline{d}$ expressed as:

$$p_{id} = \frac{T_{id}}{\hat{T}_t} \qquad \text{where:} \tag{30}$$

$$\hat{T}_t = \sum_i \sum_d \hat{T}_{id} \tag{31}$$

The framework of the Maximum-Likelihood (ML) estimation method is that the choice of the hypothesis **H** maximizing equation (**30**), will yield a distribution of T_{id} giving the best possible fit to the survey data ($\hat{T}_{id}$). The objective function for this framework is expressed as:

$$L = c \prod_i \prod_d p_{id}^{\hat{T}_{id}} \tag{32}$$

By subtituting equation (**30-**(**31**) into equation (**32**) and taking the natural logarithm term of equation (**32**) and using the following '**Lagrangian Multiplier**' method, equation (**32**) can then be written into a single equation. That is:

to maximise $$L_1 = \sum_i \sum_d \left[\hat{T}_{id} \log_e T_{id} \right] - \hat{T}_t \log_e \hat{T}_t + \log_e c \tag{33}$$

By omitting the constant value of equation (**33**), the objective function can then be simplified and expressed as:

to maximise $$L_2 = \sum_i \sum_d \left[\hat{T}_{id} \log_e T_{id} \right] \quad \text{with respect to parameters } (\alpha,\beta) \tag{34}$$

In order to determine uniquely parameters (α,β) of the GO model which maximises equation (**34**), the following sets of equations are then required. They are as follows:

$$\frac{\partial L_2}{\partial \alpha} = f_\alpha = \sum_i \sum_d \left[\left(\frac{\hat{T}_{id}}{T_{id}} \right) \frac{\partial T_{id}}{\partial \alpha} \right] = 0 \quad (35)$$

$$\frac{\partial L_2}{\partial \beta} = f_\beta = \sum_i \sum_d \left[\left(\frac{\hat{T}_{id}}{T_{id}} \right) \frac{\partial T_{id}}{\partial \beta} \right] = 0$$

Equation (**35**) is in effect a system of 2 (two) simultaneous equations which has 2 (two) parameters (α,β) of the GO model need to be estimated. Again, the Newton's method combined with the Gauss-Jordan Matrix Ellimination technique can then be used to solve for equation (**35**).

3.3 Statistical Test

The development of good transport model needs an indication of how accurate are the resulting models and this requires a comparison between estimated and an independently observed O-D matrix using appropriate statistical indicators of this fit. In this paper, the following Root mean square error (RMSE) statistical test has been used, as suggested by **Tamin (1988b)**:

$$\text{RMSE} = \sqrt{\left[\sum_i \sum_d \frac{\left(T_{id} - T_{id}^{+} \right)^2}{N(N-1)} \right]} \quad \text{for } i \neq d \quad (36)$$

where: $\hat{T}_{id}, T_{id}$ = observed and estimated O-D matrix, respectively.

3.4 Results

In assessing the value of a new transport model one is of course interested in the accuracy of the estimated travel behavior. In this paper, the new approach offers a choice of demand models to represent trip making behavior. This flexibility enhances the value of the model but it is also important to have some feelings on how the choice of model form may affect the accuracy of the resulting O-D matrix. Therefore, we use the West-Java (inter-regional vehicle movement) O-D matrix to obtain an indication of the most suitable model in this case. Two models were fitted: Gravity (GR) and Gravity-Opportunity (GO) model.

For the GR model, three types of deterrence function (Exponential, Power and Tanner) have been used. **Table 3** shows the calibrated parameters of the GR model using estimation methods (NLLS, WNLLS and ML) as well as three different deterrence functions. **Table 4** shows the RMSE value of estimated matrices compared with the observed matrix.

Table 3 The Estimated Parameters of GR Model

Estimation Methods	Deterrence Functions			
	Exponential	Power	Tanner	
	β	β	α	β
NLLS	-0.016480	-0.713510	-2.275061	0.133754
WNLLS	-0.237260	-2.524208	2.301167	-0.269719
ML	0.038783	0.847628	**1.099669**	**-0.015412**

Table 4 The GoF Statistics of Estimated O-D Matrices (GR Model)

Estimation Methods	RMSE		
	Exponential	Power	Tanner
NLLS	1806.243	2016.608	2015.227
WNLLS	2383.436	2246.642	2003.523
ML	1483.809	1217.811	**1175.473**

It can be seen from **Table 3**, using the negative exponential function, both NLLS and WNLLS methods give negative values of β meaning that any increment in travel cost between each corresponding zones will increase the number of flows travelling between them. This does not follow what the realism is; the higher travel cost, the lower will be the number of flows between those zones. However, using ML estimation method, the value of β is positive reflecting what is we expect. The same behavior also happens using the power function.

