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Vehicle routing problem with considering multi-middle depots for perishable food delivery

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A B S T R A C T

Today, distributing high quality perishable foods is one of the challenging issues in food industry. This paper introduces a deterministic vehicle routing problem model with multiple middle depots and proposes the freshness of perishable foods as a new concept to obtain optimal delivery routes. For the proposed mathematical model, profit maximization of delivering the product, minimization of the transportation costs and vehicle traveling time, and maximum level of delivered product perishability (loss of freshness) are considered. GAMS software is implemented to show the authority of the model. Furthermore, genetic algorithm (GA) has been developed to solve the model for large size instances. Several problems are tested in order to compare the exact and the GA solutions.

1. Introduction

Perishable foods, such as, meat, milk and vegetables, often spoil during the production and maintenance and delivery processes because of extended travel times and incessant stops to serve customers. In today's changing environment good relation with customers is required to service (Akbari et al., 2013). Nearly one third of the global food production is spoiled and wasted every year (Gustavsson et al., 2011). One of the most necessary food product specifications is its quality (Smith & Sparks, 2004). Examples of this kind of products are meat, milk, vegetables and prepared meals. It is hard that manages perishability foods distribution effectively and warrant maximum freshness during dank or hot climate (Govindan et al., 2014). This study recognizes the decreasing value that customers ascribe to a low freshness state. The cross docking works well for perishable products that need to be delivered on time to preserve its freshness and quality (Agustina et al., 2014). The application of multi depots offers many benefits in distribution compared to traditional problems.

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In this paper, we fit this operational distribution planning task into the vehicle routing problem (VRP) with multi middle depots and one origin depot. The VRP is a general name referring to a class of combinatorial optimization problems that customers are to be served by vehicles (Khakbaz & Bhattacharjya, 2014). The vehicles leave the origin depot, serve customers and return to the origin depot after completion of their routes (Dantzig & Ramser, 1959). A multi-depot-based approach has to be used where customers are to be served from any of the depots using vehicle. In this paper, the variant of the vehicle routing problem known as Multiple Middle Depots Vehicle Routing Problem is considered. This problem is to be modeled using a framework in which distribution costs are minimized and the freshness of the products delivered to the customers and the expected total profit are maximized simultaneously in one objective. The distribution planning generally focuses on minimizing the delivery cost of foods and the freshness of perishable foods, because we assumed the nature or quality of perishable foods will reduce throughout their lifetimes.

In this paper two empirical hypotheses are considered: a multiple middle depots vehicle routing problem and the concept of freshness of perishability foods. A deterministic VRP model is proposed to obtain optimal delivery routes with multiple middle depots for refresh the freshness of perishable goods and one firm as the origin node. GAMS software is employed to validate authority of the proposed model in and a meta-heuristic algorithm is developed in order to solve the large size instances.

In the section 2 a brief literature review is performed, and the mathematical model is presented in Section 3. The methodology used to test the model for small and large instances is described in section 4. Also in this section a numerical example with sensitivity analysis is presented. Afterwards, the results obtained through the computational experiments are shown in section 5 and finally, the conclusions section summarizes the main findings of this study

2. Literature review

As the VRP field of research is very wide, the focus will be kept on papers dealing with the VRP with multiple depots and then VRP for perishable goods.

The VRP with multiple depots appears first in the literature on the works of Laporte et al. (1894) and Kulkarni and Bhave (1985), and Laporte et al. (1988) and Carpaneto et al. (1989). The mathematical formulation proposed by Kulkarni and Bhave (1985) was later revised by Laporte (1989). More recently, Baldacci and Mingozzi (2009) proposed mathematical models for solving several classes of vehicle routing problems including the multi-depot concept. Seth et al. (2013) studied a production process modeled as a multi-depot VRP with mobile depots. Contardo and Martinelli (2014) presented the capacitated MDVRP that route length considered as constraints.

