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An Adapted Non-dominated Sorting Algorithm (ANSA) for Solving Multi Objective Trip Distribution Problem

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Abstract Trip distribution deals with estimation of trips distributed among origins and destinations and is one of the important stages in transportation planning. Since in the real world, trip distribution models often have more than one objective, multi-objective models are developed to cope with a set of conflict goals in this area. In a proposed method of adapted non-dominated sorting algorithm (ANSA) is introduced and applied on a multi objective trip distribution model. The objectives considered are: (1) maximization of the interactivity of the system, (2) minimization of the generalized costs and (3) minimization of the deviation from the observed year. in proposed ANSA using the sorting process of NSGA II and two proposed adapted operators a new adapted algorithm is introduced and applied to solve the three-objective model. To test the performance of the proposed algorithm, a set of Hong Kong data is used and results of applying proposed algorithm is compared to other models of the literature. The results show that proposed algorithms has better performance rather than the algorithms of the literature.

Keywords Multi-objective Trip Distribution model · Multi-objective evolutionary algorithm · Non-dominated sorting algorithm · NSGA II

Mathematics Subject Classification (2010) 65Y04 · 90B50.

1 Introduction

Transportation planning is a multi-stages process that has been studied in metropolitan areas for almost 40 years and is used to analyze commuter de-

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mand and to forecast transport system inventories. In the strategic transportation planning, it was studied that better transport systems will facilitate the better environmental performance for intra-city and inter-city communication [3]. Transportation planning includes transportation models such as trip generation, trip distribution, mode choice and trip assignment.Trip distribution which is the second stage of transportation models predicts the qualification of trips in future that includes the number of commuters in each origin-destination (OD) pair and has lots of importance in real world. Estimation of trips distributed among origins and destinations can be vital to for example analyzing the work-related traffic accidents by safety organizations (50% of accidental deaths in Finland were associated with traffic accidents between 1975 and 1994) [17] and [18] and estimating emissions produced by vehicles by transportation agencies [13]. A pure trip distribution problem can be defined as follows: assume O_i that is the information of number of trips generated in origin zone i, and D_j which is the information of number of attracted trips to the destination zone j, when i,j = 1, 2,, n are available. Distribution process associates with the generations and attractions to create a trip matrix T_{ij} that is the estimated OD matrix. The total number of trips generated in origin zone i is equal to O_i and the summation of trips attracted by destination zone j is equal to D_j . These are doubly constraints that presented by [15] and mathematically are described as follows:

$$\Sigma_{j=1}^{n} = O_i, i = 1, 2, ..., n \tag{1}$$

$$\Sigma_{i=1}^{n} = D_i, i = 1, 2, ..., n \tag{2}$$

Trip distribution models can be classified into two general categories as aggregate and disaggregate models.In disaggregate models the individuals' behaviors to select the origins and destinations of their spatial movement are described while in aggregate models the total number of flows between OD zones are investigated. Aggregate models have been widely investigated in the literature in different formulations such as growth factor, Fratar, intervening opportunity and gravity model. Among these formulations gravity model is the most preferred one over the years despite all of its drawbacks [14]. The first modeling of trip distribution is derived from an analogy with Newton's law of gravitational force between two masses separated by a distance. A typical doubly constrained gravity model is expressed as follows:

