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An Efficient Algorithm for Solving a Stochastic Location-Routing Problem

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Abstract

The purpose of this paper is to determine the location of facilities and routes of vehicles, in which the facilities and routes are available within probability interval (0, 1). Hence, this study is coherent the stochastic aspects of the location problem and the vehicle routing problem (VRP). The location problem is solved by optimization software. Because of the computational complexity of the stochastic vehicle routing problem (SVRP), it is solved by a meta-heuristic algorithm based on simulated annealing (SA). This hybrid algorithm uses genetic operators in order to improve the quality of the obtained solutions. Our proposed hybrid SA is more efficient than the original SA algorithm. The associated results are compared with the results obtained by SA and optimization software.

Keywords: Location; Vehicle routing problem; Stochastic; simulated annealing; Genetic operators.

1. Introduction

The location routing problem (LRP) can be divided to the facility location problem (FLP) and the vehicle routing problem (VRP). In the first problem, all customers are directly linked to a depot. In the second problem, it can be supposed that the locations of depots are predetermined. Min et al. [1] and Nagy and Salhi [2], classified the LRP based on a number of aspects, such as facility layers, hierarchical levels, number of facilities, size of vehicle fleets, vehicle capacity, facility capacity, nature of demand/supply, number of objective functions, types of model data, planning horizon, time windows, solution space and solving procedure. In most previous studies in LRP, facilities are completely closed or opened to serve customers. In addition, routes are completely available to transit the vehicles. However, Lee and Chang [3] assumed that the facilities would not provide services for

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some reasons, such as breakdown or shutdown of unknown causes. Hwang [4, 5] considered that facilities are available in a known probability. Hassan-Pour et al. [6] developed two new aspects of the LRP considering stochastic availability of facilities and routes. Wu et al. [7] divided a multi-depot location-routing problem into a LRP and a VRP. Doerner et al. [8] solved a multi-criteria tour planning. Hwang [4] presented a supply-chain logistics system with a service level. He divided the main problem into a stochastic set covering problem (SSCP) and a VRP. Hwang [5] presented a model for a stochastic set covering problem. Zhou et al. [9] designed a bi-criteria allocation problem and proposed a genetic algorithm to solve the given problem. Chu et al. [10] extended insertion and two-phase heuristics for a periodic capacitated arc routing problem (ARP). Alumur and Kara [11] considered a location-routing problem minimizing the transportation risk and cost. Erkut and Alp [12] presented a hazardous material shipment problem to minimize the total transportation risk. Caballero et al. [13] developed a tabu search (TS) method for a multi-objective LRP. Erdogan and Esin [14] explained a routing table updating by the use of the self cloning ant colony that is based on one of the meta-heuristics. Liu and Chung [15] proposed a heuristic method, called variable neighborhood tabu search, adopting six neighborhood searching approaches, such as insertion and 2-opt. This method finds the optimal solution for the VRP with backhauls and inventory.

In this paper, we assume that facilities may be partially destroyed because of crisis conditions or unknown reasons. Also, in catastrophic conditions, the routes are not completely available. Hence, facilities and routes are in the available state with the known probability between (0, 1). Then, we solve the location problem by an SSCP approach and the multi-objective multi-depot stochastic vehicle routing problem (MO-MDSVRP) by a hybrid meta-heuristic method based on SA.

2. The model of the SSCP

According to the literature survey, we solve the location problem using an SSCP approach. The main assumptions are as follows:

- Facilities are uncapacitated.
- The establishment cost of facilities is determined.
- Every customer can be covered by multi depots simultaneously.
- The facilities are available within the probability interval (0, 1).

Hassan-Pour et al. [6, 16] presented the mathematical model of the SSCP that minimizes the establishment cost of facilities, subject to the coverage minimum of customers by some of the facilities. This model is solved by the optimization software. The illustrative results are provided and discussed in this paper.

3. Computational results of SSCP

To solve the SSCP, we use data generated at random, as shown in Table 1.