Nahmias (1982) and Raafat (1991) studied the basics of perishability production and inventory systems with deteriorating items. Tarantilis and Kiranoudis (2002) focused on the distribution of fresh milk and formulation of problem as a heterogeneous fixed fleet VRP. They proposed an open multi-depot vehicle routing problem (OMDVRP) to deal with a real life problem in Greece. Hsu et al. (2007) considered the randomness of the perishable goods delivery process and presented a stochastic VRPTW model that is further extended to consider time-dependent travel times. Osvald and Stirn (2008） developed an algorithm for the distribution of fresh vegetables that the perishability represents a critical factor； also they formulated a vehicle routing problem with time-dependent travel-times and time windows. Their model considered the impact of the perishability as the distribution costs. Amorim and Almada-Lobo (2014) proposed a multi-objective model that considers the minimization of the costs from the maximization of the freshness state of the vehicle routing products with time windows.

As mentioned in the literature review, none of the articles consider concept of freshness with middle depot and this paper proposed the new concepts of freshness and multi middle depot with one origin depot.

3. Mathematical formulation

In this section a mathematical model of vehicle routing is presented with freshness of perishable foods constraint with considering multi middle depot and one origin firm. Only one vehicle and one type perishable product is considered in this problem and the vehicle is not capacitated. In the proposed model, some customer may not receive the service because of reducing costs. So customer choice is a binary variable in the model. The freshness and value of perishable products will decay once they are produced. The revenue of the manufacturer depends on the quality and freshness of the products when they are received (Chen et al., 2009). All products that it is carrying are at their maximum freshness and it is assumed that perishable good could be refreshed in multiple middle depots. In the other hands, it is assumed that as soon as the vehicle leaves the depot (original firm depot or middle depot) all products that it is carrying are at their maximum freshness. Customers prefer goods with high freshness and also this paper considers penalty for each value of lose freshness. Other assumptions in formulating our problem are given as follows:

1. The profit per customer is known and given.
2. Service time of each customer is known, constant and deterministic.
3. Shelf-life of the perishable product is deterministic and constant.
4. Each customer can only be visited at most once

Consider the following indices, parameters, and decision variables:

Indices and Sets

$i\,;\,j\,;k;u;o$ Index for nodes (index 0 is used for the origin node)

A Set of nodes includes origin, customer and middle depot nodes

U Set of customer nodes

O Set of multiple middle depot nodes

Parameters

s_u Service time of customer u

sl Shelf-life of the perishable product

t_{ij} Travel time from node i to node j

f constant factor for time conversion costs

$c_{ij} = \mathrm{f} \times t_{ij}$ Travel cost from node i to node j

β Constant penalty for each value of freshness loss

p_u Profit for customer u

γ Coefficient of total traveling time of the vehicle

g_0 Fixed cost of opening middle depot o

M A large number

Decision variables

x_{ij} Equals 1 if the vehicle is traveled from node *i* to node *j* ; 0 otherwise

a_u Equals 1 if customer *u* is serviced; 0 otherwise

y_o Equals 1 if middle depot *o* is selected for the vehicle route; 0 otherwise

fr_{ij} Freshness level from node *i* to node *j*

α Maximum perishability level (1-freshness level) of the delivered product

dt_{ij} Time that vehicle arrived to node *j* from node

The mathematical formulation for this problem can be stated as follow:

Subject to:

$$\text{Min } z = \sum_{i\epsilon A}\sum_{j\epsilon A} x_{ij}c_{ij} + \beta\alpha - \sum_{u\epsilon U} p_u\, a_u + \gamma\sum_{i\epsilon A} dt_{i0} + \sum_{o\epsilon O} y_o g_0 \quad (1)$$

subject to:

$$\sum_{u\epsilon V} x_{0u} = 1 \quad (2)$$
$$\sum_{u\epsilon V} x_{u0} = 1 \quad (3)$$
$$\sum_{o\epsilon O} x_{0o} = 0 \quad (4)$$
$$\sum_{o\epsilon O} x_{o0} = 0 \quad (5)$$
$$\sum_{j\epsilon A} x_{ij} \le 1 \qquad \forall\, i\epsilon A \quad (6)$$
$$\sum_{i\epsilon A} x_{ij} \le 1 \qquad \forall\, j\epsilon A \quad (7)$$
$$\sum_{i\epsilon A} x_{ij} = \sum_{k\epsilon A} x_{jk} \qquad \forall\, j\epsilon A \quad (8)$$
$$dt_{ij} \ge dt_{ki} + t_{ij} + s_i - M(1 - x_{ij}) - M(1 - x_{ki}) \qquad \forall\, i\epsilon A/0\,, j\epsilon A, k\epsilon A \quad (9)$$
$$dt_{0j} \ge t_{0j} - M(1 - x_{0j}) \qquad \forall\, j\epsilon A \quad (10)$$
$$fr_{ju} \le \frac{sl - t_{ju}}{sl} \qquad \forall\, u\epsilon U\,, j\epsilon\{0 \cup O\} \quad (11)$$
$$fr_{uj} \le fr_{iu} - \frac{t_{uj} + s_u}{sl} + M(1 - x_{iu}) \qquad \forall\, u\epsilon U\,, j\epsilon\{0, O, U\}\,, i\epsilon A \quad (12)$$
$$fr_{ij} \le x_{ij} \qquad \forall\, j\epsilon A\,, i\epsilon A \quad (13)$$
$$a_u \le \sum_{i\epsilon A} x_{iu} \qquad \forall\, u\epsilon U\,, i\epsilon A \quad (14)$$
$$\alpha \le (1 - fr_{iu}) - M(1 - x_{iu}) \qquad \forall\, u\epsilon U\,, i\epsilon A \quad (15)$$
$$\sum_{i\epsilon A} x_{io} \le M y_o \qquad \forall\, o\epsilon O \quad (16)$$
$$x_{ij}\epsilon\{0,1\} \qquad \forall\, j\epsilon A, i\epsilon A \quad (17)$$
$$a_u\, \epsilon\{0,1\} \qquad \forall\, u\epsilon U \quad (18)$$
$$fr_{ij} \ge 0 \qquad \forall\, j\epsilon A, i\epsilon A \quad (19)$$

The objective function (1) is minimization of the total costs, which includes minimizing delivery costs and maximum perishability (lose freshness) of delivered product and maximizing profit of product delivery and. The value of freshness varies between 0% and 100%, when the vehicle is in the depots its freshness is 100%.

Constraints (2) and (3) ensure that the vehicle will start from origin firm and end at origin firm. Constraints (4) and (5) show that there is no route for vehicle from middle depots to origin firm and vice versa. Constraints (6) and (7) ensure that each node could only be visited once at most. Constraint (8) makes sure that the inbound and outbound traffic flows of a node should be equal. Arriving time of the vehicle to each node is obtained by using constraints (9) and (10). Constraints (11) states that as soon as the vehicle leaves the depots (original firm or middle depots), product is at the maximum freshness level. In other words, constraint (11) shows the concept of refreshing. Constraints (12) states that freshness of the product delivered from one customer to every node is obtained by subtracting the time it takes to servicing customer i and the travel time between the two customers from freshness of the previous delivered node. Constraint (13) states that when the customer i is not serviced by vehicle, its freshness is zero. Constraint (14) state the possibility or impossibility of serving to customer u. Maximum level of the perishability (1-freshness) of the delivered product is calculated by constraint (15). Opened middle depots are determined by using constraint (16) and finally constraints (17)-(19) define domain of the variables.

4. Methodology

In this paper an exact solve with GAMS software is employed for validation our model.