$$T_{ij} = A_i * B_j * O_j * D_j * f(c_{ij}) \tag{3}$$

Where

$$A_i = \frac{1}{\Sigma_{j=1}^{n} B_j D_j f(c_{ij})} \tag{4}$$

$$B_j = \frac{1}{\Sigma_{i=1}^{n} A_j O_i f(c_{ij})} \tag{5}$$

In this model, O_i is total trip production by zone i, D_j is total trip attraction to zone j, A_i and B_j are the balancing factors to ensure that (1) and (2) are satisfied and $f(c_{ij})$ is defined as friction function between zone i and zone j that c_{ij} is a generalized cost with one or more components consists of travel cost, waiting time, etc. Different forms of friction according to the characteristics of the problem are defined in the literature such as exponential function,$e^{-\alpha(c_{ij})}$; power function,$c_{ij}^{-\beta}$; and tanner (or gamma),$a * e^{-\alpha(c_{ij})} * c_{ij}^{-\beta}$. In addition to gravity model, [19] presented a mathematical model based on the principal of maximum entropy for trip distribution problem. In this model the interactivity in the system is represented by an entropy function that is maximized subject to a set of constraints. The difference in the model structure between the entropymaximization model and the gravity model is that right-hand-side values in the constraints are specified in the former and parameter values in generalized cost function are calibrated in the latter Leung. It is notable that the optimal solution of entropy-maximization model and gravity model is the same. During the past years, numerous techniques have been proposed in the literature to solve different types of transportation planning models such as mathematical programming; fuzzy sets theory,heuristic and meta-heuristic methods.For example [21] presented alterative formulations for a combined trip generation, trip distribution, model split and trip assignment model. In this paper, alterative formulations including mathematical programming (MP) formulation and variational inequality (VI) formulations are provided for a combined travel demand model. [12] proposed an entropy maximization model for the trip distribution problem with fuzzy and random parameters. Due to complexity of real transportation problems, heuristic and meta-heuristic algorithms have attracted many interests among different methods in recent studies.Among these studies following papers can be introduced. [7] proposed a hybrid particle swarm optimization algorithm with artificial immune learning for solving the fixed charge transportation problem. [11] presented a trip distribution modeling using fuzzy and genetic fuzzy systems. [16] proposed a heuristic-exact hybrid algorithm to solve the balanced transportation models. In addition to these papers, studies to calibrate and validate appreciate parameters in the gravity model have been taken to consideration in the literature widely. For example [6] investigated the reliability of the gravity model to predict future travel patterns. [1] developed gravity models with travel deterrence for trips made for different purposes using different modes of transport. [14] in 2010 investigated the sample size needed for calibrating trip distribution and behavior of the gravity model [14] . Using an empirical study he showed that sample sized as small as 1000 could be as dependable as large sample surveys using a line search calibration algorithm. [18] presented an empirical model for trip distribution of commuters in Netherlands, to assess its transferability in space and time. [2] calibrated a trip distribution gravity model with double constraints satisfied by trip purposes for the city of Alexandria. Moreover, using a small sample, the model was calibrated for different trip purposes. In the real world, transportation problems usually have multiple objectives that should be considered together,so multi-objective transportation problems especially multi-objective trip distribution problems have been introduced and solved in the literature. [8] presented a theoretical framework of a multi-objective model for the trip distribution problem with target values and applied this model to a problem in Sweden. Also [9] introduced a new fuzzy multi-objective programming that is entropy based geometric programming and applied it on transportation problems. As multi-objective models often are difficult models to solve with normal methods like simplex in terms of the required computational resources such as time and memory, they are rated as NP-Hard problems. As a result, meta-heuristic algorithms can be efficient to provide a near optimal solution for different large-sized multi-objective transportation problems in a reasonable amount of computational time. Only few meta-heuristic algorithms to solve multi-objective trip distribution problems have been presented in the literature. Islam and Roy in 2006 presented a Pareto optimal solution to solve the transportation model [9] and Leung presented a non-linear goal programming model and a genetic algorithm to solve a multi-objective trip distribution problem. Regarding the absence of different meta-heuristic algorithms to solve multi-objective trip distribution problem in the literature, this paper presents a proposed adapted non-dominated sorting algorithm for solving a three-objective trip distribution problem.In the next section three-objective trip distribution problem is described. Then in section 3 Proposed adapted non-dominated sorting algorithm presented. In section 4 proposed algorithm is evaluated on a set of Hong-Kong data to test the efficiency of the algorithm in comparison with paper of Leung followed by the conclusions of the paper in section 5.

2 Three-objective trip distribution problem

[8]presented three single objective mathematical programming models consist of maximum entropy, transportation problem and information theory for the trip distribution problem.As in the real world problems we need a methodology that considers several objectives which may have conflict with each other, following model shows a multi-objective model with three mentioned objectives for trip distribution problem Leung

$$\begin{aligned} Objective(1): Max z_1(T_{ij}) &= -\Sigma_{i=1}^{n}\Sigma_{j=1}^{n}T_{ij}\ln T_{ij}, \\ Objective(2): Min z_2(T_{ij}) &= \Sigma_{i=1}^{n}\Sigma_{j=1}^{n}c_{ij}T_{ij}, \\ Objective(3): Min z_3(T_{ij}) &= \Sigma_{i=1}^{n}\Sigma_{j=1}^{n}T_{ij}\ln\frac{T_{ij}}{T_{ij}^{0}}. \end{aligned} \tag{6}$$