Table 1 Data generated to solve the SSCP

Entity	Parameter	Value/ Data
Customer	No. of customers	50,75 and 100
Depot	No. of depots	10 and 20
	Covering coefficient of customer *i* by facility *j*	U(0, 1)
	Availability of facility *j*	U(0, 1)
	Covering probability of customer *i* by some of the available facilities	U(0.9, 1)

By considering these data generated, six problems are solved by the optimization software. This software is used to find the optimal solution in the case where the average CPU time for the SSCP is always less than one second. Computational results of facilities location are shown in Table 2.

Table 2 Computational results of SSCP

Problem name	No. of customer	No. of depots	OFV	No. of depots used
P1	50	10	93061	8
P2	50	20	146968	14
P3	75	10	104509	9
P4	75	20	161625	14
P5	100	10	115415	10
P6	100	20	175189	16

4. Mathematical formulation of the MO-MDSVRP

In the MO-MDSVRP module, we consider a VRP with two objective functions and multiple depots. Also, the decision variables should be found under a stochastic environment, namely, facilities and routes are available within the probability interval (0, 1). We develop the MO-MDSVRP model under assumptions as follows:

- The vehicle fleet is homogeneous.
- The depots are multiple.
- The capacity of each vehicle is limited.
- The total demand served by each vehicle cannot exceed its capacity.
- The working time of each vehicle is limited.
- The service time in each node is given.
- Each node is visited only once by a single vehicle.
- The availability of each route is probabilistic.
- We formulate the MO-MDSVRP as follows:

Minimize $$Z_1 = \sum_{i=1,\dots,N} \sum_{j=1,\dots,N} \sum_{v=1,\dots,NV} C_{ij} X_{ijv} \tag{1}$$

Maximize $$Z_2 = \sum_{v=1,\dots,NV} \left(\prod_{i=1,\dots,N} \prod_{j=1,\dots,N} P_{ij} X_{ijv} \right) \tag{2}$$

s.t.

$$\sum_{i=1,\dots,N} \sum_{v=1,\dots,NV} X_{ijv} = 1 \quad , \quad j = M+1,\dots,N \tag{3}$$

$$\sum_{j=1,\dots,N} \sum_{v=1,\dots,NV} X_{ijv} = 1 \quad , \quad i = 2,\dots,N \tag{4}$$

$$\sum_{i=1,\dots,N} X_{ipv} - \sum_{j=1,\dots,N} X_{pjv} = 0 \ , \ v = 1,\dots,NV \ ; \ p = M+1,\dots,N \tag{5}$$

$$\sum_{i=1,\dots,N} d_i \left(\sum_{j=1,\dots,N} X_{ijv} \right) \le C_v \quad , \quad v = 1,\dots,NV \tag{6}$$

$$\sum_{i=1,\dots,N} t_{iv} \sum_{j=1,\dots,N} X_{ijv} + \sum_{i=1,\dots,N} \sum_{j=1,\dots,N} t_{ijv} X_{ijv} \le T_v \quad , \quad v = 1,\dots,NV \tag{7}$$

$$\sum_{i=1,\dots,M} \sum_{j=M+1,\dots,N} X_{ijv} \le 1 \quad , \quad v = 1,\dots,NV \tag{8}$$

$$\sum_{v=1,\dots,NV} \sum_{i \in S} \sum_{j \in S} X_{ijv} \le |S| - r(S) \ , \ \forall S \subseteq A - \{1\} \ , \ S \ne \varnothing \qquad (9)$$

$$X_{ijv} \in \{0,1\} \ , \ \forall i, j, v \qquad (10)$$

Notations:

M Number of facilities.
N Number of demand nodes or facilities (depot is at the node $i = 1$).
NV Number of available vehicles.
i, j Index of demand nodes or facilities ($1 \le i, j \le N$).
V Node set in graph $G(V,A)$ that is equal to $\{1, \dots, i, \dots, N\}$.
A Arc set in graph $G(V,A)$ that is equal *to* $\{(i, j): i,j \in V, i \ne j\}$.
S Arbitrary subset of set v.
$r(S)$ Minimum number of vehicles needed to serve set S.
C_v Capacity of vehicles.
d_i Demand at node i.
t_{iv} Service time (time for rendering service) to node i by vehicle v.
t_{ijv} Travel time between arc (i, j) by vehicle v.
T_v Maximum service time and travel time for the vehicle v.
C_{ij} Travel cost between arc (i, j).
P_{ij} Availability of path between arc (i, j).
Q_{ij} Unavailability of path between arc (i, j), where $Qij = 1- P_{ij}$.
X_{ijv} 1, if arc i, j is traversed by vehicle v; 0, otherwise.

