ESTIMATION OF MULTICLASS ORIGIN-DESTINATION MATRICES USING GENETIC ALGORITHM*

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1. Introduction

An origin-destination (O-D) is an essential of transportation planning and traffic operation. Traditionally, estimation of O-D matrix is derived from interview, roadside surveys or forecasting from transportation planning model. However, it is rather difficult, costly and labor intensive to obtain a large set of data. Estimation of O-D matrix from link traffic counts is more attractive and took a growing interest since it is relatively inexpensive to obtain the data. This method, therefore, has been paid attention for more than two decades and several works have been proposed to use link traffic counts for O-D matrix estimation e.g. Cascetta[1)].

Most of existing methods applied the concept of passenger car equivalent unit (PCU) by converting a mixture of vehicles or multiclass into PCU. The amount of other vehicle types, particularly truck type sometimes is significant and necessary for transportation planning, particularly, urban goods movement characteristics and appraising the policy. It, therefore, is better to estimate multiclass O-D matrices using the useful information from multiclass link traffic counts and historical O-D matrices. Recently, there is a small amount of works estimated the multiclass O-D matrices such as Wong *et al.*[2)].

The O-D matrix estimated from link traffic counts is difficult to obtain the global solution since it is the nature of the bilevel programming problem. A genetic algorithm (GA), a kind of heuristics search technique, is possible to reach the global solution. This study, therefore, focuses on the multiclass O-D matrices estimation which includes a set of truck and passenger car on a general network using the GA. Then, the performances of the proposed model are illustrated on totally 32 (or 4x4x2) cases consisting of a set of proportion of trucks 4 cases, a set of an initial O-D matrices 4 cases and a set of target O-D matrices 2 cases. This study also compares the results with the method proposed by Baek *et al.*[3)] on mentioned 32 cases. The organizations of this study, therefore, are as follow. Chapter 2 describes the model concept. Chapter 3 illustrates the results and discussions. Chapter 4 concludes the study.

2. Model Formulation

(1) Traffic Assignment Formulation

A fundamental relationship between a set of link flows and an O-D matrix can be described by using the linear relationship shown as Equation (1). Additionally, a link usage probability is also employed following multinomial logit model. In this study, a traffic assignment illustrated by Yang *et al.*[4)] is adopted. It is performed based on logit-based stochastic user equilibrium (SUE) (see more details in Yang *et al.*[4)]).

$$y_a^m = \sum_{od \in n_{OD}} \left(p_{a,od}^m x_{od}^m \right), \quad a \in A \tag{1}$$

where y_a^m is a link flow of vehicle type m on link a.

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x^{m}_{od} is an O-D element pair *od* of vehicle type *m*.

$p^{m}_{a,od}$ is a link usage probability of an O-D element pair *od* of vehicle type *m* on link *a*.

To avoid path enumeration following the logit-based, there are many existing algorithms compute the link usage probability such as Akamatsu[5] and Bell[6]. This study, however, adopts the second methodology from Bell[6] to calculate it.

Toint and Wynter[7] illustrated the affect of various kinds of the travel time functions. They also suggested using the travel time function that should be monotonic increasing. This study, therefore, adopts the usual BPR function since its characteristics follows the recommendations by Toint and Wynter[7]. Moreover, the speeds of all vehicle types tend to travel at the same speed during congestion. The congestion affect, then, is considered to ensure that the travel time of both passenger car and truck are nearly the same at congestion condition as Equation (4) since the speed of both vehicle types should be equal or nearly the same. On the other hand, Baek *et al.*[3] did not consider the behavior of speed during congestion in their model. The related formulations are illustrated as follow:

$$t_a^{truck} = t_a^{truck(0)}\left[1+\omega_{truck}\left(\frac{y_a}{C_a}\right)^4\right] \tag{2}$$

$$t_a^{car} = t_a^{car(0)}\left[1+\omega_{car}\left(\frac{y_a}{C_a}\right)^4\right] \tag{3}$$

$$t_a^{car,real} = \begin{cases} t_a^{car} + \left(t_a^{truck} - t_a^{car}\right)\cdot\left(\dfrac{y_a}{C_a}\right) & if\ y_a \le C_a \\ t_a^{car} + \left(t_a^{truck} - t_a^{car}\right) = t_a^{truck} & if\ y_a > C_a \end{cases} \tag{4}$$

$$y_a = y_a^{car} + \eta_{truck}\, y_a^{truck} \tag{5}$$

where C_a denotes a capacity of link *a* in PCU

η_{truck} denotes a PCU of truck

t_a^{truck}, t_a^{car} denote a travel time of truck and passenger car, respectively.

$t_a^{car,real}$ denotes a real travel time of passenger car considered the affect of congestion or the volume/capacity ratio (y_a/C_a)

$\omega_{truck}, \omega_{car}$ denote a coefficient value of truck and passenger car, respectively.

