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Multi-objective metaheuristics for a location-routing problem with multiple use of vehicles on real data and simulated data ☆

C.K.Y. Lin [a,*], R.C.W. Kwok [b]

[a] Department of Management Sciences, City University of Hong Kong, 83 Tat Chee Ave., Kowloon Tong, Hong Kong
[b] Department of Public and Social Administration, City University of Hong Kong, 83 Tat Chee Ave., Kowloon Tong, Hong Kong

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Abstract

We address an integrated logistic system where decisions on location of depot, vehicle routing and assignment of routes to vehicles are considered simultaneously. Total cost and workload balance are common criteria influencing decision-making. Literature on location-routing problems addressed the location and vehicle routing decisions with a common assumption of assigning one route to one vehicle. However, the cost of acquiring vehicles (and crew) is often more significant than the routing cost. This notion of assigning several routes to a vehicle during the routing procedure is explored in our integrated model. We apply metaheuristics of tabu search and simulated annealing on real data and simulated data, to compare their performances under two versions: simultaneous or sequential routes assignment to vehicles. A new statistical procedure is proposed to compare two algorithms on the strength of their multi-objective solutions. Results show that the simultaneous versions have advantage over the sequential versions in problems where routes are capacity-constrained, but not in the time dimension. The simultaneous versions are also more effective in generating non-dominated solutions than the sequential versions.

Keywords: Logistics; Multi-objective; Metaheuristics; Location-routing; Multiple use of vehicles

1. Introduction

Logistics operations often involve sending out staff from their offices/depots to customers in various areas to perform on-site tasks. In providing delivery service from multiple depots using vehicles and crew, there are several decisions to be

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* Corresponding author. Tel./fax: +852 2788 9485.
E-mail address: mslincky@cityu.edu.hk (C.K.Y. Lin).

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considered: selecting the depot locations, scheduling routes from selected depots to customers and assigning routes to vehicles/crew. These decisions are often inter-dependent and multi-objective in practice. The total cost is an obvious and primary concern of management. This includes the fixed cost of selected depots, travelling cost of the routes and cost of vehicles and crew. Workload balance of vehicles also reflects equity in work assignment and affects employee satisfaction. One of the measures can be the range (difference between the highest and lowest) of load carried and working hours assigned to vehicles. This paper will examine the integrated model on the total cost and workload balance criteria that are important to both management and operational staff. The methodology can be applied to other multi-criteria problem with quantifiable metrics.

Renting vehicles and employing full-time or part-time crew are common in delivery services. A distribution manager has to estimate the vehicle/crew requirement for planning and budgeting purposes. Eilon (1977) stated that the vehicle fixed cost accounts for nearly 80% of the total cost associated with the vehicle. Even if vehicles are rented, the rental cost is more significant than the routing cost. The latter cost has been the main focus in vehicle routing and location-routing literature. A common assumption in past literature is the resulting routes formed by the proposed method are each assigned to one vehicle. Eilon et al. (1971, p. 222) pointed out that the solution for a cost minimization problem must depend not just on the size of the vehicle fleet nor the distance, but on the cost of both. By allowing multiple use of vehicles, further cost can be saved, but this may violate the common assumption of one route assigned to one vehicle. When vehicles are constrained in multiple dimensions (like in both time and load carried), a route may be fully utilized in one dimension while underutilized in other dimensions. For instance, a truck carrying a full truckload of goods to a nearby customer can still have excess time to return to its depot for replenishment, and to start another delivery trip within its specified working hours. Hence, neglecting the vehicle fleet size (whether it is purchased/rented) in the design of routes will affect the performance of the logistic system. This study attempts to incorporate the routes assignment to vehicles into the routing phase and to examine the differences with the sequential approach.

Tuzun and Burke (1999) indicated that one shortcoming in the past location-routing studies is the lack of comparative studies that evaluate the relative performance of the heuristics. Besides, multi-objective location-routing studies with real instances are rare in literature. This paper will explore the application of tabu search and simulated annealing to a multi-objective integrated problem with real data obtained from a local delivery service, as well as randomly generated instances. The single cost objective has been examined in Lin et al. (2002) by use of simulated annealing and its hybrid. Additional data collection was made possible by use of geographical information systems and regression techniques. This paper extended the earlier work in considering equity criteria important to operational staff—workload balance (total trip times and load), and its tradeoff with the total cost. Simultaneous routing and multiple use of vehicles have received little attention in multi-objective location-routing literature. We also devise a new statistical procedure to test any significant differences in the (approximated) non-dominated solutions produced.

2. Literature review

Location-routing problem (LRP) consists of two subproblems: the facility location problem (FLP) and vehicle routing problem (VRP). Both of them are shown to be NP-hard (Karp, 1972). Hence, LRP also belongs to the class of NP-hard problems. The current integrated problem consists of a LRP with simultaneous consideration of routes assignment to vehicles. It implies that this more complicated integrated problem is NP-hard even on the single cost objective.

A survey on LRP (Min et al., 1998) has classified this problem with regard to its problem perspective or solution method. The general LRP can be formulated as integer or mixed integer programs with three-index variables defining the node-to-node connection and route association

(Perl and Daskin, 1985; Hansen et al., 1994; Tuzun and Burke, 1999). Capacity constraints on vehicle (and facility) are considered (but not the working time restriction). In one LRP model with no facility capacity constraint (Laporte et al., 1988), transformation of the multi-depot vehicle-routing problem (VRP) and LRP into a constrained assignment problem through graphical representation can solve up to 80 demand nodes. Another LRP model involves using Clarke-Wright savings method in a case with stochastically processed demands (Chan et al., 2001). Exact solutions can only be obtained for not very large problems (from mixed integer program or branch-and-bound algorithm with special branching rules). These can serve as lower bounds for heuristics validation.

Heuristic approach is also common in solving LRP. These include deterministic heuristics based on location–allocation and savings concepts. Madsen (1983) recommended two procedures: alternate location–allocation-savings and savings-drop procedure. Other iterative approach includes opening (closing) all depots initially, and then closing (opening) depots systematically one by one based on cost savings (Srivastava, 1993; Hansen et al., 1994). Min (1996) considered a two-level location–allocation problem of terminals to customer clusters and supply sources by use of a hierarchical approach consisting of both exact and heuristic procedures. In a multi-period dynamic location-routing problem (Laporte and Dejax, 1989), approximation formula was applied to estimate the distribution cost under hypotheses that users (demand nodes) are uniformly distributed in a convex, compact user-space and the Euclidean travel metric is used. Other common approach includes decomposition of LRP into subproblems where each is solved either optimally or heuristically (Perl and Daskin, 1985; Srivastava, 1993; Wu et al., 2002).

