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# A BI-OBJECTIVE TRAFFIC COUNTING LOCATION PROBLEM FOR ORIGIN-DESTINATION TRIP TABLE ESTIMATION

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In this study, we consider the bi-objective traffic counting location problem for the purpose of origin-destination (O-D) trip table estimation. The problem is to determine the number and locations of counting stations that would best cover the network. The maximal coverage and minimal resource utilization criteria, which are generally conflicting, are simultaneously considered in a multi-objective manner to reveal the tradeoff between the quality and cost of coverage. A distance-based genetic algorithm (GA) is used to solve the proposed bi-objective traffic counting location problem by explicitly generating the non-dominated solutions. Numerical results are provided to demonstrate the feasibility of the proposed model. The primary results indicate that the distance-based GA can produce the set of non-dominated solutions from which the decision makers can examine the tradeoff between the quality and cost of coverage and make a proper selection without the need to repeatedly solve the maximal covering problem with different levels of resource.

KEYWORDS: Traffic counting location, O-D trip table estimation, multiobjective optimization, genetic algorithm

## 1. INTRODUCTION

A common input required in many transportation models is an origin-destination (O-D) trip table. The O-D trip table depicts the spatial distribution of trips among traffic analysis zones (TAZ) in a transportation network. It is required for traffic assignment and simulation models, which are used to analyze a wide variety of transportation applications ranging from long-term strategic transportation planning to short-term transportation management. Traditionally, the O-D trip tables are estimated through large-scale surveys such as household and roadside interviews, license plate matching, etc. These survey techniques are expensive, time consuming, and labor intensive. In addition, if there is a rapid change in land-use patterns, the estimated trip table will soon become outdated. Therefore, repeating the large-scale survey within a short-time period may not be feasible due to financial and time constraints. During the past two decades, significant research efforts (see namely Van Zuylen and Willumsen, 1980; Maher, 1983; Bell, 1984; Cascetta, 1984; Spiess, 1987; Fisk, 1988; Yang et al., 1992; Ashok and Ben-Akiva, 1993; Sherali et al., 1994; Bell and Shield, 1995; Hazelton, 2000; Maher et al., 2001) have been devoted to the development of efficient and inexpensive methods for inferring the O-D trip table from traffic counts, which are considered to be more economical and can provide more up-to-date travel demand pattern. Extensive studies on this topic during these several years demonstrated that the quality of estimated O-D trip table is dependent not only on the underlying route choice models, but also the quality of observations (Lam and Lo, 1990) and the number and locations of traffic counts (Yang et al., 1991; Yang and Zhou, 1998).

A central problem in the traffic counting location problem is to determine the number and locations of traffic counting stations that would best cover the network. In general,

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traffic counting stations are selected at the critical locations of road network such as congested intersections and freeway entrances. This selection procedure is clearly subjective and there is no guarantee on the quality of information obtained. Lam and Lo (1990) suggested a feedback mechanism to systematically select traffic counts that can contribute to the O-D estimation process. The selection of traffic counts is iterated among the already available counts in some specific manners and only those contributing to the improvement of O-D estimation are used. Yang et al. (1991) proposed the O-D covering rule in which traffic counting stations are located in such a way that the total trips between each O-D pair are at least partially observed. Using the concept of maximal possible relative error (MPRE) proposed by Yang et al. (1991), Yang and Zhou (1998) further derived four location rules and formulated various integer programs to select the traffic counting stations. Beside the information related to path flows, these formulations also require path enumeration. These requirements may be difficult to fulfill for general road networks. Recently, Yang et al. (2001) relaxed these assumptions and formulated the traffic counting location problem using the O-D separation rule in which path enumeration is not required and only network topology is considered. Trips between a particular O-D pair are considered observed if and only if there is no path able to bypass the selected traffic counting locations. A genetic algorithm (GA) was used to solve two traffic counting location problems: one is to locate a given number of traffic counting stations to separate as many O-D pairs as possible and the other is to determine the minimal number and locations of traffic counting stations required to separate all O-D pairs. Intuitively, these two problems (or objectives) are conflicting and cannot be achieved simultaneously. The best solution considering both objectives is rarely apparent unless the preferences of both objectives are defined a priori. On the other hand, there usually exists a set of non-dominated solutions, which are considered better in one objective, but worse in another. Under this circumstance, it is important to understand the tradeoff between these two objectives in order to make a proper decision. Multi-objective optimization techniques have been considered to fulfill this requirement. Among the many commonly used techniques, genetic algorithm (GA) is considered as one of the most practical techniques due to its simplicity and flexibility. In addition, GA is very suitable for exploring non-dominated solutions of multi-objective optimization problems since it works with a population of solutions. In order to apply GA to the multi-objective optimization problems, a fitness of each solution in accordance with the multiple objectives has to be properly determined. There are two main approaches to determine the fitness: the generating approach and the preference-based approach (Gen and Cheng, 2000). The former approach explicitly generates an approximate set of Pareto solutions from which the fitness is determined, while the later utilizes the preference supplied by decision makers (e.g., priority or weight) to select the best solution.

The goals of this study are to formulate a bi-objective traffic counting location problem and to develop multi-objective GA procedures for solving this combinatorial problem. Specifically, two solution techniques for the multi-objective GA are investigated: the weighted-sum method and the distance-based method. The organization of this paper is as follows. Section 2 briefly describes the characteristics of the traffic counting location problem and its formulations. Section 3 discuses the solution techniques for multi-objective GA. Numerical results are presented in Section 4, while conclusions drawn from the case studies are provided in Section 5.