The coefficient value of ω_{truck}, ω_{car} and η_{truck} are 0.15, 0.43 and 2.0, respectively since the speed of truck is assumed to be the lowest speed. This study, then, performs a method of successive averages (MSA) described by Sheffi[8] following logit-based SUE of multiclass traffic. Conversely, Baek *et al.*[3] perform a small modification of the Frank-Wolf algorithm. However, both concepts are difficult to guarantee the uniqueness of the solution for all cases because the link travel time functions are asymmetric. This study, then, makes use of a sensitivity analysis based on the MSA to calculate a set of link flows of both passenger car and truck on the Sioux Falls network and others. Each network was assigned the different sets of initial link flows for all links including random value, constant value and from the all-or-nothing concept. Moreover, this study employed a set of different step size as 1/n, 3/n and 5/n. Finally, the results of all cases converged to nearly the same value. It, therefore, is possible to apply the MSA to multiclass traffic assignment following logit-based SUE.

The multiclass traffic assignment procedures are briefly illustrated as follow. Firstly, the free flow travel times of both vehicle types are performed to calculate the link usage probability. Then, the link flows are computed from

Equation (1). The travel times of both vehicle types are updated by using the value from Equation (2) and (4) for next iteration. Finally, the procedure following the MSA is continuously performed till it satisfies the criterion.

(2) O-D Matrices Estimation Formulation

There are many algorithms to estimate O-D matrices such as entropy maximization, least square, Bayesian, and others. This study, however, adopts the simple form of generalized least squares method to estimate O-D matrices since this method provides well-known statistical properties. Both information consisting of the observed link flows and the initial O-D matrices, therefore, are used to evaluate the objective function or Equation (6) to obtain the multiclass O-D matrices. The objective function and related formulations for O-D estimation are as follow:

$$Min.\ \ Z^m(x_{ij}^m) = \frac{1}{2}\sum_{a\in A}(y_a^m - \bar{y}_a^m)^2 + f\cdot\frac{1}{2}\sum_{od\in n_{OD}}(x_{od}^m - \bar{x}_{od}^m)^2 \qquad (6)$$

subject to

$$y_a^m - \sum_{od\in n_{OD}}\left(p_{a,od}^m x_{od}^m\right) = 0,\ \ a\in A \qquad (7)$$

$$x_{od}^m \geq 0,\ \ od\in n_{OD} \qquad (8)$$

where f reflects the reliability of the initial O-D matrices.

$\bar{y}_a^m$ is the observed link flows from link traffic counts of vehicle type ***m*** on link ***a***

$\bar{x}_{od}^m$ is the initial O-D element pair *od* of vehicle type ***m***.

(3) Solution Algorithm Based on the GA

There are some researches that perform the GA to estimate static O-D matrices such as Yin[9]. This mentioned research applied PCU concept to obtain one O-D matrices. Baek *et al.*[3] developed the model to estimate multiclass O-D matrices including passenger car and truck types. However, their methodology has some limitation when the O-D elements in the same origin fluctuate too much. It may not reach the satisfied result. This study, therefore, develops the GA to estimated multiclass O-D matrices using all available information. Both information consisting of the observed link flows and the initial multiclass O-D matrices are performed in the model to obtain the stable O-D matrices. The procedures of multiclass O-D matrices estimation based on the GA are depicted in Figure 1 and illustrated as follow:

Step 0. Initialize GA parameters. Set the GA parameters consisting of a mutation ratio (m_{rate}), a maximum iteration (max_{iter}), a number of population (*pop*) or a set of chromosome containing the potential solutions of the multiclass O-D matrices, a variation of initial O-D (q_{dev}, $0.00 < q_{dev} < 1.00$). Then, set counter for the whole procedure, n = 1.

Step 1. Generate a set of initial random chromosome (c) of multiclass O-D matrices within a specific range $(1-q_{dev}) \leq u_{ij}^m \leq (1+q_{dev})$. Michalewicz[10] illustrated the result of their experiments of random floating point which provided faster, more consistent and higher precision than binary coding. This study, therefore, generates a set of random floating point. Additionally, the whole elements of one chromosome where n=1, are set to be one to use the exactly value of the initial O-D matrices.

Step 2. Calculate a set of multiclass O-D matrices by using multiplication of the set of initial O-D and initial random chromosome.

Step 3. Calculate a multiclass SUE link flows for each chromosome by performing the MSA.

Step 4. Calculate a set of fitness value from Equation (6).

Step 5. Sort the set of fitness value in order of ascent. Keep the best fitness value in the separate variable because it is used for searching and selecting the lowest fitness value later.