Recently, metaheuristics as tabu search, simulated annealing and genetic algorithms were proposed. A two-phase tabu search was applied iteratively to improve decisions in the location phase and routing phase (Tuzun and Burke, 1999). Taillard et al. (1996) also realized possible savings in allowing multiple use of vehicles in VRP. They applied tabu search in a 3-step procedure to design vehicle routes with multiple use of vehicles to minimize the total cost of routes. A tabu search based adaptive memory procedure was introduced in another VRP model with a min-max objective (Golden et al., 1997). The objective favored an equity criterion (minimizing the maximum distance travelled by any vehicle) and multiple use of vehicles is allowed. In a newspaper delivery problem with location–allocation concern and the objective of reducing total lateness (Ree and Yoon, 1996), the problem was decomposed into two deterministic sub-problems. Simulated annealing was applied to improve the solution. Other studies on VRP and LRP (Breedam, 2001; Wu et al., 2002) had suggested building hybrid metaheuristics, like tabu search and simulated annealing, to combine their best features.

Metaheuristics have become prominent approaches in tackling complex, multi-objective problems (Jones et al., 2002). Recent examples include a bus driver scheduling problem (Lourenço et al., 2001) and a resource-constrained project scheduling problem (Viana and Pinho de Sousa, 2000). The latter has pointed out the importance in working with real instances. To the best of our knowledge, no LRP literature (not to mention the integrated problem) has used this approach to tackle multiple objectives. As an extension of the previous work (Lin et al., 2002) on the single cost objective, this paper will examine the performance of metaheuristics on the multi-objective integrated problem.

3. Problem formulation

The multi-objective integrated problem allowing multiple use of vehicles is to determine the depot site(s) and delivery routes for vehicles belonging to a depot, so that all customer demand are fulfilled and management objectives achieved. The related conditions include:

1. Each demand node must be visited exactly once and fulfilled from a single source.
2. Multiple capacitated (homogeneous) depots are to be selected from a number of potential depot sites.

3. All vehicles are identical and are constrained in both time and load capacity. Each vehicle starts at a depot, visits a set of customers on a route and returns to the same depot.
4. Multiple use of a vehicle (several routes assigned to a vehicle) is allowed within the vehicle's working time constraint.
5. The multiple objectives consider reducing the total cost and workload imbalance (load, working time) among vehicles.

4. The proposed heuristics

Past literature mostly focused on location routing problems (LRP) and the assignment of routes to vehicles are usually assumed a one-to-one relationship. The design of the proposed heuristics aims to achieve two purposes:

1. To examine the effect of multiple use of vehicles on the multi-objective problem. Two versions for each proposed metaheuristic (Sections 4.3 and 4.4) are designed. One considers solving the problem as a multi-objective LRP and assigning the resulting routes to vehicles (Section 4.1), the other takes into account multiple use of vehicles during the route design phase (Section 4.2).
2. Explore and compare the ability of some well-known metaheuristics in solving multi-objective LRP problems. Also compare metaheuristic results with a sample of manual results provided by the Operations Manager of the company.

The underlying logic of the manual method is based on a cluster-first-route-second method. Nodes (housing estates) are first clustered into a number of districts. Routes in each district are formed by visiting nodes with the largest demand first until the vehicle capacity or trip time limit in the route is exceeded. This manual approach takes slightly less than an hour for a problem of 4 potential depots and 27 nodes (Area 1 in Section 5).

4.1. Sequential approach

Fig. 1 depicts the flowchart of the heuristic design of the multi-objective LRP version. It is an extension of the algorithm in Lin et al. (2002) for the problem with single cost objective. The solution procedure is divided into three phases: facility location, routing and assignment of routes to vehicles.

The first step in the location phase is to determine the minimal number of facilities, n_f, capable to cope with all demand. (n_f is simply determined by the total demand divided by the facility capacity.) A list of facilities sorted in descending order of the number of nearest demand nodes will be created. In every iteration of the location phase, a distinct set of n_f facilities will be selected from the list (by a tree search) to carry out the subsequent routing and assignment phases. This greedy selection approach enables better solutions to be found early in the heuristic. (If the number of open facilities is comparatively smaller than the number of demand nodes, the heuristic design can explore all sets of n_f facilities within reasonable time. In case the number of facilities is large, the greedy selection approach will search for promising solutions first.)

The three phases will repeat iteratively for each set of n_f facilities to search for the low cost routes using metaheuristics in the routing phase. Additional parameters recording the imbalances in workload (i.e., the difference between the highest and lowest load and working time, respectively) among all routes will be stored for each feasible incumbent solution. In other words, each feasible solution will be evaluated in three performance fields: total cost (TC), load imbalance ($L_{\max} - L_{\min}$), working time imbalance ($T_{\max} - T_{\min}$). These will be compared with future solutions. Dominated solutions will be eliminated. Non-dominated solutions will form approximations to the efficient frontier, which will be updated and continuously refined as the algorithm proceeds.

The routing phase adopts a multi-start approach with initial routes formed by one of the three procedures: Clarke and Wright savings algorithm, modified Clarke and Wright procedure (Golden et al., 1997) and Nearest Neighbour rule. Intra-route improvement is sought by applying either the traveling salesman algorithm (TSP) or 2-opt (depending on the problem size). Two sets of moves are performed during the inter-route improvement step:

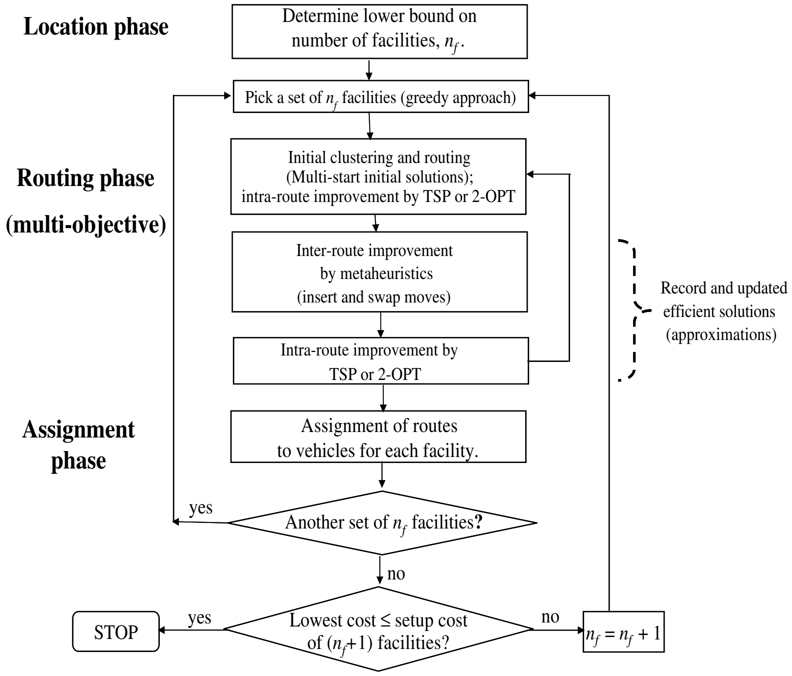

Fig. 1. Flowchart of heuristic design for LRP.

- Insert moves displace a selected demand node to a position after (or before) another selected demand node in a different route.
- Swap moves exchange the positions of two selected demand nodes belonging to two different routes.

