TRANSPORT

Special Issue on the Multiple Criteria Decision Making (MCDM) and Sustainability in Transportation Systems

ISSN 1648-4142 / eISSN 1648-3480

Article in press

https://doi.org/10.3846/transport.2021.14464

MULTI-OBJECTIVE GREEN MIXED VEHICLE ROUTING PROBLEM UNDER ROUGH ENVIRONMENT

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Submitted 16 October 2019; resubmitted 12 December 2019; accepted 3 February 2020; first published online

Abstract. This paper proposes a multi-objective Green Vehicle Routing Problem (G-VRP) considering two types of vehicles likely company-owned vehicle and third-party logistics in the imprecise environment. Focusing only on one objective, especially the distance in the VRP is not always right in the sustainability point of view. Here we present a bi-objective model for the G-VRP that can address the issue of the emission of GreenHouse Gases (GHGs). We also consider the demand as a rough variable. This paper uses the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to solve the proposed model. Finally, it uses Multicriteria Optimization and Compromise Solution (abbreviation in Serbian – VIKOR) method to determine the best alternative from the Pareto front.

Keywords: green VRP, multi-objective VRP, evolutionary methods, NSGA-II, VIKOR, sustainability.

Notations

ACO – ant colony optimization;
ACVRP – asymmetrical CVRP;
ALNS – adaptive large neighbourhood search;
CO_2 – carbon dioxide;
CVRP – capacitated VRP;
FCR – fuel consumption rate;
G-VRP – green VRP;
GHG – greenhouse gas;
GPS– global positioning system;
NSGA-II – non-dominated sorting genetic algorithm II;
PAES – Pareto archived evolution strategy;
PMX – partially mapped crossover;
SCVRP – symmetrical CVRP;
SPEA – strength Pareto evolutionary algorithm;
TOPSIS – technique for order of preference by similarity to ideal solution;
TSP – travelling salesman problem;
VIKOR – multicriteria optimization and compromise solution (in Serbian: *Višekriterijumska optimizacija I KOmpromisno Rešenje*);
VRP – vehicle routing problem;
VRPTW – VRP with time windows.

Introduction

One of the essential requirements for living beings is air. Nevertheless, it should be fresh as the polluted air can be the source of several diseases. Air pollution becomes the biggest threat to human beings. There are several sources of air pollution. One of the vital sources is transportation. Most of the developed cities are facing this problem, which increases day by day. This fact leads us to this research work. Generally, the transportation agencies focus their viewpoint on the profit based on shortest distance or time. They are not bothering about the pollution that the vehicles generate in nature. So the time has come to look at this particular issue; otherwise, the question will arise

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on the existence of our next generation. In EU, more than 0.4 million early deaths are recorded in 2016 because of this polluted air as per the report published by Ekblom (2019). Due to this air pollution, our society suffers several adverse impacts like the decrease of agricultural lands and yields, a detrimental effect on our ecosystems and threat to biodiversity, deterioration of historic buildings. The result of transport in the environment is a burning issue as it is the primary user of energy and it burns petroleum. It produces nitrous oxides, particulates and CO_2 that are a significant contributor to global warming. So road transport has to be appropriately planned with a vision to keep our environment green as much as possible. The government passed several environmental regulations to reduce the air pollution caused by the personal vehicle's emission. We need to study the potential pathways to reduce the carbon emissions of road vehicles. The transportation sector is the primary source of GHG semissions. In 2017, 28.9% of US GHG emissions were from transportation as per the report published in report by the EPA (2019b). 14% of global CO_2 emissions was because of the transport sector as per the report published in report by the EPA (2019a). Besides, the emissions also depend on the driving quality as well as the load of the vehicle. In this scenario, researchers need to consider both the energy and environmental issues while designing the transport route.

The VRP is a topic associated with the transportation sector that plans how to distribute the products to different customers placed in different geographical locations. The VRP has a similarity with the TSP as here instead of one salesman it deals with more than one salesman or vehicles. TSP finds the shortest possible route to cover all the cities of the system visited by a single sales representative. In the 1930s, Merrill Flood first introduced the concept of TSP while solving a problem of school bus routing (Lawler *et al.* 1985). Hassler Whitney first coined the term of TSP (Schrijver 2002). The VRP, in its most straightforward form CVRP, finds the shortest possible route to cover all the cities of the system served by several vehicles started from a central depot to supply products to the different customers. Here each vehicle will have some limited capacity. The term CVRP was first coined by Dantzig and Ramser (1959), when they published a paper on the dispatching problem of trucks. Then onwards several works published in this field, and gradually researchers introduced different variants of VRP in literature. The variety of VRP comes based on different needs like the type of goods to carry the service quality, the customer type and the vehicle type. The VRP can be static where the demands of customers are fixed and are known a priori, or it can be dynamic where the demands may become known after the vehicles start their journey. The CVRP can be either SCVRP or ACVRP based on their cost matrix or distance matrix. There are several types of VRP (Braekers *et al.* 2016). These are VRP with backhauls, VRP with both pickup and delivery, multi-depot VRP, stochastic VRP, periodic VRP, multi-compartment VRP, site-dependent VRP, VRP with splitting of delivery, fuzzy VRP, multi-echelon VRP, VRPTW, etc. All the VRPs can be closed or open depending on whether the vehicles are returned to the central depot or not respectively. Most of the papers on VRP have focused on the minimization of distance or time. However, we should also consider some other important issues while solving the VRP. These are like maximization of profit, maximization of customer satisfaction, minimization of CO_2 emissions, minimization of employee workload and others. In the global scenario, we need to take the minimization of emissions of CO_2 and other pollutants as one of the essential factors while solving the VRP. The models that consider these environmental issues are called G-VRP. So instead of thinking only one objective while solving VRP, it is always better to consider more than one objectives and one of the goals must be related to the environmental issue so that our mother nature sustains.

