Green Vehicle Routing Problem with Safety and Social Concerns

Arghavan Sharafi[a], Mahdi Bashiri[b,*]

[a]*MSc, Department of Industrial Engineering, Faculty of Engineering Shahed University, Tehran, Iran*

[b] *Professor, Department of Industrial Engineering, Shahed University, Tehran, Iran*

Received 14 March 2016; Revised 08 May 2016; Accepted 13 May 2016

Abstract

Over the two last decades, distribution companies have been aware of the importance of paying simultaneous attention to all economical, environmental, social, and safety aspects of a distribution system for success in the global market. The economic issue is often used in case of the Vehicle Routing Problem (VRP) literature, while the environmental, the safety and the social concerns constitute less proportion of studies. The Green vehicle routing problem (GVRP) is one of the recent variants of the VRP, dealing with environmental aspects of distribution systems. In this paper, two developed mixed integer programming models are presented for the GVRP with social and safety concerns. Moreover, a Genetic Algorithm (GA) is developed to deal efficiently with the large-sized problem . Different numerical analyses have been performed to validate the presented algorithm in comparison to exact solutions and to investigate the influence of several key factors such as the effect of increasing the cost of safety aspect on route balancing and customer's waiting time. The results confirm that the proposed algorithm performs well and has more social and safety benefits, including more balanced tours and fewer customers' waiting time than those of the classic GVRP.

Keywords: Logistics, Green vehicle routing problem, Route balancing, Mixed integer linear programming, Genetic algorithm.

1. Introduction

Among harmful impacts that transportation has on the environment, air pollution is the most important one concerning (Bektaş & Laporte, 2011). One approach to deal with this problem is to switch vehicle fuels from fossil fuels to alternative ones. Nowadays, many energy policies such as those of government regulations, tax incentives, and motivated plannings are considered to motivate companies to use new green fuels in order to protect the environments and decrease the amount of air pollution. There are many obstacles to use a fleet of AFVs , such as the short driving ranges of alternative fuel vehicles (AFVs), lack of infrastructures for alternative fueling stations (AFSs), and unevenly distribution of AFSs. The GVRP, as a new variant of the VRP, takes into account these additional challenges associated with using AFSs (Erdoğan & Miller-Hooks, 2012).

In the social and safety aspects, providing employees with a safer workplace and equity increased the job satisfaction among workers. Many companies pay their staff based on the working hours; therefore, the substantial differences between working hours can be considered unfair. So, substantial differences among drivers' working time could be considered unfair, too. ((Lee & Ueng, 1999)); this may increase the numbers of accidents, caused by the tired drivers who work in lengthier tours. So, considering the social aspect which seeks to decrease the difference between tours' lengths executed by drivers, one can claim that it can serve as a motivation for drivers to remain loyal to companies. On the other hand, when the firm's fleet distributes cargoes in parallel, customers may receive their goods sooner. So, customers' waiting time decreases and the freshness of goods increases. The Vehicle Routing Problem with Route Balancing (VRPRB) is introduced to deal with these problems.

So, the increase of staff's loyalty to company and customers' satisfaction, and, on the other hand, the decrease of the amount of air pollutions can be considered as some managerial implications of the obtained results.

In this study, two models for GVRP with social and safety concerns are presented. In the first one, an aggregated model is presented to investigate the trade-off between the economic aspect (minimizing the total travelled distance and the refueling cost) and the social aspect (minimizing the difference between tour lengths "duration") for a predetermined number of vehicles). In the other model, the economic aspect and the risk costs for probable accidents, which may occur during the tour length, are considered without a predefined number of vehicles. The results of the different computational experiment are

* Corresponding author Email address: Bashiri@shahed.ac.ir

reported to assess models and different key factors. To solve the model for large instances, we develop a GA and analyze its performance in the next sections.
The structure of this paper is organized as follows: In the next section, a brief review of recent related studies is presented. Then, the mathematical models are presented in section 3. In section 4, some sensitivity analyses, performed to investigate the effect of different factors, are reported. Finally, concluding remarks are provided in the last section.