(The insert moves are performed systematically for every distinct pair of nodes. When there is no improvement on the total cost for a given number of iterations, intra-routes improvement step is again implemented. The neighbourhood move will then change to swap moves and a similar procedure is designed as in the insert moves.)

The assignment of routes to vehicles is a classical bin-packing problem, where items are routes and bins are vehicles. Item size is the trip time of a route and bin capacity is the vehicle's working hours. When the number of routes is not too large, the exact approach applied to find the best assignment is a tree search, which starts with sorting the trip times of routes in non-increasing order into a list, and systematically assigns routes from the list to a vehicle that has sufficient remaining working hours. Initially, the upper bound of vehicles is set equal to the number of routes. Whenever a full assignment is complete with fewer vehicles than the upper bound, the upper bound will be updated. If the number of vehicles used at any stage is larger than the upper bound, the current node (vehicle index) will be discarded and the tree search will backtrack to a previous level. This continues until all feasible nodes are searched. The upper bound will then give the minimum number of vehicles required. For problems with more routes, the first-fit-decreasing heuristic is applied.

The sequential approach will terminate when the setup cost with an additional facility exceeds the lowest total cost found. The result is a set of solutions approximating the efficient frontier and each solution is characterized by the three performance measures (total cost, vehicle load imbalance, working hour imbalance).

4.2. Multiple use of vehicles in route design

The motivation here is to examine whether the simultaneous consideration of routes assignment to vehicles and routing will lead to better performance on the multiple objectives. The location phase is the same as in the sequential approach. To allow multiple use of vehicles (during routes formation) in order to save vehicle rental cost (and messenger salary), the algorithm design incorporates the assignment phase into the route design phase by solving a bin-packing problem (as in Section 4.1) in every neighbourhood move.

4.3. Tabu search

Tabu search (TS) has been effectively applied to classical vehicle routing problems with a single objective. We apply a general TS design (Glover and Laguna, 1993) on this 3-objective problem and denote the version of sequential approach by TS_{seq}, and the version allowing multiple use of vehicles by TS_{mult}. In both versions, some special features are adopted. Two tabu lists are maintained with respect to the two neighbourhoods—the insert tabu list and the swap tabu list. Adopting a probabilistic tabu duration will avoid cycling. The duration is randomly generated from the interval $[l_b, u_b]$, where l_b and u_b denote parameters of the shortest and longest tabu length, respectively. An aspiration criterion is set to revoke a tabu when the move will result in a total cost lower than the best known total cost. Infeasible solutions (violating the capacity constraints of depot or route, or trip time limit of a route) are allowed with penalties imposed on the total cost objective. The penalty weights are the associated costs of setting up an additional depot or employing an additional vehicle. As with the standard TS, the best admissible move is made when searching for a new solution. The design of the TS algorithms is outlined as follows:

Algorithms TS_{seq} and TS_{mult}

Step 1. Estimate the minimum number of facilities (n_f) required to cope with all demand.

Step 2. Select a set of n_f facilities (choosing facility with the largest number of nearest demand nodes first).

Step 3. Determine initial routes from one of the three procedures: Clarke and Wright savings algorithm, modified Clarke and Wright, or Nearest Neighbour rule. Improve the initial routes by TSP or 2-opt procedure (for routes with small or large number of nodes, respectively). Let s denote the incumbent solution containing all current routes. (If the first initial solution is generated, set s as the best solution recorded, i.e., $s_{best} = s$ and $TC^* = TC(s)$.)

Step 4. In solution s, find the routes assignment to vehicles by a (exact or heuristic) bin-packing algorithm. Calculate the values for the three objectives and record them as $Z(s) = (TC(s), L_{max}(s) - L_{min}(s), T_{max}(s) - T_{min}(s))$. Update the (approximated) efficient frontier with $Z(s)$.

Step 5. Generate new solutions and update the (approximated) efficient frontier.

(i) Set the neighbourhood structure N (insert or swap move) and the initial tabu list $L_N = \phi$.

(ii) For each pair of demand nodes $(i,j) \notin L_N$ belonging to different routes in s, perform a trial neighbourhood move to obtain a trial solution s'.

- For TS_{seq}: calculate total cost $TC(s')$, assuming one route one vehicle.
- For TS_{mult}: determine the optimal routes assignment to vehicles in solution s' by a bin-packing algorithm, and calculate the total cost $TC(s')$.

(Adopt aspiration level: If a neighbourhood move (i,j) leads to a total cost lower than TC^*, consider this as a possible move even if $(i,j) \in L_N$, and record its $TC(\ )$.)

(iii) Find the best admissible move in *Step 5*(ii) giving the lowest $TC(\ )$. Denote the resulting solution by s_{new}.

(iv) Set s_{new} as the new incumbent solution s. If s_{new} is a feasible solution, determine $Z(s_{new}) = (TC(s_{new}),$

$L_{\max}(s_{\text{new}}) - L_{\min}(s_{\text{new}})$, $T_{\max}(s_{\text{new}}) - T_{\min}(s_{\text{new}})$) and update the (approximated) efficient frontier with $Z(s_{\text{new}})$. If $\text{TC}(s_{\text{new}}) < \text{TC}^*$, set $s_{\text{best}} = s_{\text{new}}$ and $\text{TC}^* = \text{TC}(s_{\text{new}})$. Update the tabu list L_{N} with the reverse move of (i,j) and a probabilistic duration randomly generated from the interval $[l_{\text{b}}, u_{\text{b}}]$.

(v) When the neighbourhood move in *Step 5*(ii)–(iv) is performed for a given number of iterations with no improvement on TC* (denoted by *max_no_imp*), improve each route by TSP or 2-opt procedure (depending on the number of nodes on the route). Record and update any improvement on TC* and the efficient frontier.

(vi) If both types of neighbourhood structure (insert and swap moves) have been executed, goto *Step 5*(vii). Otherwise, switch the neighbourhood structure N, clear the tabu list and repeat from *Step 5*(ii).

(vii) Restart from *Step 3* with another initial solution. If all three initial solutions have been exhausted, goto *Step 6*.

Step 6. For TS_{seq} only: assign routes in solution s_{best} to a minimum number of vehicles (by a tree search or first-fit-decreasing bin-packing heuristic) and calculate the total cost $\text{TC}(s_{\text{best}})$. If $\text{TC}(s_{\text{best}}) < \text{TC}^*$, set $\text{TC}^* = \text{TC}(s_{\text{best}})$.

Step 7. Examine another set of n_{f} facilities and repeat from *Step 2*. If all sets have been examined, goto *Step 8*.

Step 8. If the setup cost with an additional facility exceeds the best known total cost TC*, STOP. Otherwise, $n_{\text{f}} \to n_{\text{f}} + 1$ and repeat from *Step 2*.

The algorithm terminates with a set of approximations to the efficient frontier. The performance of TS_{seq} and TS_{mult} will be tested using various combinations of the parameters: maximum number of iterations with no improvement on TC* (*max_no_imp*), shortest and longest tabu length (l_{b} and u_{b} respectively).