This model determines vehicle routings and transportation schedules for the facilities, which are determined by the SSCP model. The objective function (1) minimizes the transportation cost, and the objective function (2) maximizes the probability of delivery to customers. Constraints (3) and (4) cause each customer is served by one vehicle. Constraint (5) defined for equivalence in input and output of each node. Constraint (6) indicates the maximum capacity of vehicles. Constraint (7) shows the maximum working time for each vehicle. Constraint (8) causes that each vehicle travels only from one depot to customers. Constraint (9) ensures that sub-tours do not establish. Constraint (10) defines the type of decision variables.
We interpret how the objective function (2) can be changed from multiplication to summation, and so from the minimum to the maximum (Hassan-Pour et al. [6]). The objective function Z_2 is in the multiplication form. To prevent that the value of Z_2 become zero, a fixed value added to it. Then, to convert it to a linear function, the logarithm of the obtained function is maximized. Finally, in order to change it to maximization, the objective function is multiplied by -1. According to this interpretation, the objective function (2) is changed by:

$$Z_2' = \text{Min} \sum_{i=1,\dots,N} \sum_{j=1,\dots,N} \sum_{v=1,\dots,NV} Q_{ij} X_{ijv} \qquad (11)$$

A multi-objective solution technique should be adopted for the MO-MDSVRP. Rahimi-Vahed et al. [17] classified five methods for multi-objective optimization problems, such as scalar methods, interactive methods, fuzzy methods, meta-heuristic methods, and decision-aided methods. We employ a linear composition objective function for the ease of applications as good as Alumur and Kara [11], Erkut and Alp [12], and Caballero et al. [13].

Based on a convex combination of transportation cost (Z_1) and unavailability of routes (Z_2), the combined objective function obtained as follows (Hassan-Pour et al. 2009):

$$Min \quad Z_{opt} = \lambda\left(\frac{Z_1}{Z_1^{\max}}\right) + (1-\lambda)\left(\frac{Z_2'}{Z_2'^{\max}}\right) \qquad (12)$$

In this equation, $Z_1^{\max}$ and $Z_2'^{\max}$ are the maximum cost and the maximum unavailability of routes, respectively.

5. SA methodology

The SA methodology is a meta-heuristic method that uses a stochastic approach to direct the search. To crystallize a solid in the annealing operation, it is heated to a high temperature and gradually cooled to low. This heating process allows the atoms to move randomly in order to reach a minimum energy state. This analogy can be used in solving any combinatorial optimization. It makes the search to proceed to a neighboring state even if the move causes the value of the objective function to become worse (Tavakkoli-Mogaddam et al. [18]).

5.1. Hybrid SA algorithm

We generate an initial solution by a heuristic method and improve the quality of the solution by the genetic operators. Hence, we hybridize the SA algorithm with the genetic operators. The flowchart for our hybrid SA algorithm is shown in Fig 1.

