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A differential evolution algorithm to solve new green VRP model by optimizing fuel consumption considering traffic limitations for collection of expired products

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Abstract

The purpose of this research is to present a new mathematical modeling for a vehicle routing problem considering concurrently the criteria such as distance, weight, traffic considerations, time window limitation, and heterogeneous vehicles in the reverse logistics network for collection of expired products. In addition, we aim to present an efficient solution approach according to differential evolution (DE) procedure to solve such a complicated problem. By using mathematical modeling tools for formulating the environmental sensitivities in vehicle routing problems, the reverse logistics must be managed according to criteria such as cargo weight carried by the vehicle, the vehicle speed and the covered distance by the vehicle. This leads to optimization and reduction of transportation fuel consumption and hence reduction of air pollution and environment concerns. This concept has led to creation and study of the green vehicle routing problems in this paper. Numerical analysis indicates that performance of the proposed DE algorithm can be validated in terms of CPU run time and optimality gap for solving the proposed model. Furthermore, sensitivity analysis show that extending maximum travelling distance by each vehicle, and increasing capacity of vehicles lead to reduction of total cost in the problem.

Keywords: Green vehicle routing problem, reverse logistics, expired products, transportation system, differential evolutionary algorithm

1-Introduction

Transportation is one of the greatest parts of supplies which has irreplaceable and unchangeable fundamental infrastructure for the economic growth of a country. Overuse of energy and hence the air pollution in recent years is a warning and a threat to the environment. This has attracted the attention of transportation system players and has forced them to think about appropriate and applicable solutions in order to reduce and optimize fuel consumption of the transportation system. Achievement to these solutions helps in protection of environmental health and cost saving in the fleet fuel.

Transportation has irreparable effects on the environment. Emission of greenhouse gases and carbon dioxide from vehicles fuel directly affects the people health and can cause destruction of the ozone layer.

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Greenhouse gases from the transportation system are significant portions of air pollution in different countries of the world. Therefore, increase of concerns about these dangerous effects, shows implementation necessity of a program in the transportation system; routing models of the green vehicles based on reduction of fuel consumption and hence decrease of air pollution can be a suitable solution. Green vehicles routing problem is introduced by compatible subjects with the environment and economic costs considering the effective paths for encountering and achieving the financial indicators and environmental importance. Green vehicle routing is classified into three main groups including: green vehicle routing problem, pollution routing problem and vehicle routing problem in reverse logistics. In the rest of this paper, section 2 indicates literature survey and literature gap for motivating in this paper. Section 3 introduces mathematical formulation. The solution procedure is presented in section 4. Section 5 shows the numerical experiments and the results. Finally, section 6 summarizes the paper.

2- Literature review

During recent years, different models are proposed considering various standards for the sake of this purpose. According to the literature, vehicle speed, weight of collected expired products and the transportation distance are effective factors on the fuel consumption of transportation. Kara et al. (2007) studied the transportation real cost which is affected by the vehicle load and the covered distance. They considered the vehicle routing problem with the aim of energy reduction as a routing problem with capacity limitation and with a new purpose of cost. The cost function is product of the whole load (including curb vehicle) and the path length. They used this to facilitate the relationship between the minimum consumed energy and the variable problem situations. Xiao et al. (2012) calculated fuel cost for the transportation parts and its whole based on crude oil. They came to the conclusion that decrease of the fuel consumption and improvement of the transportation performance in a practical level are possible and presented a fuel consumption formula. They suggested the fuel consumption rate regarding the vehicle routing problem with capacity limitation and developed the vehicle routing problem with capacity limitation with the aim of fuel consumption minimization. In their suggested model, the covered paths and the load are considered as the factors which determine the fuel costs. Fuel consumption rate is considered as a function dependent to the capacity and the proposed model of fuel consumption rate is linearly continuous with the vehicle capacity. Kuo (2010) presented a time dependent model for calculation of the fuel consumption in the vehicle routing problem. In this model, three factors of transportation distance, transportation speed and the collected expired products weight have been considered. In this study, impassable paths are not overlooked while they are usually neglected in vehicle routing problems. The proposed method proposed a better path with less fuel consumption but with longer transportation times and distances. It is expressed that there may be an interaction between the fuel consumption, the transportation times and the transportation distance. Erdogan et al. (2012) considered for first time the vehicle recharge and refueling possibility in the vehicle routing problem. They showed this problem as the green vehicle routing problem in which the fuel station of the vehicle which is allowed to refueling during travel can increase the travel length. This model limits the refueling danger with the aim of minimizing the trip. They considered the service time of each customer and the maximum time limitation in each selected path. Schneider et al. (2014) studied the green vehicle routing problem with fuel consumption optimization target considering the time window. Tavares et al. (2009) investigated road slope effect and the vehicle load on the fuel consumption amount in waste collection problem and only for three levels. Half load during waste collection, complete load during going to the unloading place and without load in the return path. Relationship between the fuel consumption rate and the full load is not considered in their study. However, it is obvious that when the vehicle services to a node, its load amount reduces which results in reduction of fuel consumption rate in the path length. Therefore, considering the fuel rate dependent to the load is essential in costs accurate calculation. Suzuki (2011), in addition of considering load amount effect on the vehicle fuel consumption, investigated vehicle waiting time effect in the service beginning to costumers on the fuel consumption. Pronello et al. (2007) considered more realistic models than the previous researches in this filed for measurement of the generated pollution from the vehicle during paths that computation of more factors such as trip time when the vehicle engine is cold is needed. Sbihi et al. (2007) studied a time dependent vehicle routing problem. Based on when vehicles are in the suitable speed, less pollution is provided; their control far from congestion has more compatibility with the environment; even if this leads to increase of the trip length. Palmer (2007) presented a model of carbon dioxide emission and an integrated routing and also calculated the amount of released CO_2 in trip and the trip time and distance. This paper investigates dependency of speed effects in reduction of CO_2 emission in different traffic scenarios with time window. Results show that about 5 percent reduction of CO_2 can be achieved. Buhrkal al. (2012) performed a case study in Denmark for city garbage collecting through vehicle routing problem with time window limitation. The aim of this study was finding a path with optimized cost for city garbage collecting vehicles and garbage transmission to the waste recycling centers in a time window which meets the citizens sat is faction. Le Blanc et al. (2006) also investigated a case study about components recycling of old vehicles to optimize logistics network for collecting containers which are used in Netherland to deliver expired materials from scrappers They considered a vehicle routing model by putting several warehouses and simultaneous removal and delivery. Krikke et al. (2008) studied stock routing problem in components collection from vehicles scraps which their lifetime is ended. Use of available stock data and also stock levels are seen in this model and MUST and CAN instructions are used for creation and planning of components collecting plans. Kim et al. (2009) investigated reverse logistics flow for recycling electronic commodities that their lifetime is ended in South Korea. Demir et al. (2012) presented a great adaptive neighborhood search for pollution routing problem based on increase of consumption efficiency for vehicle routing problem with great and average sizes. Faulin et al. studied (2011) a vehicle routing problem with capacity limitation with environmental standards and considering environmental complex effects. Expect traditional economic costs measurement and environmental costs which are created by the emissions, environmental costs resulted from noise and crowd have been considered in the infrastructure.