4.4. Simulated annealing

Simulated annealing (SA) is distinguished by allowing hill-climbing moves to help the local search escape from local minimum. Asymptotic proofs of convergence were available (Lundy and Mees, 1986; Anily and Federgruen, 1987), but no such proofs exist for the general tabu search. Similar to TS_{seq} and TS_{mult}, the two versions of SA representing the sequential approach and the one allowing multiple use of vehicles are denoted by SA_{seq} and SA_{mult} respectively. The cooling schedule in either version is adopted from Lundy and Mees (1986), where the temperature sequence of length K is recursively derived from the following:

$$T_{i+1} = \frac{T_i}{1 + \beta T_i}, \quad i = 1, \ldots, K-1 \tag{1}$$

and β is the rate parameter expressed in terms of the input parameter values T_1, T_K and K:

$$\beta = \frac{T_1 - T_K}{(K-1)T_1 T_K}. \tag{2}$$

The SA design mainly affects the routing and assignment phase. Problem-specific design includes allowing infeasible solutions after the routing and assignment phase has elapsed for a given proportion, I_{f}, out of a total of K iterations. (The penalty weights on constraint violations are the same as in the tabu search algorithms.) Otherwise, the design of algorithms SA_{seq} and SA_{mult} are very similar to TS_{seq} and TS_{mult} respectively, apart from the acceptance of new solutions based on the temperature parameter.

The performance of SA_{seq} or $\text{SA}_{\text{multiple}}$ will be tested using various combinations of the parameters: maximum number of cycles with no improvement (*max_no_imp*), proportion of total iterations allowing only feasible moves (I_{f}), and length of the temperature sequence (K).

5. Collection of real data and estimation

The multi-objective problem originated in a local telecommunication service company in Hong

Kong in which printing and delivering bills to customers in housing estates is one of their routine tasks. Many customers resided in large housing estates and hence, it will be convenient to consider housing estates as demand nodes with on-site delivery time. We shall test the algorithms on real data available from the company. Data not available for certain areas will be estimated by appropriate methods described in this section.

The city is divided geographically by the Victoria Harbour into two major geographical areas—Kowloon peninsula and Hong Kong Island. Our computational tests will focus on these two areas which have high customer density. Tables 1 and 2 summarize the problem parameters.

The data for area 1 are taken from Lin et al. (2002). In particular, the time-related data (node-to-node travel time, on-site delivery time) had been provided by company drivers based on their experience. Apart from the number of potential depots, demand nodes and time-related data, other parameters are the same in the two areas. All depots are homogeneous with the same capacity and setup costs. For area 2, the travel times and on-site delivery times are not available and are estimated by GIS (Appendix A) and regression model (Appendix B) respectively.

Table 1
Physical parameters

Area		1 (Kowloon)	2 (Hong Kong Island)
	Number of potential depots	4	5
	Number of demand nodes (housing estates)	27	89
Depot	Capacity (=25,000 bills per day)		
Demand node	Demand quantity (number of bills) On-site delivery time		
Vehicle	Capacity (=5000 bills per route) Working hour limit (=8 hours/day)		
Travel time	(For every pair of potential depot/demand nodes)		

Table 2
Cost parameters

Fixed cost	Depot setup cost (=HK$300,000 per depot)
Variable cost	Depot rental cost (=HK$1800 per day) Vehicle rental cost (=HK$1200 per day) Vehicle operating cost (=HK$70 per hour) Messenger salary (=HK$300 per day)

6. Evaluation of multi-objective results

The performance of a heuristic is usually measured by two main attributes—solution quality and the amount of computational effort required. For this multi-objective problem, performance comparison will be designed to achieve the two purposes stated in Section 4.

6.1. Difference between sequential assignment and multiple use of vehicles in routing

As no benchmark solutions are available for this local problem, our comparison between the two versions of each metaheuristic will be based on four proposed criteria: (1) relative non-dominance, (2) coverage, (3) superiority on each objective and (4) computational time. Relative non-dominance of an algorithm is measured by the proportion of its (approximated) efficient solutions not being dominated by those from other algorithm(s). Coverage here refers to the ability of an algorithm to generate efficient solutions spanning a wider range of values than another algorithm for each separate objective. The more wide-spread are the solutions, the more flexibility is offered to the decision-maker. We first define an algorithm A "covers" another algorithm B if after eliminating the dominated efficient solutions among themselves, the non-dominated solutions from A embrace those from B in each objective. To illustrate on a minimization problem with three objectives, if the non-dominated solutions from A and B range in the intervals $[Z^A_{k,\min}, Z^A_{k,\max}]$ and $[Z^B_{k,\min}, Z^B_{k,\max}]$ respectively on the kth objective ($k = 1, 2, 3$), then algorithm A "covers" algorithm B if

$$Z^A_{k,\min} \leqslant Z^B_{k,\min} \quad \text{and} \quad Z^A_{k,\max} \geqslant Z^B_{k,\max}, \qquad k = 1, 2, 3. \tag{3}$$

The coverage metric has not been proposed in past literature. (The same name has been used (Sarker and Coello, 2002), but the concept is different in that it measures the fraction of equal or dominated solutions of one algorithm by another algorithm.) Superiority on a single objective is the simple comparison among algorithms to find the efficient solution with the best recorded value on an objective. Various ranges of parameters are tested on each version of metaheuristic $\{TS_{seq}, TS_{multi}, SA_{seq}, SA_{multi}\}$ as shown in Table 3.

(The number of samples created for each metaheuristic version refers to the number of distinct sets of parameters tested.) The parameters selected in the SA versions for the two areas are different (apart from the initial and final temperatures). If the same parameters were used for both areas, the particular route characteristics in area 2 result in long running time. Hence, parameter values are selected such that the running time in each area is reasonable. The final temperature is chosen such that there remains a small positive probability (0.007) of accepting a solution which is 1 unit worse than the current solution. All algorithms were coded in Compaq Visual Fortran Professional Edition 6.6a and run on a 2.5 GHz Pentium 4 processor. The two versions of each metaheuristic are subject to the same stopping condition based on the parameter *max_no_imp*. However, their resulting running times could be different.

On the relative non-dominance measure, we propose a new statistical comparison based on the hypothesis testing of difference between two population proportions (Z-test). Under each test environment, the output from two algorithms (the two versions under the same metaheuristic) is compared and the non-dominated solutions in their combined solution set is identified. Say algorithms A_{seq} and A_{mult} have produced n_{seq} and n_{mult} efficient solutions (approximated) respectively. Among the $(n_{seq} + n_{mult})$ solutions, x_{seq} solutions from A_{seq} and x_{mult} solutions from A_{mult} are non-dominated. The Z-test of difference between the two population proportions ($\hat{p}_{mult} - \hat{p}_{seq} = \frac{x_{mult}}{n_{mult}} - \frac{x_{seq}}{n_{seq}}$) is performed to test if algorithm A_{mult} produces a larger proportion of non-dominated solutions than algorithm A_{seq}, or vice versa. (Note that relative non-dominance here is measured by the relative performance between the two algorithms, A_{mult} and A_{seq}, when both are using the same parameters, as it may be practically impossible to carry out parameter tuning for each algorithm for every new set of data.) On the criterion of coverage, the number (or fraction) of samples that one metaheuristic version "covers" another will be given. Similar comparison applies to the criterion of superiority (for each single objective, respectively).