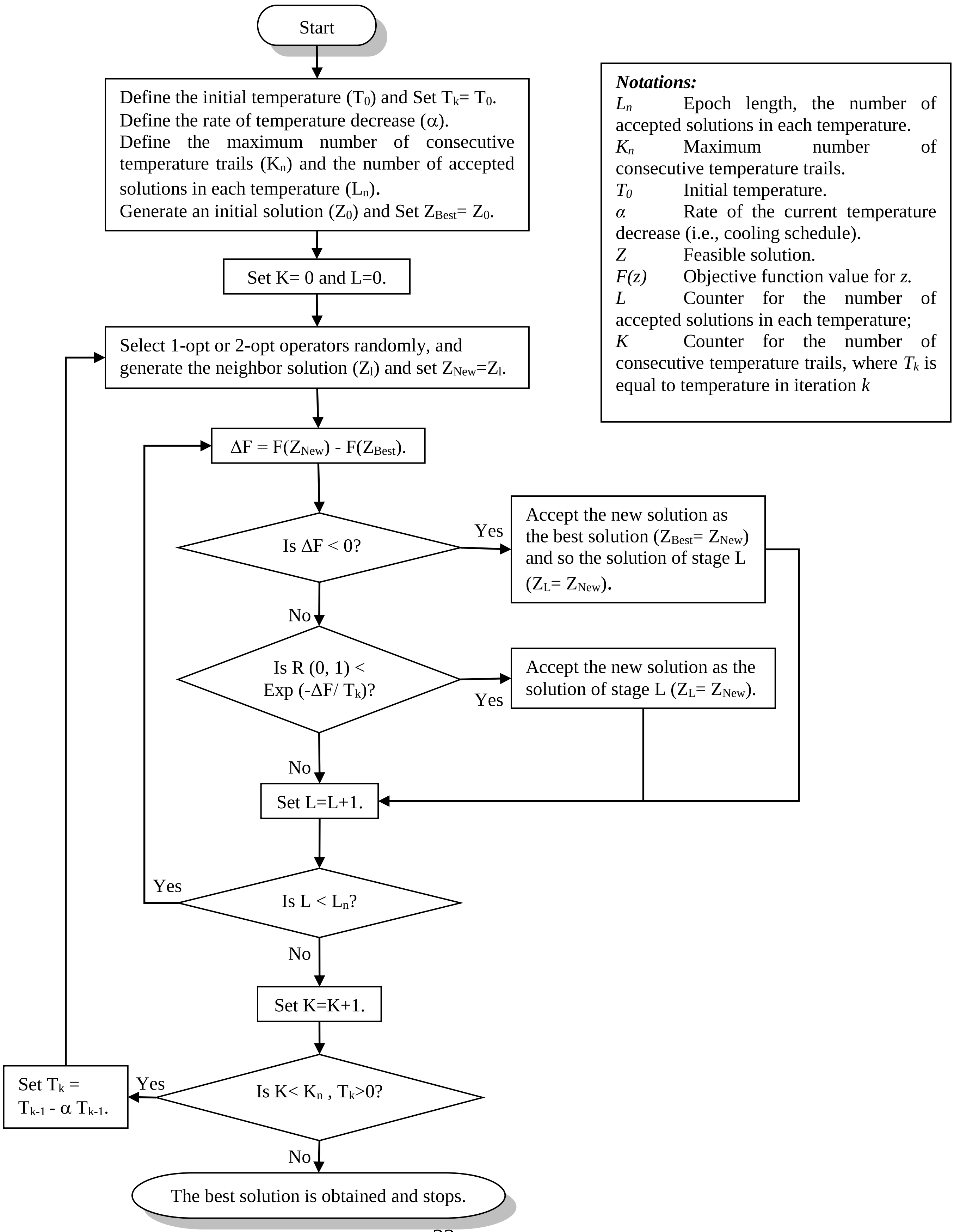

Fig. 1 Flowchart for the hybrid SA algorithm

5.2. Initial solutions

An initial solution is generated by a heuristic method based on the capacitated VRP model. In this model, each vehicle serves to one node. The homogeneous fleet is used. First, an un-served node is selected at random for each route, and then a vehicle is allocated to that. Until the capacity of the vehicle is violated, another un-served node is searched at random continually. Also, the capacity of the allocated vehicle is updated at each route.

5.3.Neighborhood solution

To obtain a neighborhood solution, the genetic operators, namely mutation (i.e., 1-opt) and crossover (i.e., 2-opt), are embedded in the SA algorithm. Hence, these operators are selected randomly in order to improve the solution in each iteration of the algorithm. Tables 3 and 4 show the representation of some of the solutions in the genetic operators. In mutation operator, two routes of two vehicles are randomly chosen out of the existing feasible solutions, and then a customer is deleted from a route and added to the other route (e. g. customer C_3 in table 3). In crossover operator, two routes belonging to two vehicles are randomly chosen from the existing feasible solutions, and then two nodes out of two routes are exchanged with each other (e. g. customer C_2 and customer C_3 in table 4).