One of the most important studies on the application of innovative methods in VRP with time windows is done by Niu et. al. (2018). They have examined different innovative approaches on this problem and compared the results. VRP with stochastic elements has received some attentions. Pierre and Zakaria (2016), Hafezalkotob et. al., (2017) and Zhang et. al. (2016) have employed stochastic optimization techniques to solve small size problems.

Some researchers integrated multi criterion decision-making techniques with routing problems. Torfi et. al. (2016) applied a new analytical technique for determining the relative weights of evaluation criteria using trapezium fuzzy numbers in, and then, the previous results integrated with a location routing problem. Gribkovskaia et al. (2008) studied a similar problem to Prive et al. (2006) with difference that each costumer has two visit permits. Aras et al. (2012) considered a multi-warehouse vehicles routing problem with removal selection and pricing during which the client selection was optional and was dependent to if the visit is profitable and if the remaining space of vehicle meets all the recycling products of the customer. Bipartite collection was illegal. Maden et al. (2010) considered vehicle routing problem with time window limitation in which the speed was dependent to the trip time. In addition, an innovative algorithm was proposed for problem solving. In their results, they achieved to 7 percent of saving in the generated carbon dioxide in a case study in England. Jabali et al. (2009) considered a problem similar to Maden with difference that the generated pollution amount is estimated based on a linear function of vehicle speed and presented an analysis to find the optimized speed considering the pollutions amount. Moreover, a prohibited repetitive search algorithm was used for solving vehicle routing problem samples. Ahmadizar et. al. (2015) proposed a model that studies two-level vehicle routing together with cross-docking. They considered transportation costs and the fact that a specified product type may be supplied by different suppliers at different prices. Bauer et al. (2010) explicitly worked on greenhouse gases minimizing greenhouse gases emissions in a multi-aspect transportation model and showed the ability of this model to reduce the greenhouse gases emissions. Fagerholt et al. (2010) attempted to demonstrate decrease of fuel consumption and carbon dioxide emission show with speed optimization in sending and transportation scenario. Considering constant transportation paths and time windows, speed of every section of the path was optimized for fuel saving. Bektas and Laporte (2011) presented a pollution problem with and without time window and a comprehensive cost function which combined minimizing carbon dioxide emissions costs with drivers operating costs and fuel consumption was proposed. However, their model assumed a minimum flow speed of 40 km/h which is in conflict with the real world condition in which crowd occurs. Dell'Amico et al. (2006) defined a linear zero/one programming model and investigated the category technique and price in this problem solving. Alshamrani et al. (2007) studied a real problem of blood distribution and blood vessels collecting. Penalty cost was considered whenever these blood vessels were not picked. In addition, potential demands and periodic visits were considered in this developed model. Mingyong et al. (2010) presented a mixed planning model for vehicle routing problem with time window for commodities distribution and collection with the aim of cost saves and environment protection and solved the model with the differential evolution algorithm.

Based on the literature gap that is detected in this paper, no researches considers concurrently green considerations with some real limitations such as traffic network and time windows in order to formulate a model in the reverse logistics for collection of expired products. To fill this gap, we aim to develop a novel mathematical model in order to reduce fleet fuel consumption that has an important role in reducing air pollution. This model considers the criteria such as distance, weight, traffic network, time window limitation and heterogeneous vehicles. Finally, to solve such a complicated model an efficient meta-heuristic method based on the differential evolution algorithm will be proposed.

3-Mathematical modeling

In this section, mixed integer nonlinear programming model is presented for reduction of fleet fuel consumption which is heterogeneous and perform reverse logistics of the city expired products. Generally, to achieve this target, the criteria such as the covered distance by the vehicle, the carried load by the vehicle, traffic and vehicle speed must be considered. The following assumptions are considered:

- Each customer is visited exactly once during the path
- Each vehicle starts from the warehouse and gets back to there at the end of service
- Total demand of each route must not overpass the vehicle capacity
- Heterogeneous vehicles are considered
- Number of vehicles from each type must be considered limited
- The place of collecting center is fixed and is pre-defined
- Vehicle speed is constant
- All expired products from the customers must be collected by the heterogeneous fleet

In the following, the indexes, parameters, and model decision variables are introduced.

Indexes:

n : clients node index which $i,j \in n$ and i=0 shows depot.
v: vehicle index (v=1, 2,…, v).
r: all accessible routes index
e: work shift index (e= 1, 2, 3)

Parameters:

Q_v: capacity for vehicle v,
S_i : service time for customer i.
a_i : earliest arrival time to the node ith.
b_i: latest arrival time to the node ith.
T_{ijrev} : trip time between nodes i,j from route r by vehicle v in the work shift e.
M: an upper bound for each constraint or decision variable.
d_{ij}: the distance between nodes i,j,

L_{maxv} : maximum mileage distance by vehicle vth.
p_j : returned products amount from node j.
Fc_{ijrev} : unit of fuel consumption by v vehicle through r route between nodes i , j in work shift e.
L_e^1 : eth work shift beginning time for transportation.
L_e^2 : eth work shift end time for transportation.

