KKU ENGINEERING JOURNAL 2016;43(S2):359-363 Research Article

KKU Engineering Journal

https://www.tci-thaijo.org/index.php/kkuenj/index

A genetic algorithm with local search for multi-product inventory routing problem with a fleet of multi-compartment vehicles

Wanida Laoraksakiat and Krisada Asawarungsaengkul*

Department of Industrial Engineering, Faculty of Engineering, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand.

Received April 2016
Accepted June 2016

Abstract

This paper presents a genetic algorithm (GA) with local search method to determine the solution for the inventory routing problem (IRP) with a homogeneous fleet of multi-compartment vehicles. The objective is to minimize the total cost including the rental cost, the travelling cost, and the inventory cost. Each customer is allowed to have multiple visits by vehicles. The multi-product with known demands and limited tank capacities at customers are in our consideration. The mathematical model for this IRP is presented and classified as the mixed integer programming. Since the IRP is considered as the NP-hard problem, GA is developed to deal with the large-scale problem. The proposed GA with local search method is utilized to determine both the order quantities and routes for distribution. The chromosome representation, GA operators, and GA parameters are described in this paper. The numerical examples reveal that, for the problems having high complexity, the proposed GA can yield better quality of solutions than the solutions of the optimization software namely CPLEX 12.4. Moreover, the computational time of the proposed GA is significantly lower than that of CPLEX 12.4 for the large-size problem.

Keywords: Inventory routing problem, Genetic algorithm, Multi-product, Multi-compartment vehicle, Optimization

1. Introduction

The IRP considers the replenishment and the distribution of products which are organized by a supplier. In IRPs, the delivery company operates under the restriction that the shortage of products is not allowed at the customer level. IRPs try to minimize the major costs including the distribution cost and the inventory management cost and this will result in reducing the overall logistics cost.

The decomposition approach for the inventory routing problem is presented by [1]. The VMI concept in distribution of petrol products to service stations can be found in [2]. [3] presented a ship inventory routing and scheduling problem with undedicated compartments. They consider four sub-problems including route selection, ship selection, loading, and unloading activities procedures, simultaneously.

Heuristics for an IRP with production decisions was proposed by [4]. The MIP was formulated. The performance of these procedures is better than CPLEX. An inventory and routing costs in strategic location model was resented by [5]. The objective of their paper is to minimize the total cost including location cost and inventory cost at distributions, and the transportation cost in the supply chain. A hybrid genetic algorithm for multi-product multi-period inventory routing problem with a fleet of homogeneous vehicles was proposed by [6]. The performance of GA was also compared to CPLEX 12.4 which is used to solve a mathematical model. It is found that GA can yield the better solutions when the number of suppliers is greater or equal to 50. [7] proposed a metaheuristic which adapts large neighborhood search scheme to solve some sub-problems. The proposed algorithm can determine a good compromise between cost and quality. A variable neighborhood search heuristic for the multi-product multi-period IRP in fuel delivery was done by [8]. The multi-compartment homogeneous vehicles and the deterministic demand was in their interest. [9] presented a genetic algorithm for vendor managed inventory control system. GA was employed to find the order quantities and the maximum backorder levels so that the total inventory cost of the supply chain will be minimized. The routing of vehicles was not considered in their paper. The literatures on IRP can be found in [10-11] as well.

In this paper, a genetic algorithm is proposed to solve the inventory routing problem with a homogeneous fleet of multi-compartment vehicles. The proposed GA is used to find the order quantity and the routes for distribution. The computational experiments and results will be provided to evaluate the performance of GA.

2. Problem definition and mathematical formulation

The mathematical model for this IRP is adapted from [12]. Their mathematical model is modified to fit with multi-product IRP. The objective function (1) is to minimize the total cost which consists of the traveling cost, the rental cost, holding cost, and ordering cost. There are important

*Corresponding author.
Email address: krisadaa@kmutnb.ac.th; a.krisada@gmail.com
doi: 10.14456/kkuenj.2016.129

constraints, such as the limitation of the maximum quantity of a fuel type up to tank capacity at customers in each period, the determination of the ending inventory in each period, the demand of a customer is satisfied without shortage and the restrictions of the routing and the vehicle fleet, etc. Notations of variables are as follows.