Table 3 The representation of solution in the mutation operator.

	Customers	C_1	C_2	C_3	C_4	C_5	Tout planning
Previous solution	Route 1, Vehicle 1	1	0	1	1	0	C_1- C_3- C_4
	Route 2, Vehicle 2	0	1	0	0	1	C_2- C_5
Next solution	Route 1, Vehicle 1	1	0	0	1	0	C_1- C_4
	Route 2, Vehicle 2	0	1	1	0	1	C_2- C_3- C_5

Table 4 The representation of solution in the crossover operator.

	Customers	C_1	C_2	C_3	C_4	C_5	Tout planning
Previous solution	Route 1, Vehicle 1	1	0	1	1	0	C_1- C_3- C_4
	Route 2, Vehicle 2	0	1	0	0	1	C_2- C_5
Next solution	Route 1, Vehicle 1	1	1	0	1	0	C_1- C_2- C_4
	Route 2, Vehicle 2	0	0	1	0	1	C_3- C_5

5.4. Assessment of the hybrid SA efficiency

The illustrative results are provided to the model verification and large-sized problems. Our proposed hybrid SA is programmed in the Microsoft Visual Basic 6.0 and executed on a Pentium 4 CPU 2.4GHz with 256MB RAM.

5.5.Parameter settings

To solve the MO-MDSVRP, we use data generated at random, as shown in Table 5. We solve this problem with the various values of λ between 0 and 1 in increments of 0.1. As the decision maker is concerned about the cost and probability, based on trade-off curve, it is expected to select a solution generated by λ between 0.4 and 0.6. Hence for to simplicity, the coefficient of the objective function is set to 0.5.

Table 5 Data required to solve the MO-MDSVRP

Entity	Parameter	Value/ Data
Depot	No. of depots (M)	Output of SSCP (Optimization software)
	Covering coefficients	Output of SSCP (Optimization software)
	Travel cost (C_{ij})	U(500, 1000) cost unit
	Travel time (t_{ijv})	U(0.3, 1.8) Hour
	Availability of arcs i and j (p_{ij})	U(0, 1)
Customer	No. of customers (N)	6 to 10 Customers for small size and 20, 25, 35, 50,75,100 Customers for large size problems
	Demand (d_i)	U(0.1, 1.1) Ton
	Travel cost (C_{ij})	U(500, 1000) cost unit
	Travel time (t_{ijv})	U(0.3, 1.8) hours
	Service Time (t_{iv})	U(0.3, 0.8) hour
	Availability of arcs i and j (p_{ij})	U(0, 1)
Vehicle	No. of vehicles (NV)	3,4 Vehicles for small size and 5 to 7, 30, 40 and 50 vehicles for large size problems
	Vehicles capacity (C_v)	2 Ton
	Work time (T_v)	8 Hours
Program control	No. of accepted Solution in each temperature (L_n)	100
	Maximum no. of consecutive(K_n) temperature trials	100
	Initial temperature (T_0)	5
	Final temperature (T_k)	0
	Rate of decreasing temp. (α)	0.95
Objective coefficient	λ	0.5 (0.1 to 0.9 in trade-off curve)

5.6.Model verification for small-sized problem

Seven small-sized test problems are solved by the optimization software and the hybrid SA algorithm. Table 6 reports the results obtained of solving a number of problems with 3 and 4 vehicles and 6 to 10 customers. For each solution method, this table presents the objective function value (OFV), the computation time expressed in seconds, and the gap (in percent) between the optimal solution values obtained from two methods. It also shows that our hybrid SA algorithm is as good as mathematical programming in term of the solution quality. This approach solves such a hard problem in the maximum gap of 1.3%. In addition, the average percentage gap of solutions obtained by the optimization software and the hybrid SA is 0.5% showing the verification of our hybrid SA.