## 2. OPTIMAL TRAFFIC COUNTING LOCATION PROBLEM

Traffic counts on road network are essential for efficient traffic control, design, planning, and management. Traditionally, they are collected manually at roadside, which is labor-intensive and time consuming. Due to the rapid advancement in detection technology, this data collection process has become more convenient and can be collected frequently. However, budget constraint often prohibits the full installation of the detection devices onto the whole road network. In order to obtain the useful and up-to-date traffic condition, the limited number of detection devices should be strategically installed in such a way that traffic flows within the network are captured as much as possible.

Yang et al. (2001) proposed two mathematical programs to identify the optimal locations of counting stations for the purpose of O-D estimation. Optimality could be defined by two criteria: (1) the maximum number of O-D pairs being observed with a given number of traffic counting stations and (2) the minimum number of traffic counting stations used to separate all O-D pairs. As mentioned earlier, these two criteria are generally conflicting. One way to get around this issue is to consider one criterion as the objective and the other as the constraint. The mathematical programs corresponding to these two criteria (Yang et al., 2001) and notation used are given below.

### *2.1 Notation*

$L$: Number of traffic counting stations,

A: A set of links in the network, and |A| is the number of links in set A,

W: A set of O-D pairs, and |W| is the number of O-D pairs in set W,

$u_w$: A minimum virtual travel time between O-D pair $w$,

$\Phi(\cdot)$: Activation function, $\Phi = 1$, if its argument is greater than zero, or $\Phi = 0$, otherwise,

$x_a$: Decision variables indicating whether or not link $a$ is selected as a traffic counting station {0,1}.

### *2.2 Maximal coverage for a given number of traffic counting stations*

$$\text{Maximize} \quad Z_1 = \sum_{w \in \mathrm{W}} \Phi_w\left(u_w(\mathbf{x})\right), \tag{1}$$

subject to

$$\sum_{a \in \mathrm{A}} x_a \le L\,, \tag{2}$$

$$x_a = \begin{cases} 1, & \text{if link } a \text{ is selected} \\ 0, & \text{otherwise} \end{cases}, \quad \forall a \in \mathrm{A}\,. \tag{3}$$

In order to determine whether the O-D pair is separated or not, a shortest path algorithm is applied to a set of specially defined link travel times called *virtual* link travel times used in Yang et al. (2001). If a link is selected as a traffic counting station, its travel time is triggered to 1; otherwise, it stays at 0. The activation function ($\Phi$) indicates that if the minimum travel time between O-D pair $w$, ($u_w$) is zero, the O-D pair is not separated by this set of traffic counting stations. In other words, for O-D pair $w$, there is at least one path that can avoid passing through these traffic counting stations. Apparently, the travel time on the shortest path indicates the number of traffic counting stations along the path. The summation of Φ over the set of O-D pairs (W) indicates the number of O-D pairs being separated by the given number of traffic counting stations ($L$) constrained by equation (2).

*2.3 Minimum number of traffic counting stations to separate all O-D pairs*

Although selecting all network links as traffic counting stations can provide the maximum coverage of traffic information, it is not cost-effective. For the O-D estimation problem, only the stations necessary to separate all O-D pairs should be used. The objective of this problem is to minimize the number of traffic counting stations required to separate all O-D pairs. The formulation is provided as follows:

$$\text{Minimize} \quad Z_2 = \sum_{a \in A} x_a \tag{4}$$

subject to

$$\sum_{w \in W} \Phi_w\left(u_w(\mathbf{x})\right) = |W|, \tag{5}$$

$$x_a = \begin{cases} 1, & \text{if link } a \text{ is selected} \\ 0, & \text{otherwise} \end{cases}, \ \forall a \in A. \tag{6}$$

For this formulation, the objective in equation (4) is to minimize the number of traffic counting stations required to separate all O-D pairs in equation (5).

*2.4 Bi-objective traffic counting location problem*

The two formulations described above use only one of the two criteria (i.e., coverage or cost) as the objective and treat the other as the constraint. In the first formulation, the objective is to maximize the number of O-D pairs being separated subject to a resource constraint on the number of available traffic counting stations. In the second formulation, the objective is to minimize the number of traffic counting stations (or cost) subject to all O-D pairs being separated. Here, we simultaneously consider both criteria by using the multi-objective optimization approach. Consequently, the proposed bi-objective optimization model has no explicit constraint except the binary integer requirement on the location variables. The formulation of proposed model is given as follows.

$$\text{Maximize} \quad \begin{Bmatrix} Z_1 = \sum_{w \in W} \Phi_w\left(u_w(\mathbf{x})\right) \\ Z_2^* = -\sum_{a \in A} x_a \end{Bmatrix} \tag{7}$$

subject to

$$x_a = \begin{cases} 1, & \text{if link } a \text{ is selected} \\ 0, & \text{otherwise} \end{cases}, \ \forall a \in A. \tag{8}$$

Equation (7) simultaneously considers both objectives defined in the two previous sections: quality and cost of coverage. For consistency, we use the maximization operator for both objectives. This can be easily accomplished by multiplying “-1” to $Z_2$ to convert a minimization objective to a maximization objective. Equation (8) requires the location variables to be binary.

