Green Vehicle Routing Problem with Safety and Social Concerns

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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

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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

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

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

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

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

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

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

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

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

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

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

$$tv_k - u_k \le th \qquad \forall k \in K \qquad (23)$$

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

$$u_k \ge 0, \forall k \in K \qquad (25)$$

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.

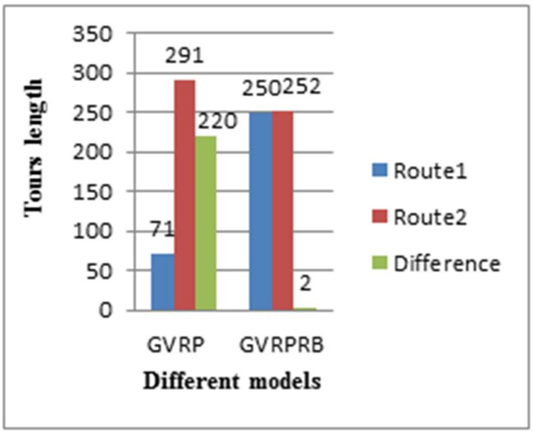

Fig. 1. Effect of green tour balancing model

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.

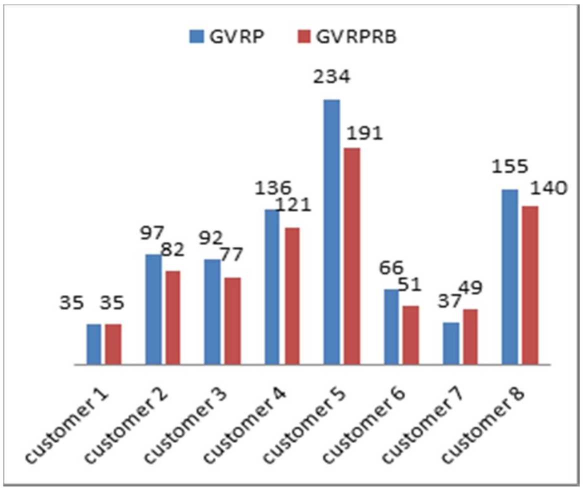

Fig. 2. Effect of route balancing on the strategic points of customers' waiting time

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.

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