Decision variables:
x_{ijrev} : 1 , if vehicle V travels from customer i to customer j through route r and in work shift e, otherwise 0.
y_{iv} : all picked up demand by vehicle V in i node.
Wa_{iev} : waiting time for vehicle V in work shift e in node i.
w_{iev} : beginning service time for vehicle V at customer i in work shift e.
α_{iev} : 1, if Vehicle V in work shift e visit node i, otherwise 0.
Then VRP model can be formulated into the mixed integer nonlinear programming model.

$$MinTF \tag{1}$$

$$\text{s.t} \sum_i \sum_r \sum_e \sum_v x_{ijrev} = 1 \ \forall_j \tag{2}$$

$$\sum_j \sum_r \sum_e \sum_v x_{ijrev} = 1 \ \forall_i \tag{3}$$

$$\sum_i \sum_r \sum_e \left(x_{ijrev} - x_{jirev} \right) = 0 \ \forall_{j,v} \tag{4}$$

$$\sum_i \sum_j \sum_r \sum_e x_{ijrev} d_{ij} \le L_{Maxv} \ \forall_v \tag{5}$$

$$\sum_r \sum_j \sum_e x_{0jrev} \le 1 \ \forall_v \tag{6}$$

$$\sum_j \sum_r \sum_e \left(x_{0jrev} - x_{j0rev} \right) = 0 \ \forall_v \tag{7}$$

$$\sum_j y_{0jv} = 0 \ \forall_v \tag{8}$$

$$\sum_i \sum_j \sum_r \sum_e x_{ijrev} \le M \sum_i \sum_r \sum_e x_{0irev} \ \forall_v \tag{9}$$

$$y_{jv} \ge y_{iv} + p_j - M \times \left(1 - \sum_r \sum_e x_{ijrev} \right) \forall_{ijv} \tag{10}$$

$$y_{iv} \le Q_k \ \forall_v \tag{11}$$

$$w_{iev} + s_i + t_{ijrev} + wa_{iv} - w_{jev} \le M \times \left(1 - x_{ijrev} \right) \forall_{ijrev} \tag{12}$$

$$\sum_e w_{iev} \ge a_i \sum \sum \sum x_{jirev} \quad \forall_{iv} \tag{13}$$

$$\sum_{e} w_{iev} \le b_i \sum_{j}\sum_{r}\sum_{e} x_{jirev} \ \forall_{iv} \tag{14}$$

$$w_{iev} \ge L_e^1 \times \sum_{j}\sum_{r} x_{ijrev} \ \forall_{iev} \tag{15}$$

$$w_{iev} \le L_2^e \sum_{j}\sum_{r} x_{jirev} \ \forall_{iev} \tag{16}$$

$$L_e^2 - \left(w_{iev} + s_i \times \sum_{j}\sum_{r}\sum_{e} x_{ijrev} + wa_{iev} \right) \le M \times \alpha_{iev} \ \forall_{iev} \tag{17}$$

$$wa_{iev} \le M \times \sum_{j}\sum_{r} x_{jkrev} \ \forall_{iev} \tag{18}$$

$$\sum_{j}\sum_{r} x_{ijrev} \le M \times \alpha_{iev} \ \forall_{iev} \tag{19}$$

$$\sum_{r}\sum_{e} x_{ijrev} \times e \le \sum_{k}\sum_{r}\sum_{e} x_{jkrev} \times e \ \forall_{ijv} \tag{20}$$

$$\sum_{r}\sum_{e} x_{00rev} = 0 \ \forall_{v} \tag{21}$$

$$TF = \sum_{i}\sum_{j}\sum_{r}\sum_{e}\sum_{v} x_{ijrev} \times fc_{ijrev} \times (1 + y_{iv}) \tag{22}$$

$$x_{ijrev}, Se_v, \alpha_{iev} \in \{0,1\} \tag{23}$$

$$wa_{iev}, w_{iev}, y_{iv} \ge 0 \tag{24}$$

Constraint (1) which is the objective function reduces the fuel consumption of the whole fleet. Constraint (2) ensures that every demand node is entered once. Constraint (3) ensures that each demand node is departed once. Constraint (4) ensures the balance between arrival and departures of vehicle from the demand node. Constraint (5) ensures the maximum allowed distance for v_{th} vehicle. Constraint (6) ensures that each vehicle does not exit more than once from the warehouse. Constraint (7) is ensures the balance between arrivals and departures of vehicle from the warehouse. Constraint (8) ensures that the vehicle is empty when leaving the warehouse. Constraint (9) explains that can't go to any demand node until it leaves the warehouse. Constraint (10) shows the amount of returned product from each demand node. Constraint (11) ensures that the returned products by every vehicle should not be over its load. Constraint (12) meets service beginning limitation and fulfills demand of the next node, and also this constraint prevents cycling in the route. Constraint (13) ensures that the service beginning time occurs in the time window lower bound of the corresponding node. Constraint (14) ensures that the service beginning time is smaller than the time window upper bound of the corresponding node. In fact, constraints (13) and (14) state that service to each node must be done in the considered interval time. Constraints (15) and (16) are related to the time window of the whole service in the considered work shift interval time and represents that service must be done in the considered work shift interval time. Constraint (17) ensures that the service to the demand nodes must be done the determined work shift interval time. Constraint (18) is the logic limitation and states that there will be waiting time in a node only in case of visiting that node. Constraint (19) ensures that only when a node has a demand in an interval time, the vehicle is sent for servicing from the considered path to the considered node. Constraint (20) is the logic constraint and shows order of nodes visits and explains that the visit time of the previous node is smaller than next nodes. Constraint (21) prevents occurrence of prohibited route. Constraint (22) shows fuel consumption of the transportation fleet. Constraints (23) and (24) explain variables domains.

4- Solution method

VRP problem is classified as Np-hard problems in combinatorial optimization problems (Miranda and Conceição, 2016). Differential evolution (DE) algorithm is considered as a powerful and fast method for optimization problems in continues space. It is one of newest search methods which were presented by Stone and Pries in 1995. They indicated that this algorithm has proper ability in optimization of differentiable nonlinear functions. This algorithm is presented to cover the main defect of genetic algorithm which is lack of local search. In the selection operator of genetic algorithm, chance of response selection, as one of the parents, depends on competency. It means that their selecting chance depends on their competency. When a new response is generated by using a self-regulation mutation and intersection operator, the new response will be compared to the previous one and will be replaced in case of being better. One of the benefits of this algorithm is having a memory which keeps suitable solutions data in recent population. Other advantage of this algorithm is related to the operation selection. In this algorithm, all responses have a same chance to be chosen as one of the parents. The algorithm stages are as following:

4-1- Initiation population

One of most important components in the recommended solution algorithm is the representation structure of the problem responses. Since the problem responses must indicate service routes to sets of customers, hence if the clients' number in *n* and the vehicles' number in *v*, then the response representation is the permutation solution of *n* customers with (*v-1*) vehicles which has used rand perm function. In continuation, by using the FIND function which a value greater than *n*, the response will obtained and interpreted as follows:

N=8 and *V=4* is a permutation as in following and are interpreted as follows:

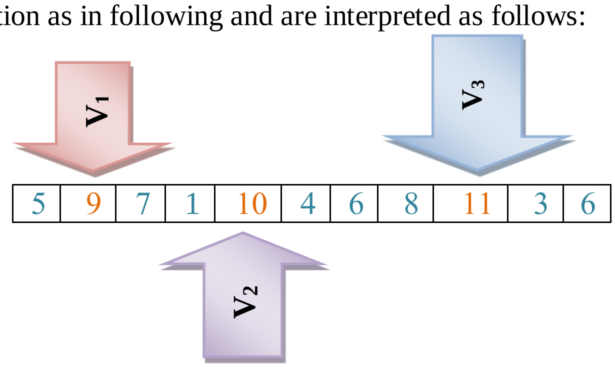

Fig 1. Permutation for *N=8* and *V=4*

In the solution representation, total number of nodes is $n + (v\text{-}1)$ where n denotes number of customers and v indicates number of vehicles. In the shown permutation, numbers 1, 2, …, 8 denotes number of customers nodes and numbers 9, 10 and 11 denotes number of vehicles nodes.