## 3. MULTI-OBJECTIVE GENETIC ALGORITHM

Due to its flexibility and non-restricted mathematical properties, GA can be efficiently applied to the multi-objective optimization problem with the same advantages as in the single objective case. The only difficulty is how to determine the fitness of each solution when multiple objectives are considered simultaneously. As an extension of the single objective optimization problem, the multi-objective optimization problem can be expressed as:

$$\text{Maximize} \quad Z_m(\mathbf{x}), \quad \forall m = 1,2,...,M \ , \tag{9}$$

subject to

$$\mathrm{g}_n(\mathbf{x}) \le b_n, \quad \forall n = 1,2,...,N \ , \tag{10}$$

where **x** is the solution vector, $Z_m(\cdot)$ is the *m*th objective among M objectives, and $\mathrm{g}_n(\cdot)$ is the *n*th constraint. When the objectives are conflicting, there is, in general, no single optimal solution that can simultaneously optimizes all aspects. A solution may be best in one objective, but worst in the others. It is difficult to distinguish the best solution in a multi-objective problem unless a preference structure of all objectives is explicitly defined. According to Gen and Cheng (2000), there are two main approaches to handle this problem: the preference-based approach and the generating approach.

The preference-based approach simply converts the multiple objectives into a single objective according to the preference structure supplied by the decision makers. This however requires a good knowledge of the problem. Using improper weight factor will lead to the domination of one objective over the others (Coello, 1999). Goal programming is one of the preference-based methods that require defining a goal for each objective (Charles and Cooper, 1961). The problem becomes one of minimizing the deviation between the expectations (or goals) and the achieved performances. Another method in this family is using the utility concept in which all objectives are combined into a single abstract utility. All methods in this family have a common drawback, which is the determination of preference on each criterion.

For the generating approach, the concept of Pareto optimality is adopted. The solution is “Pareto optimal” or “non-dominated” if there were no other feasible solutions that could improve some objectives without worsening at least one other objective. A set of non-dominated solutions generally forms the so-called “Pareto front” or “efficient frontier”, which represents the relationship (tradeoff) among multiple objectives. Besides the non-dominated solution, all other feasible solutions (if any) can be classified either as a “superior” solution or an “inferior” solution. If a superior solution exists, the problem has a single best solution that can simultaneously maximize all objectives. During the evolution of GA, the superior solution (found so far) would be assigned the highest fitness value while the inferior solution would receive the lowest fitness value. Each non-dominated solution is considered equally good, and would be assigned the same fitness value. The major difficulty of this approach is the necessity to maintain a diverse solution set (Coello, 1999; Gen and Cheng, 2000). The simplest way to maintain the diversity of non-dominated solutions is to increase the population size. A more sophisticated way is to determine the selection pressure or fitness based not only on the type of solution, but also on the crowdedness of solutions. An example of such techniques is the fitness sharing or niche formation (Goldberg, 1989). In this study, we consider two solution techniques, which are the weighted-sum method and the distance-based method, for comparison.

*3.1 Weighted-sum method*

If the preference or weight of each objective is available, all objectives could be aggregated into a single objective. The problem essentially becomes a single objective optimization problem. Since each objective is usually measured in different scales, the original objectives need to be normalized, $\tilde{Z}_m(\cdot)$, before being weighted. The summation of weights ($\lambda$) of all objectives is one. The weight can be viewed as a relative importance of each objective compared to the others. The transformed mathematical program is given by:

$$\text{Maximize} \quad \sum_{m=1}^{\mathrm{M}} \lambda_m \tilde{Z}_m(\mathbf{x}) , \tag{11}$$

subject to

$$\mathrm{g}_n(\mathbf{x}) \le b_n , \quad \forall n = 1,2,..., N . \tag{12}$$

After the transformation, a simple GA can be applied to solve this single objective problem. The strength of this method is the capability to generate a strongly non-dominated solution (Coello, 1999). A set of non-dominated solutions can be further generated by varying the weight factors. However, some of non-dominated solutions, called the duality gap points (Daskin, 1995), may not be attainable since there is no proper combination of weights that is able to represent such a solution (we shall see this characteristic later in the numerical example). For the traffic counting location problem, the value of both objectives can be normalized as follows.

$$\tilde{\mathrm{Z}}_1 = Z_1 / \left| \mathrm{W} \right| \text{ and } \tilde{\mathrm{Z}}_2 = \left( \left| \mathrm{A} \right| - \mathrm{Z}_2 \right) / \left| \mathrm{A} \right| . \tag{13}$$

For this problem, it can be easily seen that the highest value that $Z_1$ can take is the number of O-D pairs in the network (|W|), while the lowest value that $Z_2$ can take is zero. According to the normalized objectives in Equation (13), the better solutions will take the fitness values closed to one.

*3.2 Distance-based method*

The distance-based method, which was proposed by Osyczka and Kundu (1995), is one of the generating approaches. The main idea is to evolve the genetic search toward the ideal Pareto solutions in which all individual objectives are simultaneously achieved at the highest possible level. In practice, such solutions are rarely known; therefore, an alternative benchmark, which is the current set of non-dominated solutions, is considered. Accordingly, there are two sets of solutions involved: population (**x**) and non-dominated (**y**) sets. The population set is used to perform a genetic search while the non-dominated set is the solutions to the problem. The solutions are improved by distancing away from the existing set of non-dominated solutions (**y**). Its relative distance ($d_k$) to the existing non-dominated solutions ($\mathbf{y}_k$) defines the fitness of new solution (**x**) generated by the GA operators (see Equation 14). In addition, the current set of non-dominated solutions must be updated whenever new non-dominated solutions are found (adding) or the existing solutions are found to be inferior (discarding). The fitness evaluation according to the distance-based method is summarized as follows.