It can be seen from **Table 4**, for the negative exponential and power functions, the ML estimation method produces the best estimated O-D matrix compared to the observed one (Power function is better than negative exponential function). However, the best estimated O-D matrix (GR model) is obtained by using Maximum-Likelihood (ML) estimation method and Tanner's deterrence function.

The use of Tanner's function gives better fit compared with the use of negative exponential and power functions. This was expected since Tanner's function has more parameters that than those other functions (negative exponential and power). In fact, the negative exponential and power functions can be obtained as a special case of the Tanner's function. However, this does not guarantee it will always give better fit in other region or province.

In the GO model, the choice between gravity or opportunity is decided empirically and statistically by restriction on parameters, ε and μ, which control the global functional form of the trip distribution mechanism. By setting ε=**1**, the GO model will behave as the GR model since the opportunity part is omitted from the opportunity function (**15**) and similarly, by omitting the cost part of equation (**15**), the OP model is then created.

By using various values of ε and μ, we can then calculate the values of **S**. It is found that the minimum value of **S** is obtained at points ε=**0.1** and μ=**1**. This means that for the West-Java case it is the GO model the one that gets closer to reproduce the observed O-D matrix thus offering some improvement over the gravity model. These parameter values will change depending upon the characteristic of movement in certain study area.

Table 5 shows the calibrated parameters of the GO model using estimation methods (NLLS and ML) and **Table 6** shows the RMSE value of estimated matrices compared with the observed matrix.

Table 5 The Estimated Parameter of GO Model

Estimation Methods	**Ω=1, Φ=1**		**Ω=1, Φ=0**		**Ω=0, Φ=1**	
	α	β	α	β	α	β
NLLS	-0.00220	0.21602	**0.00058**	**1.21546**	N.A	N.A
ML	0.00005	-0.02214	0.00011	0.12344	-0.13786	-0.02514

Table 6 The GoF Statistics of Estimated O-D Matrices (GO Model)

Estimation Methods	**RMSE**		
	Ω=1, Φ=1	**Ω=1, Φ=0**	**Ω=0, Φ=1**
NLLS	1209.808	**1008.713**	N.A
ML	1272.051	1187.419	1297.171

It can be seen from **Table 6** that the best estimated O-D matrix (GO model) is obtained by using Non-Linear-Least-Squares (NLLS) estimation method. It can be seen that GO model performs better that the GR model since the value of RMSE of GO is less than those for GR. It was not unexpected that the performance of GO was better than that of GR since GO have more parameters than GR. In fact, the GR model can be obtained as a special case of the GO model. However, this does not guarantee it will always give better fit in other region or province. It is also found that the use of GO model requires longer computer time to run compared with the use of the GR model.

4. CONCLUSIONS

Two types of model have been used in this study: gravity (GR) and gravity-opportunity (GO) model and tested using West-Java data (inter-regional vehicle movements), of which the study area was divided into 21 internal zones and 2 external zones. Some conclusions can be drawn from the result obtained:

- Whereas the gravity model is deficient in intervening-opportunities effects, the opportunity model constructed is equally deficient in omitting the trip impedance. It seems logical that an ideal model (GO) should contain both these distinct effects since the behavior of people's movement in certain varies greatly.

- It is shown that the standard gravity (GR) model and the opportunity (OP) model can be obtained as a special case of the GO model. Different values of the parameters controlling these transformations generate contrasting families of models, notably the EO model, the LO model and the GR model.

- It is found that for the West-Java case, for the GR model, the combination of Tanner's deterrence function with ML estimation method will give the best estimated O-D matrix. For the GO model, the NLLS method is found to be the best estimation method.

- It is found that the GO model produces the best model for West-Java. It is shown that the optimum values for West-Java is obtained at points ε**=0.1** and μ**=1**. These parameter values will change depending upon the characteristic of movement in certain study area.

- It is found that the GO model is more time consuming that the GR model since they use more complicated algebra and procedures which require longer time to solve.

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