2. Literature Review

In VRP literature, models considering fuel tank capacity limitations are rare. As described in the introduction, (Erdoğan & Miller-Hooks, 2012) introduced GVRP for the first time and solved it with two modified heuristics. (Schneider, Stenger, & Goeke, 2014) extended the GVRP model. They considered capacity and time window restrictions and solved the model with a hybrid metaheuristic. (Yang & Sun, 2015) studied routing plan of a fleet of capacitated electric vehicles (EVs). They considered the strategic decision of determining the best location of AFSs and proposed two heuristics to solve the problem.
One of the other related problems to our study is VRPRB. In VRPRB models, two intrinsically conflicting objectives are optimized. Some researchers formulate this problem as an aggregated single objective, while some others consider it as a multi-objective optimization problem (MOP) and use multi-objective evolutionary algorithms (MOEA) to approximate the Pareto set. In VRPRB, different tour’s workloads, such as the number of visited customers, the number of delivered goods, the tour’s lengths (distance or time), make different balancing objectives ((Jozefowiez, Semet, & Talbi, 2008)). However, there is no study which considers safety aspects in this type of problems. A brief history of related research papers is shown in Table 1.

Table 1
A brief review of previous studies on the route balancing

Researchers	Problem	Solution Methods	Workload	Objectives
(Sutcliffe & Boardman, 1990)	VRP	MILP	TT,C	Min.TD, Max. EVTT, Max. C
(Ribeiro & Ramalhinho Dias Lourenço, 2001)	MPVRD	A-ILS	VT	Min.TD, MIN. DVT, Max. D/C R
(Jozefowiez, Semet, & Talbi, 2006) (Jozefowiez, Semet, & Talbi, 2002) (Jozefowiez, Semet, & Talbi, 2007) (Jozefowiez, Semet, & Talbi, 2009)	VRP	MOEA/MT	TT	Min.TD Min. DWT
(Ramos, Gomes, & Barbosa-Póvoa, 2014)	MDPVRPI	MT	TT	Min.TD ,Min. DWT
(Oyola & Løkketangen, 2014)	CVRP	H	TT	Min. TRC ,Min. DWT
(Lacomme, Prins, Prodhon, & Ren, 2015)	VRP	MSSPR	TT	Min. TRC ,Min. DWT
This research	GVRP	MT	TT, SC	Min. TRC, Min TT,

VRP: Vehicle Routing Problem; MILP: Mixed Integer Linear Programing; TT: Tour Time; C: Capacity; TD: Total Distance; EVTT: Equalization of the Vehicle Travel Times; A: Aggregation; H: Heuristic; MPVRD: Multi-Period Vehicle Routing Problem; ILS: Iterated Local Search; VT: Volume Transported; DVT: Difference between Volume Transported; D/C R: Driver/Customer Relationship ; MOEA: Multi-Objective Evolutionary Algorithms; MDPVRPI :Multi-Depot Periodic Vehicle Routing Problem with Inter-depot routes; MT: Metaheuristic; TRC: Total Routing Cost; CVRP: Capacitated Vehicle Routing Problem; MSSPR: Multi-Start Split based Path Relinking approach; SC: safety cost.

Sets:

v_0	Depot
I	Set of customers

3. Problem Definition

In this paper, for both models, a fleet of AFVs, which delivers customer demands from a single depot, was studied. AFVs leave the depot with full tank capacity and defeat their limited driving range by visiting a set of AFSs existed in the route. Vehicles can visit a station many times and should complete their tours in a pre-specified limited time (T_{MAX}). For the first model, called Green Vehicle Routing Problem with Route Balancing (GVRPRB) 1 (GVRPRB1), the non-linear model is presented, and then we try to linearize it. Finally, an alternative model is presented. To clarify the model, notations, used in this paper, are listed as follows.