Variables:

P is the number of products ($p = 1,\dots,P$); N is the number of customers ($i, j = 1,\dots,N$ *and* $j = 0$ *represents the depot);* T is the number of periods ($t = 1,\dots,T$); K is the number of vehicles ($k = 1,\dots,K$); L_{jp} is the capacity of tanks of customer j on product p; D_{jpt} is the demand of customer j on product p in period t; O is the ordering cost per time; H_p is the holding cost of product p; Bjp is the beginning inventory of customer j on product p; C is the shipping cost per km.; R is the rental cost per vehicle k; S_{ij} is the distance from customer i to customer j; Cap is the capacity or number of compartment in a vehicle; M is the large positive value.

Decision variables:

Q_{jpt} is the order quantity of customer j on product p in period t; E_{jpt} is the ending inventory of customer j on product p in period t; X_{ijt} is the number of times that the directed arc (i, j) is visited by vehicles in period t; Y_t is the the total of utilized vehicles in period t; d_{it} is the delivery quantity of customer i in period t; q_{ijt} is the quantity transported through the directed arc (i, j) in period t; V_{jt} is the decision on the ordering (1 if order is placed); Z_{kit} is the quantity transported in vehicle k from depot to customer i in period t.

The mathematical model for this IRP can be formulated as follows:

$$\textit{Minimize}\ \text{Total Cost} = C\sum_{t=1}^{T}\sum_{i=0}^{N}\sum_{j=0}^{N}S_{ij}X_{ijt} + R\sum_{t=1}^{T}Y_t + O\sum_{j=1}^{N}\sum_{t=1}^{T}V_{jt} + \sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T}E_{jpt}H_p \quad (1)$$

$$Q_{jpt} + E_{jp(t-1)} \le L_{jp} \qquad \forall\, j,p,t;\ j=\{1,\dots,N\} \quad (2)$$

$$Q_{jpt} \le MV_{jt} \qquad \forall\, j,p,t;\ j=\{1,\dots,N\} \quad (3)$$

$$E_{jpt} = E_{jp(t-1)} + Q_{jpt} - D_{jpt} \qquad \forall\, j,p,t;\ j=\{1,\dots,N\} \quad (4)$$

$$E_{jpt} \ge 0 \qquad \forall\, j,p,t;\ j=\{1,\dots,N\} \quad (5)$$

$$E_{jp0} = B_{jp} \qquad \forall\, j,p;\ j=\{1,\dots,N\} \quad (6)$$

$$d_{it} = \sum_{p=1}^{P} Q_{jpt} \qquad \forall\, t;\ j=\{1,\dots,N\} \quad (7)$$

$$\sum_{i=1}^{N} X_{i0t} \le K \qquad \forall t; i=\{1,\dots,N\}, i \ne j \quad (8)$$

$$X_{ijt} \le 1 + \left[\left(q_{ijt}-1\right)/Cap\right] \qquad \forall i,t;\ j=\{1,\dots,N\}, i\ne j \quad (9)$$

$$\sum_{k=1}^{K} Z_{kit} = q_{0it} \qquad \forall t; i=\{1..N\}, i\ne j \quad (10)$$

$$\sum_{k=1}^{K} A_{kit} = X_{0it} \qquad \forall t; i=\{1,\dots,N\} \quad (11)$$

$$\sum_{j=0}^{N} X_{ijt} = \sum_{k=1}^{K} A_{kit} + \sum_{j=1}^{N} X_{jit} \qquad \forall t; i=\{1,\dots,N\}, i\ne j \quad (12)$$

$$\sum_{i=1}^{N} X_{i0t} = \sum_{i=1}^{N}\sum_{k=1}^{K} A_{kit} \qquad \forall t \quad (13)$$

$$\sum_{k=1}^{K} Z_{kit} + \sum_{j=1}^{N} q_{jit} - \sum_{j=0}^{N} q_{ijt} = d_{it} \qquad \forall t, i=\{1,\dots,N\}, i\ne j \quad (14)$$