Table 6 Computational results for small-sized problems

Problem name	No. of Depots/ Customers/ Vehicles	Exact algorithm		Hybrid SA		Gap (%)
		OFV	Time (sec.)	OFV	Time (sec.)	
P7	1/ 6/ 4	5.5	32	5.5	1.12	0
P8	1/ 7/ 3	5.32	58	5.32	0.98	0
P9	1/ 7/ 4	5.88	305	5.88	1.25	0
P10	1/ 8/ 4	6.34	2612	6.34	1.39	0
P11	1/ 9/ 3	5.93	1496	6.01	0.86	1.3
P12	1/ 9/ 4	6.54	7451	6.62	1.31	1.2
P13	1/ 10/ 3	6.56	15751	6.62	1.23	0.9
Average gap						0.5

Fig. 2 indicates the average CPU time related to the hybrid SA and exact method solutions in respect to 3 and 4 vehicles and 6 to 10 customers given in Table 6. This figure shows the solution time for the mathematical approach rises drastically when the problem size increases.

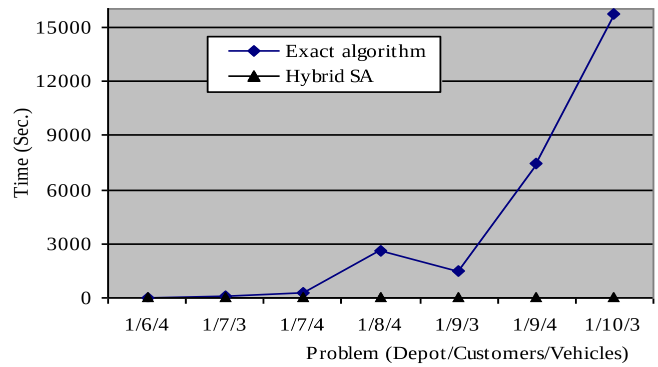

Fig. 2 CPU time for small-sized problems

5.7. Model efficiency for large-sized problems

Since the optimization software packages are unable to solve large-sized problems, we can simplify the mathematical model by relaxing some of the constraints and obtain the lower bound (LB) solutions. Then, the results of hybrid SA is compared with lower bound (LB) solutions in five test problems. Even by relaxation constraints, the optimization software cannot obtain the LB solution at reasonable time in more than one depot, seven vehicles, and thirty five customers, as shown in Table 7. Fig. 3 illustrates the average CPU time related to the hybrid SA and LB solutions in respect to 5 to 7 vehicles and 20, 25 and 35 customers as given in Table 7. This figure indicates the solution time for the mathematical approach rises drastically when the problem size increases. In addition, as shown in Table 7, we solve large-sized problems by the SA algorithm with 8, 9, 10, 14, and 16 depots; 50, 75, and 100 customers; and 30, 40, and 50 vehicles that are located in the SSCP. Although, usually the solution of exact method are better than the hybrid SA, the average gap between the hybrid SA and LB solution is equal to 21%, which is an acceptable outcome for large dimensions.
To demonstrate the efficiency of the hybrid SA, we solve large-sized problems by the SA algorithm without 1-opt and 2-opt operators. As shown in Table 7, for large sizes, the average gap between solutions obtained by the SA (without operators) and hybrid SA is equal to 16%, which demonstrates the hybrid SA algorithm is more efficient than the SA algorithm. However, the solution time for the hybrid SA is better than SA in most large-sized problems. Fig. 4 illustrates the average CPU time related to the SA and hybrid SA solutions in large-sized problem as given in Table 7.

Table 7 Computational results for large-sized problems

Problem name	No. of depots/ customers/ vehicles	LB		Strategy I: Hybrid SA		Strategy II: SA (Without operators)		LB & I	I & II
		OFV	Time (sec.)	OFV	Time (sec.)	OFV	Time (sec.)	Gap (%)	Gap (%)
P14	1/ 20/ 5	8.05	178	9.52	7.17	-	-	18	-
P15	1/ 20/ 6	7.62	478	8.85	8.3	-	-	16	-
P16	1/ 35/ 6	12.95	3127	16.35	19.2	-	-	26	-
P17	1/ 35/ 5	12.63	4484	15.93	14.4	-	-	26	-
P18	1/ 25/ 7	9.96	6922	11.90	13.7	-	-	19	-