In this paper, we have considered two objectives. One is the minimization of distance, and the other is the minimization of carbon emission. The main reason behind these is to find such a solution set that gives a trade-off between these two objectives rather than concentrating on a particular goal. We can refer the model as multi-objective mixed G-VRP. Here both the features of open VRP and closed VRP have been considered. We describe the concepts of closed, open and mixed VRP in Figures 1–3. The vehicles used in this model are of the same capacity. The model has been solved using NSGA-II (Deb *et al.* 2002), a multi-objective type algorithm. There are several other methods, which can also be applied in this type of multi-objective type Problem. These are like PAES (Knowles, Corne 1999), improved SPEA (SPEA2) (Zitzler *et al.* 2001), etc. But in most of the cases, NSGA-II is performing better as it selects a good range of output and good convergence near the non-dominated results. Here also it shows a satisfactory result. Finally, the VIKOR method (Mardani *et al.* 2016) is used to get the decision-maker's choice from many alternatives that are very close to each other, and this will produce the best-optimized solution among all the Pareto front solutions in terms of sustainability.

The contribution of this paper is given below:
- the multi-objective mixed G-VRP is introduced in this paper;
- the demand is considered a rough variable to manage the imprecise nature;
- this work proposes an application of the NSGA-II and the VIKOR method to get the most suitable alternative solution from the approximate front as per the decision-maker's choice.

In the remaining portion of the paper, we have briefly discussed the literature review on the existing VRP in Section 1. The motivation of the work is discussed in Section 2. Then, the problem definition and modelling of the proposed multi-objective mixed G-VRP is presented in Section 3. While in Section 4, the brief discussion on NSGA-II

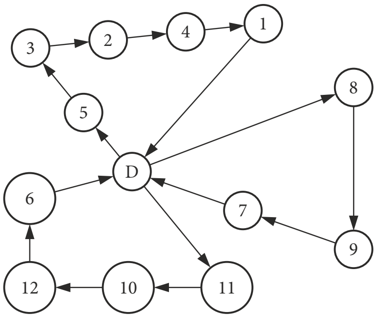

Figure 1. Closed VRP

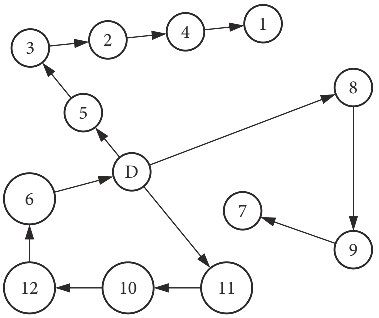

Figure 2. Open VRP

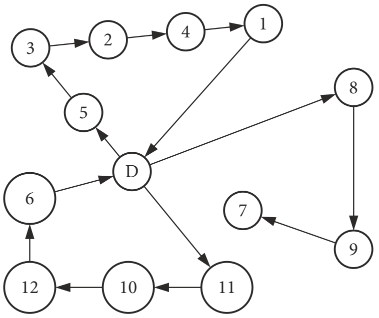

Figure 3. Mixed VRP

algorithm and its implementation are discussed. Section 5 offers a numerical illustration of the work. Section 6 presents the simulation results of the proposed work and its analysis. Finally, we have concluded the paper in the last section.

1. Literature review

A vast number of papers already published on VRP considering single-objectives. In multi-objective case of VRP, the literature does not have much research works in comparison with the single-objective type. Gambardella *et al.* (1999) proposed multi-objective VRPTW where one of the targets is to minimize the count of vehicles used, and the other is to minimize the time of travelling. Ribeiro and Lourenço (2001) introduced a multi-objective type of model on a multi-period kind of VRP. The author tried to reduce the travelled distance as minimum as possible along with an attempt to optimize the number of visited customers. Murata and Itai (2005) also proposed a multi-objective type VRP. Then Murata and Itai (2007) also published a paper on local search applied in the earlier version of VRPs. Tan *et al.* (2006) published a paper on VRPTW having two objectives like minimization of the count of vehicles, and the distance travelled. In the same year, Ombuki *et al.* (2006) presented a multi-objective type of genetic algorithm for VRPTW concept having the same two objectives as the previous one. Pacheco and Martí (2006) published one more paper in the same year on multi-objective routing problem where the authors used tabu search to resolve the issue. Jozefowiez *et al.* (2008) published a review paper on different research work on multi-objective VRP. Jozefowiez *et al.* (2009) also developed an evolutionary algorithm for the problem with two objectives that will minimize both distances travelled and route imbalanced. Liu and Jiang (2012) proposed a new version of the VRP by considering the concepts of both close and open VRP. The aim of this work is to minimize the cost of delivering the products. The authors' used mix integer programming and memetic algorithm to solve the model. Demir *et al.* (2014) published a paper on pollution-routing problem with two objectives to reduce fuel consumption and travelled time. They use a hybrid method combining ALNS algorithm with speed optimization procedure to find the result. Matl *et al.* (2018) provide an analysis of classical and other equity functions for multi-objective VRP models. Matl *et al.* (2019a) present ε-constraint-based frameworks to leverage directly on single-objective VRP heuristics in new multi-objective settings. Matl *et al.* (2019b) also present a paper on the classification of workload resources and equity functions. The G-VRP is a particular form of VRP with eco-friendly motive. The study on G-VRP was started in 2006. Erdoğan and Miller-Hooks (2012) have formulated a G-VRP model and solved the model by considering various types of fuel for the vehicles. It has used the mixed integer programming for modelling and solved using heuristics. Lin *et al.* (2014) published a survey paper on the types of VRP and highlighted the focus on the G-VRP. Qian and Eglese (2014) present time-dependent network model to minimize GHG emissions. Wen and Eglese (2016) publish a paper on bi-level pricing model that tries to minimize the CO_2 emissions and the total travel time in case of small network. Qian and Eglese (2016) present a paper on G-VRP using column generation based tabu search algorithm. Montoya *et al.* (2016) developed a heuristic using two different phases to solve the G-VRP, which consider various types of fuels and having different kinds of tank capacity. Kancharla and Ramadurai (2018) developed a variety of G-VRP by introducing the concept of fuel consumption estimation based on driving cycle from the GPS's data. Granada-Echeverri *et al.* (2019) publish a paper on VRP with backhauls. Granada *et al.* (2019) also develop a model on the open location-routing problem. They consider the topological attribute of the tour-paths.