Sets:

F	Set of AFSs
F'	Set of stations and dummies (which is considered to permit several visits from

each station)

Set:

I_0 Set of customers and depot, $I_0 = \{v_0\} \cup I$

V Set of real vertices, $V = \{v_0\} \cup I \cup F$

V' Set of vertices, including dummies vertices, $V = \{v_0\} \cup I \cup F'$

K Set of vehicles

Non-decision variables and parameters:

F_0 Set of AFSs and depot , $F_0 = \{v_0\} \cup F'$

l_k Difference between tour lengths and average of all tour lengths

o_k Difference between tour lengths (which are longer than the average) and average of all tour lengths

s_k Difference between tour lengths (which are shorter than the average) and average of all tour lengths

τ_j Time variable specifying the time of arrival of a vehicle at vertex j

tv_k Tour length for vehicle k

$\bar{t}$ Average of tours time

Non-decision variables and parameters:

y_j Fuel level variable specifying the remaining tank fuel level upon arrival to vertex j.

W_1 Traveling cost for each unit of traveled distance

W_2 Social cost for each unit of staffs' dissatisfaction, because of unfair assigned tours' length

W_3 The fix refueling cost in each visit of AFSs

r Vehicle fuel consumption rate (gallons per mile)

Q Vehicle fuel tank capacity

T_{MAX} Maximum tour lengths

d_{ij} Distance between vertex i and j

t_{ij} Travelling time between vertex i and j

m Number of vehicles

Decision variables:

x_{ijk} Binary variable equals to 1 if vehicle k travels from vertex i to j;0, otherwise

$$\text{Min } W_1 (\sum_{i\in V'} \sum_{j\in V', j\neq i} \sum_{k\in K} d_{ij} x_{ijk}) + W_2 (\sum_{k\in K} l_k, w) + W_3 (\sum_{i\in V'} \sum_{j\in F', j\neq i} \sum_{k\in K} x_{ijk}) \tag{1}$$

$$\sum_{j\in V', j\neq i} \sum_{k\in K} x_{ijk} = 1 \qquad \forall i \in I \tag{2}$$

$$\sum_{j\in V', j\neq i} x_{ijk} \leq 1 \qquad \forall i \in F_0, \forall k \in K \tag{3}$$

$$\sum_{i\in V', i\neq j} x_{ijk} - \sum_{i\in V', i\neq j} x_{jik} = 0 \qquad \forall j \in V', k \in K \tag{4}$$

$$\sum_{i\in v_0} \sum_{j\in V' \setminus \{v_0\}} \sum_{k\in K} x_{ijk} = m \tag{5}$$

$$\sum_{i\in v_0} \sum_{j\in v' / \{v_0\}} x_{ijk} = 1 \qquad \forall k \in K \tag{6}$$

$$\tau_j \geq \tau_i + (t_{ij} + p_j) x_{ijk} - T_{MAX} (1 - x_{ijk}) \qquad \forall i \in V', j \in V' \setminus \{v_0\}, k \in K \text{ and } i \neq j \tag{7}$$

$$\sum_{i\in V'} \sum_{j\in V', j\neq i} (t_{ij} + p_j) x_{ijk} = tv_k \qquad \forall k \in K \tag{8}$$

$$tv_k \leq T_{MAX} \qquad \forall k \in K \tag{9}$$

$$\bar{t} = (\sum_{k\in K} tv_k) / m \tag{10}$$

$$|tv_k - \bar{t}| = l_k \qquad \forall k \in K \tag{11}$$

$$y_j \le y_i - (r.d_{ij})x_{ijk} + Q(1 - x_{ijk}) \qquad \forall j \in I, i \in V', k \in K \text{ and } i \ne j \tag{12}$$

$$y_j \ge (r.d_{ij})x_{ijk} \qquad \forall j \in V', i \in V', k \in K \text{ and } i \ne j \tag{13}$$

$$y_j = Q \qquad \forall j \in F_0 \tag{14}$$

$$x_{ijk} \in \{0,1\} \quad \forall i, j \in V', \forall k \in K \qquad , \forall i, j \in V', \forall k \in K \tag{15}$$