Customers 6 and 3 are covered by vehicle 3 that is located in node 11; customers 4, 6 and 8 are covered by vehicle 2 that is located in node 10. Customers 1 and 7 are covered by vehicle 1 that is located in node 9. Customer 5 is covered by vehicle 4 that is located in node 12 where node is not shown. The constraints 2, 3, 4, 6, 7, 21 are regarded with this chromosome. In continuation of the program, this chromosome is reviewed in 20,…, 9, 5 constraints. A penalty function is considered if the constraints are not met. Therefore, in case of customer visit before the time window beginning, the vehicle must decide to service out of the time window and take the second demand or wait until the time window beginning. If this limitation is not met, its penalty function is zero. Otherwise, it will be fined according to the prolongation time and exit of the considered time-window. It should be mentioned that selection of the work shift numbers is asked from the customer and a choice will be considered for vehicle and path selection which has the least fuel consumption.

4-2- Fitness function

To use the concept of a response dominancy over another response and also to rank the responses, it is needed to calculate the total fuel consumption which used by a vehicle in different tours for every response. This amount which is particular for every response is sum of the tours' total fuel consumption and the displaced load. As mentioned, in this paper, the penalty strategy is used to prevent infeasible solutions occurrence. Sum of penalty costs is added to the objective values. Used penalty parameters are fault penalty for each capacity unit of the vehicle and also fault per every violation unit from the maximum trip time for each vehicle and the allowed travel for every vehicle.

4-3- Mutation operation

The aim of this operator is search of more points in the solution space and prevention from early convergence. After generation of the initial solutions, in this step, considering DE algorithm structure, 3 chromosomes must be chosen randomly from the population and the new chromosome is as follows:

$v = Chrom(a,:) + beta \times [Chrom(b,:) - Chrom(c,:)]$

It should be noted that the considered chromosome is of the sequential kind. Therefore, with this formula, the values like [-71, 13, 2, 3.36, 3, 5.55, 14, 8.23, 3, 4.678, 10] may be obtained which are not acceptable and are rejected according to the integer order criterion(IOR) rule; thus, an operations is done for correcting, making positive and preventing from over passing the value of *n+v-1*, the number of considered nodes. Finally, application of this operator needs regulation of the mutation rate parameter, beta. In this paper, this value is considers *0.5*.

Example:

a	5	9	7	10	4	6	8	1	3	2
b	7	9	10	6	8	1	3	2	4	5
c	4	2	1	10	4	6	8	9	5	3

b-c	3	7	9	-4	4	-5	-5	-7	-1	2

a+(b-c)	8	16	16	6	8	1	3	-6	2	4

According to the obtained node negative values, duplicate and larger amounts resulting from the number of nodes that are unacceptable، By law IOR This chromosome to a chromosome becomes acceptable and The chromosomes for crossover operator used.

y	8	6	1	3	2	4	5	7	9	10

4-4- Crossover operation

After the mutation operation of DE algorithm, interaction operation must be done according to the following equation. The interaction rate is considered as 0.2 pcr.

$$\text{Chrome}\left(\mathrm{j}^{\mathrm{G}+1}\right)=\begin{cases}\text{chrom}\left(\mathrm{j}^{\mathrm{G}+1}\right) & \text{rand(j)} \leq \text{per} \\ \text{chrom}\left(\mathrm{j}^{\mathrm{G}+1}\right) & \text{otherwise}\end{cases}$$

RAND (i) is a random value between 1 and n+v-1. In this way, using the new generation of interaction operator, the selection is placed in the evaluation function and will be in the set of optimized solutions in case of being better.

4-5- Algorithm stop condition

Finally, the number of algorithm execution must be regarded. In this paper, the strategy of implementation number is considered which evaluates 100 times by considering 50 people as the primary population.

5- Model numerical experiments

In this section, validation of the model and the proposed solution method is considered. To do so, the developed solution method in large, average and small sizes is compared with the obtained exact solution from the Gams software. Then, the model sensitivity will be analyzed.

5-1- Evaluation of the solution method in small and large sizes

In this section, performance of the proposed algorithm will be investigated. In order to do so, two problem groups are designed: one in the small size and one in the large size. In the first group, a group of sample problems are solved by the proposed meta-heuristic algorithm and results are compared with the model solution results of Gams software. The first examination target is investigating the ability of the proposed method in obtaining the optimized responses. In the second group, performance of the proposed meta-heuristic algorithm is studied in large problems with real sizes. Also, programs execution is done by a computer with CPU of 2.5 GHz and internal memory of 4.5 GB. Related value of the earliest arrival time to the customer is 0. Latest arrival time to the customer is calculated randomly by the uniform distribution of parameters 10 and 12. Amount of expired products which are collected from each customer is calculated randomly by using the uniform distribution in interval of 10 and 40. Customer service time is obtained randomly by using the uniform distribution of 1 and 4. Trip time between two nodes is calculated randomly by the multiplication of vehicle kind, route, work shift and distance between two customers, fuel consumption amount is obtained randomly by the multiplication of vehicle kind, rout, work shift, distance between two customers and the uniform function between 0.8 and 1.2. Customers servicing is done in three working shifts during a day and night. Vehicle capacity is specified according to the vehicle kind and that the maximum distance that each vehicle can travel is 100; and 1000 is a considered as a large number.