4.1. Numerical example

In this numerical example, there are 4 customer nodes, 2 middle depot nodes and one origin node, then an exact solve with GAMS software is employed to solve the model. Service time, profit and travel times used in the example are shown in Tables (1-3), respectively. Parameters $\beta, \gamma, f \text{ and } sl$ are considers as 30, 4, 0.8 and 40, respectively. Fixed cost of middle depots opening (g_o) are considered as 10.

Table 1
Service time for customers

Customer 1	Customer 2	Customer 3	Customer 4
2.687	5.373	4.202	3.205

Table 2
Profit of delivering perishable product to customers

Customer 1	Customer 2	Customer 3	Customer 4
58.766	66.722	70.495	69.688

Table 3
Travel times between nodes

	Origin	Customer 1	Customer 2	Customer 3	Customer 4	Middle depot 1	Middle depot 2
Origin	0.000	8.003	14.974	9.102	14.876	11.672	2.830
Customer 1	9.956	0.000	4.501	10.365	7.095	6.036	5.920
Customer 2	2.841	3.101	0.000	12.632	4.231	10.320	11.862
Customer 3	5.251	2.547	8.033	0.000	13.214	4.712	5.001
Customer 4	9.315	11.118	9.795	7.493	0.000	2.648	5.399
Middle depot 1	1.652	5.740	3.549	10.040	8.850	0.000	5.169
Middle depot 2	10.255	11.582	9.784	4.974	2.210	2.435	0.000

The optimal route for this numerical example is shown as follow (Fig. 1). As it is seen in the Fig. 1, vehicle starts its route from origin to customer 3 and then keeps on its route to customer 1 and 4, respectively. Freshness of the products decay from 1 (origin) to 0.772 (time that product is delivered to customer 3) and then from 0.772 to 0.604 and 0.359. Products of the vehicle are refreshed in the first middle depot and then with 0.911 freshness level product is delivered to customer 2 and finally vehicle return to the origin. Arriving time of the vehicle to each of the nodes is shown in the Fig. 1. Total travel time of the vehicle is 43.149.

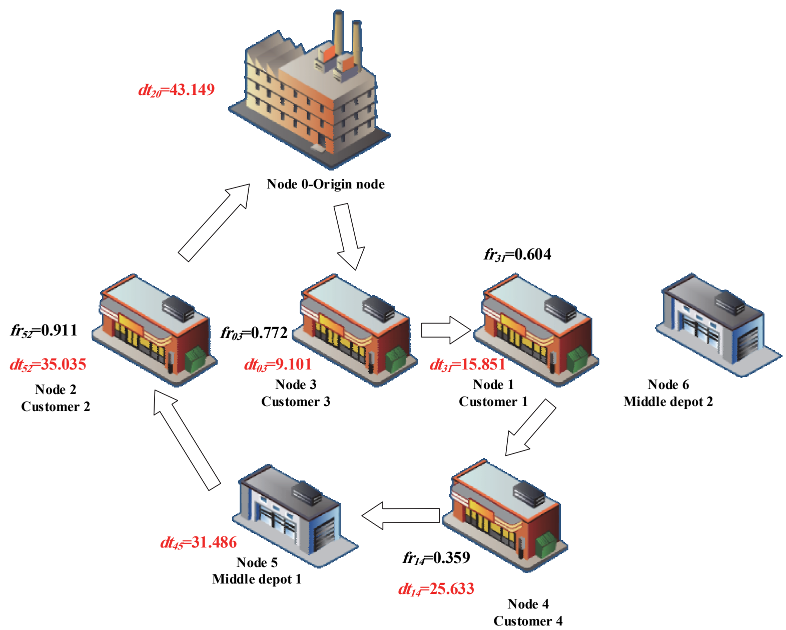

Fig. 1. Numerical example, β=30 and γ=4

Maximum perishability level of products in delivering time to customers is α=*max*(1-0.772,1-0.604,1-0.359,1-0.911)=0.641. By increasing value of the β (penalty for perishability level) from 30 to 70, optimum delivery route is changed as Fig. 2. As it is expected, minimum level of the freshness (1-maximum level of the perishability (α)) is increased by increasing value of the β.