If we focus on both the multi-objective and the green logistics, there are very limited papers in the literature. Siu *et al.* (2012) proposed a paper on a multi-objective

VRP, which tries to make optimization on the emissions of CO_2 and the path reduction. Molina *et al.* (2014) proposed a paper on G-VRP that considered multi-objective and heterogeneous fleet. It used Tchebycheff method. The three objectives are the minimization of costs, minimization of CO_2 emission and minimization of NO_x. Jabir *et al.* (2015) published a paper on multi-objective optimization of G-VRP. It has solved the model using ACO to get the paths for the vehicles. It has also used a variable neighbourhood search to reduce the emission of CO_2. Very recently, Poonthalir and Nadarajan (2018) published a paper on fuel efficient G-VRP, which has two objectives. These are cost and fuel minimization. They have used goal programming and PSO algorithm to solve the model. Turkson *et al.* (2016) applied NSGA-II in a multi-objective optimization problem in the automobile domain to sort out a trade-off between engine performance and hydrocarbon emissions. Zhou *et al.* (2016) also applied NSGA-II to solve a multi-objective problem in the automobile domain. VRP is such an important area that requires a lot of research even in the coming future. Recently, Huang *et al.* (2017) published a paper on sustainable process planning in the manufacturing domain by considering two objectives namely minimization of costs and carbon emission. They have applied a hybrid NSGA-II to solve the problem and finally used TOPSIS method to get the best solution among several Pareto optimal solutions. Mohammed *et al.* (2017) published a paper on VRP using an improved version of the nearest neighbour method. Toro *et al.* (2017a) proposed a new Multi-Objective model on capacitated location-routing problem. They also focused on the minimization of fuel consumption. In the same year, they also published another paper on green open location-routing problem Toro *et al.* (2017b). They considered economic and environmental costs in this model.

2. Motivation

VRP is one of the significant problems in the field of combinatorial optimization. Most of the papers published earlier are based on a single-objective function. In the last decade, the multi-objective version of VRP is also published. Recently, the G-VRP gets a high focus for the researchers because of the increasing level of air pollution due to transportation. Global warming becomes a significant threat to society, and we are focusing more and more on a sustainable environment. In this regards, the model of G-VRP is the perfect solution for transportation. Most of the papers on G-VRP are single-objective based. Very few works are there on multi-objective G-VRP, which focus on both the environment as well as the profit of the organization. All the papers considered the demand of the customers as exact quantity and known a priory. In reality, demand is generally imprecise. Not only this, all the works on G-VRP have considered only the company-owned vehicles that is the closed model of VRP. Whereas in the real-life scenario, the demands of the customers are always neither known a priory nor the companies are continually using their owned vehicles. As in most of the time, companies are using third-party logistics. That is the reason we need to consider both types of vehicles. This limitation becomes the motivation of this work. This paper considers both types of vehicles like company-owned and third-party vehicles. Because of the imprecise nature of the demand, here the demand is considered as a rough variable. This work reflects more real-life scenarios.

3. Problem definition and mathematical model

The travelling cost in VRP problem depends on many parameters. These are the distance between a pair of cities, travelling time from a city to another, load carried by a vehicle, type of vehicle, speed of the vehicles, types of road, the rate of fuel consumed per kilometre, price of fuel per litre and others. Out of all the parameters, distance and load are the prime factors. Fuel consumption is mainly dependent on distance and load. If two vehicles run at the same speed the vehicle having more loads will consume more fuel. The expense of fuel is a significant issue in any vehicle. That is VRP problem can be modelled in two different aspects. One is the distance or travelling time and another is the fuel consumption that considers the parameter load. Now based on travelling time, the VRP problem is a minimization problem that tries to get a solution, which will take the least time to complete its task. So, mathematically it is like the below equation:

$$\min Z_1 = \left(M - P\right) \cdot F_C + \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} C \cdot x_{ijk} \cdot t_{ij}, \tag{1}$$

where: N – the total count of customers; M – total count of vehicles required to serve all the customers; k is used as the index in the equation to represent vehicle number, where the range of k is 1, 2, 3, 4, …, P, …, M; P – total count of owned vehicles of the company that have to return to the company after the end of service; (M – P) vehicles are hired vehicles, these will not return to the depot; F_C is the fixed cost per hired vehicle; C is the unit freight of a vehicle per unit time and can be designed as:

$$C = \begin{cases} C_1, & \text{when } k \le P; \\ C_2, & \text{otherwise,} \end{cases}$$

where: C_1 is the unit freight of an owned vehicle per unit time; C_2 is the unit freight of a hired vehicle per unit time;

$$x_{ijk} = \begin{cases} 1, & \text{when } k\text{th vehicle moves} \\ & \text{from point } i \text{ to } j; \\ 0, & \text{otherwise,} \end{cases}$$

where: d_{ij} – distance between node i and j; t_{ij} – travel time from point i to j.

So, here the problem will be the mixed type of problem. That is closed VRP and Open VRP both.

Again based on fuel consumption, the VRP is a minimization problem where the challenge is to find a solution that will consume the least amount of fuel. Xiao *et al.* (2012) proposed a load-dependent function named FCR using the below model.

Let Q_0 be the vehicle's no-load weight and Q_1 be the carried load. FCR, $\rho(Q_1)$ is designed as a linear function dependent on load Q_1. Using:

$$\rho\left(Q_1\right) = \alpha \cdot \left(Q_0 + Q_1\right) + b, \tag{2}$$

where: α, b – constants.