$$\sum_{i=1}^{N}\sum_{k=1}^{K} Z_{kit} = \sum_{i=1}^{N} d_{it} \qquad \forall t \quad (15)$$

$$q_{ijt} \le X_{ijt}\cdot Cap \qquad \forall t;\ i,j=\{1,\dots,N\}, i\ne j \quad (16)$$

$$\sum_{k=1}^{K} Z_{kit} \le Cap\cdot\sum_{k=1}^{K} A_{kit} \qquad \forall t; i=\{1,\dots,N\} \quad (17)$$

$$\sum_{k=1}^{K}\sum_{i=1}^{N} A_{kit} = Y_t \qquad \forall t \quad (18)$$

$$\sum_{i=0}^{I} A_{kit} \le 1 \qquad \forall t,k \quad (19)$$

$$X_{ijt} \ge 0 \qquad \forall i,j,t;\ i\ne j \quad (20)$$

$$d_{it} \ge 0 \qquad \forall t; i=\{1,\dots,N\} \quad (21)$$

$$Z_{kit} \ge 0 \qquad \forall k,i,t \quad (22)$$

$$q_{ijt} \ge 0 \qquad \forall i,j,t; i\ne j \quad (23)$$

$$Q_{jpt} \ge 0 \qquad \forall\, j,p,t;\ j=\{1,\dots,N\} \quad (24)$$

$$Y_t \ge 0 \qquad \forall t \quad (25)$$

$$X_{ijt}\in \text{int.}, Y_t \in \text{int.}, A_{jkt}\in\{0,1\}, V_{jt}\in\{0,1\} \quad (26)$$

This mathematical model will be solved by an optimization software, CPLEX 12.4. The objective is to minimize the total cost of IRP. Equality and inequality (2)-(26) are utilized for the following constraints: the capacity of vehicle and fuel tank, demand of customers, inventory level, and routing constraint.

3. Genetic algorithms for IRP

Genetic algorithms which are stochastic search technique are employed to determine the optimal or near optimal solution. GA mechanism starts with the initial population or initial solutions. An individual solution in population is called a chromosome. The chromosomes will be evaluated their fitness. The evolution of chromosome occurs through successive generations. In each generation, new chromosomes called offspring are generated by two genetic operations including crossover and mutation. The chromosomes are selected to the genetic operation based on their fitness. The fitness of chromosomes finally converges to near optimal solution after certain generations.

3.1. GA parameters

To perform GA, we have to set up its parameters which are:

(1) Population size (*Pop_size*): the number of chromosomes in each generation,

(2) Crossover rate (*Pc*): the probability for operating the crossover, and

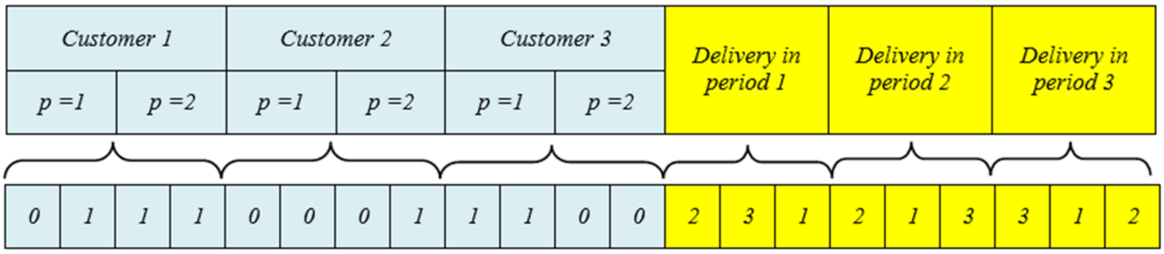

Figure 1 The chromosome representation

Customer	(p_1,t_1)	(p_1,t_2)	(p_1,t_3)	(p_2,t_1)	(p_2,t_2)	(p_2,t_3)
1	5	4	3	3	4	3
2	4	4	4	1	3	2
3	8	3	5	2	3	4

(a)

Customer	(p_1,t_1)	(p_1,t_2)	(p_1,t_3)	(p_2,t_1)	(p_2,t_2)	(p_2,t_3)
1	1	0	1	1	1	1
2	1	0	0	1	0	1
3	1	1	0	1	1	0