Step 1. If there exist some non-dominated solutions, go to step 2. Otherwise, add the $q$th solution from the population set into the non-dominated set. Arbitrarily assign the fitness value to the $q$th solution ($v_q = P_{\max}$). Set the number of non-dominated solutions, $K = 1$. Note that $P_{\max}$ is the initial fitness of the non-dominated solution and it would be updated through the evolution of GA (e.g., when better non-dominated solutions are found).

Step 2. Determine the minimum distance ($d_{\min}$) and the corresponding non-dominated solution ($\ell$) by equation (14). $\ell$ is the non-dominated solution index with the minimum distance ($d_{\min}$). The fitness of the newly generated solution is determined by referencing to the closest non-dominated solution.

$$d_{\min} = \underset{\forall k}{\mathrm{Min}} \left\{ \sqrt{\sum_{m=1}^{M} \left( \frac{Z_m(\mathbf{y}_k) - Z_m(\mathbf{x}_q)}{Z_m(\mathbf{y}_k)} \right)^2} \right\}. \qquad (14)$$

Step 3. Determine the type of solution. If the $q$th solution is a superior solution (better in all objectives), add this solution into the non-dominated set and removes all dominated solutions ($r$ solutions). Set $K = K - r + 1$, compute the fitness of the new non-dominated solution ($p_k$) using Equation (15) and go to step 4.

$$p_k = P_{\max} + d_{\min}. \qquad (15)$$

If the $q$th solution is a non-dominated solution, add this solution to the non-dominated set. Set $K = K + 1$, and compute the fitness of the new non-dominated solution ($p_k$) using equation (16) and go to step 4

$$p_k = p_\ell + d_{\min}. \qquad (16)$$

If the $q$th solution is an inferior solution, compute the fitness using equation (17), and go to step 5.

$$v_q = \mathrm{Max}\{0, p_\ell - d_{\min}\}. \qquad (17)$$

Step 4. Compute the fitness of the $q$th solution using equation (18). Update the fitness of the non-dominated set according to equations (19).

$$v_q = p_k. \qquad (18)$$

$$P_{\max} = \mathrm{Max}\,\{P_{\max}, p_k\}. \qquad (19)$$

Step 5. If $q$ equals the population size, set the fitness of all non-dominated solutions to $P_{\max}$, and return to genetic search; otherwise, consider the next solution ($q$+1).

## 4. NUMERICAL EXAMPLES

### *4.1 A small grid network*

For demonstration purpose, the bi-objective model is applied to locate traffic counting stations for the network depicted in Figure 1. This network is taken from the study of Yang et al. (2001). It consists of 9 nodes and 12 unidirectional links. There are 6 O-D pairs: (1,6), (1,8), (1,9), (4,6), (4,8), and (4,9). For this example, the population size of GA is arbitrarily set at 32 while there is no limit on the number of non-dominated solutions. The chromosome representation (location variable) is a binary integer with a fixed length of 12 (the number of network links). The value of each gene indicates whether the corresponding link is selected as a traffic counting station or not. The uniform crossover (one of the multi-point crossovers) with a crossover rate of 0.5 is adopted here. A very low mutation rate of 0.02 is used for this bi-objective integer program. Two solution techniques for the multi-objective GA detailed earlier are used to solve this problem. 1,000 generations of GA are performed for each weight combination in the weighted-sum method for a total of 11 weight combinations and 5,000 generations are used for generating non-dominated solutions in the distance-based method. It should be noted here that only a single best solution would be obtained for each weight combination. Therefore, at most 11 non-dominated solutions would be generated from a total of 11,000 generations spent by the weighted-sum method for the 11 weight combinations as opposed to 5,000 generations spent by the distance-based method.

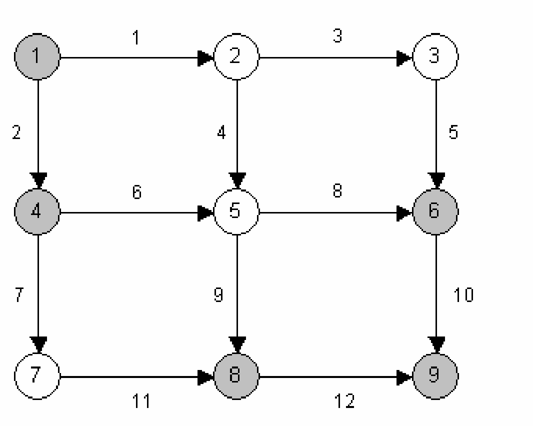


FIGURE 1: First test network

The results based on the weighted-sum method are summarized in Table 1. It can be expected that different preference structures will lead to different solutions. If a higher weight is put on the minimum number of traffic counting stations, GA tends to recommend the do-nothing option (no need to install any traffic counting station). On the other hand, if an extremely high weight is put toward the number of O-D pairs being separated, any solutions that can separate all O-D pairs will be considered equally good regardless of the corresponding number of traffic counting stations used (there is no contribution from the second objective function, $Z_2$). For this network, the solution seems insensitive when the weight ($\lambda$) given to $Z_1$ is greater than 0.20. The same solution is recommended for almost all the cases. However, this may not be the case for networks of realistic size. To separate all 6 O-D pairs, the solution suggests that 3 traffic counting stations are required. It should be noted that there might be several combinations that can separate all O-D pairs. In other words, the solution is not unique. Figure 2 depicts two possible locations: links 1, 6, 7, and links 1, 6, 11.