Let, Q be the maximum limit the vehicle can carry. Let, ρ^* be the FCR on fully loaded condition and ρ_0 be the FCR of the empty vehicle. Therefore:

$$\rho_0 = \alpha \cdot Q_0 + b; \tag{3}$$

$$\rho^* = \alpha \cdot \left(Q_0 + Q\right) + b. \tag{4}$$

From the Equations (3) and (4):

$$\alpha = \frac{\rho^* - \rho_0}{Q}.$$

So, Equation (2) can be written as:

$$\rho\left(Q_1\right) = FCR = \rho_0 + \frac{\rho^* - \rho_0}{Q} \cdot Q_1. \tag{5}$$

The Equation (5) indicates the linear relationship between FCR and the load the vehicle carry where the intersection point is at ρ_0 and slope is $\frac{\rho^* - \rho_0}{Q}$.

Consider, C_0 – cost of unit amount of fuel; ρ_{ij} – FCR on the path from i to j; d_{ij} – distance between i and j; r – the count of the customers on the path; C_{fuel} – cost of fuel for one vehicle:

$$C_{fuel} = \sum_{i=1}^{r} \sum_{j=1}^{r} C_{Fuel}^{ij} \cdot x_{ij} = \sum_{i=1}^{r} \sum_{j=1}^{r} C_0 \cdot \rho_{ij} \cdot d_{ij} \cdot x_{ij}, \tag{6}$$

where: x_{ij} will be 1 if a vehicle moves from i to j else 0.

Let, y_{ij} be the weight of the goods over the vehicle that moves from point i to point j.

So, from Equation (2):

$$\rho_{ij} = \rho_0 + \alpha \cdot y_{ij}, \; i, j = 1, \ldots, n.$$

Let ρ_{ijk} is the FCR on the path from i to j for kth vehicle.

Now, the VRP problem can be mathematically represented in terms of FCR as:

$$\min Z_2 = \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} d_{ij} \cdot \rho_{ijk} \cdot x_{ijk} = \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} d_{ij} \cdot \left(\rho_0 + \alpha \cdot y_{ijk}\right) \cdot x_{ijk}, \tag{7}$$

where: y_{ijk} – the weight of the goods over the vehicle k that moves from point i to point j. Furthermore, we can refine the above objective from minimization of fuel consumption to the minimization of CO_2 emission as given below. Let, δ^{kw} will be 1 if kth vehicle consumes the fuel of category w and $ef^{CO_2,w}$ be the factor for CO_2 emission that is the quantity of CO_2 released per unit of w category fuel burned.

Now,

$$\min Z_2 = \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} \sum_{w=1}^{W} \delta^{kw} \cdot ef^{CO_2,w} \times d_{ij} \cdot \left(\rho_0 + \alpha \cdot y_{ijk}\right) \cdot x_{ijk}. \tag{8}$$

Therefore considering the two objectives of VRP, Z_1 and Z_2 the VRP may be designed as multi-objective problem that consider both closed and open VRP and by involving both the aspect of consumption of fuel and CO_2 released, it also includes future of G-VRP. The model (Equations (1) and (9)) is given below:

$$\min Z_1 = \left(M - P\right) \cdot F_C + \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} C \cdot x_{ijk} \cdot t_{ij};$$

$$\min Z_2 = \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} \sum_{w=1}^{W} \delta^{kw} \cdot ef^{CO_2,w} \times d_{ij} \cdot \left(\rho_0 + \alpha \cdot y_{ijk}\right) \cdot x_{ijk}.$$

subject to:

$$\sum_{k=1}^{M} \sum_{i=0}^{N} x_{ijk} = 1, \; j = 1, 2, \ldots, N; \tag{9}$$

$$\sum_{j=1}^{N} x_{0jk} = 1, \; k = 1, 2, \ldots, M; \tag{10}$$

$$\sum_{i=1}^{N} x_{i0k} = 1, \; k = 1, 2, \ldots, P; \tag{11}$$

$$\sum_{j=0}^{N} \sum_{k=1}^{M} x_{ijk} = 1, \; i = 1, 2, \ldots, N; \tag{12}$$

$$\sum_{i=0}^{N} \sum_{k=1}^{M} x_{ijk} = 1, \; j = 1, 2, \ldots, N; \tag{13}$$

$$\sum_{i=0}^{N} \sum_{j=1}^{N} q_j \cdot x_{ijk} \le Q, \; k = 1, 2, \ldots, M; \tag{14}$$

$$x_{ijk} \in \left\{0, 1\right\}, \; k = 1, 2, \ldots, M, \; i, j = 0\left(1\right)N; \tag{15}$$

$$\sum_{k=1}^{K} \sum_{i \in S} \sum_{j \in S, i \neq j} x_{ijk} \le \left|S\right| - 1, \; \forall S \subseteq V \setminus \left\{0\right\}. \tag{16}$$

Constraint – Equation (9) – guarantees that exactly one route will visit every customer where 0 denotes depot. Constraint – Equation (10) – refers that each vehicle leaves the depot. Constraint – Equation (11) – refers that each owned vehicle returned to depot. Constraints – Equations (12) and (13) – refer that every customer is served by a single vehicle. The carrying limit of vehicle is presented by constraint – Equation (14) – where q_j is the demand for city j and Q – vehicle capacity. Constraint – Equation (15) – defines whether vehicle k is travelled from city i to city j. The sub-tour elimination is defined using constraint – Equation (16).

Mathematical model for rough demand

In real-life scenario, most of the time the exact demand of a city is not available a priory. Because of this uncertain nature of demand of the city, this paper has considered q_j, the demand for jth city as the rough variable, where:

$$q_j = \left(\left[q_j^1, q_j^2\right], \left[q_j^3, q_j^4\right]\right),$$

where: $q_j^3 \le q_j^1 < q_j^2 \le q_j^4$.