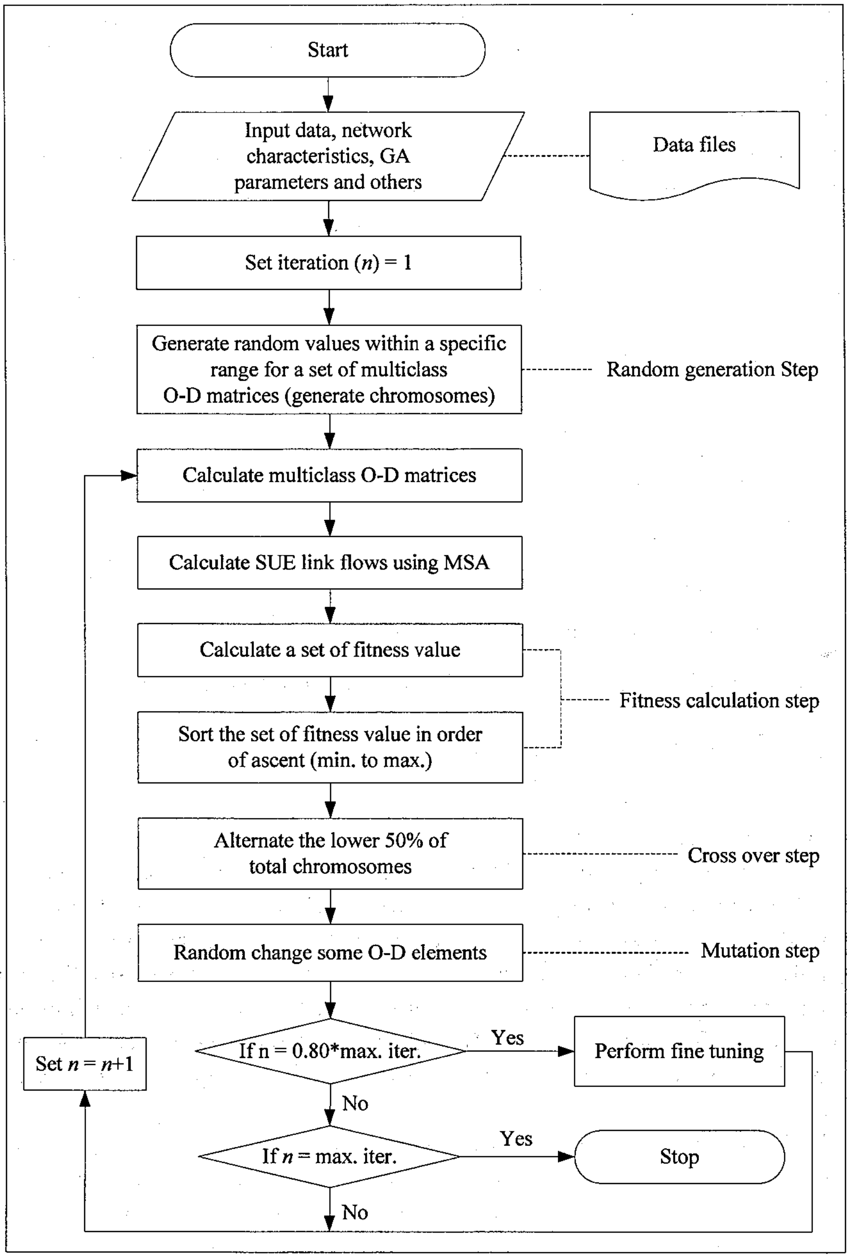

Figure 1: Solution algorithm based on the GA

Step 6. Perform the crossover operator by alternating the lower 50% of total population and using arithmetic crossover as Equation (9).

$$x_{od}^{m,c2} = x_{od}^{m,c1} + u\left|x_{od}^{m,c1} - x_{od}^{m,c1+1}\right| \qquad (9)$$

where $c1$ is a set of chromosome 1, 2,…,(pop/2)

$c1+1$ is a set of chromosome 2, 3,…,(pop/2)+1

$c2$ is a set of chromosome (pop/2)+1, (pop/2)+2,…, pop

u is a random value following uniform distribution range (0,1)

Step 7. Perform the mutation operator by a random choice with probability m_{rate}. Generate a new random number, followed uniform distribution range (0, 1), as step 1 in case it is less than m_{rate}. A new set of chromosome, therefore, is created for the next iteration.

Step 8. Perform a fine tuning if the iteration is equal to 80% of the maximum iteration. Reduce the deviation parameter (q_{dev}) by setting ($new\ q_{dev}$) = 0.15($old\ q_{dev}$). Additionally, select a new initial O-D set which has the lowest fitness value among the past 80% of total iterations. Then, generate the new chromosomes set as same as step 1.

Step 9. Check the convergence. If the iteration n is equal to the max_{iter}, then stop GA process and obtain the optimal solution by searching the lowest fitness value among all iterations kept in sep_{var}. Else increase n by 1 or set $n = n+1$ and return to Step 2.