TABLE 1: Solutions for the first network generated by the weighted-sum method

| Weight for $Z_1$ | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1.0 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Number of counting stations | 0 | 0 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 5 |
| Number of O-D pairs separated | 0 | 0 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 |

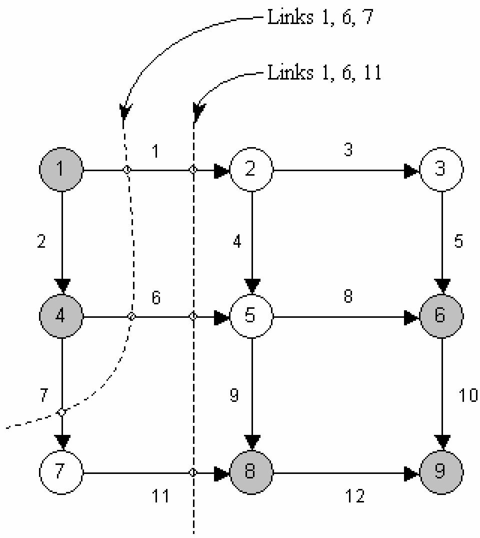


FIGURE 2: Two possible locations of 3 traffic counting stations separating all 6 O-D pairs

The result obtained by the distance-based method is a set of non-dominated solutions. The evolution of non-dominated solutions through many generations of GA is depicted in Figure 3. It is found that the two solutions generated by the weighted-sum method are a subset of four non-dominated solutions generated by the distance-based method. It appears that the distance-based method can produce more non-dominated solutions including the solutions in the duality gap (solutions **2** and **3**), which may not be generated by any weight combinations using the weighted-sum method (Daskin, 1995). Figure 4 shows the variation of fitness values of these four non-dominated solutions under different weight combinations used earlier (see Table 1). The computed fitness values confirm that solutions **2** and **3** will never be recommended as the best solution by the weighted-sum method under any weight combinations albeit they are non-dominated.

*4.2 A medium-size network*

This section is provided to illustrate the application of the proposed model on a medium-size network (modified from the Sioux Falls network) taken from Yang et al. (2001). The network consists of 24 nodes, 76 links, and 182 O-D pairs. For this example, the weighted-sum method is no longer considered due to its limitation demonstrated in the first test network. Only the distance-based method is used to generate the non-dominated solutions. Due to the problem size (the number of network links), the population size of GA and the maximum number of generations are increased to 128 and 50,000, respectively. Other parameters used in GA remain unchanged. The initial distance required in the distance-based method is set at 0.001. However, it should be noted that the value of initial distance does not have a significant effect on the performance of GA since the relative fitness is used to determine the selection pressure (Chen et al., 2004).

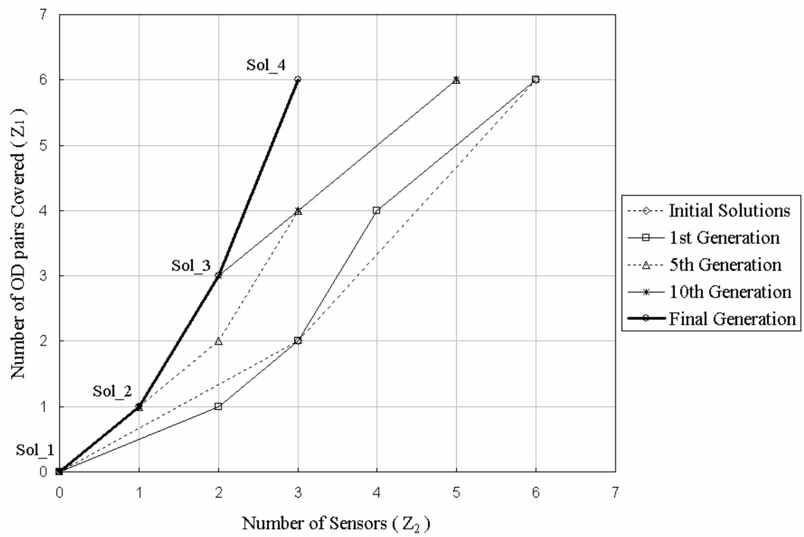


FIGURE 3: Evolution of non-dominated solutions by the distance-based method

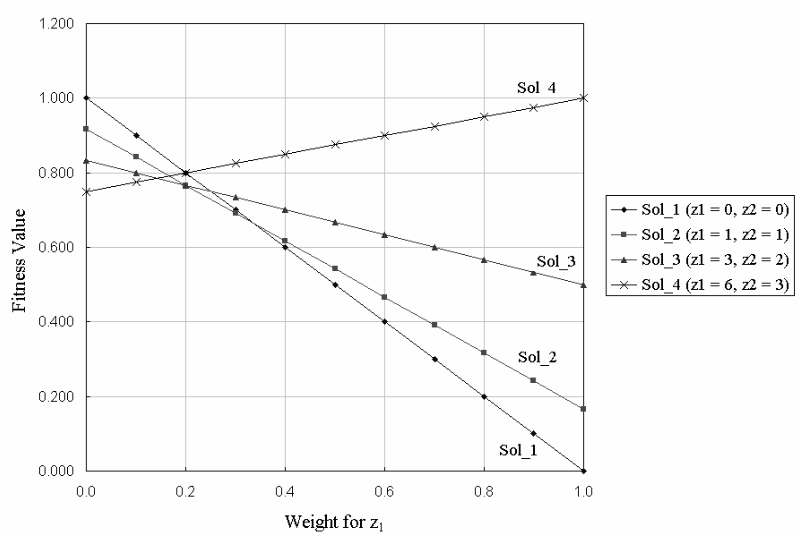


FIGURE 4: Fitness of four non-dominated solutions for different weight combinations