$$l_k \ge 0 \qquad \forall k \in K \tag{16}$$

$$y_i \ge 0 \qquad \forall i \in V' \tag{17}$$

The objective function (1) minimizes three criteria simultaneously: the total cost of travelled distance, the total cost of refueling in each visit of AFSs, and the difference between each tours' time with an average of all ones. The value of variables determines the concerned constraints (11). Constraints (2) ensure that each customer's demand is satisfied by a vehicle. Constraints (3) ensure that each AFS (or associated dummy vertices) can be visited one time or not at all and will have one successor (a customer, AFS or depot vertex) if any vehicle visits it. Constraints (4) guarantee continuity of tour in the network. Constraint (5) denotes that exactly *m* vehicles leave the depot. Constraints (6) make certain that each vehicle is assigned to only one trip. Constraints (7) track time at each vertex, visit based on vertex sequence, and also eliminate the possibility of sub tour formation. Constraints (8) calculate tour length for each vehicle. Constraints (9) make sure that each time trip is not longer than T_{MAX}. Constraint (10) calculates the average of all tour lengths. Constraints (11) compute deviation of each tour length from the average of all tours' lengths. Vehicles' fuel levels based on customer sequence are tracked by Constraints (12). Constraints (13) guarantee that vehicles can pass a route if they have enough fuel to pass it. Constraints (14) reset fuel tank level to Q , when vehicles leave the depot or AFSs. Finally, the decision variables' binary and positive natures are stated by constraints (15), (16), and (17). For linearizing constraints (11), two new non-decision variables are presented.

Non-decision variables	
o_k	Difference between tour lengths (which are longer than the average) and average of all tour lengths
s_k	Difference between tour lengths (which are shorter than the average) and average of all tour lengths

The objective function, constraints (11) and (16) are changed to:

$$\text{Min} \quad W_1 (\sum_{i \in V'} \sum_{j \in V', j \ne i} \sum_{k \in K} d_{ij} x_{ijk}) + W_2 (\sum_{k \in K} (o_k + s_k)) + W_3 (\sum_{k \in K} \sum_{i \in F'} \sum_{j \in V'} x_{ijk}) \tag{18}$$

$$tv_k - \bar{t} = (o_k - s_k) \qquad \forall k \in K \tag{19}$$

$$o_k, s_k \ge 0 \qquad \forall k \in K \tag{20}$$

It is worth mentioning that the newly-defined variables will not get a value simultaneously, because the existence of two new positive non-decision variables in the objective function makes one of these two variables always zero to minimize the objective function. In the previous model, it is assumed that the numbers of vehicles are predefined, but it is preferable to find an optimum number of vehicles in real cases, so a new model, called GVRPRB 2, is presented without the necessity of the required number of vehicles. This model aims to reduce the risk of accidents. By increasing the drivers' working time, the risk of accident increases, too. So, the model considers two different risk costs per hour for two levels of tour length. It is clear that the second one has a higher value because of its importance (the risk of the accident increases by the tiredness of the drivers). The presented model intends to reduce the risk of the accident through reducing risk cost on level 2 of the whole tours. For presentation of models, these extra notations are used:

Non-decision variables and parameters:	
tc_k	Total cost pertaining to vehicle *k*
c_1	Risk cost per hour in level 1
c_2	Risk cost per hour in level 2
th	Pre-defined threshold for calculating saving safety cost in level 2
u_k	The difference between tour length and threshold

The new GVRP with safety aspect is presented in the following::

$$\text{Min } W_1 (\sum_{i \in V'} \sum_{j \in V', j \ne i} \sum_{k \in K} d_{ij} x_{ijk}) + W_2 \sum_{k \in K} tc_k + W_3 (\sum_{k \in K} \sum_{i \in F'} \sum_{j \in V'} x_{ijk}) \tag{21}$$