Subject to doubly constraints (1) and (2) and non-negativity constraints of $T_{ij} \geq 0 i, j = 1, \ldots, n$. Objective 1 is maximum entropy model that was introduced by [19]. As mentioned before Wilson showed that the solution to an optimization model based on the principle of maximum entropy is identical to the solution that is based on the gravity model in (3). If the entropy increases, the interactivity in the system formulated in the entropy function will increase too. In objective 2 the aim of minimizing the generalized total costs between origins and destinations are considered. In fact the cheapest pair among origin-destination pairs will be fully assigned with the amounts of goods as large as possible, while the expensive pairs will be considered later. Objective 3 is related to information theory. In fact in forecasting trip distribution models decision makers always intend to reproduce similar patterns in the future by minimizing the deviation between the past data and the obtained future solution. In this objective T_{ij}^0 is observed the past data. It is notable that in three-objective trip distribution problem, objectives (1) with aim of optimizing total efficiency of society and objective (2)which tend to optimize total accessibility objective of the individuals are conflict. Also two entropy functions of objective (1) and objective (3) are conflict too because in objective (1) It is necessary for T_{ij} to take the smallest possible value due to the maximization of entropy,while according to objective (3) T_{ij} should take the closest possible value to T_{ij}^0 due to the minimization of deviations from observed data.

3 Proposed adapted non-dominated sorting algorithm

In this section, a new adapted non-dominated sorting algorithm (ANSA) with two operators to solve the three-objective trip distribution problem with regard to characteristics of the problem is proposed. In the first step, algorithm generates initial population of size popsize using procedures 1 and 2.

3.1 Generating initial solutions

In this paper, a solution is represented by a matrix of $T = [T_{ij}]_{nn}$ that T is trip matrix.To generate initial solutions, procedure 1 and procedure 2 are proposed. In procedure 1, using given parameters of the problem, different initial trip matrixes that satisfy doubly constraints are generated as initial solutions. According to objectives (1) and objective (3), the value of T_{ij} cannot be zero, so procedure 2 presents an algorithm to exchange the produced initial trip matrixes containing one or more zero elements,with a new trip matrix without zero element. In procedure 1 to generate one solution, at first a cell of matrix is selected randomly,Assume the selected cell placed in row i and column j with the value of T_{ij}, then a number between 1 and the minimum value of O_i and D_j is determined as W_{ij}. W_{ij} is placed as T_{ij} in matrix T and the values of O_i and D_j will be updated with subtracting W_{ij} from them. This process will be continued until the summation of all O_i and D_j values becomes zero $(i, j = 1, 2n)$. In procedure 2, for a trip matrix with zero element in row i and column j while $T_{ij} = 0$, at first two random numbers are generated between 1 and n as r_2 and c_2 . Assume four cells of trip matrix with coordinates of $(i, j), (r_{2,}j, (i, c_2)$ and $(r_{2,}c_2)$ that $T_{ij} = 0$ and $T_{r_2j}, T_{ic_2} \neq 0$. To change the value of T_{ij}, the minimum value of T_{ic_2} and $T_{r_2c_2}$ is chosen

Table 1 Procedure 1: Creating initial Solutions

```
Input: Origin array (O), Destination array (D), PopSize (the number of initial solutions)
Repeat following steps PopSize times
Set Dnew=D
Set Onew=O
    Do while sum(Dnew) != 0 and Sum(Onew)!= 0
        Set a n*n zero matrix as X
        Select a random cell in matrix X asRC(i,j)
        if min (Onew(i),Dnew(j)) != 0
            set W= a random number between 1 and min (Onew(i),Dnew(j))
            set RC(i,j)= RC(i,j) + W
            set Onew(i)=Onew(i) - W
            set Dnew(j)=Dnew(j)- W
Output: Initialpop (pop: population of algorithm)
```

Table 2 Procedure 2: Make sure that there is no zero element in initial solutions

```
Input: pop
For all members of pop do
    While there is any zero element do
        Set (i, j) as position of the element that is 0
        Set A= pop(i,j)
        While A=0 do
            Create a different random number with respect to i, between 1 and matrix dimension and set it as r2
            Create a different random number with respect to j, between 1 and matrix dimension and set it as c2
            Set C=pop(r2,j)
            Create a random number between 0 and 1 as addPercent2
            Calculate: addp2 =[ (addPercent2 . min(pop(i,c2),pop(r2,c2))) ]
            Set A = A + addp2
            Set C = C addp2
            Pop(i,c2) = Pop(i,c2) addp2
            Pop(r2,c2) = Pop(r2,c2) addp2
            Pop(r2,j) = C
            Pop(i,j) = A
Output: pop
```

and a random percentage of this minimum value is determined asaddp2.addp2 should be added to T_{ij}. In addition, for satisfying doubly constraints in the trip matrix, addp2 must be added to$T_{r_2c_2}$ and subtracted from T_{ic_2} and T_{r_2j}. Pseudo-codes of two proposed procedures are described follow. It is notable that in procedure 2 parameter addPercent2 is a random number between zero and one that is used to determine the value that should be added to zero element in an initial trip matrix with element of zero.