The main differences of the GA proposed by Baek *et al.*[3] and this study comprises of random generation and mutation. Baek *et al.*[3] proposed to generate a set of potential solution of O-D matrices using the aggregate value of each origin. On the other hand, this study makes use of the value of each O-D element directly. In addition, the formulation to use the mutation process of both model are different.

This study also implements to run the GA several times to employ the average value because the results from the GA quite fluctuate. On the other hand, Baek *et al.*[3] used the result from the GA calculated only one time. Therefore, the average value of O-D matrices is computed as follows:

$$x_{od}^{m} = \frac{1}{r}\sum_{i=1}^{r} x_{od,i}^{m} \tag{10}$$

where r is a number of running the GA.

(4) Statistical Test

The performance of the model is demonstrated by using the relative mean absolute error (MAE) based on Iida *et al.*[11]. The MAE is performed to compare the estimated and target O-D matrices as follows:

$$MAE(\%) = \frac{\sum_{od \in n_{OD}} \left| x_{od}^{m} - x_{od}^{m,+} \right|}{\sum_{od \in n_{OD}} x_{od}^{m,+}} \times 100 \tag{11}$$

where $x_{od}^{m,+}$ is a target O-D element pair od of vehicle type m.

To illustrate the performances of the concept in Equation (10), this study makes use of both Avg.[a] and Avg.[b]. Both variables are compared in term of the MAE. The former is obtained from mainly two steps. Firstly, the MAE of each run the GA is calculated. Then, the average value of the MAE of r times is calculated which is assigned to Avg.[a]. The latter, firstly, calculates the average value of O-D matrices from running the GA r times. It, then, is performed to calculate the MAE which is assigned to Avg.[b]. The briefly procedures are depicted in Figure 2.

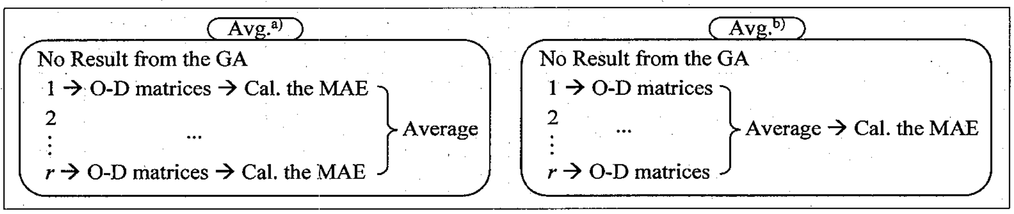

Figure 2: The briefly procedures of Avg.[a] and Avg.[b] calculation

3. Results and Discussions

(1) A Numerical Example

This study performs the multiclass O-D matrices estimation based on the GA on a test network from Yang[12] shown in Figure 3. There are 9 nodes, 14 links and 8 O-D pairs. Additionally, this study assumes an incomplete set of 9 observed link flows consisting of link 1, 4, 5, 6, 8, 9, 10, 13 and 14, respectively. The GA parameters of both model concepts are shown in Table 1.

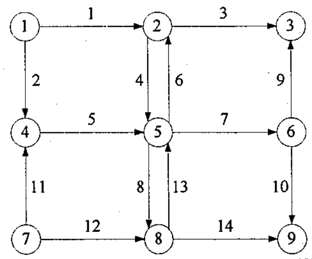

Figure 3: An example network (Yang[12)])

Table 1: GA parameters

GA parameters	Proposed concept	Baek *et al*. concept	
	O-D set 1 and 2	O-D set 1	O-D set 2
Max. iteration	500	500	500
Population	20	20	20
Variation of int. OD, q_{dev1}	0.3	0.3	0.7
Variation of int. OD, q_{dev2}	-	0.2	0.2
Mutation ratio	0.2	0.2	0.2

Table 2: The target O-D matrices

O-D pair	O-D set 1					O-D set 2				
	Target O-D (PC)	Target O-D (Truck)				Target O-D (PC)	Target O-D (Truck)			
		15%	20%	25%	30%		15%	20%	25%	30%
1 - 3	385	67	95	123	158	255	51	74	98	125
1 - 5	245	49	70	91	117	210	35	50	66	84
1 - 9	420	57	81	105	135	450	79	113	151	193
5 - 3	210	51	73	95	122	250	40	57	76	97
5 - 5	0	0	0	0	0	0	0	0	0	0
5 - 9	245	49	70	91	117	130	21	30	40	51
7 - 3	420	67	95	123	158	520	100	143	190	242
7 - 5	280	48	68	88	113	150	24	35	46	59
7 - 9	350	76	108	140	180	225	38	54	72	92