Then using the trust-measure the Equation (14) of the above crisp model can be transformed as follows:

$$\mathrm{Tr}\left(\sum_{i=0}^{N}\sum_{j=1}^{N} q_j \cdot x_{ijk} \le Q\right) \ge \beta, \tag{17}$$

where: β is the trust value.

Now using the lemma proposed by Kundu *et al.* (2017), the above equation can be transformed into:

$$\sum_{i=0}^{N}\sum_{j=0}^{N} x_{ijk} \cdot (1 - 2\cdot\beta)\cdot q_j^3 + 2\cdot\beta\cdot q_j^4 \le Q,$$
$$\text{when } \beta \le \frac{q_j^1 - q_j^3}{2\cdot\left(q_j^4 - q_j^3\right)}; \tag{18a}$$

$$\sum_{i=0}^{N}\sum_{j=0}^{N} x_{ijk} \cdot \left((1-\beta)\cdot q_j^3 + (2\cdot\beta - 1)\cdot q_j^4\right) \le Q,$$
$$\text{when } \beta \le \frac{q_j^2 + q_j^4 - 2q_j^3}{2\cdot\left(q_j^4 - q_j^3\right)}; \tag{18b}$$

$$\sum_{i=0}^{N}\sum_{j=0}^{N} \frac{x_{ijk}\cdot p}{\left(q_j^2 - q_j^1\right) + \left(q_j^4 - q_j^3\right)} \le Q, \text{ otherwise,} \tag{18c}$$

where:

$$p = q_j^3 \cdot \left(q_j^2 - q_j^1\right) + q_j^1 \cdot \left(q_j^4 - q_j^3\right) + 2\cdot\beta\cdot\left(q_j^2 - q_j^1\right)\cdot\left(q_j^4 - q_j^3\right).$$

4. Multi-objective evolutionary algorithm for the proposed model

There are some specific real-life problems where optimization of one objective is not enough to solve those problems. Multi-objective evolutionary algorithms are suitable to solve such kind of problems. There are several multi-objective algorithms in the literature. One of such algorithms is NSGA-II, which is used here to solve the above-mentioned model.

4.1. NSGA-II

Genetic search is a highly successful bio-inspired metaheuristic algorithms based on natural selection and genetics. It can be applied in combinatorial optimization problems. Generally, it can be used in problems where the number of objectives is one. Here, this paper has designed multi-objective G-VRP problem, which can be solved successfully using the multi-objective variant of GA, NSGA-II. It is already a stable and widely used algorithm. The Pareto optimality concept is applied in the entire multi-objective GAs. Instead of exhaustive search, this method will produce Pareto optimal fonts, which are very useful to get a set of optimal solutions. Compared to its earlier methods the NSGA-II (Deb *et al.* 2002) is capable of producing the fastest non-dominated output. To get a non-dominated region this is the quickest method. To keep the diversity in the solutions it does not need to fix any parameter, and this becomes the superiority of this method. That is why we have decided to adopt this algorithm to this problem of G-VRP. In this method, the parent population is first randomly filled, and then the child population is generated from the parent. After that, both the parent and child population is accumulated and a new population of double size is generated. Then the new double-sized population is sorted according to the principle of dominance. Now in the next step, all the non-dominated solutions are collected and removed from the population, and they become the first front solutions. These solutions are assigned a fitness value of 1. Then after with the remaining population once again, the same steps have to be done, and we will get the second-front solutions. These solutions are assigned a fitness value of 2. Here a concept of crowding distance is used to select the set of solutions that will be stored in the population to preserve diversity in the solutions. Several times the NSGA-II is compared with other parallel strategies in reference (Deb *et al.* 2002), and they found it is showing far better results. That encourages applying the NSGA-II into several hard and time-critical real-world multi-objective type problems.

4.2. Implementation

An integer string is used as a solution chromosome, which is a collection of customer numbers. The set of customer numbers between two zeros represents that these customers will be served by a single vehicle. For example, (0, 4, 7, 0, 5, 3, 9, 0, 1, 3, 6, 8, 0, 2, 0) is a solution chromosome. It indicates the solution involves 4 vehicles and their corresponding routes are (0 → 4 → 7 → 0), (0 → 5 → 3 → 9 → 0), (0 → 1 → 3 → 6 → 8 → 0) and (0 → 2 → 0). Now each sub-routes may end in 0 or not. Here 0 indicates the central depot. Here the central depot may have some owned vehicle and some hired vehicle. As per the proposed model first, the depot will use their owned vehicles and after that, if required they will hire other vehicles. So if it is owned vehicle then the sub-route will end in 0 as the vehicle has to return to the depot otherwise it will end in –1. For better understanding, an example is given here. For a solution chromosome like (0, 4, 7, 0, 5, 3, 9, 0, 1, 3, 6, 8, –1, 2, –1), the sub-routes will be (0 → 4 → 7 → 0), (0 → 5 → 3 → 9 → 0), (0 → 1 → 3 → 6 → 8) and (0 → 2). So here the total number of vehicles used will be 4, and out of these four vehicles the first two vehicles are company-owned and the remaining two are hired vehicles. For first two vehicles, it will be the case of closed VRP where the sub-routes end at the depot, and for the last two vehicles it will be the case of open VRP where sub-routes end at the last customer point. This result section considers all the three cases separately namely fully open VRP, fully closed VRP and the mixed VRP. In the above-mentioned model, P is used for the number of company-owned vehicles and M is used for the total number of vehicles used. For fully open VRP, it is considered that *P*-value is zero and for the fully closed VRP, it is considered that *P*-value is greater than or equal to *M*. For the mixed case *P* is greater than zero but is less than *M*. The size of the population used here is 100. At the very beginning, we have generated 100 chromosomes randomly keeping given vehicle capacity. Then in the selection step, we have used the tournament selection to select the parents. Then we have used the PMX, a standard crossover technique. The first step of PMX is to identify randomly, a substring having an equal length from both the parents. In the following step, we swap these two substrings between the two parents and generate a partial offspring. Then in the next step, based on the mapping relationship the numbers those are not present in the substrings are placed into the offspring. Finally, we balance the partial offspring with the mapping relationship. We have used 0.85 as the crossover probability. To do the mutation, we have used simply the swapping method. Any two numbers are selected randomly from any two different sub-routes. We then swapped those numbers if they satisfy the capacity constraint. After the swapping, we continue to insert customers one after another from any particular sub-route until it follows the capacity constraint. We do this to reduce the count of vehicle used. We have used 0.15 as the mutation probability.