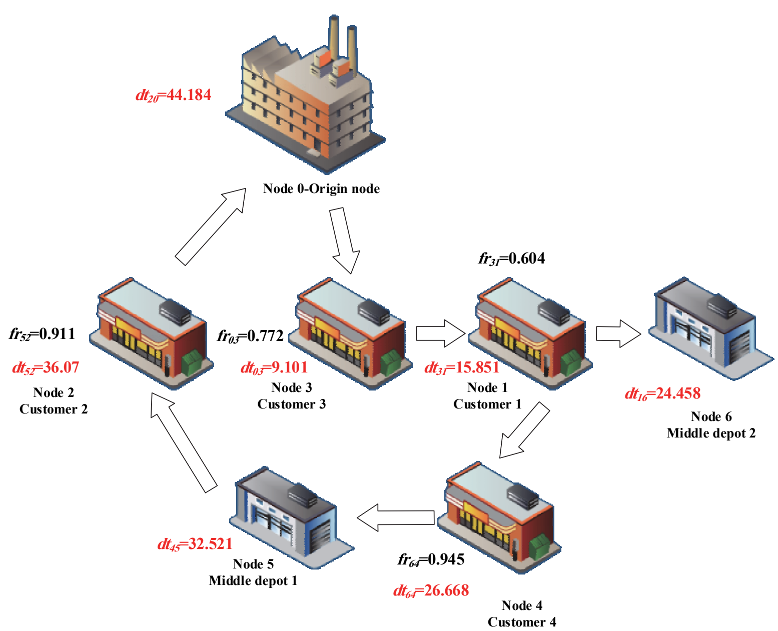

Fig. 2. Numerical example, β=70 and γ=4

Also by increasing importance of the total traveling time of the vehicle (***γ***), it is expected that length of the optimum route decreased. Fig. 3 shown results of the proposed mathematical model for the γ=6.

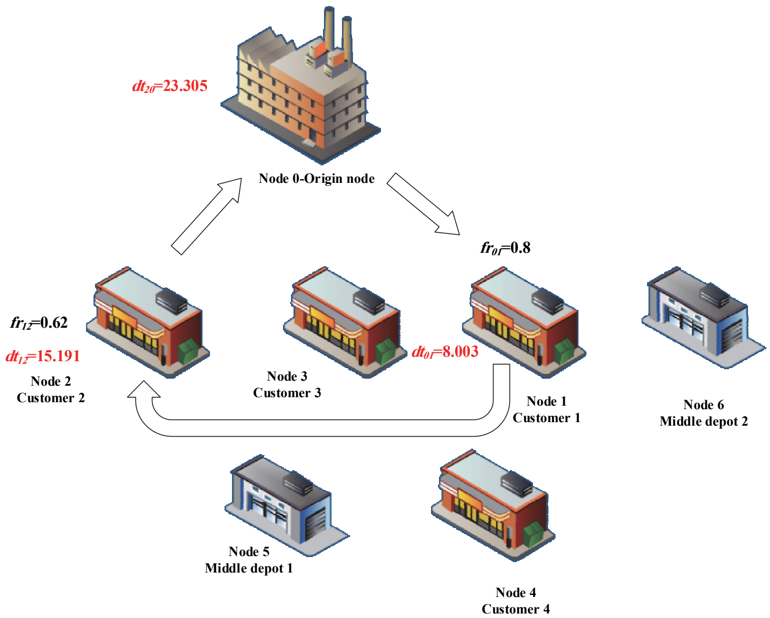

Fig. 3. Numerical example, β=30 and γ=6

As the problem is NP-HARD, a Meta-heuristic algorithm is developed. A Genetic Algorithm (GA) is developed for this perishable food vehicle routing problem. The algorithm has two parts: finding a set of feasible solutions (routes) and finding an optimal set of deliveries for a given route. The algorithm not only finds the best solution but also the best selection of customers' delivery requests for the solution.