3.2 Main steps of NSGA II

As mentioned before the initial population satisfies doubly constraints. After generating initial solutions, non-dominated sorting, crowding distance based sorting and selection procedures of NSGA II are applied. In non-dominated procedure, population is ranked to create pareto fronts. Each solution of the population under evaluation according to the objective function values obtains a rank equal to its non-dominated level (the best level is 1,2 is the next best level, and so on) where the first front contains solutions with the smallest rank, the second front includes solutions with the second rank, etc. In fact the first front solutions are completely non-dominated in the current population and solutions in the second front are dominated by the solutions of the first front and solutions of third front are dominated by both solutions of the first front and the second front and, so on. In this process solutions are ranked in ascending orders. After that the crowding distance between solutions on each front is calculated for all solutions using equation 8 to keep a diverse front by making sure that each member stays a crowding distance apart.

$$I(d_k) = I(d_k) + \frac{I(k+1).m - I(k-1).m}{f_m^{max} - f_m^{min}} \tag{7}$$

In equation (7) ,for each front F_i, Id_1 and Id_n are set ∞ , I(k) .m is the value of m-th objective function of the k-th solution in set I_i (I_i is the sorted set of F_i) and f_m^{max} and f_m^{min} are the maximum and minimum objective values of the m-th function respectively. As Solutions are selected using a binary tournament selection operator based on crowded-comparison operator, it is necessary to calculate both rank and the crowding distance of all solutions.Using this selection operator two solutions are first selected among the population,if the rank of two solutions be equal, the solution with the highest value of crowding distance is selected, else the solution with the lower rank is chosen. To generate new solutions in proposed adapted non-dominated sorting algorithm instead of crossover and mutation operators of NSGA II, two operators are introduced. These operators are designed to produce solutions that satisfy doubly constraints. Operator 1 is the neighborhood structure operator of proposed APSA and operator 2 is introduced in following section. Using these two operators a new population with size of n is created and added to current population. Finally, a population with exact size of popsize is obtained using the sorting procedure from population with size of (popsize+n). In this procedure solutions are sorted twice: first based on their ranks in ascending order, second based on their crowding distance in descending order.The pseudo-codes of the non-dominated sorting algorithm and crowding distance based sorting algorithm are described in procedure 3 and procedure 4. In next step the new population is used to generate the next new solutions using two operators of the algorithm. This process is repeated until the stopping condition is met. At the end of proposed algorithm implementation, a set of non-dominated pareto optimal solutions are obtained while all the solutions are the best in a sense of

Table 3 Procedure 3: non-dominated sorting algorithm

Input: pop
For 1 to popsize
Create Fronts as F (F is the set of all fronts)
Sort population with respect to F
Output: pop , F

Table 4 Procedure 4: crowding distance based sorting algorithm

Input: pop
Sort pop with respect to crowding distance of members
Update Pareto Fronts
Output: pop

multi-objective optimization.In the next sections, after introducing proposed operator 2, the steps of proposed ANSA are described.

3.3 Operator 2 of proposed adapted non-dominated sorting algorithm

Using this operator a new trip matrix is generated in a process that doubly constraints are satisfied. Assume that $T = [T_{ij}]_{n\times n}$ is a solution with dimensions of $n \times n$ in the population and $\acute{T} = [\acute{T}_{ij}]_{n\times n}$ is a new solution generated using proposed operator. At first, two different random numbers are generated between 1 and n as the row numbers $r1$ and $r_2(r_1 < r_2)$, and also two other different random numbers are generated between 1 and n as column numbersc1 and $c_2(c_1 < c_2)$. Using these four numbers, four cells of matrix with coordinates of (r_1, c_1) , $(r_1, c_2), (r_2, c_1)$ and (r_2, c_2) and values of $T_{r_1c_1}$, $T_{r_1c_2}$, $T_{r_2c_1}$ and $T_{r_2c_2}$ are selected. These four cells and the cells between them construct a sub matrix of matrix T called H.H is $a(r_2 - r_1 + 1) \times (c_2 - c_1 + 1)$ matrix. The value of the cell of matrix H that is in the last row and the last column is considered as .If we name values of the last row cells except α as $\theta_{c_1}, \theta_{c_1+1}, \ldots, \theta_{c_2-1}$ and values of the last column cells except α as $\delta_{r_1}, \delta_{r_{r_1+1}}, \ldots, \delta_{r_2-1}$, the following steps are applied to generate new solution $\acute{T} = [\acute{T}_{ij}]_{nn}$ using other cells of matrix H. At first a cell is randomly selected with value of T_{mn} while $r_1 \le m \le r_2 - 1, c_1 \le n \le c_2 - 1$. Then a random number is created between 0 and $min(\delta_m, \theta_n) - 1$ as addp7. This value (addp7) is added to T_{mn} and then to satisfy the doubly constraints in producing new solution $\acute{T}$, addp7 should be subtracted from values of δ_m and θ_n and added to value of α . This process is repeated for all other cells of the matrix H except the cells which are in the last row and last column. After this step the new matrix of H is set in matrix T and new trip matrix of $\acute{T}$ is generated. A sample of changing the value of