Table 4 shows that different area characteristics can lead to different results. Area 2 has smaller total demand, yet more demand nodes (housing estates). This results in a single depot with more demand nodes per route. Accordingly, more computational time is required due to the larger problem size. Area 1 has higher density per demand node. Hence, more depots (=2) are required and each route contains relatively fewer nodes. The effect of multiple use of vehicles in either metaheu-

Table 3
Parameter settings in metaheuristics by geographical area

Metaheuristic versions	Area (s)	Parameters {values} [Number of samples]
TS_{seq}, TS_{mult}	1, 2	*max_no_imp* $= \{20, 30, 40, 50\}$; $(l_b, u_b) = \{(3,3), (3,5), \ldots, (3,15), (5,5), (5,7), \ldots, (15,15)\}$ [112 samples for each area]
SA_{seq}, SA_{mult}	1	*max_no_imp* $= \{20, 30, 40, 50\}$; $I_f = \{0.25, 0.5, 0.75, 1.0\}$; $K = \{500, 1000, 2000\}$; $T_1 = 1{,}000{,}000$; $T_K = 0.2$ [48 samples]
SA_{seq}, SA_{mult}	2	*max_no_imp* $= \{5, 10\}$; $I_f = \{0.33, 0.665, 1.0\}$; $K = \{100, 500, 1000\}$; $T_1 = 1{,}000{,}000$; $T_K = 0.2$ [18 samples]

ristic (TS or SA) is significant in area 2. By carrying out the Z-test of difference between the two proportions in each sample, $\mathrm{TS}_{\mathrm{mult}}$ and $\mathrm{SA}_{\mathrm{mult}}$ produce more samples with a significantly larger proportion of "relative non-dominated" solutions than their counterparts. On the coverage criterion, $\mathrm{TS}_{\mathrm{mult}}$ and $\mathrm{SA}_{\mathrm{mult}}$ contain more samples in which the solutions "cover" those of their counterparts, $\mathrm{TS}_{\mathrm{seq}}$ and $\mathrm{SA}_{\mathrm{seq}}$ respectively. The tradeoff is the larger computational time required in $\mathrm{TS}_{\mathrm{mult}}$ and $\mathrm{SA}_{\mathrm{mult}}$. However in area 1 (with higher density per demand node), the differences between the two versions are not always significant probably due to its smaller problem size.

In both areas, it is observed that the routes generated are close to the working time limit, than the capacity limit. Hence, the number of routes is often equivalent to the number of vehicles.

To summarize, the area (or problem) characteristics is a significant factor in differentiating the performances between the two metaheuristic versions (sequential assignment or allowing multiple use of vehicles in the routing phase). Results in Table 4 reveal that under the same parameters, allowing multiple use of vehicles will lead to better solutions in problems with more demand nodes per route.

6.2. Comparison among metaheuristics

This section will examine the multi-objective performance of all metaheuristics, each in their best set of parameters and given equal running time. Comparison of metaheuristic results will be made with respect to solutions in a reference set. As the exact efficient solutions are not available, we can only approximate the reference set by the union set of all (approximated) efficient solutions obtained in Section 6.1, and those in this section, when all dominated solutions are eliminated. The resulting approximated reference set, denoted by R, will be used in evaluating the quality of all metaheuristic solutions. We considered the evaluating functions used in Viana and Pinho de Sousa (2000), originally proposed by Czyżak and Jaszkiewicz (1998). Given that a heuristic generates a set of (approximated) efficient solutions denoted by M, to measure the closeness between a heuristic solution $x \in M$ and a solution $y \in R$, a closeness function $c(x, y)$ is designed:

$$c(x,y) = \max_{k=1,2,3} |w_k \times (Z_k(x) - Z_k(y))|, \tag{4}$$

where $Z_k(x)$ denotes the objective value of x in the kth objective ($k = 1, 2, 3$ in the current problem). The weight of the kth objective, w_k, is set as

$$w_k = 1/\Delta_k, \tag{5}$$

where Δ_k is the range of objective Z_k in the reference set R. Three metrics are then defined to measure the closeness of the heuristic results in set M with respect to the reference set R:

$$\mathrm{Dist1} = \frac{1}{\mathrm{card}\{R\}} \sum_{y \in R} \left\{ \min_{x \in M} \{c(x,y)\} \right\}, \tag{6}$$

$$\mathrm{Dist2} = \max_{y \in R} \left\{ \min_{x \in M} \{c(x,y)\} \right\} \tag{7}$$

and

$$\mathrm{Dist}Z_k = \min_{x \in M} \{c(x, Z_k^*)\}, \quad k = 1, 2, 3, \tag{8}$$

where card$\{R\}$ refers to the number of elements (solutions) in set R. The first metric Dist1 gives information about the average distance of a solution in the reference set R from its closest solution in the heuristic solution set M. The second metric Dist2 indicates the worst-case distance of a solution $y \in R$ from its closest solution in M. The last set of metric DistZ_k measures the closest distance of a solution in M from the Zeleny point, Z_k^*, which is the optimal point obtained by minimizing the kth objective separately ($k = 1, 2, 3$).

The best set of parameters for each metaheuristic version are selected among all the tested samples (Table 3). For each metaheuristic version, we first eliminate dominated solutions among results from all its algorithms using different parameter values. Among the non-dominated solutions, the set of parameter values producing relatively more non-dominated solutions is chosen for comparison with other metaheuristics under the same running time. As the area characteristics is a significant factor in affecting the performance of heuristics, the common running time is chosen as the largest average computational time among all algorithms (Table 4) run for the same area. Results obtained are presented in Table 5.

Table 4
Performance comparison of multiple use of vehicles vs. sequential assignment in heuristics

Metaheuristic version	Total number of samples	Relative non-dominance[a]	Coverage[b]	Superiority[c]			Average computational time (CPU seconds)
				Total cost	Workload imbalance		
					Working hours	Load	
Area 2 (Hong Kong Island)[d]							
TS_{mult}	112	43 (0.384)	39 (0.35)	48 (0.43)	108 (0.96)	72 (0.64)	237.47
TS_{seq}	112	17 (0.152)	0 (0.0)	57 (0.51)	4 (0.04)	10 (0.09)	13.66
SA_{mult}	18	14 (0.778)	7 (0.39)	11 (0.61)	15 (0.83)	17 (0.94)	2813.80
SA_{seq}	18	2 (0.111)	0 (0.0)	7 (0.39)	1 (0.06)	1 (0.06)	420.36
Area 1 (Kowloon)[e]							
TS_{mult}	112	17 (0.152)	7 (0.06)	71 (0.63)	57 (0.51)	48 (0.43)	9.30
TS_{seq}	112	32 (0.286)	0 (0.0)	0 (0.0)	39 (0.35)	52 (0.46)	0.70
SA_{mult}	48	20 (0.417)	2 (0.04)	24 (0.5)	20 (0.42)	28 (0.58)	899.65
SA_{seq}	48	18 (0.375)	4 (0.08)	24 (0.5)	22 (0.46)	19 (0.40)	162.53