22 samples are solved by the Gams software and the differential evolution (DE) algorithm in small and medium sizes are compared in the Table (1). In this table, the first column represents the problem number; the second and the third columns are the costumer index and the route index, respectively; the fifth and sixth ones show the vehicle index and the value of the objective function which is obtained from running each specimen; the seventh column is the running time of each specimen by the Gams software which is considered as 1800 seconds in this study. Column 8 is the value of the objective function which is resulted from running the specimen by the proposed differential evolution algorithm and the next column shows the time needed for running the algorithm. Column 10 calculates the gap between DE algorithm and the Gams. In other words, this measurement indicates the percent of achieving the optimal solution by the proposed DE algorithm. Column 11 presents the run time of DE algorithm against run time of the Gams Software. Finally, the last column shows the error message of running Gams.

The procedure of generating all parameters is described by the following rules.

No. of customers	$\Rightarrow$	Random uniform integer number from interval (4, 22)
No. of vehicles	$\Rightarrow$	Random uniform integer number from interval (2, 5)
Amount of returned products amount from node j	$\Rightarrow$	random uniform integer number from interval (35, 160)
Vehicle capacity	$\Rightarrow$	Random selection of scenarios 20, 30, 40
the distance between nodes i,j,	$\Rightarrow$	Random uniform integer number from interval (2, 12)

Table 1. Comparison between the GAMS performance and the proposed DE (optimality and runtime)

Problem number	Indices				GAMS DE-Baron		DE		Comparison (DE/GAMS DE-Baron)		GAMS error message
	Customers	Route	Shift work	Vehicles	Objective value	Runtime	Objective value	Runtime	$(1-\frac{DE-GAMS}{GAMS})$ Objective value	$(\frac{DE}{GAMS})$ Runtime	
1	4	2	1	2	6899	32.54	6899	10.19	1	0.313	-
2	5	2	1	2	7260	45.04	7260	13.43	1	0.2981	-
3	5	2	1	3	5828	66.84	5828	14.77	1	0.2209	-
4	5	2	2	2	5487	75.21	5487	14.19	1	0.1886	-
5	5	2	2	3	5217	102.49	5217	13.09	1	0.1277	-
6	6	2	2	2	6244	135.66	6244	16.77	1	0.1236	-
7	6	2	2	3	8592	168.19	8592	18.36	1	0.1091	-
8	7	2	2	3	10598	232.04	10942	23.32	0.967541	0.1005	-
9	7	3	2	3	10256	245.69	10474	24.73	0.978697	0.1006	-
10	7	3	2	3	9856	348.43	10221	37.39	0.962967	0.10731	-
11	10	3	2	3	10365	421.36	10850	48.72	0.953218	0.1156	-
12	12	3	3	4	10185	541.66	11076	66.91	0.912517	0.1235	-
13	13	3	3	4	13268	698.42	13994	70.14	0.946247	0.1004	-
14	15	3	3	4	14744	769.04	15721	76.34	0.933736	0.0992	-
15	16	4	3	4	18657	981.28	19708	79.36	0.943648	0.0808	-
16	17	4	3	4	20518	1154.18	22001	81.84	0.927722	0.0709	-
17	19	4	3	4	20931	1648.65	22738	86.14	0.913647	0.0522	-
18	20	4	3	4	21005	1730.96	23238	88.64	0.893657	0.0512	-
19	20	4	3	5	22470	1765.33	24983	92.99	0.888162	0.0526	-
20	21	4	3	4	25913	1690.11	28438	96.36	0.902546	0.0570	-
21	21	4	3	5	27136	1785.25	29508	102.35	0.912598	0.0573	-
22	22	5	3	5	28553	1800	29812	110.28	0.955907	0.0612	Resource limit exceeded
Min	-	-	-	-	-	-	-	-	0.8881	0.0526	-
Mean	-	-	-	-	-	-	-	-	0.9542	0.1187	-
Max	-	-	-	-	-	-	-	-	1	0.313	-

From table 1, it is found that the proposed DE algorithm is able to reach to optimal solution by 95.42% (in average) accuracy for small and medium examples. In addition, ratio of run time for DE algorithm against Gams solver is 0.1187 that indicates DE algorithm is faster that Gams solver to find the best solution.

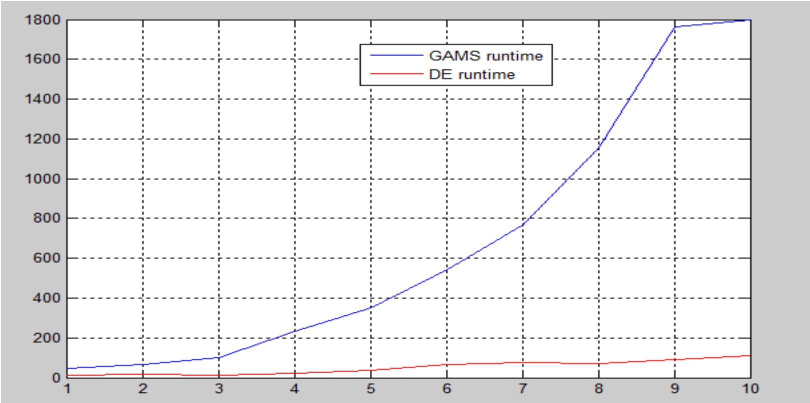

Fig 2. DE vs. GAMS

Considering figure 1, the exact time solution increases exponentially while the size of problems increases. Comparing the exact solution time and the time of Meta-heuristic algorithm from figure (1) and table (1), it can be seen that Meta-heuristic algorithm has reached to 95% of optimal solution after only 12% of exact time solution. This result makes the applicability of the algorithm clear.

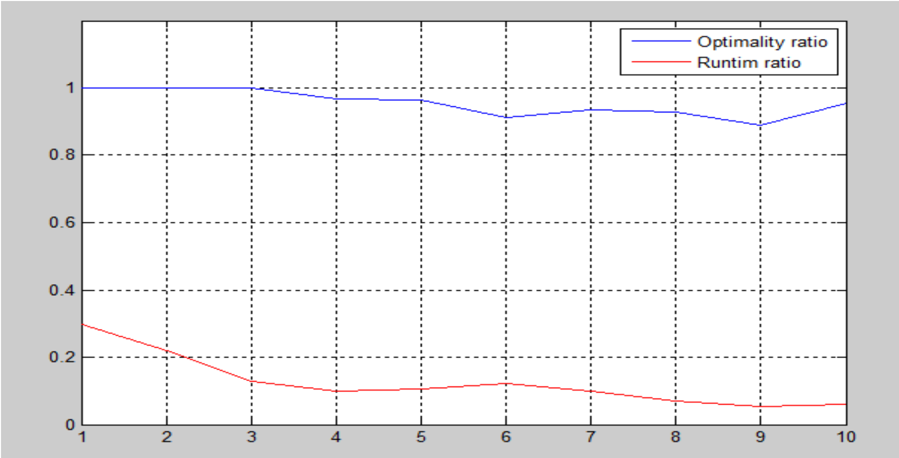

Fig 2. Descending trend of the relative optimality and runtime ratios

The above figure shows the optimization processes and the solution time. From this figure, it can be said that the slope decrease versus time is greater than the optimization process decrease. This leads to the conclusion that the meta-heuristic algorithm is very applicable.