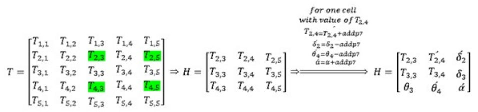

Fig. 1 Changing the value of one cell of matrix H regarding solution T

Table 5 Procedure 5: operator 2 for proposed adapted non-dominated sorting algorithm

```
Input: one random member of pop
Create two different random number between 1 and matrix dimension as (c1,c2)
Create two different random number between 1 and matrix dimension as (r1,r2)
Set minimum(c1,c2) as c1, And maximum(c1,c2) as c2
Set minimum(r1,r2) as r1, And maximum(r1,r2) as r2
Create matrix Res with zero elements (r2,c2)
    For i=r1 to r2-1 do
        For j=c1 to c2-1 do
        Set a random number between 0 and minimum (pop(r2,j),pop(i,c2)-1) as addp7
            Set Res(i,j)= addp7
            Set pop(i,j)= pop(i,j)+addp7
            Set Res(r2,j)=Res(r2,j)+addp7
            Set pop(r2,j)=pop(r2,j)-addp7
            Set Res(i,c2)=Res(i,c2)+addp7
            Set pop(i,c2)=pop(i,c2)-addp7;
Set pop(r2,c2)=pop(r2,c2) + Σi Res(i,c2)
Output: new matrix pop
```

one cell of matrix H is shown in Fig.1 for a trip matrix T with dimensions of 5×5 . The pseudo-code of operator 2 is described in procedure 5.

3.4 General steps of proposed adapted non-dominated sorting algorithm

The general steps of the proposed adapted non-dominated sorting algorithm are described as a pseudo-code in procedure 8. In the proposed algorithm after producing initial solutions using procedures 1 and 2, the population is sorted using procedures 5 and 6. Then a percentage of the number of population (popsize) is determined for each operator of the algorithm and new solutions are added to the current solution. The percentage that is considered for operator 1is calledpercentage1 and for operator2is namedpercentage2. After sorting all solutions, a population with size of popsize is selected and sorted using procedures 5 and 6. This process will be continued until the stop condition is met. In this algorithm the number of iterations is determined as the stop condition. Finally the solutions with rank 1 are introduced as pareto front. In procedure 8, T0 is the matrix of observed data related to objective (3) and C is the cost matrix related to objective (2).

Table 6 Procedure 8: general steps of the proposed adapted non-dominated sorting algorithm

```
Input : T0, O , D , C , number of iterations
Initialize parameters : popsize, number of iterations, percenage1, percentage 2
Set nopr1 = round(percentage1 *pop size)
Set nopr2 =round(percentage2*pop size)
Create Initial Solution with procedure 1and procedure 2
Evaluate objective functions for each member of pop
Do non-Dominated Sorting  procedure 5
Calculate Crowding Distance for pop members-
Do crowding distance based sorting  procedure 6
For 1 to number of iterations do
    For 1 to nopr1
        Do operation1 and set it as popOp1
    Evaluate objective functions for each popop1
    For 1 to nOpr2
        Do operation2 and set it as popOp2
    Evaluate objective functions for each popOp2
Merge pop as [pop,popop1,popOp2]
    Do non-Dominated Sorting procedure 5
    Calculate Crowding Distance for pop members-
Do crowding distance based sorting  procedure 6
    Select pop (1 to pop size) as pop
    Do None Dominate Sorting procedure 5
    Calculate Crowding Distance for pop members
Do crowding distance based sorting  procedure 6
Output : pop, F
```