(b)

Customer	(p_1,t_1)	(p_1,t_2)	(p_1,t_3)	(p_2,t_1)	(p_2,t_2)	(p_2,t_3)
1	9	0	3	3	4	3
2	12	0	0	4	0	2
3	8	8	0	2	7	0

(c)

Customer	(t_1)	(t_2)	(t_3)
1	12	4	6
2	16	0	2
3	10	15	0

(d)

Figure 2 (a) Demand matrix, (b) Ordering matrix, (c) Order quantities for each product, (d) Delivery quantity matrix

(3) Mutation rate (*Pm*): the probability for operating the mutation.

3.2 Chromosome representation

For IRP, a chromosome comprises of 2 sections which are 1) the order quantity section and 2) the permutation of customer's nodes as shown in Figure 1. A chromosome in the 1st section is specified by a binary of size ($N \times P \times (T$-1)). The value 1 in a bit of section 1 means an order have to be placed on that period; while the value 0 is otherwise. In the first period, the beginning inventory in each customer is zero; therefore all products of customers have to be ordered. Thus, the values in the first period for all products of all customers are 1 which is not displayed in the chromosomes. The back ordering is not allowed in this problem. For the 2nd section, the size of the chromosome is ($N \times T$). Initial route in each period is defined by the sweep nearest algorithm (SWNA) that was presented by [13].

Figure 1 illustrates an example of the chromosome representation for a problem that consists of 3 customers, 3 periods and 2 types of fuel oil. Thus, the size of this chromosome in the 1st section is 12 bits and in section 2 is 9 bits. In Figure 1, the first bit and second bit are 0 and 1, respectively. That means customer 1 places the orders have only on period 1 and 3. For the delivery in period 1, the sequence for routing is customer 2, 3 and 1.

The demand and the ordering data are depicted in Figure 2 (a) and Figure 2 (b), respectively. Figure 2 (c) shows the total order quantity for each product in each period while Figure 2 (d) displays the delivery quantity in each period.

3.3 The fitness value and evaluation function

The total cost can be find by decoding the chromosome. The delivery quantity in each period as in Figure 2 (d) is loaded to compartments of vehicles sequentially. The demand can be split. Routes are conducted by following the 2nd section of the chromosome. The fitness of chromosomes has to be measured by evaluation function (*Eval*). In this paper, the objective function in equation (1) is utilized as fitness of each chromosome. However, there is the limitation of the maximum quantity of a fuel type up to tank capacity at customers in each period. Some chromosomes may be the infeasible ones; therefore the penalty is added to the objective function as follow:

$$Eval = \begin{cases} 1/\text{Total cost} & \text{when} \quad Q_{jpt} + E_{jp(t-1)} \le L_{jp} \\ 1/\left[\text{Total cost} + \alpha \sum_{j=1}^{N}\sum_{p=1}^{P}\sum_{t=1}^{T}((Q_{jpt} + E_{jp(t-1)}) - L_{jp})\right] & \text{when} \quad Q_{jpt} + E_{jp(t-1)} \ge L_{jp} \end{cases};$$

where α = a large positive value for penalty.

3.4 Crossover operation

In this IRP, the crossover procedure is to mate pairs of chromosomes in order to create the offsprings. The uniform crossover is used in the 1st section. The second section, we utilize partial mapped crossover (PMX) to exchange pairs of chromosomes.

3.5 Mutation operation

In the first section that is binary bits, binary mutation randomly selects bit and change it from 1 to 0 and vice versa. Number of bits to be mutated for a chromosome is equal to *Pm* x *P* x *J* x (*N*-1). The swap mutation is employed to perform the mutation for the 2nd section that is for the order delivery.

3.6 Selection and termination rule

This paper uses the roulette wheel to perform the selection process. The termination rule for this IRP is the maximum generation.

3.7 Local search method

2-Opt is a local search employed to improve the solution after GA operation. This paper proposed three solution procedures which are GA-I, GA-II and GA-III. The difference of each procedure is the maximum generations and the application of improvement by 2-Opt local search as shown in Table 1.