Table 3: The initial O-D matrices

OD set	OD pair	Initial O-D matrices of various truck proportions which bias from the target O-D matrices as															
		Truck proportion = 15%				Truck proportion = 20%				Truck proportion = 25%				Truck proportion = 30%			
		5%	10%	15%	20%	5%	10%	15%	20%	5%	10%	15%	20%	5%	10%	15%	20%
	PC																
	1 - 3	404	424	443	462	404	424	443	462	404	424	443	462	404	424	443	462
	1 - 5	233	221	208	196	233	221	208	196	233	221	208	196	233	221	208	196
	1 - 9	399	378	357	336	399	378	357	336	399	378	357	336	399	378	357	336
	5 - 3	221	231	242	252	221	231	242	252	221	231	242	252	221	231	242	252
	5 - 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5 - 9	233	221	208	196	233	221	208	196	233	221	208	196	233	221	208	196
	7 - 3	399	378	357	336	399	378	357	336	399	378	357	336	399	378	357	336
	7 - 5	266	252	238	224	266	252	238	224	266	252	238	224	266	252	238	224
	7 - 9	368	385	403	420	368	385	403	420	368	385	403	420	368	385	403	420
1	Truck																
	1 - 3	70	74	77	80	100	105	109	114	129	135	141	148	166	174	182	190
	1 - 5	47	44	42	39	67	63	60	56	86	82	77	73	111	105	99	94
	1 - 9	54	51	48	46	77	73	69	65	100	95	89	84	128	122	115	108
	5 - 3	55	57	59	61	78	81	84	88	101	106	109	114	129	135	140	146
	5 - 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5 - 9	47	44	42	39	67	63	60	56	86	82	77	73	111	105	99	94
	7 - 3	64	60	57	54	90	86	81	76	117	111	105	98	150	142	134	126
	7 - 5	46	43	41	38	65	61	58	54	84	79	75	70	107	102	96	90
	7 - 9	80	84	87	91	113	119	124	130	147	154	161	168	189	198	207	216
	MAE (%)	5.00	10.07	15.04	19.97	5.01	10.02	14.99	20.03	5.04	10.00	15.04	20.02	5.06	10.01	15.08	20.00
	1 - 3	268	281	293	306	268	281	293	306	268	281	293	306	268	281	293	306
	1 - 5	221	231	242	252	221	231	242	252	221	231	242	252	221	231	242	252
	1 - 9	473	495	518	540	473	495	518	540	473	495	518	540	473	495	518	540
	5 - 3	263	275	288	300	263	275	288	300	263	275	288	300	263	275	288	300
	5 - 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5 - 9	137	143	150	156	137	143	150	156	137	143	150	156	137	143	150	156
	7 - 3	546	572	598	624	546	572	598	624	546	572	598	624	546	572	598	624
	7 - 5	158	165	173	180	158	165	173	180	158	165	173	180	158	165	173	180
	7 - 9	236	248	259	270	236	248	259	270	236	248	259	270	236	248	259	270
2	Truck																
	1 - 3	54	56	59	61	78	81	85	89	103	108	113	118	131	138	144	150
	1 - 5	33	32	30	28	48	44	42	40	63	59	56	53	80	76	71	67
	1 - 9	75	71	67	63	107	102	96	90	143	136	128	121	183	174	164	154
	5 - 3	42	45	46	48	60	64	67	68	81	85	88	92	102	107	113	116
	5 - 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5 - 9	20	19	18	17	29	27	26	24	38	36	34	32	48	46	43	41
	7 - 3	95	90	85	80	136	129	122	114	181	171	162	152	230	218	206	194
	7 - 5	23	22	20	19	33	32	30	28	44	41	39	37	56	53	50	47
	7 - 9	40	42	44	46	57	59	62	65	76	79	83	86	97	101	106	110
	MAE (%)	5.12	10.05	15.13	20.02	5.10	10.05	15.11	20.03	5.12	10.11	15.12	20.01	5.11	10.02	15.16	19.98

This study makes use of truck proportions of the target O-D ranged from 15 to 30 percent as shown in Table 2. The target O-D matrices of truck are made considering the proportion between the total flows of truck O-D matrix over the total flows of multiclass O-D matrices to be approximately 15, 20, 25 and 30 percent, respectively. Table 2 also presents the target O-D matrices of two sets of different O-D structures made based on the mentioned concept. Moreover, at each truck proportion, the initial O-D matrices are created based on the target O-D matrices as shown in Table 3. Additionally, some elements of the target O-D are increased and some of them are decreased proportionally by 5 to 20 percent according to the MAE (%) calculated from the target and the initial O-D matrices. They, then, are assigned to be the initial O-D matrices which are biased from the target O-D matrices as approximately 5, 10, 15 and 20 percent, respectively. The performances of the proposed model, therefore, are demonstrated on totally 32 cases consisting of a set of proportion of trucks 4 cases, a set of an initial O-D matrices 4 cases and a set of target O-D matrices 2 cases. The target O-D matrices are assumed to be known for comparing the performances of the model. The O-D elements from the same origin of the first set are not so different. These O-D elements, however, are quite different in the second set.