All constraints are used in model 1 except (5), (10), (11), and (20). New constraints are presented as below:

$$\sum_{k \in K} \sum_{j \in V' \setminus \{v_0\}} x_{0jk} \le m \tag{22}$$

$$tv_k - u_k \leq th \qquad \forall k \in K \tag{23}$$

$$tc_k = c_1(tv_k) + (c_2 - c_1)u_k \qquad \forall k \in K \tag{24}$$

$$u_k \geq 0, \forall k \in K \tag{25}$$

The objective function (21) minimizes the total risk cost, computed by constraint (24), and economic aspects. Constraint (22) denotes that up to m vehicles can leave the depot. Constraints (23) declare that if time length passes the predefined threshold, the risk cost for level 2 is calculated. Constraints (24) calculate the total risk cost for each vehicle. The u_k positive nature is stated by Constraint (25).

4. Computational Experiment

In the following sections, the effect of different parameters is investigated to show the model performance as well as to check its validity. The models and algorithms were implemented in Gams (version 22) and Matlab software products, respectively. Furthermore, To investigate the effect of the presented model on medium and large sizes, the performance of the proposed genetic algorithm is analyzed. The data, used in this paper, are available at http://neo.lcc.uma.es/vrp/vrp-instances/.

4.1. Test instance and parameter setting

(Augerat et al., 1995) introduced three sets of instances, of which part A, A-N32-K8 was used to solve small-sized problems (1-25 customer) in Table 3. Instead of using all customers in the instance, each instance only contains the first *(n+s)* nodes. For example, "A-n11-4s" uses the first 15 nodes: the first eleven nodes as customers and the remained four nodes (from 12 to 15) as stations. The driving range is set to$Q = 2d_{max}$, where d_{max} is the maximal Euclidean distance between any two points in the network. For samples 1 to 7, the amounts of W_1,W_2, and W_3 for the first model are set to 1, 2, and 100 respectively, and for the remained samples, the amount of W_2 changes to 5. The amounts of T_{MAX} for different instances are presented in the last column of Table 3. Service times were assumed to be two hours at customer locations and one hour at AFS locations. The crossover and mutation rate is set to 0.4. The rates of using the elitist and the worst chromosomes in next iterations are set to 0.1. Furthermore, the parameters of the proposed algorithm have been set as follows: (1) the maximal number of iterations is set as 10, 50, 200, and 800 for the first, second, third,and other remained instances. (2) The number of populations for the first two samples is set to 10 and 20 for others.

4.2. The Effect of presented GVRPRB1 model in comparison with classical GVRP model

In this analysis, we focus on the effect of the presented model. In the selected example (A-n8-1s), two routes exist. The length difference between the two routes in classic GVRP, which does not consider social aspect, is substantially greater than that of GVRPRB1. The results are depicted in Fig 1. It shows that by using the proposed model, the network tends to balance routes and cause social benefits.

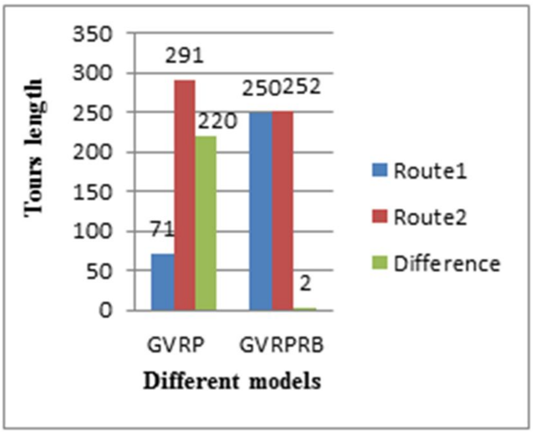

Fig. 1. Effect of green tour balancing model

4.3. Effect of tour balancing on customers' waiting time

The outcomes of considering social aspect in classical GVRP may not be limited to equity between employees. When firm's fleet works in parallel, the cargo distribution will be completed as soon as possible. So, the customers' waiting time may decrease, and the freshness of goods increases in several cases in the GVRPRB in comparison to the GVRP. This result is valuable to firm's reputations.