29 samples of large problems have been solved by Gams and the proposed differential evolution algorithm and the results were shown in table (2). It can be found that the Gams software reports the best solution (not optimal solution) of 26 problems during 1800 seconds that time limitation is considered for running the software, while differential evolution algorithm solved all the problems in a small amount of time. From table 2, solutions found by the proposed DE algorithm are 12.88% better than best solutions found by Gams software during 1800 seconds time limitations. Furthermore, once size of an examples

increases more (examples 27, 28 and 29), Gams software cannot find the best solution while DE algorithm can do it.

Table 2. Computational Result Of DE for 29 Large-size Problems

Problem number	Indices				GAMS DE-Baron		DE		Comparison (DE/GAMS IDE-Baron)		GAMS error message
	Customer	Route	Shift work	Vehicle	Objective value	Runtime	Objective value	runtime	$\frac{GAMS-DE}{GAMS}$ Objective value	$(\frac{DE}{GAMS})$ Runtime	
1	50	3	3	5	148930.5	1800	121626	192.11	0.183337	0.106728	Resource limit exceeded
2	50	2	3	6	152425.4	1800	124940	194.418	0.180318	0.10801	Resource limit exceeded
3	52	2	3	5	130198.3	1800	128185	196.5222	0.015465	0.109179	Resource limit exceeded
4	52	2	3	6	151019.5	1800	136166	199.953	0.098354	0.111085	Resource limit exceeded
5	54	2	3	5	144743.4	1800	138464	200.4459	0.04338	0.111359	Resource limit exceeded
6	54	2	3	6	152456.4	1800	148011	202.3506	0.02916	0.112417	Resource limit exceeded
7	56	2	3	5	179024.4	1800	152107	205.1144	0.150355	0.113952	Resource limit exceeded
8	56	2	3	6	186119.3	1800	152986	207.1201	0.178022	0.115067	Resource limit exceeded
9	58	2	3	5	184291.7	1800	155913	208.7914	0.153986	0.115995	Resource limit exceeded
10	58	2	3	6	187166.4	1800	158431	210.4231	0.15353	0.116902	Resource limit exceeded
11	60	3	3	5	190700.4	1800	167245	210.4753	0.122995	0.116931	Resource limit exceeded
12	60	3	3	6	208777.6	1800	176007	213.2954	0.156962	0.118497	Resource limit exceeded
13	62	3	3	5	220914.5	1800	179547	213.44	0.187254	0.118578	Resource limit exceeded
14	62	3	3	6	223313.8	1800	182886	215.9436	0.181038	0.119969	Resource limit exceeded
15	64	3	3	5	189618.8	1800	186742	217.4173	0.015169	0.120787	Resource limit exceeded
16	64	3	3	6	231825.5	1800	192003	221.2183	0.171778	0.122899	Resource limit exceeded
17	66	3	3	5	208953.6	1800	202224	222.729	0.032204	0.123738	Resource limit exceeded
18	66	3	3	6	254875.3	1800	215284	223.8144	0.155335	0.124341	Resource limit exceeded
19	68	3	3	5	244381.8	1800	221170	226.7261	0.09498	0.125959	Resource limit exceeded
20	68	2	3	5	284196.7	1800	227746	226.8616	0.198632	0.126034	Resource limit exceeded
21	70	3	3	5	272650.4	1800	240198	227.1119	0.119025	0.126173	Resource limit exceeded
22	70	3	3	6	300537.1	1800	247453	227.4724	0.176632	0.126374	Resource limit exceeded
23	72	3	3	5	313790.5	1800	252558	228.4925	0.195138	0.12694	Resource limit exceeded
24	72	3	3	6	330090.4	1800	267038	228.7276	0.191015	0.127071	Resource limit exceeded
25	74	3	3	6	309573.9	1800	272829	229.6612	0.118695	0.12759	Resource limit exceeded
26	75	2	3	5	312398.9	1800	298092	237.37	0.045797	0.131872	Resource limit exceeded
27	100	4	2	5	-	-	783331	288.03	-	-	Out of memory
28	150	5	2	5	-	-	1506477	351.90	-	-	Out of memory
29	200	6	3	5	-	-	2634424	440.84	-	-	Out of memory
Min									0.015169	0.106728	-
Mean									0.128790	0.11940	-
Max									0.198632	0.131872	-

5-2- Solution of a small sample problem

Now in this second part, solution of a small size problem is described. Indexes of the customer nodes, vehicle type, working shift and route are listed in the table below.

Table 3. Sample indexes

i,j = 0,1,2,3,4,5
V = 1,2,3
r = 1,2
e = 1

The following table displays the matrix of the distance between nodes *i* and *j*. The matrix row shows the customer *i* and the matrix column represents the customer *j*. For example, $i = 0, j = 2 = 9.45$ means that the distance between the customer and the warehouse is *9.45km* and the remaining distances are in the same order.

Table4. Matrix distance (km)

I \ J	0	1	2	3	4	5
0	0	16.82	9.45	3.96	13.18	4.69
1	16.82	0	16.83	12.97	11.38	13.57
2	9.45	16.83	0	9.99	19.32	12.13
3	3.96	12.97	9.99	0	9.96	2.20
4	13.18	11.38	19.32	9.96	0	8.49
5	4.69	13.57	12.13	2.20	8.49	0

Some parameters and variables that are mostly paid attention and affect the fuel consumption can be seen in the following tables.

Table 5. Variable values y_{iv} (kg)

y_{iv}	1	2
1		50
2		21
3	28	
4		63
5		76

Raw of above table represents the vehicle v and its column shows customer i. For example,$y_{1,2}$=50demonstratesthatthe expired products which are collected from the beginning to the second customer by the second vehicle is 50kg;and also the vehicle capacity is 100 kg.

Table 6. Variable values W_{iev}

	I	E	v	Value
W	1	1	2	29
W	4	1	2	49
W	5	1	2	65

W_{112}=29 means that the beginning time of the second vehicle to the first customer service in the first working shift is second29. It should be mentioned that the day is divided into three working shifts and in this working shift, L1 = 0 and L2 = 480.