4 computational results on Hong Kong data

The performance of proposed algorithm of adapted non-dominated sorting to solve the three-objective trip distribution problem is tested on Hong Kong data, and in continues of this section the reports of examinations are described. Proposed algorithm are coded by MATLAB programming language and run on a 2.4 GHz Pentium IV PC with 4 GB of RAM.The data is cached from the paper presented by Leung (2007). This data is related to trips were made by workers with similar economic backgrounds. The trip matrix in the observed year contains 12 districts, D1 to D12 which primarily cover a part of Hong Kong. The observed data for the year 2006 is shown in table 1. According to the Table 1, D1 and D2 shared a large proportion of trips because they are in the central business district, while D11 and D12 produce a smaller number of inter-district trips because they are located in more remote areas.

The generalized cost is shown in fig.3. In this figure, the generalized cost from and to districts D11 and D12 are relatively high in comparison with other districts, because these districts are in rural areas.

It is notable that there are trips and generalized cost from one origin to itself in fig.2 and fig.3, because some commuters start their trips from one

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	Sum
D1	1543	1579	841	935	584	2112	268	710	59	56	32	6	8725
D2	1937	3587	1054	1007	879	2211	287	732	60	256	33	8	12051
D3	346	305	202	327	123	495	104	268	22	10	11	7	2220
D4	769	698	675	946	302	1255	391	1037	78	28	26	8	6213
D5	1245	1646	766	971	545	1370	267	678	55	48	24	10	7625
D6	396	361	206	275	113	494	84	222	16	15	10	2	2194
D7	474	600	429	769	194	906	1008	1745	127	13	97	24	6386
D8	549	615	520	1029	227	983	859	1802	135	11	61	17	6808
D9	350	450	293	548	143	661	572	1106	211	9	45	20	4408
D10	361	860	180	229	146	376	99	221	21	136	7	4	2640
D11	643	801	451	791	272	1028	888	1567	140	20	2885	1023	10509
D12	1443	203	122	189	61	297	201	374	33	2	749	479	4153
Sum	10056	11705	5739	8016	3589	12188	5028	10462	957	604	3980	1608	

Fig. 2 Observed data in 2006

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
D1	5	6	7	7	6	8	10	9	9	10	16	16
D2	7	5	9	9	6	9	11	10	11	8	17	18
D3	6	7	5	6	6	7	8	7	7	10	14	15
D4	7	8	7	5	7	8	8	7	7	11	14	14
D5	6	6	8	8	4	9	10	9	10	9	16	17
D6	6	7	7	7	7	6	9	8	8	10	15	15
D7	11	13	11	10	11	12	4	6	7	15	10	11
D8	10	11	9	8	9	10	6	5	6	13	12	13
D9	11	13	11	10	11	12	7	7	4	15	13	13
D10	11	9	13	13	10	13	15	14	15	7	21	22
D11	19	20	19	18	19	20	12	15	13	23	6	8
D12	20	22	20	19	20	21	14	17	15	25	9	4

Fig. 3 Generalized cost (HK$; US$=HK$7.8).

district and end at the same district and travel cost, waiting cost, etc. are incurred to make such trips.

4.1 Results of applying proposed ANSA on Hong Kong data

In this section, the results of applying the proposed ANSA on Hong Kong data are examined. In four runs of this algorithm, four different pareto fronts have been obtained. In continue, fig.2 shows spare to front graphs of each run separately with different parameters of number of initial population, the number of iterations and the number of solutions in pareto front.

According to results, pareto front that is obtained from run number 3 can be considered as the best pareto front, so third run solutions are better than solutions of other runs. But as one can see in fig.5, there are very little differences between answers obtained from third run and fourth run. So, with

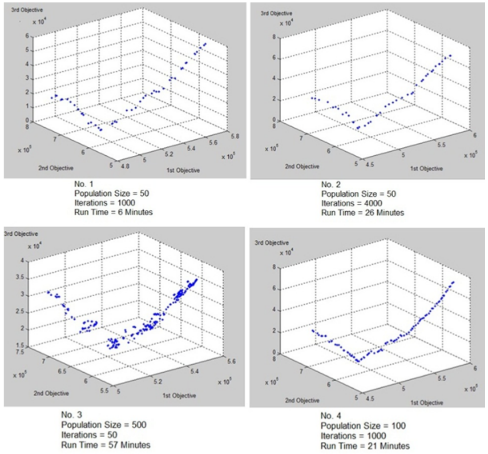

Fig. 4 Pareto front graphs of four runs of proposed ANSA with different parameters

	First Run			Second Run		
	f1	f2	f3	f1	f2	f3
1	505288	659392	1902	489021	784013	17141
2	490720	775962	16994	588864	540102	69131
3	574705	556251	57824	504643	657959	347
	Third Run			Fourth Run		
	f1	f2	F 3	f1	f2	f3
1	503821[A]	660779[A]	117[A]	488945	782660	16974
2	488909[B]	782971[B]	17014[B]	504366	658722	222
3	593268[C]	538626[C]	72955[C]	592203	539258	72570

Fig. 5 The objective function values of three solutions in four different runs of proposed ANSA

regard to the time constraint, it can be said that the forth run performance with 100 initial population and 1000 iterations is the best.