4.2. Genetic Algorithm

Holland (1992) introduced GA and Lawrence and Mohammad (1996), for the first time, applied it to VRP. GA starts with an initial population composed of a number of individuals. Each individual represents a solution of the problem and has a corresponding fitness which is related to the objective function value. In this study, an individual represents customers be served and the other representation shows the rout with considering that customers and depots. The overall number of individuals in a population is called population size. GA provides a mechanism to improve the population's quality by generation. New individuals in a new generation are made by the operations of crossover and mutation on some selected individuals. The new individuals are called offsprings and the selected ones are parents. A new population is generated from these offsprings. Similar to the biological processes, the offspring with better fitness are more likely to survive and reproduce and it is believed that such process will result in improvement in population's fitness.

As we have discussed in the previous section, this problem could be divided in two parts: first, a representation of customers be serviced and second representation of the rout with considering that customers and depots.

4.2.1. Representation of a Chromosome and Routing Scheme

In Genetic algorithm, one type of chromosome has a length equivalent to the number of customers and other type has a length equivalent to the number of customers and middle depots in a given instance. Each gene contains a node (customer or middle depots) and the gene sequencing represents the order in which they are visited. For that end, a two-step routing structure translates the input chromosome into a cluster of routes.

The first step, a chromosome has a length equivalent to the number of customers and a random binary number is produced for each gen. In the other hands, this chromosome represents solution of customers. Then we consider a chromosome has a length equivalent to the number of customers and middle depots and random permutations of the total customer and middle depot nodes are generated. In the second step for any gen that gives 0 in first step, this gen is removed from the chromosome, also for ensuring feasibility, if middle depots get consecutive in second step or first or last consist of middle depots, one of these gens is eliminated randomly. As described above, the chromosome representation adopted in this paper for 4 customers (1, 2, 3, 4) and 2 middle depots (5, 6) and one origin depot (0) is in Figs. (4-6).

First step:

1	0	1	1

Fig. 4. Chromosome representation of customers

1	3	6	5	2	4

Fig. 5. Chromosome representation of customers and central depots

Second step:

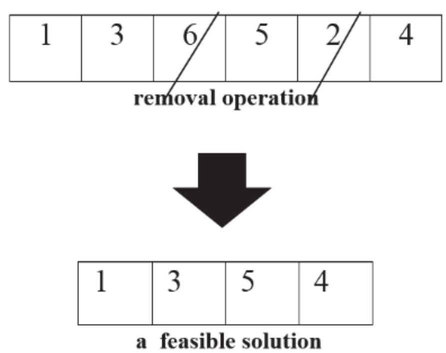

Fig. 6. Repair process of the chromosome

4.2.2. Parameter tuning for Genetic algorithm

Performance of the meta-heuristic algorithms depends on values of the effective parameters. So Before starting to generate an initial population, effective parameters of the GA must be tuned. In this study, Taguchi method is employed in order to tune effective parameters of the GA. Parameters of the GA which impacts in the performance with their levels are shown in Table 4.

Table 4
Effective parameters of the GA with their levels

Effective parameters	Levels			
	1	2	3	4
Population size	75	100	125	150
Crossover rate	0.3	0.4	0.5	0.7
Mutation rate	0.3	0.4	0.5	0.7
Pressure coefficient	3	4	5	6

Beta is pressure coefficient for selection operator (in this study, Roulette wheel operator is applied) and by increasing value of this parameter, probability of selecting better solutions will be increase. Results of the Taguchi method, using MINITAB software, are shown in Fig. 7. As it is seen, the optimal setting for the parameters of the GA are determined as 150, 0.7, 0.7 and 3 for population size, crossover and mutation rate and beta parameter, respectively.