Figure 5 shows how the fitness of Pareto set (a set of non-dominated solutions) improves as the generation number increases. The increased fitness indicates that the new non-dominated solution(s) is found and the Pareto front is moved toward the ideal front. It should be noted that some of the current non-dominated solutions become inferior and must be discarded from the current set when the new non-dominated solutions are found. Therefore, the number of non-dominated solutions does not always increase as the fitness of Pareto set increases. Figure 5 also shows the number of (approximate) non-dominated solutions found at each generation as represented by the bar graph. Clearly, it is not strictly increasing. Figure 6 depicts the evolution of non-dominated solutions in the objective space. At the final generation, the approximate Pareto set contains 45 non-dominated solutions. The conflict between the two considered objectives indicated by this Pareto front is as expected. That is, more O-D pairs are likely to be separated with more traffic counting stations, which unfortunately need to be minimized.

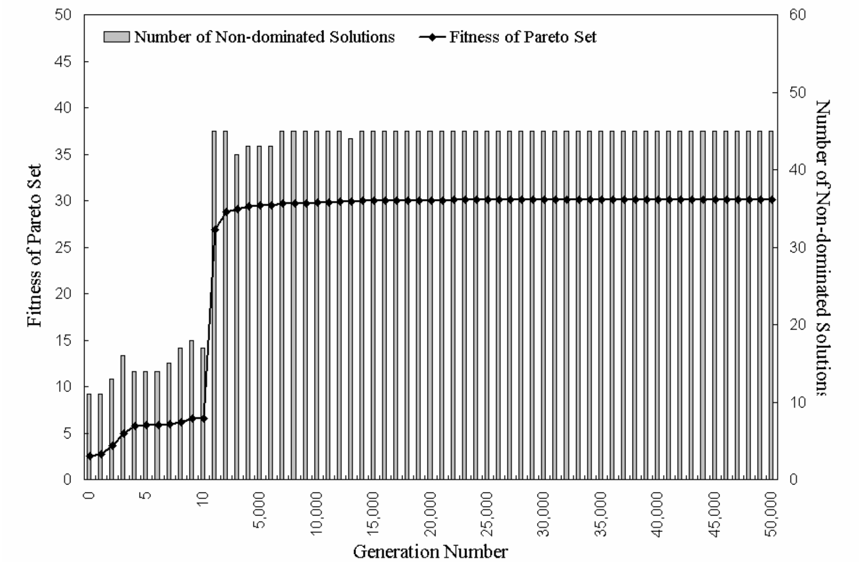


FIGURE 5: Fitness of Pareto set and number of non-dominated solutions in each generation

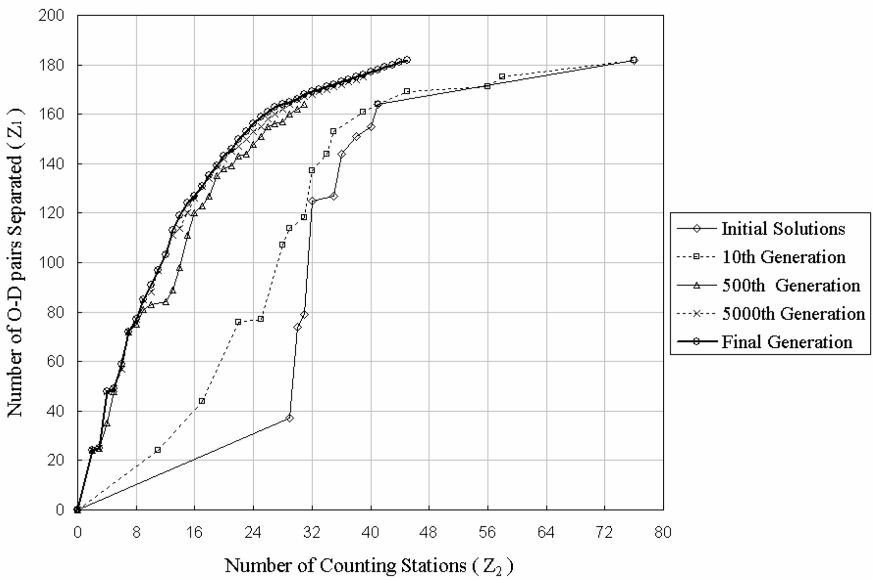


FIGURE 6: Evolution of non-dominated solutions for Sioux Falls network

The generated non-dominated solutions range from the do-nothing plan ($Z_1$ = 0 and $Z_2$ = 0) to the solution of set covering problem (minimum number of traffic counting stations required to separated all O-D pairs). For this network, 45 traffic counting stations, if optimally located, are required to separate all 182 O-D pairs. Each solution along the Pareto front can be interpreted as a compromise solution (i.e., the minimum number of traffic counting stations and their corresponding locations required to separate a specific number of O-D pairs or the maximum number of O-D pairs separated with a given number of traffic counting stations when optimally located). Again, as noted in the previous example, for a given pair of $Z_1$ and $Z_2$ (see Figure 6), the solution is not unique. There might be several different combinations of locations with the same number of traffic counting stations that can separate the same number, but not necessarily the same set of O-D pairs. Figure 7 summarizes the number of multiple solutions found for each pair of $Z_1$ and $Z_2$ during the evolution of GA. The performance of these non-dominated solutions is further investigated using the flow capturing analysis in the next section.