Table 1 The maximum generations and the application of local search method for each solution procedure

Solution procedures	GA-I	GA-II	GA-III
Maximum generations	1,000	1,000	500
Application of 2–Opt	No	Yes	Yes

4. Experiment results and discussion

In order to evaluate the performance of the proposed GA, test problems range from 5 to 100 customers are studied. The results of GA on the test problems are compared to the result of CPLEX 12.4 utilizing the mathematical model in section 2. CPLEX 12.4 and the proposed GA are operated on the desktop PC with a 3.10 GHz - Core i5 processor with 4 GB of Ram.

The data used in the test problems are shown in Table 2 and Table 3. The holding cost per in each data set is obtained from a discrete random in [10%, 15%, 20%, 25%] of product cost. All customers have zero beginning inventory in the first period. The planning horizons are 5, 7 and 10 periods. The number of customers used in test problems are 5, 10, 20, 30, 40, 50, 60, 75, and 100 customers. For all test problems, the computational time for solving the mathematical model by CPLEX 12.4 is limited at 3600 seconds. In computational experiments, parameters for GA-I, GA-II and GA-III are listed as follows:

Population size = 100, Crossover probability = 0.6 and Mutation probability = 0.4.

Table 2 Data for ordering and transportation

Rental cost	Ordering cost	Travelling cost	Number of Compartments in each vehicle
2200	100	10	16

The solutions are presented in Table 4 that include the best integer, lower bound and % gap obtained from CPLEX 12.4. The genetic algorithm is observed 5 runs for each test problem. The % different in solution between the upper bound from CPLEX 12.4 and the best objective from GA are calculated as following equation:

$$\%\text{Difference} = \frac{\text{Upper Bound}_{\text{CPLEX}} - \text{Best Objective}_{\text{GA}}}{\text{Upper Bound}_{\text{CPLEX}}} \times 100\%.$$

The % Gap of the solution from CPLEX 12.4 can be calculated as following equation:

$$\%\text{Gap} = \frac{\text{Upper Bound}_{\text{CPLEX}} - \text{Lower Bound}_{\text{CPLEX}}}{\text{Upper Bound}_{\text{CPLEX}}} \times 100\%.$$

From Table 4, GA-III and GA-II are better than GA-I. It implies the 2-Opt method improves the routing of GA-II and GA-III that is performed with the best chromosome in each run. Although, GA-II can find the solutions that is better than the other solution procedures but it requires high computational time. Therefore, the maximum generation of GA-II is decreased from 1,000 generations to 500 generations which is called GA-III. It is seen that the solutions of GA-III is not significantly different from GA-II.

CPLEX 12.4 cannot find the optimal solution within 3,600 seconds for all test problems because of %Gap is not equal to zero. The complexity of this IRP can be obtained by multiplying the number customers by the number of periods. When the complexity is increased, for instant, the problem of 60C5T, 50C7T and 30C10T etc., GA with local search yields better solutions than CPLEX 12.4. It is noticed that the computational time of GA for all problems are lower than those of CPLEX 12.4 because CPLEX 12.4 are stopped by the time limit of 3,600 seconds. Moreover, it is also seen that GA with local search are able to find the solutions with low variation, since the %coefficient of variation (CV) of each problem is lower than 1%.

5. Conclusions

This paper proposes a genetic algorithm and the local search method to determine the order quantities in each period and the routes for the distribution the fluid products by utilizing the homogeneous fleet of vehicles with identical multi-compartment. The results from the computational experiments reveal that the proposed GA enables us to find the good quality of solutions within the reasonable computational time. When dealing with the high complexity of the problem, GA with local search outperforms than CPLEX 12.4.

6. References

[1] Campbell AM, Savelsberg MWP. A Decomposition Approach for the Inventory-Routing Problem. Transportation Sci 2004;4:488-502.

[2] Bersani C, Minciardi R, Sacile R. Economic and risk implications in the distribution of petrol products to service stations under retailer managed and vendor managed inventories. Int J Sus Transportation 2010;4:129-153.

[3] Siswanto N, Essam D, Sarker R. Solving the ship inventory routing and scheduling problem with undedicated compartments. Comput Ind Eng 2011;61:289-299.