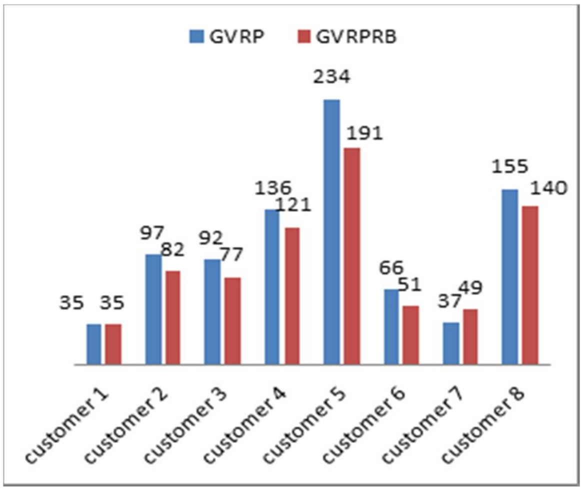

Fig. 2. Effect of route balancing on the strategic points of customers' waiting time

4.4. Effect of increasing the risk cost on the second level in GVPRPB2

As demonstrated in Fig 3, by increasing the risk cost on level 2 from $c_2 = 10$ to $c_2 = 110$, the difference between tour lengths is decreased to reduce the amount of total risk cost (the amount of risk in level one is fixed and equal to 10). It leads to a reduction in the potential for the accident caused by the tired drivers who work in lengthier tours.

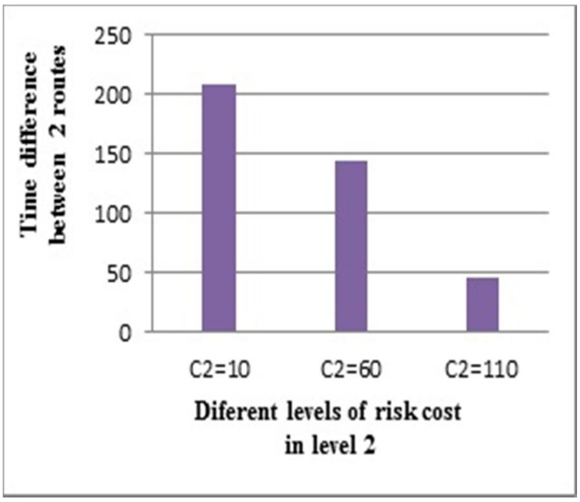

Fig. 3. Effect of increasing the risk cost of accident in the second level

4.5. The effect of the two presented models on tour balancing

Both presented models can obtain the same results by using particular coefficients. Table 2 represents this fact: three exact examples are performed which are solved by both models and have the same results with equal tour lengths. Actually, the main difference between presented models is that in the first one, the number of used vehicles is fixed, but in the last one, it is considered as a decision variable.

Table 2
Results of comparison between GVRPRB1 and GVRPRB2

sample	GVRPRB1		CVRPRB2		
	DTB	C_1	C_2	TH	DTB
A-n5-2s	46	5	10	180	46
A-n6-2s	53	5	20	230	53
A-n8-1s	46	0	100	240	46

DT=Difference between tour times, TH= Pre-defined threshold

4.6. Computational result of the presented algorithm

Based on the presented parameter setting and algorithmic structure, the proposed algorithm is tested on different instances. A comparison is made between the proposed GA algorithm and the exact algorithm in CPLEX Solver for small-sized instances. In Table 3, "*" represents feasible solutions found by Gams within three hours (hrs). "#" denotes that Gams failed to obtain a feasible solution in 3 hrs. The data in columns 5-7 are obtained by averaging data from five-time run of the genetic algorithm. The gaps in column 8 are defined as corresponding average objective value - objective value obtained by Gams, or objective value obtained by Gams.

Fig 4 shows the difference between maximum and minimum tours' lengths in classic GVRP and GVRPRB for each sample of Table 4. The data are obtained by reporting the difference between maximum and minimum tours' lengths in the best answer. (If the best answer cannot be found by Gams in three hours, the best answer, found by GVRP algorithm in five-time run, is reported). The length difference between routes in GVRP, which does not consider social aspect, is substantially greater than that of GVRPRB. The results show that by using the proposed model, the network tends to balance routes and cause social benefits.