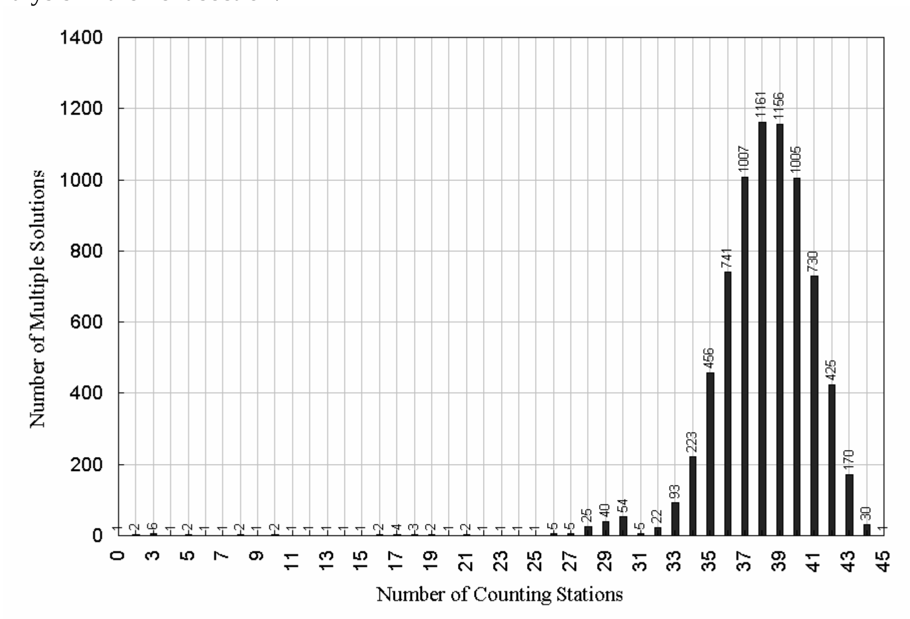


FIGURE 7 Multiplicity of each non-dominated solution

### *4.3 Flow capturing analysis for a medium-size network*

In order to assess the performance of traffic counting locations, we perform the user equilibrium traffic assignment to determine the amount of flows captured by the selected locations. Using the O-D demand and characteristics of the Sioux Falls network provided by Yang and Zhou (1998), three different levels of travel demand (1.0, 1.5, and 2.0 times of the original demand) are assigned onto the network to represent different congestion levels of flow patterns. The performance of traffic counting locations is defined by the percentage of traffic flows observed at least once by the selected traffic counting stations. The performances of non-dominated solutions under different congestion levels are summarized in Figure 8. It is clear that, with the same set of traffic counting stations, approximately the same fraction of flows will be captured across all congestion levels. This confirms the intention of the original models proposed by Yang et al. (2001) that the traffic counting locations are selected solely based on the topology of network, not on the travel demand.

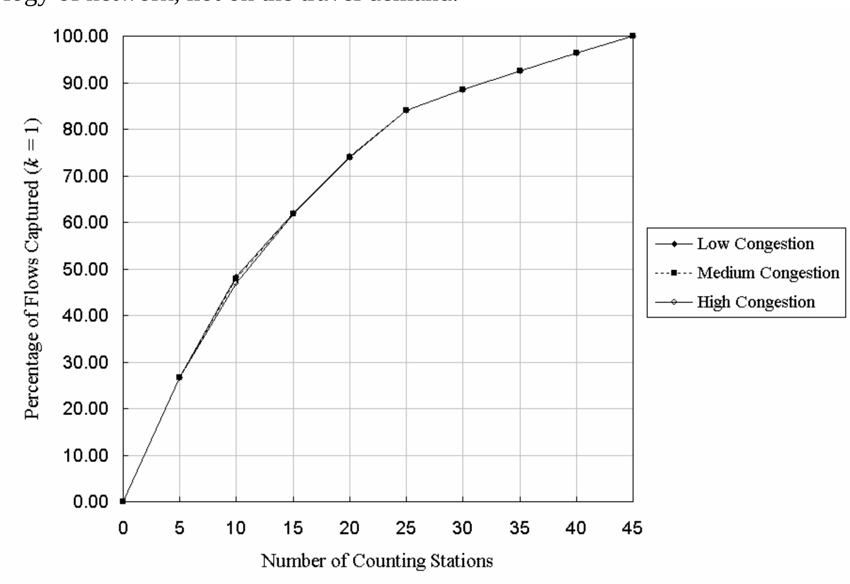


FIGURE 8: Percentage of flows captured under different congestion levels

Finally, the analysis is further performed on two solutions (A and B), which are able to separate 166 O-D pairs with 30 traffic counting stations. The locations of 30 traffic counting stations of these two plans are depicted in Figure 9. In Figure 9, "a" represents the locations selected in plan A, "b" for plan B, and "c" indicates the common locations in both plans. There are eight common locations in both plans. These two plans separate different sets of O-D pairs. In addition to the 155 common O-D pairs separated, plan A can separate O-D pairs 4-5, 14-11, 15-10, 15-19, 15-22, 20-19, 20-21, 20-22, 20-24, 21-22, and 21-24 while plan B separates O-D pairs 5-10, 11-4, 11-10, 19-10, 19-15, 19-20, 21-20, 22-15, 22-20, 22-21, and 24-13. Figure 10 shows the flow capturing analysis for these two plans at the medium congestion level. A double counting effect of the traffic counting stations, the percentage of flows observed for at least a certain number of times (*k*) along all used paths, is also considered. This double counting effect is beneficial when the locations of traffic counting stations are also considered for the purpose of travel time collection.