In continue figures 5, 6 and 7 present the trip matrixes of the selected solutions of fig.9 in four runs of the proposed algorithm that are marked as A, B and C in this fig.

4.2 Discussion

In this section, the results of applying the proposed algorithm of this paper to solve the three-objective trip distribution problem are discussed and compared with results of the paper of Leung. As said before, Leung applied goal programming on three-objective trip distribution problem and solved it using genetic algorithm. Table 11 shows the minimum value of each objective function of the problem that is obtained from various runs using three algorithms of the literature.

A	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
O1	1542	1559	875	937	572	2136	262	703	55	56	24	4
O2	1931	3708	1009	1018	995	2021	328	705	58	249	24	5
O3	361	293	192	325	119	532	98	265	14	10	7	4
O4	797	686	679	886	292	1344	358	1051	68	24	22	6
O5	1319	1556	765	994	488	1453	243	693	47	43	18	6
O6	399	371	215	283	94	511	76	212	13	12	6	2
O7	474	601	433	769	202	912	991	1745	130	12	99	18
O8	500	606	566	1064	241	945	914	1752	140	13	56	11
O9	345	432	282	524	139	623	626	1149	226	8	43	11
O10	326	879	182	239	131	395	87	222	16	156	6	1
O11	649	827	456	781	271	1047	856	1610	162	20	2795	1035
O12	1413	187	85	196	45	269	189	355	28	1	880	505

Fig. 6 Trip matrix related to solution A in fig.5

B	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
O1	1174	1370	753	896	393	1380	568	1304	123	77	482	205
O2	1702	1853	909	1294	586	1983	859	1679	168	109	641	268
O3	318	357	150	213	96	407	132	359	24	16	109	39
O4	771	986	497	687	329	1025	409	917	79	58	333	122
O5	1043	1221	572	823	396	1232	529	1076	105	64	414	150
O6	274	400	168	214	85	420	143	291	28	16	116	39
O7	851	1022	523	691	331	981	419	902	95	52	363	156
O8	955	1093	466	803	339	1114	467	966	75	53	348	129
O9	638	705	319	481	217	756	304	588	48	31	228	93
O10	397	440	198	259	124	462	156	371	25	24	131	53
O11	1372	1556	865	1207	503	1731	771	1420	142	72	600	270
O12	561	702	319	448	190	697	271	589	45	32	215	84

Fig. 7 Trip matrix related to solution B in fig.5

C	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
O1	5772	1	423	1	1	2521	1	1	1	1	1	1
O2	884	9860	12	1	1	1287	1	1	1	1	1	1
O3	1	1	2209	1	1	1	1	1	1	1	1	1
O4	1	1	2	6201	1	1	1	1	1	1	1	1
O5	3337	1	224	1	3578	478	1	1	1	1	1	1
O6	1	1	1	1	1	2183	1	1	1	1	1	1
O7	1	1	16	3	1	45	465	5850	1	1	1	1
O8	1	1	1269	776	1	2126	1	2629	1	1	1	1
O9	1	1	501	358	1	1265	1	1367	910	1	1	1
O10	55	1835	1	1	1	149	1	1	1	593	1	1
O11	1	1	313	210	1	841	4546	608	26	1	3960	1
O12	1	1	768	462	1	1291	8	1	12	1	10	1597

Fig. 8 Trip matrix related to solution C in fig.5

Objective functions	Minimization of f1		Minimization of f2		Minimization of f3	
	Algorithms		Algorithms		Algorithms	
	GP	ANSA	GP	ANSA	GP	ANSA
f1	626 128	488909	769 942	592774	643 316	503821
f2	996 300	782971	679 390	538936	841 802	660779
f3	-	17014	-	72501	-	117

Fig. 9 Comparison of objective function values of proposed algorithms and algorithm of Leung (2007)

Because Leung did not mention any value for the third objective in his paper; it cannot be compared with two proposed algorithms. According to fig.9, the minimum value of all objectives among these three algorithms belongs to proposed ANSA. In comparison of three algorithms, the results indicate that the proposed ANSA algorithm clearly has better performance rather than others.