(2) Results and Discussions

The different objective function, where f equals 0.0 and 0.5, is performed to illustrate the performances of the model. The performances of the proposed concept and the concept from *Baek et al.*[3] are firstly compared by assuming f=0.0. The objective function, therefore, focuses on minimizes the difference between observed link flows and estimated link flows only. Figure 4 presents the fluctuation of the results in term of the minimum and the maximum MAE (%).

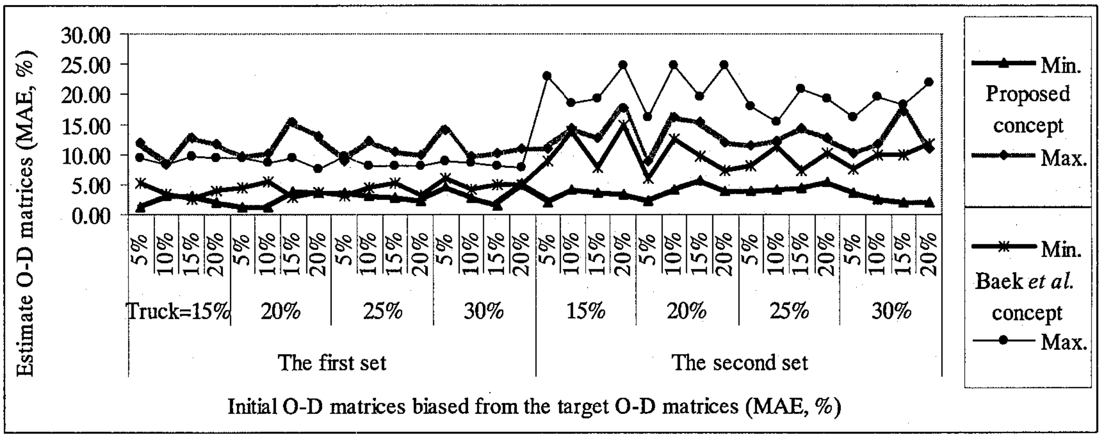

Figure 4: The maximum and the minimum MAE of both concepts where f=0.0

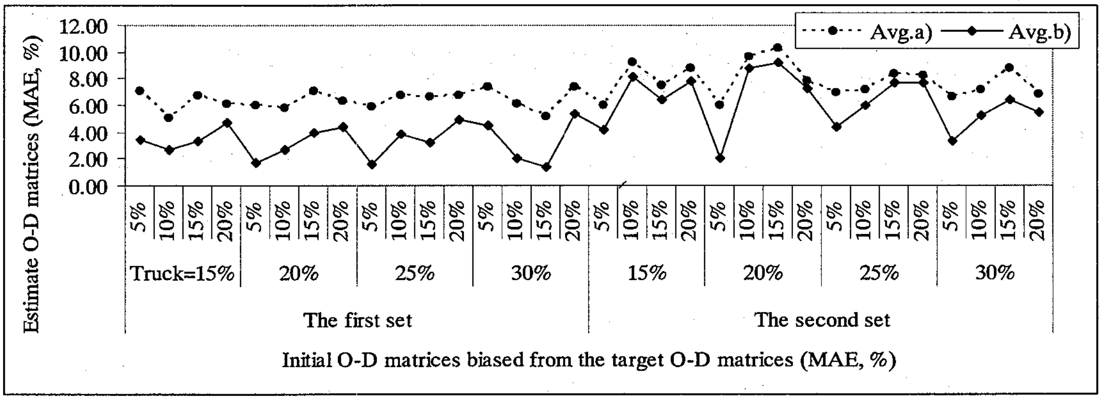

Figure 5: The average value of this study where f=0.0

From Figure 4, the results of the model are sometimes really nice and are sometimes not so satisfied. Although the objective values are quite similar, the structures of O-D matrices are quite different. Moreover, it cannot judge the results from the GA in case the target O-D matrix is unknown. This study, then, implements to run the GA several times and employ the average value of these results. It found that the results of Avg.[b)] are always better than the results of Avg.[a)] as shown in Figure 5. Additionally, some values from the Avg.[b)] are sometimes nearly equal the best results. It, therefore, is better to use the average value. Figure 6 presents the MAE of the final results (Avg.[b)]) of both mentioned concepts. From this figure, the results of the proposed concept are better than the others.