5. Numerical illustration

Some of the benchmark problems of VRP collected from *VRP Library* (NEO 2013; Ralphs 2003; VRP-REP 2018) have been tested to judge the performance of the new model. Here the NSGA-II method is applied to solve two objectives G-VRP instances. The proposed model was tested with the help of Augerat *et al.* (1995) Set P dataset. The performance of the proposed method is judged by applying the different instances of the above-mentioned dataset. The instances that we have used are having nodes between 23 and 101. These instances are P-n23-k8, P-n40-k5, P-n45-k5, P-n50-k10, P-n51-k10, P-n55-k10, P-n60-k15, P-n70-k10, P-n76-k5 and P-n101-k4. The numbers in the middle and end of the instances are the count of vehicles used and the count of customers respectively. There is no benchmark data available for the rough model in the literature. That is why we have considered the coordinates of the cities of some benchmark dataset from VRP library. For the value of rough demands corresponding to the coordinates of the different cities, we have generated randomly. These data can be found from the *Google Drive* (Barma 2018).

6. Results and discussion

This method is coded using *C* language on *Intel Core 2 DUO CPU T6500* at *2.10 GHz*, running *Windows XP Professional*. The number of generations used as the stopping criteria for every test is 300. The proposed model is solved for all three types of cases. These are fully closed G-VRP, where all the vehicles used, are company-owned, fully opened G-VRP where all the vehicle used are third-party logistics and mixed G-VRP where both types of vehicles are used. There is no reference Pareto optimal front available for the proposed multi-objective model. Therefore, to generate the reference approximate front for the instances, we conducted 20 independent runs on each instance. The solutions of the first non-dominated front of each run are stored in an external archive. Finally, a non-dominated sorting is performed on the archive and the members in the first front are considered as the approximate front. The results of the first front of an independent run for each instance for all the different models (viz., closed, open and mixed) are presented in Table 1–3, respectively. The results of the model considering rough demand for different levels of β (trust level) for an independent run is presented below.

The approximate front and first non-dominated front of an independent run for the instance P-n45-k5 of Table 1 is depicted in Figure 4. The approximate front and first non-dominated front of an independent run for the instance P-n23-k8 of Table 2 is depicted in Figure 5. The approximate front and first non-dominated front of an independent run for the instance P-n23-k8 of Table 3 is depicted in Figure 6.

Here we have presented only the solutions found in the first front. That is all the non-dominated solutions are enlisted here. As per the definition of dominance, if we collect two solutions *i* and *j* of first front, if the value of objective 1 of *i* is greater than the value of objective 1 of *j*, then definitely the value of objective 2 of *i* is not more than that of the value of objective 2 of *j*.

After getting the first front solutions using the above method, most of the time, it is very difficult to choose a particular solution among a set of Pareto optimal solutions. Here the VIKOR method is adopted to get the closest solution to the ideal solution. Some of the best solution corresponding to the different instance of problem and the particular case whether full open or full closed or mixed are enlisted in Table 4. It can be seen from Table 2, which is the case of the full open model the instance P-n23-k8 has five non-dominated solutions. After applying the VIKOR method, decision-maker will choose the second solution that is (305.896423, 1753.271484). The parameters w_1, w_2, v of the VIKOR method are set as 0.5.

Table 1. Results of independent runs of the multi-objective fully closed G-VRP

Slope No	Instance	Total No of vehicles used	No of owned vehicles	Vehicle capacity	Objective 1, distance [km]	Objective 2, CO_2 emission [kg]	Time [s]
1	P-n23-k8	9	9	40	533.634155	2439.176758	10.78430
					541.566589	2415.676270	
					537.756348	2419.952148	
2	P-n40-k5	5	5	140	456.633453	2365.712891	17.69812
					445.661011	2445.344727	
					452.368530	2391.379150	
3	P-n45-k5	5	5	150	550.467651	2773.997070	21.99761
					535.032776	2839.370361	
					544.120117	2786.631836	
					536.167969	2813.621338	
					547.509644	2774.844238	
4	P-n50-k10	10	10	100	807.088379	4019.036377	34.72134
					787.672729	4028.653809	
					788.374390	4022.514893	
					795.563965	4019.529053	
					794.753052	4020.481934	
5	P-n51-k10	10	10	80	1020.386475	5702.314941	36.78896
					1019.386470	5706.199707	
6	P-n55-k10	10	10	115	867.991028	4353.755371	52.23107
					846.152283	4382.785645	
					857.002991	4360.377441	
7	P-n60-k15	15	15	80	1166.716431	5526.352539	57.99801
					1153.111084	5572.475098	
					1160.749023	5542.501465	
8	P-n70-k10	10	10	135	1043.324219	5325.773926	64.73389
					1044.250854	5320.470215	
					1046.774170	5266.271973	
9	P-n76-k5	5	5	280	829.649231	4673.174805	69.00678
					831.018127	4666.365234	
10	P-n101-k4	4	4	400	1168.274048	6028.094727	81.3092
					1168.786377	6025.255859	
					1169.205688	6005.471680	