Table 3 Demand, Product cost, and tank capacity of products for all customers

Data customer	Product 1	Product 2	Product 3	Product 4	Product 5
Demand	Uniform[1,5]	Uniform[1,3]	Uniform[0,2]	Uniform[0,2]	Uniform[1,3]
Product cost (baht/kl.)	35.68	38.13	34.68	43.05	29.99
Tank capacity at petrol station (x 4 kl)	20	20	20	20	20

Table 4 Computational results for CPLEX 12.4 and Genetic Algorithm

Data set	CPLEX 12.4			GA-I					GA-II					GA-III				
	LB ($\times 10^3$)	UB ($\times 10^3$)	Gap (%)	Best ($\times 10^3$)	Dif. (%)	CPU Time	Avg. ($\times 10^3$)	CV (%)	Best ($\times 10^3$)	Dif. (%)	CPU Time	Avg. ($\times 10^3$)	CV (%)	Best ($\times 10^3$)	Dif. (%)	CPU Time	Avg. ($\times 10^3$)	CV (%)
5C5T	46.802	48.647	3.79	49.425	1.60	354.64	49.886	0.85	49.425	1.60	545.64	49.886	0.85	49.439	1.63	161.54	49.736	0.66
10C5T	93.146	95.318	2.28	101.526	6.51	491.48	101.850	0.24	101.526	6.51	749.37	101.850	0.24	101.528	6.51	230.83	101.943	0.30
20C5T	190.122	195.447	2.72	201.822	3.26	774.02	203.107	0.41	201.288	2.99	1,160.24	202.251	0.31	201.877	3.29	372.83	202.254	0.18
30C5T	288.596	297.785	3.09	306.376	2.88	1,076.14	307.297	0.26	304.648	2.30	1,533.89	305.187	0.17	305.314	2.53	519.28	305.549	0.10
40C5T	379.352	393.929	4.40	396.086	0.55	1,319.02	396.815	0.18	395.308	0.35	1,918.13	395.893	0.20	396.297	0.60	660.53	397.337	0.21
50C5T	467.016	490.408	5.77	492.252	0.38	1,605.04	493.002	0.10	490.273	-0.03*	1,646.51	490.898	0.13	490.440	0.01	802.90	491.343	0.13
60C5T	560.040	593.396	5.62	593.601	0.03	1,910.43	594.565	0.17	588.297	-0.86*	1,937.59	590.205	0.26	588.450	-0.83*	967.21	590.477	0.22
75C5T	697.395	N/A	N/A	742.511	-	2,365.79	743.065	0.08	736.131	-	2,379.08	736.492	0.06	736.350	-	1,191.10	736.506	0.01
100C5T	919.149	N/A	N/A	971.948	-	3,089.00	972.901	0.13	965.687	-	3,101.68	966512	0.06	966.742	-	1,553.52	967.040	0.04
5C7T	73.992	76.303	3.03	79.044	3.59	429.64	80.045	0.72	80.099	4.97	415.04	80.308	0.23	80.171	5.07	210.00	80.433	0.34
10C7T	131.165	135.178	2.97	139.064	2.87	630.24	139.932	0.85	139.487	3.19	608.95	140.575	0.76	139.615	3.28	303.25	141.267	0.93
20C7T	259.544	268.714	3.41	274.154	2.02	1,063.67	274.722	0.21	272.911	1.56	1,013.94	273.461	0.13	273.165	1.66	506.52	273.498	0.08
30C7T	386.220	400.491	3.56	405.926	1.36	1,486.75	406.929	0.19	404.293	0.95	1,411.11	405.188	0.17	404.331	0.96	705.25	404.983	0.19
40C7T	510.316	534.867	4.59	539.342	0.84	1910.10	541.127	0.24	536.618	0.33	1,807.67	537.690	0.23	537.059	0.41	908.78	538.764	0.20
50C7T	644.181	682.330	5.59	684.246	0.28	2,344.23	685.217	0.10	679.710	-0.38*	2,223.42	681.032	0.11	680.003	-0.34*	1,118.71	681.241	0.12
60C7T	766.244	N/A	N/A	816.536	-	2,770.79	819.296	0.23	810.785	-	2,631.69	812.694	0.17	811.717	-	1,319.38	813.448	0.15
75C7T	943.663	N/A	N/A	1,007.519	-	3,411.09	1,009.565	0.21	1,001.130	-	3,247.20	1,002.094	0.06	1,002.406	-	1,628.34	1,003.175	0.11
100C7T	1,249.566	OUT	OUT	1,336.034	-	4,435.80	1,337.453	0.09	1,324.194	-	4,278.64	1,325.619	0.09	1,325.074	-	2,150.42	1,327.001	0.11
5C10T	88.231	90.487	2.49	97.127	7.34	464.59	98.257	0.99	97.127	7.34	469.79	98.249	0.99	98.129	8.45	237.31	99.051	0.89
10C10T	184.156	191.090	3.63	193.685	1.36	516.22	194.495	0.50	193.681	1.36	749.30	194.409	0.49	193.473	1.25	371.40	194.988	0.61
20C10T	366.918	382.036	3.96	384.508	0.65	1,297.39	385.888	0.21	384.329	0.60	1,333.02	385.504	0.18	386.114	1.07	657.50	387.111	0.21
30C10T	545.170	573.021	4.86	571.877	-0.20*	1,887.29	573.433	0.21	569.528	-0.61*	1,894.88	570.701	0.20	569.179	-0.67*	949.92	570.396	0.14
40C10T	731.533	777.442	5.91	767.463	-1.28*	2,471.91	768.911	0.14	764.549	-1.66*	2,476.40	765.638	0.10	764.752	-1.63*	1,241.68	765.317	0.09
50C10T	901.072	N/A	N/A	951.614	-	3,054.63	952.956	0.13	944.257	-	3,050.94	945.804	0.11	944.334	-	1,525.48	946.553	0.22
60C10T	1,080.882	N/A	N/A	1,150.619	-	3,632.11	1,152.292	0.15	1,142.344	-	3,634.28	1,143.155	0.07	1,141.658	-	1,816.82	1,142.796	0.08
75C10T	1,353.547	N/A	N/A	1,432.753	-	4,514.38	1,434.953	0.09	1,424.339	-	6,252.69	1,425.627	0.06	1,424.087	-	2,258.68	1,425.276	0.06
100C10T	1,777.521	OUT	OUT	1,896.771	-	5,988.44	1,898.277	0.08	1,882.998	-	5,955.08	1,883.487	0.02	1,880.287	-	2,995.43	1,882.021	0.09