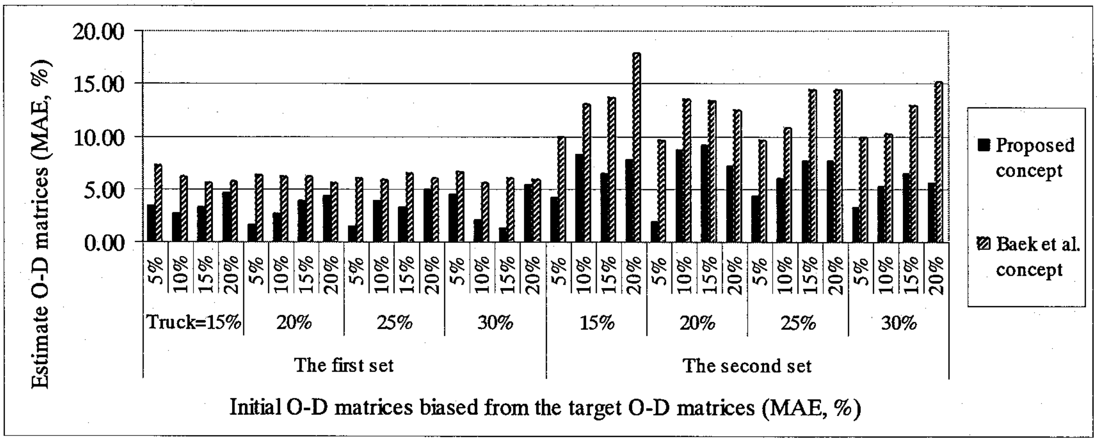

Figure 6: The average value of Avg.[b)] of both concepts where *f*=0.0

This study, then, compares the performances of both concepts by assuming *f*=0.5. The objective, therefore, is to obtain the more stable results of estimated O-D matrices because the results of the first case (f=0.0) quite fluctuated. Figure 7 presents the fluctuation both concepts. These results, however, fluctuated less than the first case. From Figure 8, the results of Avg.[b)] are always better than the results of Avg.[a)]. Figure 9 presents the final results of both concepts. The performances of the model are dropping when the bias of initial O-D matrices are increasing. The results are not so satisfied because the estimated O-D matrices depend on the initial O-D matrices too. This study, therefore, recommends reducing the *f* value when the initial O-D matrices are very different from the estimated O-D matrices.