[a] Relative non-dominance is measured by the number (fraction) of samples with significantly larger proportion of non-dominated solutions than the other version of the same metaheuristic (Z-test performed at 5% significance level).
[b] Coverage is measured by the number (fraction) of samples where the non-dominated solutions from one metaheuristic version "cover" those of the other version.
[c] Superiority on an objective is measured by the number (fraction) of samples where the best objective value among the non-dominated solutions from one version is superior to those from the other version.
[d] Characteristics of heuristic results for area 2: single depot with 7–9 routes and 7–9 vehicles. Each route has between 2 and 20 demand nodes.
[e] Characteristics of heuristic results for area 1: Two depots with 11–12 routes and 11–12 vehicles. Each route has relatively fewer demand nodes (between 1 and 5).

Table 5
Evaluation of metaheuristics under similar running time

Metaheuristic version	Dist1	Dist2	DistZ_k			Average computational time (CPU seconds)
			($k = 1$) Total cost	Workload imbalance		
				($k = 2$) Working hours	($k = 3$) Load	
Area 2 (Hong Kong Island)						
TS_{mult}	0.130	0.507	0.417	0.073	0.480	3309
TS_{seq}	0.206	0.427	0.415	0.297	0.129	3002
SA_{mult}	0.073	0.419	0.419	0.016	0.090	3041
SA_{seq}	0.054	0.421	0.421	0.016	0.088	3009
Area 1 (Kowloon)						
TS_{mult}	0.035	0.223	0.059	0.104	0.084	901
TS_{seq}	0.028	0.345	0.059	0.345	0.148	900
SA_{mult}	0.051	0.337	0.053	0.337	0.123	842
SA_{seq}	0.041	0.355	0.059	0.355	0.000	1082
Manual method	4.158	4.559	4.559	3.766	3.595	(About an hour)

In area 2 where a typical solution contains more demand nodes per route and sufficiently long running time (3000 CPU seconds) is allowed, the two SA algorithms outperform the TS algorithms in

Table 6
Computational results of simulated instances (average distance from reference set)

Problem	No. of depots	No. of demand nodes	Vehicle capacity	Proportion of nodes with FTL demand	Dist1				Dist2				No. of solutions belonging to reference set (no. of solutions generated)			
					TS_{mult}	TS_{seq}	SA_{mult}	SA_{seq}	TS_{mult}	TS_{seq}	SA_{mult}	SA_{seq}	TS_{mult}	TS_{seq}	SA_{mult}	SA_{seq}
1	10	100	300	0	0.080	0.212	0.383	0.356	0.456	0.550	0.619	0.579	205(327)	25(51)	56(297)	3(56)
2	10	100	300	0.25	0.002	0.334	0.226	0.398	0.064	0.860	0.405	0.869	529(567)	6(34)	4(253)	1(54)
3	10	100	300	0.50	0.021	0.340	0.103	0.244	0.399	0.957	0.544	0.887	494(521)	22(44)	50(116)	8(45)
4	10	100	150	0	0.325	0.688	0.059	0.650	0.893	0.921	0.426	0.826	320(322)	26(37)	422(600)	0(55)
5	10	100	150	0.25	0.014	0.659	0.089	0.658	0.484	0.937	0.522	0.941	835(847)	18(77)	66(421)	0(56)
6	10	100	150	0.50	0.014	0.780	0.099	0.747	0.284	1.131	0.311	1.132	668(671)	3(47)	90(378)	0(37)
7	10	100	75	0	0.109	0.649	0.070	0.612	0.545	0.902	0.617	0.950	165(184)	37(61)	346(442)	0(76)
8	10	100	75	0.25	0.149	0.609	0.080	0.611	0.600	0.948	0.519	0.947	356(365)	41(86)	234(482)	0(71)
9	10	100	75	0.50	0.072	0.758	0.052	0.744	0.446	1.042	0.450	1.034	633(639)	10(55)	486(716)	0(54)
10	20	200	300	0	0.152	0.262	1.064	0.676	0.726	0.860	1.399	0.984	336(379)	36(51)	116(555)	1(28)
11	20	200	300	0.25	0.134	0.370	0.961	0.794	0.684	0.880	1.230	1.053	216(242)	10(32)	31(141)	8(51)
12	20	200	300	0.50	0.035	0.200	0.157	0.262	0.383	0.978	0.520	0.875	169(217)	24(32)	28(118)	10(37)
13	20	200	150	0	0.615	0.674	0.044	0.602	0.939	0.943	0.333	0.808	164(213)	15(28)	578(743)	8(37)
14	20	200	150	0.25	0.136	0.333	0.122	0.245	0.578	0.974	0.637	0.804	212(238)	16(37)	219(329)	14(45)
15	20	200	150	0.50	0.044	0.294	0.141	0.277	0.536	0.976	0.623	0.856	282(292)	8(34)	75(224)	9(52)
16	20	200	75	0	0.161	0.401	0.069	0.340	0.461	0.989	0.332	0.736	108(184)	52(57)	279(464)	3(38)
17	20	200	75	0.25	0.175	0.581	0.066	0.569	0.485	0.979	0.504	0.944	218(218)	16(59)	393(490)	0(49)
18	20	200	75	0.50	0.132	0.646	0.071	0.618	0.385	1.075	0.461	1.078	343(343)	4(49)	503(543)	0(37)
				Average	0.132	0.488	0.214	0.522	0.519	0.939	0.581	0.906				

Table 7
Computational results of simulated instances (average distance from Zeleny point)