As can be seen from Figure 10, the percentages of flows observed at least once by these two plans are slightly different (88.42% and 88.49%). This is due to the fact that they separate the same number, but slightly different sets of O-D pairs. Here the knowledge about the study area (types of traffic analysis zones) may play a major role in the selection of solution. The weights reflecting the importance of different O-D pairs can be incorporated into the computation of the first objective, $Z_1$. It is more reasonable to pick a plan that can separate the important O-D pairs rather than those O-D pairs with insignificant flows. For these two plans, plan A seems more appropriate for the travel time collection since a larger portion of flows (34.04% compared to 23.68% by plan B) is double counted.

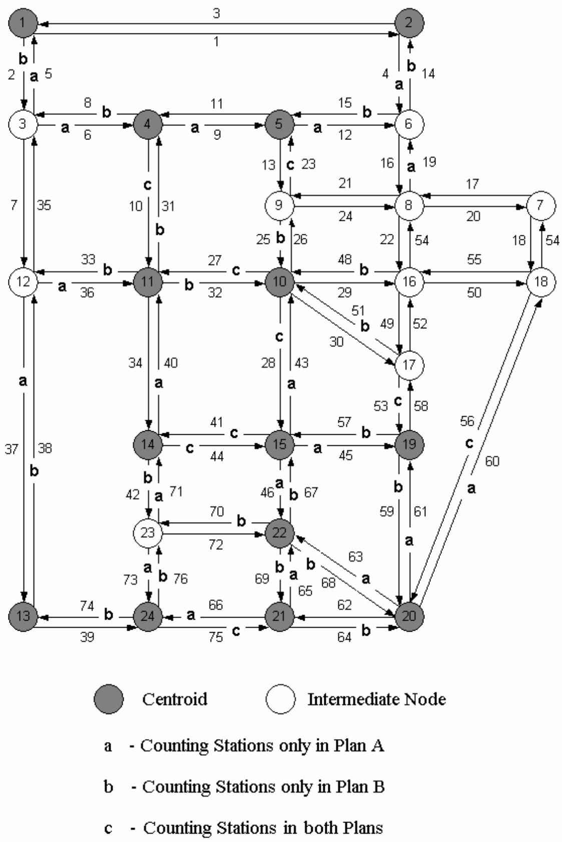


FIGURE 9: Locations of traffic counting stations for two solutions with $Z_1$=166 and $Z_2$=30

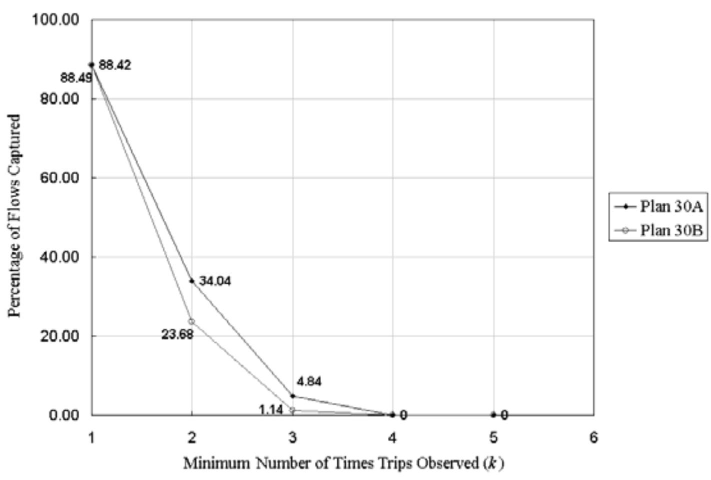


FIGURE 10: Performance of two locations of 30 counting stations

## 5. CONCLUSION AND FUTURE RESEARCH

In this study, a bi-objective model for locating traffic counting stations for the purpose of O-D trip table estimation has been proposed. The two objectives explicitly consider the tradeoff between the quality and cost of coverage. The objective for the quality of coverage is to maximize the number of O-D being separated, and the objective for the cost of coverage is to minimize the number of traffic counting stations. Under the multi-objective environment, there may not exist a single best solution that simultaneously optimizes all aspects. Thus, two solution techniques for the multi-objective GA, which are the weighted-sum method and the distance-based method, were used to generate an approximate set of non-dominated solutions. The results indicated that the distance-based method could provide a better picture of the quality-cost tradeoff compared to the weighted-sum method. In addition, as demonstrated by the first example, the distance-based method is able to generate the non-dominated solutions in the duality gap that could not be represented by any weight combinations.

It should be noted however that the distance-based method might not perform well if the diversity of solutions cannot be maintained. As a result, the non-dominated solutions generated will cluster on some portions of the Pareto front. In other words, the distance-based method may end up with a subset of non-dominated solutions. Therefore, proper attention should be paid on this issue to enhance the performance of the distance-based method. Instead of using a large population, mechanisms capable of maintaining the diversity of solutions such as fitness sharing or niche formation should be considered. Besides, it is evident that there are multiple solutions (locations of traffic counting stations) delivering the same amount of coverage. The performance of these solutions should be rigorously examined so that some secondary objectives or criteria (e.g., the percentage of flow captured) could be identified to select the solution that best fits the need of decision makers.

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