Table 2. Results of independent runs of the multi-objective fully open G-VRP

Slope No	Instance	Total No of vehicles used	No of owned vehicles	Vehicle capacity	Objective 1, distance [km]	Objective 2, CO_2 emission [kg]	Time [s]
1	P-n23-k8	8	0	40	309.717590	1751.187500	8.62890
					305.896423	1753.271484	
					307.873322	1751.760254	
					303.933533	1758.559692	
					302.127136	1760.312378	
2	P-n40-k5	5	0	140	375.901764	2136.007568	15.31002
					372.088654	2146.454590	
					374.212433	2141.201416	
3	P-n45-k5	5	0	150	513.039856	2743.869873	17.87012
					504.378754	2790.049561	
					510.222351	2750.608398	
4	P-n50-k10	10	0	100	601.817200	3464.385742	24.22510
					599.112427	3487.923096	

End of Table 2

Slope No	Instance	Total No of vehicles used	No of owned vehicles	Vehicle capacity	Objective 1, distance [km]	Objective 2, CO_2 emission [kg]	Time [s]
5	P-n51-k10	10	0	80	744.487000	4897.581055	26.40236
					740.822327	4913.603516	
6	P-n55-k10	10	0	115	602.078735	3579.873779	35.99121
					600.427368	3604.896973	
7	P-n60-k15	15	0	80	812.449097	4540.724609	44.39017
					811.343018	4542.951172	
8	P-n70-k10	10	0	135	861.279053	4836.739258	51.00678
					857.637939	4838.102539	
					861.279053	4836.739258	
					860.599731	4837.003906	
					858.317261	4837.837891	
9	P-n76-k5	5	0	280	807.335510	4598.143555	61.91205
					807.008362	4625.926270	
10	P-n101-k4	4	0	400	1109.738403	5865.573242	75.82014
					1102.859741	5867.583008	

Table 3. Results of independent runs of the multi-objective mixed G-VRP

Slope No	Instance	Total No of vehicles used	No of owned vehicles	Vehicle capacity	Objective 1, distance [km]	Objective 2, CO_2 emission [kg]	Time [s]
1	P-n23-k8	8	4	40	386.759003	1995.332031	9.72660
					389.995514	1990.418091	
					391.842102	1986.246582	
					384.912415	1999.503662	
2	P-n40-k5	5	3	140	443.188782	2342.264893	16.49023
					437.617767	2377.966309	
					441.155487	2346.647949	
3	P-n45-k5	5	2	150	533.550781	2799.590088	19.94491
					529.882324	2804.781250	
					531.193237	2800.432129	
4	P-n50-k10	10	5	100	701.724365	3705.358398	30.60901
					695.228455	3719.603271	
					698.218445	3708.154053	
5	P-n51-k10	10	5	80	894.975525	5345.306152	32.98000
					892.920837	5376.732910	
					893.308350	5372.028320	
6	P-n55-k10	10	5	115	688.032349	3852.808838	45.11901
					682.803589	3866.145752	
					684.589600	3856.329346	
7	P-n60-k15	15	8	80	959.418091	4964.879883	55.95671
					968.792603	5004.875488	
8	P-n70-k10	10	5	135	1017.865417	5343.324707	59.70112
					1012.755432	5355.051270	
					1016.856140	5348.973145	
9	P-n76-k5	5	3	280	874.226929	4875.469727	66.27169
					844.664001	4683.958984	
10	P-n101-k4	4	2	400	1100.233521	5733.073242	78.50237
					1101.224609	5718.858398	
					1096.201904	5741.236328	
					1099.468506	5740.473633	

Table 4. Results of VIKOR method after applying on some set of Pareto optimal solutions

Slope No	Instance	Model	Alternatives		Decision-maker's choice	
1	P-n23-k8	full open	309.717590	1751.187500	305.896423	1753.271484
			305.896423	1753.271484		
			307.873322	1751.760254		
			303.933533	1758.559692		
			302.127136	1760.312378		
2	P-n50-k10	full closed	804.219543	3983.710205	800.364502	4018.805420
			797.731384	4025.704346		
			803.688049	3989.494873		
			802.937073	4011.796143		
			800.364502	4018.805420		
3	P-n23-k8	mixed	386.759003	1995.332031	386.759003	1995.332031
			389.995514	1990.418091		
			391.842102	1986.246582		
			384.912415	1999.503662		