Table 7. Parameter values P_j (kg)

J	p_j
0	**0**
1	**29**
2	**21**
3	**28**
4	**13**
5	**13**

The above table shows first column show the customer j and the second column illustrates the value pj. p1=29 means that amount of the expired products of the first customer is 29 kg.
Now, by keeping some parameters constant and changing the other parameters, the effect on the fuel consumption is investigated.

Table 8. The effects of change in indices r, e on the value of objective function

	The effects of changes in e			The effects of changes in r		
	a	b	c	d	e	f
Indexes	i =5 v =3 r =2 e=1	i =5 v =3 r = 2 e = 2	i =5 v =3 r =2 e = 3	i =5 v =3 r =1 e=1	i =5 v =3 r = 2 e =1	i =5 v =3 r =3 e = 1
The value of objective function	5828	5489	4835	6185	5828	5566

As it is obvious in the above table, by keeping the indexes *i*, *v*, *r* constant and changing the parameter *e* which its results are brought in columns*2*,*3*and*4*,reduction of the objective function by changing the working shifts states that the working shift and hence the reduction of the objective function play an important role. In this manner, the results of columns*4*, *5* and*6*alsorepresentthat by keeping the indexes *i*, *v*, *e* constant and route increase, fuel consumption reduction and objective function decrease are accepted.

5-3- Schematic view of the customer visit

In figure 3, the order of customer visit by vehicles is illustrated where D represents the warehouse, $C_1$is the first customer, $C_2$is the second customer, $C_3$is the third customer, $C_4$is the fourth customer and finally, the fifth customer is displayed by C_5.Forbetter understanding, the figure 3(a) is being explained. In this figure, as it can be seen, the first vehicle begins its trip from the depot to the second customer through the first path; then, from the second customer to the first customer via the first path and from the first customer to the fourth customer through the first path and at the end from the fourth customer to the warehouse via the first path. In continuation, the second vehicle leaves the warehouse to collect the expired products of the two remaining customers and goes to the third customer through the first path and continues to the fifth customer from the same path and finally, it returns to the warehouse via the same path after collecting the expired products from the fifth customer.

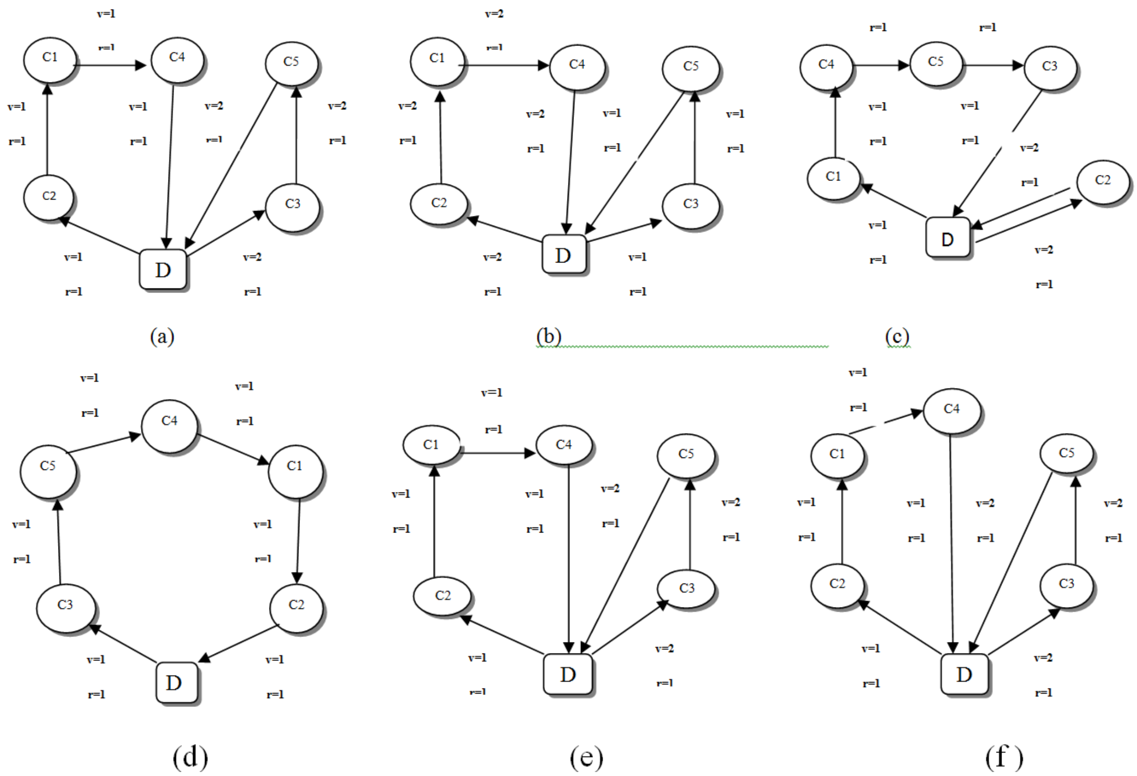

Fig 3. Schematic view of the customer visit

5-4- Sensitivity Analysis

In this part, step-change is performed on the model parameters which have essential role on the vehicle fuel. Parameters sin each stage has been increased to 0.2, separately. Thus, a sensitivity analysis is being done focusing on parameters $L_{Max\ v}$ and Q_v and Fc_{ijrev} in the Gams.

5-4-1- Sensitivity Analysis of $L_{Max\ v}$ Parameter

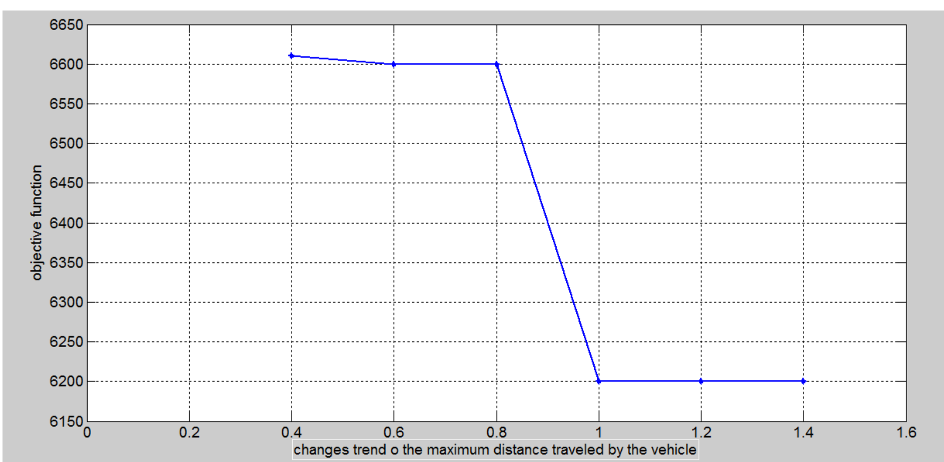

Fig 4. Changes in the objective function to change maximum distance traveled by the vehicle

As specified in the figure 4, with increasing L_{Maxv}, feasible space becomes larger and this makes it possible to make the better solution. Therefore, it is expected that with increasing L_{Maxv}, the objective function is improved. The figure shows that with increasing L_{Maxv}, the objective function is reduced until L_{Maxv} equals to 1 which is its assumed value in the problem. In this case, the objective function value is reached to its minimum value and in fact, the constraints of L_{Maxv} are relaxed.