5 Conclusion

In this paper, a proposed adapted of adapted non-dominated sorting algorithm was implemented for a three-objective trip distribution problem with doubly constraints. In adapted non-dominated sorting algorithm using the sorting procedures of NSGA II and two proposed operators with regard to satisfaction of doubly constraints a new sorting algorithm for three-objective trip distribution problem was introduced. The performance of the proposed algorithm was evaluated by a set of Hong Kong data in comparison to the algorithm of Leung in the literature. The results showed that the proposed algorithm has better performance rather than the algorithm of Leung in aspect of the values of objective functions.

References

1. V.T. Arasan, M. Wermuth, and B.S. Srinivas, Modeling of stratified urban tripdistribution, J. TranspEng, 122 (1996) 342–346.
2. M.M.M. Abdel-Aal, Calibrating a trip distribution gravity model stratified by the trip purposes for the city of Alexandria, Alexandria Engineering Journal, 53 (2014) 677–689.
3. M.J. Bruton, Introduction to Transportation Planning, UCL Press, London (1985).
4. B. Cakir, F. Altiparmak, and B. Dengiz, Multi-objective optimization of astochastic assembly line balancing: A hybrid simulated annealing algorithm, Computer & Industrial Engineering, 60 (2011) 376–384.
5. P. Czyzak, A. Jaszkiewicz, Pareto simulated annealing: A metaheuristic technique for multipleobjective combinatorial optimization. Journal of Multi-Criteria Decision Analysis, 7 (1998) 34–47 .
6. L.N. Duffus, A.S. Alfa, and A.H. Soliman, The reliability of using the gravity model for forecasting trip distribution, Transportation, 14 (1987) 175–192.
7. M.M. El-Sherbiny, R.M. Alhamali, A hybrid particle swarm algorithm with artificial immune learning for solving the fixed charge transportation problem, Computers & Industrial Engineering, 64 (2013) 610–620.

8. A. Hallefjord, K. Jornsten, Gravity models with multiple objectives: theory and applications, Trans Res B., 20 (1986) 19–39.
9. S. Islam, S., Kumar Roy, A new fuzzy multi-objective programming: Entropy based geometric programming and its application of transportation problems, EuropeanJournal of Operational Research, 173 (2006) 387–404.
10. S. Kirkpatrick, C.D. Gellat, and M.P. Vecchi, Optimization by simulated annealing. Science, 220 (1983) 671–680.
11. M. Kompil, H.M. Celik, Modelling trip distribution with fuzzy and genetic fuzzy systems, Transportation Planning and Technology, 36(2) (2013) 170–200.
12. X. Li, Z. Qin, L. Yang, and K. Li, Entropy maximization model for the trip distribution problem with fuzzy and random parameters, Journal of Computational and Applied Mathematics, 235 (2011) 1906–1913.
13. K.S. Lin, D.A. Niemeier, Temporal disaggregation of travel demand for high resolution emissions inventories, Trans Res 3D, (1998) 375–387.
14. C. Murat, Sample size needed for calibrating trip distribution and behavior of the gravity model, Journal of Transport Geography, 18 (1994) 183–190.
15. S. Ortuzar, L.G. Willumsen, Modeling Transport, Wiley, New York (1994).
16. M.S. Sabbagh, H. Ghafari, and S.R. Mousavi, A new hybrid algorithm for the balanced transportation problem, Computers & Industrial Engineering, 82 (2015) 115–126.
17. Salminen. S. Traffic accidents during work and work commuting, Int J IndErgon 26,75–85 (2000)
18. T. Thomas, S.I.A. Tutert, An empirical model for trip distribution of commuters in The Netherlands: transferability in time and space reconsidered,Journal of Transport Geography, 26 (2013) 158–165.
19. A.G. Wilson, Entropy in urban and regional modeling, Poin, England (1970).
20. A. Zaretalab, V. Hajipour, M. Sharifi, and M.R. Shahriari, A knowledge-based archive multi-objective simulated annealingalgorithm to optimize series parallel system with choice of redundancy strategies. Computers & Industrial Engineering, 80 (2015) 33–44.
21. Z. Zhou, A. Chen, S.C. Wong, Alternative formulations of a combined trip generation, trip distribution, modal split and trip assignment model, European Journal of Operational Research, 198 (2009) 129–138.