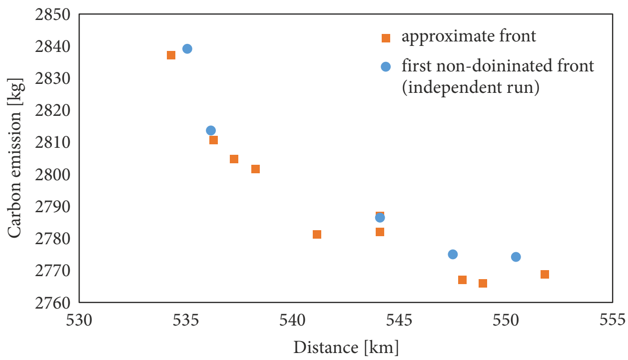

Figure 4. Instance P-n45-k5

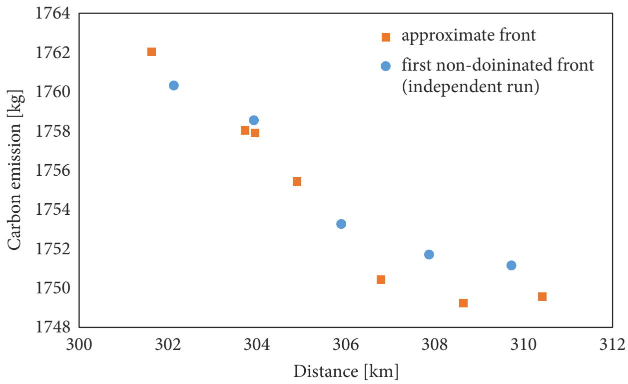

Figure 5. Instance P-n23-k8

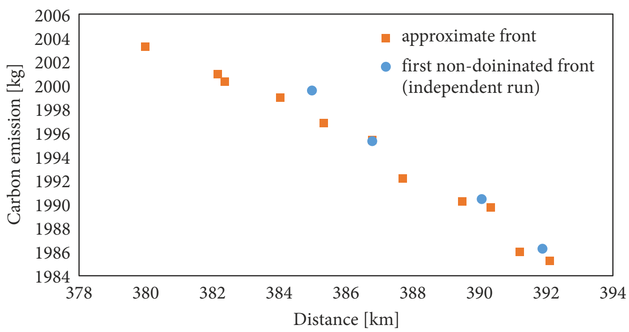

Figure 6. Instance P-n23-k8

Result of rough model

For the different trust values of β like 0.7, 0.8, 0.9 and 0.95, we have solved the proposed rough model for the rough dataset mentioned earlier and the result is presented in Table 5.

It is observed from Table 5 that the less the trust value, the better is the result for both the objectives. Now based on the trust value chosen by the decision-maker, one can quickly get the particular result. Then we can also apply the VIKOR method to get the best alternative from the Pareto front just like the crisp model previously mentioned.

Table 5. Results of the rough model

Instance	Objective 1	Objective 2
Trust measure β = 0.7		
P-n45-k5	484.481689	2337.624268
	482.118500	2359.121094
	483.143982	2342.926270
P-n50-k10	501.937195	2397.322510
	497.081299	2407.953857
P-n60-k15	832.964478	4164.316406
	837.641418	4157.640625
	847.383606	4156.848145
	848.665527	4129.271484
P-n65-k10	798.739014	4533.956055
	802.520386	4404.063477
	799.464966	4508.059570
P-n70-k10	876.613647	4397.129395
	880.587280	4358.313477
P-n76-k5	898.263977	4468.282227
	907.625793	4458.171875
	897.247375	4558.739746
	905.753113	4463.976074
P-n101-k4	1079.552979	5412.953125
	1109.119263	5322.774902
	1087.434692	5326.065918
	1081.279053	5336.755859

Continue of Table 5

Instance	Objective 1	Objective 2
Trust measure β = 0.8		
P-n45-k5	515.412415	2502.558350
	508.745026	2547.523926
	511.877991	2522.906738
	509.610413	2547.459961
	514.547058	2502.622314
P-n50-k10	622.121033	3268.045410
	629.456829	3247.679000
P-n60-k15	858.760010	4378.023438
	865.892021	4321.786534
P-n65-k10	824.451599	4174.082520
	819.864075	4264.103027
	823.043396	4196.969238
P-n70-k10	881.533936	4610.396973
	873.056152	4670.019043
	880.718384	4632.261719
	873.871704	4648.154297
P-n76-k5	829.830383	4374.750000
	824.639771	4429.854492
P-n101-k4	987.691528	5058.370605
	981.008484	5058.928223
	986.962769	5058.504883
	981.737244	5058.793945
Trust measure β = 0.9		
P-n45-k5	617.971924	2974.288574
	612.886353	2990.145264
	610.306824	3033.304688
	611.945251	3032.939697
P-n50-k10	703.333313	3655.895996
	697.169250	3657.395020
	703.333313	3655.895996
	702.493103	3656.342285
P-n60-k15	915.187012	4770.350098
	914.576599	4787.712402
	914.576660	4777.097168
P-n65-k10	898.016357	4596.649414
	900.086060	4590.073730
P-n70-k10	983.475464	5187.562988
	980.274170	5203.607910
	997.431519	5181.672363
	998.111938	5158.339355
P-n76-k5	871.165894	4600.433105
	872.995178	4592.302734
P-n101-k4	999.851868	5507.668945
	1003.014343	5383.280273
	1004.869690	5337.218262
	1007.323303	5332.721680
Trust measure β = 0.95		
P-n45-k5	640.494995	3057.592529
	633.739746	3072.136230
	634.572021	3060.224854
	639.629639	3058.725098

End of Table 5

Instance	Objective 1	Objective 2
P-n50-k10	760.458313	4070.522461
	766.267334	4006.669434
	761.545105	4035.631348
	668.334595	3757.011963
	675.071106	3720.824951
	674.810242	3722.839600
P-n60-k15	943.149597	4926.071289
	940.469421	4978.479980
	940.502625	4928.743652
P-n65-k10	944.543030	4992.268066
	944.097961	5003.912109
P-n70-k10	1000.176880	5273.604980
	995.476562	5317.383789
	996.717407	5279.326172
	995.733032	5314.230957
	996.973877	5276.172852
P-n76-k5	873.727234	4836.452637
	881.062134	4826.465332
P-n101-k4	955.617737	5264.867676
	957.585205	5232.495605

Conclusions

In most of the advanced countries, green logistic becomes an important area of importance. The G-VRP problem focuses on environmental issues so that the emissions of GHGs may reduce. The consideration of only the environmental issue may not give the best output to any transportation industry. It has to consider the travelled distance or time too. Therefore, instead of considering only one objective, it is always better to consider both the goals. That is why we have designed the G-VRP as multi-objective optimization problem where the one target is the minimization of the distance, and the other goal is the minimization of the quantity of CO_2 emissions. Here, NSGA-II is used as an evolutionary method to get better Pareto fronts for the G-VRP. We have shown the results of the first Pareto front for both the crisp and the rough model, and finally, the decision-maker will choose the best one using the VIKOR method. To implement the above model using the NSGA-II, we have used some benchmark instances from the literature of CVRP. This model can make a positive contribution towards society to maintain sustainability and a balance between the financial matter of the organization and the environmental issues. In future, the more extensive research is required in this field to develop better multi-objective optimization models, which can resolve the problems of the large problems as well as that also consider the NO_2 emissions. This work can be an excellent reference to further research on G-VRP with multi-objectives.

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