5-4-2- Sensitivity Analysis of Q_v Parameter

In this case, it can be seen that by increasing Q_v, the total amount of vehicle fuel capacity is reduced. This shows that by increasing the amount of Q_v, feasible space of the problem response increases and this makes it possible to find better solutions.

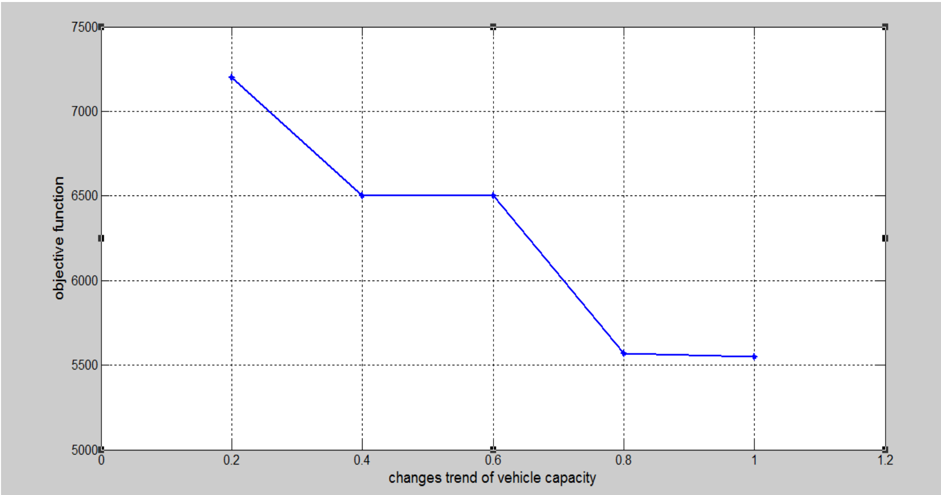

Fig 5. Changes in the objective function to change vehicle capacity

5-4-3- Sensitivity analysis of Fc_{ijrev} parameter

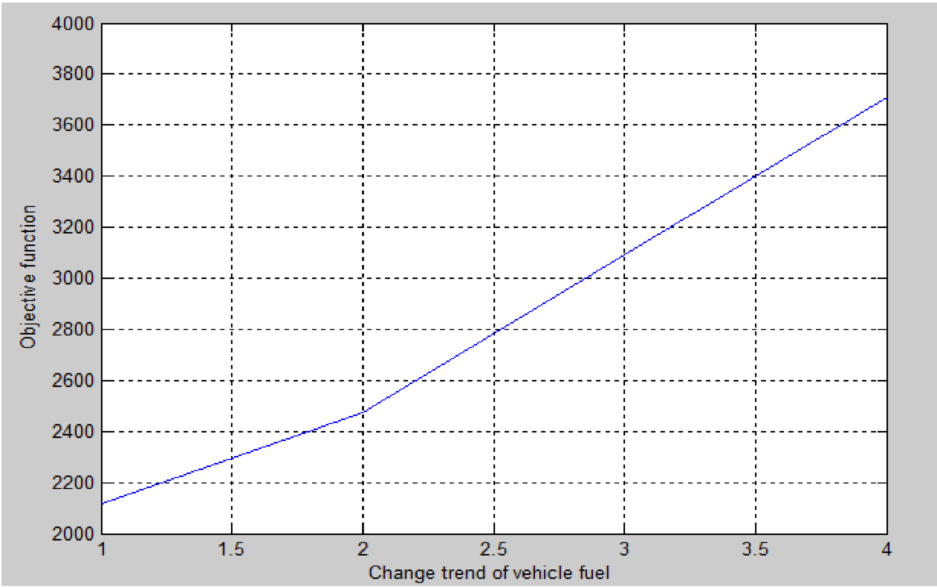

Fig 6. Changes in the objective function to change vehicle Fuel

According to the definition of FC, it is obvious that with the fuel increase for moving from node *i* to node *j* via route *r* by vehicle *v* in the working shift of *e*, the total fuel consumption of the fleet will increase. This is evident in the figure and it can be seen that the value of objective function increases with the increase of FC.

6- Conclusion

Transportation is one of the most important parts of the supply chain which has non- replaceable substructure and is an alternative for economic growth of each country. Generally, the aim of vehicle routing problem is to affect economically the transportation routes to organize transportation services. Therefore, the use of energy and hence the air pollution are serious threats during recent years.

These threats and warnings have made the researchers to pay attention to the transportation fields seriously and think to proper and applicable solutions and to reduce the fleet fuel consumption and to optimize the transportation system. Green vehicle routing problem is related to vehicle routing problem is about the fuel consumption. Logistic activities such as expired products collecting can have great effect on the environment and therefore more friendly practical methods are used for the environment. This can lead to great achievements like environment protection and cost saving of the fleet fuel. In this paper, a model is presented for reduction of fleet fuel consumption which are heterogeneous and reverse logistics of the city expired products was planned. Generally, to achieve this target, the criteria like the covered distance by vehicle, the carried weight by vehicle, traffic, vehicle speed are considered. To represent this model, the criteria such as distance, weight, and traffic and time window are regarded. This operation is done in a level of factory and customer. The model is solved by DE algorithm and the Gams software the results were presented. The results showed that differential evolution algorithm works more efficient than the Gams software.

In this paper, reverse logistics in a single-level system showed the potential to be used in future research for the reverse logistics multi-level system.

Further research may focus on different topics including:

- ✓ Periodic VRP under uncertainties in vehicles availability can be examined.
- ✓ A new recovery model in case of crisis and occurrence of any scenarios can be proposed.
- ✓ Developing the proposed model in which scheduling resources time and employees abilities can be considered.

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