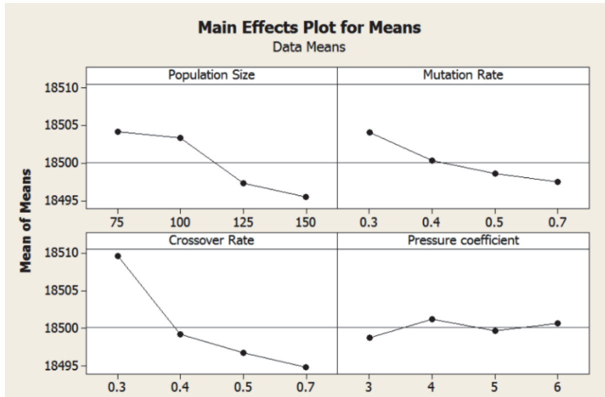

Fig. 7. Resuls of Taguchi method

4.2.3. Operators of developed GA

- **Selection Operator**

In order to make new generation, two individuals have to be selected as parents to make two offspring and then we repeat this process until offspring are generated for the next generation. Also, every parent is chosen by roulette-wheel selection method

- **Crossover**

When two parents are selected, they can be processed with a probability for the crossover operation or left unchanged to be the offspring in the next generation. We use OX crossover method for one type of our representation of chromosome and use UNIFORM crossover for another type of our representation of chromosome.

  - **OX crossover**

1. Select a substring from a parent at random.
2. Produce a proto-child by copying the substring into the corresponding position of it
3. Delete the cities which are already in the substring from the 2nd parent. The resulted sequence of cities contains the cities that the proto-child needs
4. Place the cities into the unfixed positions of the proto-child from left to right according to the order of the sequence to produce an offspring.

Parent 1 = 1 2 3 | 4 5 6 7 | 8 9

Parent 2 = 4 5 2 | 1 8 7 6 | 9 3

Offspring 1 = 2 1 8 | 4 5 6 7 | 9 3

Offspring 2 = 2 3 4 | 1 8 7 6 | 5 9

  - **Uniform Crossover**

The Uniform Crossover uses a fixed mixing ratio between two parents and evaluates each bit in the parent strings for exchange with a probability of 0.5. An example for this type of crossover is illustrated in Fig. 8.

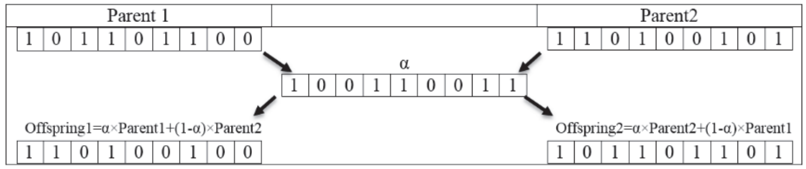

Fig. 8. Uniform crossover

- **Mutation Operator**

The Constraint Route Swap Mutation operator is designed for this problem. This mutation randomly selects two gens and swaps (Fig. 9).

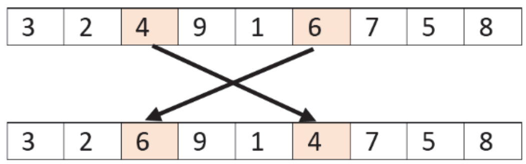

Fig. 9. Swap Mutation

After the offspring population is created, the whole population is sorted according to non-dominance ranking. The new parent population is formed by adding solutions from the better fronts until the number of chromosomes exceeds the size of the population. After specification, the initial parameters and initial generation, the GA algorithm repeats the processes of selection, crossover, mutation and fitness calculation until it reaches a certain number of iterations. The best fitness individual and its corresponding routing in all iterations is then considered as the best solution.

5. Computational Results

In order to show the quality of the algorithm, we want to compare its optimum solution with the exact method by GAMS software. Using MATLAB 2012a to solve the GA algorithm by the computer with RAM 4.00 G CPU Core i5, 2.67 GHz. Parameters of the generated instances are shown in Table 5 and results of the test problems are summarized in Table 6.