Problem	No. of depots	No. of demand nodes	Vehicle capacity	Proportion of nodes with FTL demand	DistZ_1				DistZ_2				DistZ_3			
					Total cost				Working time imbalance				Load imbalance			
					TS_{mult}	TS_{seq}	SA_{mult}	SA_{seq}	TS_{mult}	TS_{seq}	SA_{mult}	SA_{seq}	TS_{mult}	TS_{seq}	SA_{mult}	SA_{seq}
1	10	100	300	0	0.070	0.076	0.473	0.280	0.0	0.341	0.619	0.380	0.125	0.059	0.175	0.075
2	10	100	300	0.25	0.031	0.088	0.293	0.408	0.0	0.517	0.305	0.524	0.0	0.733	0.158	0.709
3	10	100	300	0.50	0.113	0.092	0.245	0.832	0.153	0.622	0.201	0.366	0.050	0.871	0.195	0.770
4	10	100	150	0	0.652	0.0	0.387	0.127	0.022	0.766	0.100	0.843	0.695	0.825	0.0	0.624
5	10	100	150	0.25	0.480	0.0	0.510	0.129	0.0	0.937	0.074	0.941	0.042	0.753	0.051	0.651
6	10	100	150	0.50	0.188	0.400	0.227	0.513	0.0	1.131	0.159	1.132	0.002	0.899	0.064	0.748
7	10	100	75	0	0.484	0.0	0.573	0.134	0.115	0.876	0.039	0.950	0.158	0.826	0.0	0.609
8	10	100	75	0.25	0.474	0.0	0.406	0.148	0.116	0.944	0.045	0.947	0.236	0.749	0.068	0.583
9	10	100	75	0.50	0.378	0.097	0.444	0.304	0.033	1.042	0.104	1.034	0.053	0.889	0.020	0.754
10	20	200	300	0	0.220	0.012	1.323	0.651	0.168	0.357	1.027	0.762	0.498	0.633	0.796	0.598
11	20	200	300	0.25	0.107	0.143	0.961	0.997	0.150	0.574	0.909	0.788	0.345	0.604	0.828	0.534
12	20	200	300	0.50	0.046	0.094	0.215	0.321	0.121	0.523	0.322	0.448	0.0	0.974	0.443	0.860
13	20	200	150	0	0.122	0.356	0.277	0.333	0.178	0.429	0.188	0.461	0.888	0.918	0.0	0.790
14	20	200	150	0.25	0.088	0.136	0.353	0.371	0.153	0.547	0.152	0.430	0.220	0.950	0.382	0.787
15	20	200	150	0.50	0.046	0.148	0.225	0.178	0.0	0.876	0.518	0.828	0.066	0.945	0.470	0.814
16	20	200	75	0	0.234	0.0	0.167	0.205	0.105	0.334	0.210	0.414	0.218	0.901	0.0	0.610
17	20	200	75	0.25	0.248	0.028	0.066	0.569	0.171	0.882	0.071	0.820	0.207	0.931	0.100	0.717
18	20	200	75	0.50	0.195	0.141	0.434	0.256	0.267	1.075	0.0	1.078	0.189	0.961	0.189	0.796
				Average	0.232	0.101	0.421	0.375	0.097	0.710	0.280	0.730	0.222	0.801	0.219	0.668

every metric, except the single objective of total cost, DistZ_1, where all algorithms give similar performances. The performance of SA is also superior in the two workload imbalance criteria separately (DistZ_2 and DistZ_3).

Between the two versions of the same metaheuristic, there is no evidence from the computational results indicating significant differences. This is probably due to the sufficiently long running time allowed.

In area 1, the performances between TS and SA algorithms are not significantly different. The probable reason is that the smaller problem size and simpler solution structure (in area 1's problem) may not be able to differentiate performances among all algorithms. Between the two versions of the same metaheuristic, no significant difference in any metric is observed. A sample solution of manual method for this area is also provided by the Operations Manager of the company (Lin et al., 2002). Results in Table 5 show that in every metric, the manual method is outperformed by all metaheuristics. The limitation in the manual method is that only one solution can be produced within an hour's time, and this solution is easily dominated by those in the reference set R, and by other metaheuristic solutions.

7. Simulated instances

We further compare the performance of the TS and SA algorithms on a test set of 90 simulated instances, corresponding to different number of depots, demand nodes and vehicle capacity. To create situations which involve multiple use of vehicles, we allow a certain proportion of all demand nodes to request for a full truckload (FTL) of demand. Tables 6 and 7 show the 18 problem types, each with five randomly generated instances. The coordinates of each facility/demand node are randomly generated from the Euclidean space of size [0–180, 0–180], assuming a maximum 3-hours (one-way) travel time. Demand quantity is randomly generated from the interval [10, 30]. Other cost parameters are adopted from the real data. Initial experiments were run to find the best set of parameters for each metaheuristic version. A running time of 1200 CPU seconds is allowed on each instance and a reference set is created from the four metaheuristic versions to allow performance comparison based on the distance functions (6)–(8).

The routes generated here tend to have short trip times but heavily loaded, which is contrary to the two real instances. Table 6 shows that TS_{mult} has the smallest average distance Dist1 and worst-case distance Dist2, followed by SA_{mult} and the sequential versions. In particular, TS_{mult} and SA_{mult} are capable of generating many more non-dominated solutions in the reference set, than their sequential counterparts.

Table 7 shows that in terms of the single total cost objective, the two TS algorithms gives the smallest distance DistZ_1 over SA algorithms. TS_{seq} produces better solutions than TS_{mult} in the cost objective at the expense of imbalanced workload. Both TS_{mult} and SA_{mult} outperform their sequential counterparts in the two workload imbalance criteria.

8. Conclusions

Multi-objective location-routing studies have not received much attention in the literature. Our contribution will be outlined as follows:

(1) We have considered a multi-objective location-routing problem integrated with the routes assignment decisions, and real instances from a local delivery service are used.

(2) We propose certain methods to estimate unavailable data: the use of GIS to estimate the travel times and a regression method to estimate the on-site service (delivery) time.

(3) We propose a new statistical procedure based on the hypothesis testing of difference between two population proportions (Z-test) to compare the relative non-dominance of multi-objective solutions between tabu search and simulated annealing.

(4) We examine the effect of allowing multiple use of vehicles in the routes formation stage with the sequential approach of routing before assignment. Each route is constrained in two dimensions: time and capacity. In problems where routes are

mostly time-constrained, but not in the capacity dimension, the routing component in the problem is dominating. The effect of multiple use of vehicles is not significant. On the other extreme, when routes are capacity-constrained, but not in the time dimension, routes have short trip times but heavily loaded. The assignment component (of demand nodes to facility and vehicles) becomes dominating over the routing component. Allowing multiple use of vehicles is more useful, as it incorporates both components, in particular, when multiple objectives are of concern.

(5) Computational results on the real data show that area characteristics play an important role in differentiating heuristic performances. In an area where demand density is low per demand node (area 2), the on-site delivery time will be small accordingly. The resulting routes will contain more demand nodes per route than in an area with high demand density. Under this characteristic, allowing multiple use of vehicles in the routing phase results in a higher proportion of non-dominated solutions than the sequential approach. These solutions also have a wider spread across the efficient frontier with statistically better performance under the two workload imbalance criteria. On the other hand, in area with high demand density per demand node (area 1), the resulting routes contain small number of nodes per route. The problem is relatively simpler than the previous one, and there is no significant difference between the two versions.

(6) In the two sets of real data, we compare tabu search and simulated annealing under the same running time and using the best set of parameter values in each version. For performance evaluation, an approximated reference set is derived from all the metaheuristic solutions. In the area with long routes (more demand nodes per route), the SA versions indicate better or similar results as the TS versions with respect to the distance metrics defined in Viana and Pinho de Sousa (2000), under sufficiently long running time (3000 CPU seconds). However, in the area with shorter routes (simpler problem in area 1), the TS versions and SA versions indicate no significant differences in their results.

(7) In the 90 simulated instances, routes generated have short trip times but close to full capacity. Here, the performances of TS_{mult} are superior to SA_{mult}, and both are better than the sequential versions considering multiple objectives. On the average, the TS has better performance over SA in each version (simultaneous or sequential). TS_{mult} and SA_{mult} can produce more non-dominated solutions than their sequential counterparts. But on the single cost objective, TS_{seq} has the best performance while creating solutions with imbalanced workload.