[4] Bard J, Nananukul N. Heuristics for a multiperiod inventory routing problem with production decisions. Comput. Ind Eng 2009;57:713-723

[5] Shen Z-JM, Qi L. Incorporating inventory and routing costs in strategic location models. Eur J Oper Res 2007;179:372-389.

[6] Moin NH, Salhi S, Aziz NAB. An efficient hybrid genetic algorithm for the multi-product multi-period inventory routing problem. Int J Prod Econ 2011;133: 334-343.

[7] Coelho LC, Cordeau J-F. Laporte G. Consistency in multi-vehicle inventory-routing. Transp Res C Emerg Technol 2012;24:270-287.

[8] Popović D, Vidović M, Radivojević G. Variable Neighborhood Search heuristic for the Inventory Routing Problem in fuel delivery. Expert Syst Appl 2012;39:13390-13398.

[9] Pasandideh SHR, Niaki STA, Nia AR. A genetic algorithm for vendor managed inventory control system of multi-product multi-constraint economic order quantity model. Expert Syst Appl 2011;38:2708-2716.

[10] Li J, Chen H, Chu F. Performance evaluation of distribution strategies for the inventory routing problem. Eur J Oper Res 2010;202:412-419.

[11] Liu S, Chen A. Variable neighborhood search for the inventory routing and scheduling problem in a supply chain. Expert Syst Appl 2012;39:4149-4159.

[12] Yu Y, Chen H, Chu F. A new model and hybrid approach for large scale inventory routing problems. Eur J Oper Res 2008;189:1022-1040.

[13] Na B, Jun Y, Kim B-I. Some extensions to the sweep algorithm. Int J Adv Manu Technol 2011;56:1057-1067.