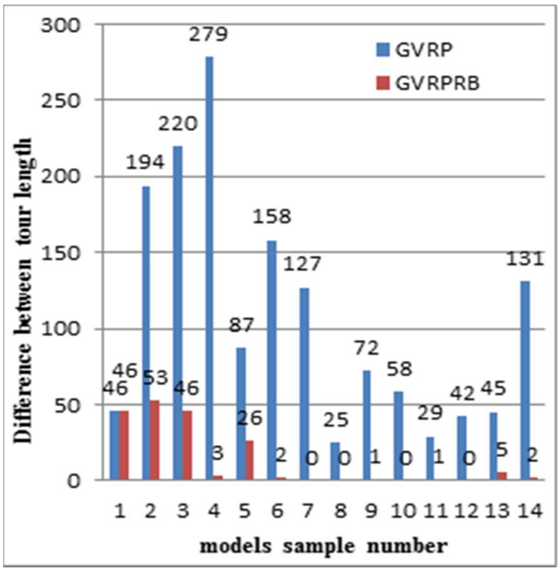

Fig. 4. Results of comparison between GVRPRB and GVRP

4.7. The impact of the proposed algorithm on dealing with large size

To investigate the efficiency of the presented GA in dealing with larger instances, one instance of 72 customers is designed with location clustered customers in two groups. Each group has 36 members. The clusters are designed to have the same tour length. The optimum tour plan for each cluster is obtained by CPLEX Solver. Then, the problem is solved by the proposed algorithm too. In the best report of ten-time repetition of the algorithm, the proposed GA (equipped with the 2-opt in the last iteration) can distinguish each of clusters, and the total distance of each cluster has 18 % and 23 % gaps from best solutions. This comparison confirms that the proposed algorithm has proper efficiency in solving the problem for large instances in an acceptable computational time.

Table 3
Results of comparison between Gams and the genetic algorithm for the generated instances

Sample number	sample	Gams			GAs					T_{MAX}
		Result	Time(s)	|k|	Best	Average	Time(s)	Gap (%)	|k|	
1	A-n5-2s	576	6.8	2	576	576	2.6	0.0	2	240
2	A-n6-2s	595	10.71	2	595	595	3.3	0.0	2	270
3	A-n8-1s	626	2132.9	2	626	629	9	0.11	2	300
4	A-n11-4s	698*	10800	2	698	700	84	0.15	2	300
5	A-n15-4s	768*	10800	2	639	666	307	-3.6	2	350
6	A-n20-4s	894*	10800	2	734	784	224	-3.7	2	350
7	A-n25-4s	#	10800	-	704	868.5	180	-	2	350
8	A-n30-5s	#	10800	-	1002	1158	206	-	3	350
9	A-n40-5s	#	10800	-	1560	1839	244	-	4	350
10	A-n50-4s	#	10800	-	1040	1881	297	-	5	350
11	A-n60-4s	#	10800	-	1315	1536	314	-	5	350
12	A-n75-4s	#	10800	-	2013	2369	240	-	5	350
13	Tia100a-n95-4s	#	10800	-	4605	4942	415	-	15	350
14	Tia150a-n145-4s	#	10800	-	8890	10716	825	-	9	1000

|k|: minimum number of used vehicles

5. Conclusion

The necessity of paying attention to environmental and social aspects in the design of distribution networks has been motivated by governments and organizations over the last decade. This fact leads to an increase in the numbers of articles considering this area; however, the articles, which studied the combination of these three concerns together, are rare. In this paper, two GVRPRB models are introduced as an extension of the classic GVRP, which take into account social, safety, and economic aspects of designing a fleet of AFVs. The models aim to minimize the differences between tour lengths that lead to maximization of social fairness and minimization of the accident risk related to tiredness of drivers. Different analyses were performed to assess the effect of the main factors of the problem in various instances. The results shown in four figures (Fig 1to 4) confirm the validity of the proposed models and also highlight the social and safety aspects' effects on such networks. Moreover, a genetic algorithm is developed with the aim of solving the real-sized instances. In the computational experiments, the comparison between the impacts of models on tour balancing and the comparison between the quality of solutions, obtained by the proposed algorithm and exact solutions, are shown in two different tables (Table 2-3). Also, the algorithm was tested for large instances. The results confirm the proposed algorithm efficiency. Considering the problem, when stations have stochastic nature of accessibility, there can be a direction for further research studies.