(8) From the above observations of real instances in (5), (6) and simulated instances in (7), the comparison between TS and SA depends on the problem characteristics and running time allowed. (SA takes more time than TS to find many good multi-objective solutions, as it tends to explore initially a large number of non-improving solutions, before looking for better solutions.) Under the multi-objective environment, the simultaneous approach outperforms the sequential approach in problems where routes are constrained by its capacity, instead of work time (Table 6). The simultaneous approach can produce a large number of alternative solutions with slightly higher cost than the sequential approach, but more balanced workload (Table 7). The trade-off is the increased algorithm complexity and the running time required. (Often, the most time-consuming procedure is the assignment phase (bin-packing). A first-fit-decreasing heuristic, instead of the exact method of tree search, is recommended for problems with many routes.)

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Appendix A. Travel time estimation by geographical information system

Travel times in area 2 have been estimated with the help of a geographical information system

(GIS). A popular GIS software ArcView 3.2 and its extension Network Analyst was used. The given addresses of housing estates (demand nodes) were first matched to a coordinate system in ArcView and a new point layer was formed. By using a digitized road network of Hong Kong, the distance between a pair of nodes can be calculated by the Shortest Path algorithm available in Network Analyst. The programming ability provided by the GIS enabled these calculations to be performed repeatedly for every pair of nodes in the problem. To estimate the travel time from the calculated distance, the average traffic speed of 20.8 km/hour in various local districts is assumed (Transport Department, Hong Kong, 2001).

Appendix B. On-site delivery time estimation by regression model

Regressing on-site delivery times on the two site-specific factors of the housing estates (number of blocks and number of bills) for data in area 1, we obtain the following model:

$$\begin{aligned}&\text{On-site delivery time(min)}\\&\quad = 2.243 + 0.714 \times (\text{number of blocks})\\&\qquad + 0.0715 \times (\text{number of bills}),\end{aligned}$$

where the number of blocks of the housing estates was obtained from government departments or local property firms. This regression model has shown strong fitness to data in area 1 (adjusted R-square > 0.99 and p-value of the model and the coefficients < 0.0001). Hence, it will be used for estimating on-site delivery time in area 2.

References

Anily, S., Federgruen, A., 1987. Simulated annealing methods with general acceptance probabilities. Journal of Applied Probability 24, 657–667.

Breedam, A.V., 2001. Comparing descent heuristics and meta-heuristics for the vehicle routing problem. Computers and Operations Research 28 (4), 289–315.

Chan, Y., Carter, W.B., Burnes, M.D., 2001. A multiple-depot, multiple-vehicle, location-routing problem with stochastically processed demands. Computers and Operations Research 28 (8), 803–826.

Czyżak, P., Jaszkiewicz, A., 1998. Pareto simulated annealing—a metaheuristic technique for multiple-objective combinatorial optimization. Journal of Multi-Criteria Decision Analysis 7, 34–37.

Eilon, S., 1977. Management perspectives in physical distribution. Omega 5 (4), 437–462.

Eilon, S., Watson-Gandy, C.D.T., Christofides, N., 1971. Distribution Management. Griffin, London.

Glover, F., Laguna, M., 1993. Tabu search. In: Reeves, C. (Ed.), Modern Heuristic Techniques for Combinatorial Problems. Blackwell Scientific Publications, Oxford, pp. 70–150.

Golden, B.L., Laporte, G., Taillard, E.D., 1997. An adaptive memory heuristic for a class of vehicle routing problems with minmax objective. Computers and Operations Research 24 (5), 445–452.

Hansen, P.H., Hegedahl, B., Hjortkjær, S., Obel, B., 1994. A heuristic solution to the warehouse location-routing problem. European Journal of Operational Research 76 (1), 111–127.

Jones, D.F., Mirrazavi, S.K., Tamiz, M., 2002. Multi-objective meta-heuristics: An overview of the current state-of-the-art. European Journal of Operational Research 137 (1), 1–9.

Karp, R., 1972. Reducibility among combinatorial problems. In: Miller, R.E., Thatcher, J. (Eds.), Complexity of Computer Computations. Plenum Press, New York, pp. 85–104.

Laporte, G., Dejax, P.J., 1989. Dynamic location-routing problems. Journal of the Operational Research Society 40 (5), 471–482.

Laporte, G., Nobert, Y., Taillefer, S., 1988. Solving a family of multi-depot vehicle routing and location-routing problems. Transportation Science 22 (3), 161–172.

Lin, C.K.Y., Chow, C.K., Chen, A., 2002. A location-routing-loading problem for bill delivery services. Computers and Industrial Engineering 43 (1), 5–25.

Lourenço, Paixão, Portugal, 2001. Multiobjective metaheuristics for the bus driver scheduling problem. Transportation Science 35 (3), 331–343.

Lundy, M., Mees, A., 1986. Convergence of an annealing algorithm. Mathematical Programming 34, 111–124.

Madsen, O.B.G., 1983. Methods for solving combined two level location-routing problems of realistic dimensions. European Journal of Operational Research 12 (3), 295–301.

Min, H., 1996. Consolidation terminal location–allocation and consolidated routing problems. Journal of Business Logistics 17 (2), 235–263.

Min, H., Jayaraman, V., Srivastava, R., 1998. Combined location-routing problems: A synthesis and future research directions. European Journal of Operational Research 108 (1), 1–15.

Perl, J., Daskin, M.S., 1985. A warehouse location-routing problem. Transportation Research B 19B (5), 381–396.

Ree, S., Yoon, B.S., 1996. A two-stage heuristic approach for the newspaper delivery problem. Computers and Industrial Engineering 30 (3), 501–509.

Sarker, R., Coello, C.A.C., 2002. Assessment methodologies for multiobjective evolutionary algorithms. In: Sarkar, R., Mohammadian, J.-W., Yao, X. (Eds.), 2002, Evolutionary Optimization. Kluwer Academic Publishers, Massachusetts, pp. 177–195.

Srivastava, L., 1993. Alternate solution procedures for the location-routing problem. Omega International Journal of Management Science 21 (4), 497–506.

Taillard, E.D., Laporte, G., Gendreau, M., 1996. Vehicle routing with multiple use of vehicles. Journal of the Operational Research Society 47 (8), 1065–1070.

Transport Department, Hong Kong, 2001. Car journey time survey for monitoring traffic congestion, Hong Kong.

Tuzun, D., Burke, L.I., 1999. A two-phase tabu search approach to the location routing problem. European Journal of Operational Research 116 (1), 87–99.

Viana, A., Pinho de Sousa, J., 2000. Using metaheuristics in multiobjective resource constrained project scheduling. European Journal of Operational Research 120 (2), 359–374.

Wu, T.-H., Low, C., Bai, J.-W., 2002. Heuristic solutions to multi-depot location-routing problems. Computers and Operations Research 29 (10), 1393–1415.