Table 5
Parameters of generated test problems

Parameter	measure of parameter	Parameter	measure of parameter
s_u	~ *Uniform* (2,6)	p_u	~ *Uniform* (50,80)
t_{ij}	~ *Uniform* (1,15)	β	40
Sl	40	g_o	~*Uniform*(10,20)
F	0.8	γ	6

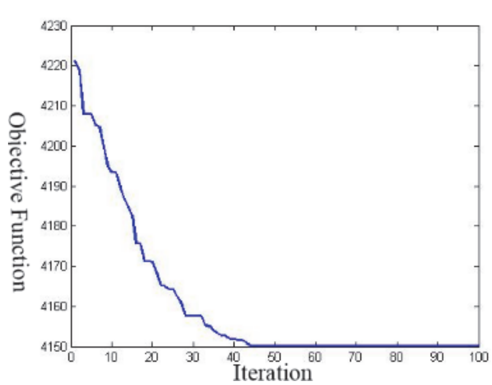

Fig. 10. Objective function for 35 customers and 5 depots

As it is seen in Table 6, small and medium size instances have been solved with acceptable GAP and large size instances have been solved with reasonable amount of time. Objective function value through the evolution process for 35 customers and 5 depots is shown in Fig. 10.

Table 6
Summarized computational results

Number problem	Customers nodes size	Central depot nodes	GAMS		GA		Gap [1]
			Objective Function	Time	Objective Function	Time	
1	5	2	47.799	0.00	47.8	10.266569	0.002
2	6	2	128.598	0.00	128.6	12.366998	0.001
3	6	3	163.568	6.86	163.6	20.903754	0.019
4	7	3	203.986	6.18	205.2	20.564982	0.595
5	7	4	310.86	5.94	311.6	16.735456	0.238
6	8	3	280.542	5.85	282.8	20.397113	0.804
7	8	4	356.871	6.00	360.6	19.207425	1.045
8	9	3	378.953	5.63	379.6	18.129834	0.17
9	10	3	444.76	7.36	447.8	19.613801	0.683
10	20	4	1711.19	37.83	1730.8	23.188853	1.146
11	25	5	2708.26	294.38	2786.6	39.167569	2.893
12	30	2	2592.78	264.80	2669	42.851618	2.94
13	30	6	3037.28	487.03	3131.8	52.542943	3.112
14	35	5	3990.653	515.93	4150.2	59.700639	3.998
15	35	10	4595.9	645.08	4731.1	82.126025	2.9412
16	50	15	11913.59	1032.62	12344.5	127.482158	3.6171
17	75	16	16651.45	1530.5	17338.01	295.605146	4.1231
18	75	20	21937.43	1470.6	22710.1	331.162799	3.5223
19	100	12	-	-	31700.4	496.465498	-
20	100	15	-	-	38218.8	570.502705	-
21	100	25	-	-	40304.2	666.506551	-
22	150	10	-	-	77709.6	1466.032037	-
23	200	16	-	-	102159	3560.742114	-
24	200	25	-	-	141299.2	3807.572584	-

6. Conclusions

In this paper, a new formulation for a vehicle routing problem dealing with multi depots, multi middle depots and one origin depot, and with freshness issues was proposed for perishable goods. The model considered the functions that minimizes transportation costs and total traveling time of the vehicle and maximizes the minimum freshness level and profit value. We have obtained an exact solution for the small size instance by GAMS software to validate the model. A genetic algorithm (GA) has been developed to solve the model for small and large size problems. The solution quality of the GA, time and cost, has been compared with the exact one by GAMS software. The results of GA have proved to be promising compared with the exact solvers in terms of CPU time for large scale problems.

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[1] GAP = $\frac{|object\ value(GAMS) - object\ value(GA)|}{object\ value(GAMS)} \times 100$

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