References

Augerat, P., Belenguer, J., Benavent, E., Corberán, A., Naddef, D., & Rinaldi, G. (1995). *Computational results with a branch and cut code for the capacitated vehicle routing problem*: IMAG.

Bektaş, T., & Laporte, G. (2011). The Pollution-Routing Problem. *Transportation Research Part B: Methodological, 45*(8), 1232-1250.

Erdoğan, S., & Miller-Hooks, E. (2012). A green vehicle routing problem. *Transportation Research Part E: Logistics and Transportation Review, 48*(1), 100-114.

Jozefowiez, N., Semet, F., & Talbi, E.-G. (2002). Parallel and hybrid models for multi-objective optimization: Application to the vehicle routing problem *Parallel Problem Solving from Nature—PPSN VII* (pp. 271-280): Springer.

Jozefowiez, N., Semet, F., & Talbi, E.-G. (2006). *Enhancements of NSGA II and its application to the vehicle routing problem with route balancing.* Paper presented at the Artificial evolution.

Jozefowiez, N., Semet, F., & Talbi, E.-G. (2007). Target aiming Pareto search and its application to the vehicle routing problem with route balancing. *Journal of Heuristics, 13*(5), 455-469.

Jozefowiez, N., Semet, F., & Talbi, E.-G. (2008). Multi-objective vehicle routing problems. *European Journal of Operational Research, 189*(2), 293-309.

Jozefowiez, N., Semet, F., & Talbi, E.-G. (2009). An evolutionary algorithm for the vehicle routing problem with route balancing. *European Journal of Operational Research, 195*(3), 761-769.

Lacomme, P., Prins, C., Prodhon, C., & Ren, L. (2015). A Multi-Start Split based Path Relinking (MSSPR) approach for the vehicle routing problem with route balancing. *Engineering Applications of Artificial Intelligence, 38*, 237-251.

Lee, T.-R., & Ueng, J.-H. (1999). A study of vehicle routing problems with load-balancing. *International Journal of Physical Distribution & Logistics Management, 29*(10), 646-657.

Oyola, J., & Løkketangen, A. (2014). GRASP-ASP: An algorithm for the CVRP with route balancing. *Journal of Heuristics, 20*(4), 361-382.

Ramos, T. R. P., Gomes, M. I., & Barbosa-Póvoa, A. P. (2014). Planning a sustainable reverse logistics system: Balancing costs with environmental and social concerns. *Omega, 48*, 60-74.

Ribeiro, R., & Ramalhinho Dias Lourenço, H. (2001). A multi-objective model for a multi-period distribution management problem. *Available at SSRN 273419*.

Schneider, M., Stenger, A., & Goeke, D. (2014). The electric vehicle-routing problem with time windows and recharging stations. *Transportation Science, 48*(4), 500-520.

Sutcliffe, C., & Boardman, J. (1990). Optimal solution of a vehicle-routeing problem: transporting mentally handicapped adults to an adult training centre. *Journal of the Operational Research Society*, 61-67.

Yang, J., & Sun, H. (2015). Battery swap station location-routing problem with capacitated electric vehicles. *Computers & Operations Research, 55*, 217-232.

This article can be cited: Sharafi, A. & Bashiri, M.(2017). Green Vehicle Routing Problem with Safety and Social Concerns. *Journal of Optimization in Industrial Engineering.* 10(21), 93-100.

URL: http://qjie.ir/article_264_37.html