P19	8/ 50/ 30	-	-	32.71	703	39.23	850	-	20
P20	9/ 75/ 30	-	-	49.19	1282	53.28	1647	-	8.3
P21	9/ 75/ 40	-	-	53.05	1911	61.11	2126	-	15.2
P23	14/ 50/ 30	-	-	33.22	1134	41.57	1184	-	25
P24	14/ 50/ 40	-	-	34.20	1782	41.98	1535	-	22.7
P25	14/ 75/ 40	-	-	51.14	3204	57.67	2694	-	12.8
P22	10/ 100/ 40	-	-	61.63	5881	70.69	6315	-	14.7
P26	16/ 100/ 50	-	-	68.93	7509	75.60	8230	-	9.7
						Average gap		21	16

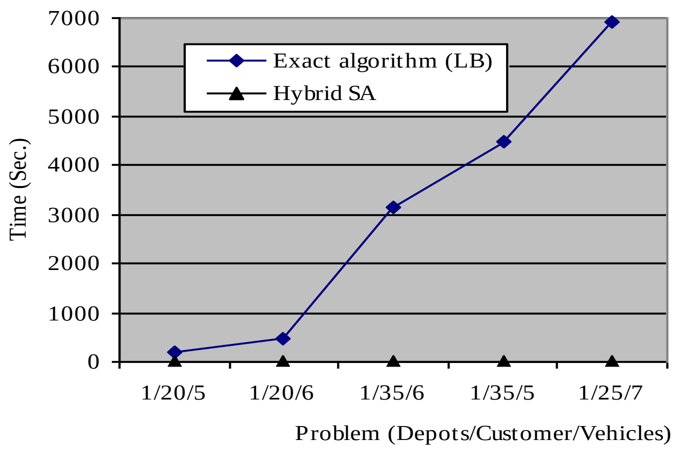

Fig. 3 CPU time for the lower bound

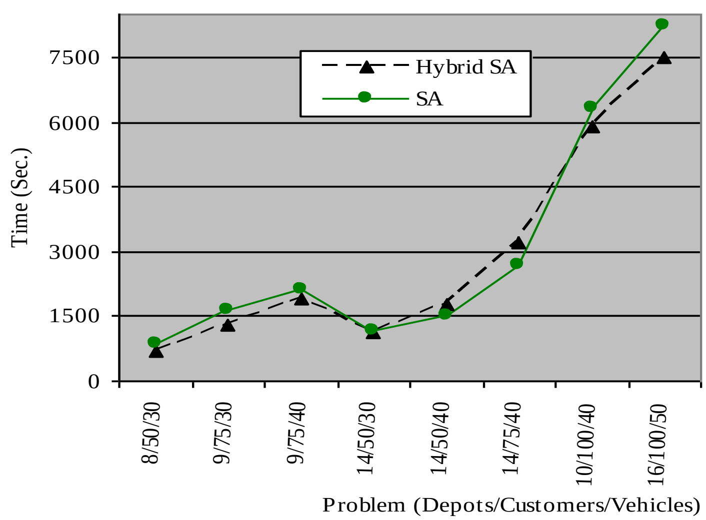

Fig. 4 CPU time for large-sized problems

6. Conclusions

In this paper, we have developed an efficient hybrid meta-heuristic method for the special type of the location-routing problem (LRP) that serviceability of facilities and availability of routes are under uncertainty. To solve this problem, we have used a hybrid SA-GA meta-heuristic. In this hybrid method, we have used two genetic operators, namely mutation and crossover that embedded in the SA algorithm. The SA algorithm allows the search to escape from local optimum, and GA operators are used to obtained the neighborhood solution and improve the quality of solutions. To show the performance of our hybrid SA algorithm, the average CPU times and the quality of solutions have been compared with the SA algorithm and optimization software. The hybrid SA works better than SA to obtain the solution. Also, the genetic operators makes the SA become more efficient in terms of the average CPU time in the most large-sized problems.

We suggest some future studies, such as other meta-heuristics can be developed to solve the presented model. Also, Or-opt and λ-opt operators can be used to generate the various initial solutions. The model can be further enhanced by including pick-up and delivery distribution processes and considering parameters as fuzzy and probabilistic.

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