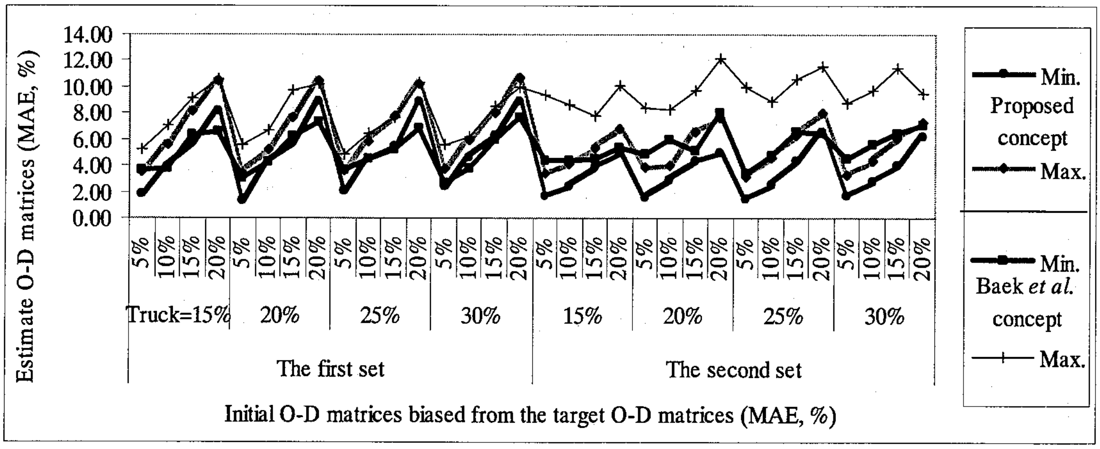

Figure 7: The maximum and the minimum MAE of both concepts where *f*=0.5

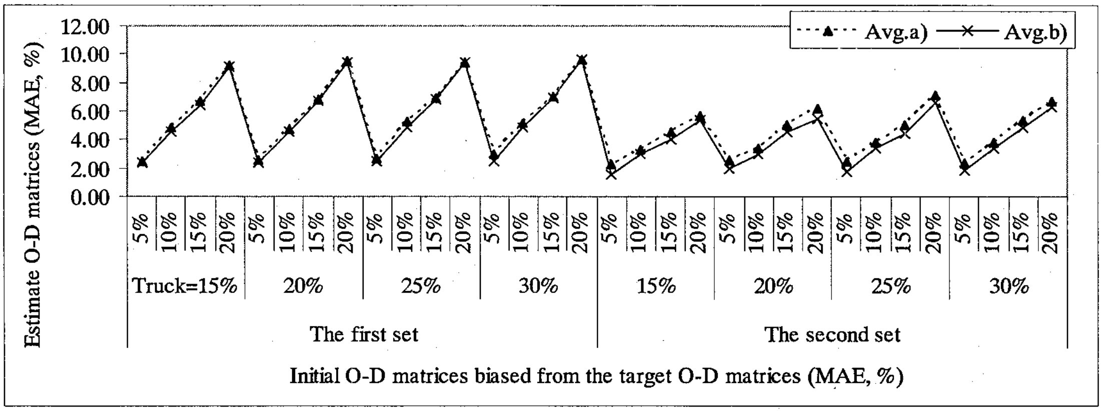

Figure 8: The average value of this study where f=0.5

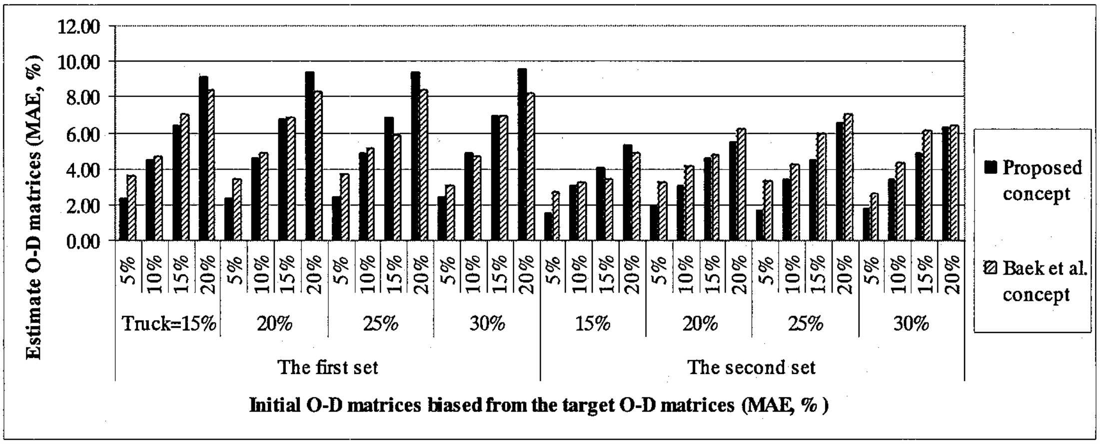

Figure 9: The average value of Avg.[b)] of both concepts where f=0.5

4. Conclusions

There are mainly three concepts proposed in this study. Firstly, the O-D estimation based on the GA concept is developed to search the optimal solution. The main difference between the proposed concept and the others are the methodology to construct the population of O-D matrices and the crossover procedure. This study also adds the fine tuning procedure to obtain more accurate result by reducing the random generation parameter by 85% at specific iteration. Secondly, this study implements to employ the average value from running the GA several times instead of using the result from running the GA one time because the results from the GA quite fluctuate. Moreover, it is also difficult to judge the O-D result since the target O-D matrices are generally difficult to obtain. It, therefore, is better to employ the average value. Finally, the multiclass O-D matrices have been formulated using monotonic increasing travel time function. The truck and passenger car O-D matrices are estimated at the same time because a number of trucks are significant for urban goods movement planning. In conclusion, most of the results of the proposed model in this study are better than the others, especially when the objective function does not rely on the initial O-D matrices.

This study still faces the same disadvantage as *Baek et al.*[3]. The main disadvantage of the GA is a large computation time due to heuristics search technique. Additionally, both models cannot guarantee the uniqueness of the multiclass traffic assignment by theoretical. This study, however, performed the sensitivity analysis of the MSA and found that it is possible to employ the MSA.

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Estimation of Multiclass Origin-Destination Matrices Using Genetic Algorithm*

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Truck origin-destination (O-D) matrix is necessary for urban goods movement planning and there are not many researches that estimate truck O-D matrix together with passenger car O-D matrix. This study, therefore, proposes a model that estimates multiclass origin-destination (O-D) matrices consisting of passenger car and truck. A genetic algorithm (GA) is implemented to search the optimal multiclass O-D matrices. This study also suggests using the average value from running the GA several times because of fluctuation of the results. From a numerical network, the model provides better results than the others, especially when the objective function does not rely on the initial O-D matrices.

GAアルゴリズムを用いた車種別OD交通量推定に関する研究*

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貨物車ＯＤ交通量は都市内物流施策を評価する際には必要なデータであるが，これまでは貨物車交通量を乗用車交通量と同時に推定する研究はあまりなされてこなかった．そこで本研究では，確率的利用者均衡配分手法とＧＡアルゴリズムを用いて，車種別のＯＤ交通量を推定する手法を提案する．数値計算の結果，本研究で提案した手法は既存の手法に比べてより良い結果を得ることができたが，初期ＯＤ交通量との差を目的関数に含めないときに特に有効な手法であることが確認できた．
