MULTI-OBJECTIVE GREEN MIXED VEHICLE ROUTING PROBLEM UNDER ROUGH ENVIRONMENT

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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;
CO₂ – 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
We need to study the potential pathways to reduce the car-
the air pollution caused by the personal vehicle's emission.
ment passed several environmental regulations to reduce
our environment green as much as possible. The govern-

significant contributor to global warming. So road trans-
port has to be appropriately planned with a vision to keep
our environment green as much as possible. The govern-
ment 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 car-
bon emissions of road vehicles. The transportation sector
is the primary source of GHG emissions. In 2017, 28.9%
of US GHG emissions were from transportation as per the
report published by the EPA (2019b). 14% of global CO₂ emissions was because of the transport sector
as per the report published by the EPA (2019a). Besides, the emissions also depend on the driving quality
as well as the load of the vehicle. In this scenario, research-

ers 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 differ-
cent 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 rep-
resentative. 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 gradu-
ally 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 sat-
isfaction, minimization of CO₂ emissions, minimization of employee workload and others. In the global scenario,
we need to take the minimization of emissions of CO₂ 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 mini-
imization 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 al-
ternative 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 Sec-
tion 1. The motivation of the work is discussed in Section 2. Then, the problem definition and modelling of the pro-
posed multi-objective mixed G-VRP is presented in Sec-
tion 3. While in Section 4, the brief discussion on NSGA-II
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 CO₂ 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 CO₂ 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 CO₂ emission and minimization of NOₓ. 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 CO₂. 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 priori. 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 a priori 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:

\[
\min Z_1 = (M - P) \cdot F_C + \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} C_{ijk} \cdot t_{ij},
\]

where: \(N\) – 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:

\[
C = \begin{cases} 
(C_1, \text{ when } k \leq P) ; \\
(C_2, \text{ otherwise}), 
\end{cases}
\]

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;

\[
x_{ijk} = \begin{cases} 
1, \text{ when kth vehicle moves from point } i \text{ to } j; \\
0, \text{ otherwise}, 
\end{cases}
\]

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 solu-
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:

$$\rho(Q_1) = \alpha \cdot (Q_0 + Q_1) + b,$$

where: \(\alpha, b\) – constants.

Let, $Q$ be the maximum limit the vehicle can carry. Let, $\rho^*$ be the FCR on fully loaded condition and $\rho_0$ be the FCR of the empty vehicle. Therefore:

$$\rho_0 = \alpha \cdot Q_0 + b;$$

$$\rho^* = \alpha \cdot (Q_0 + Q) + b.$$  \(\text{Equation (3) and (4):}\)

From the Equations (3) and (4):

$$\alpha = \frac{\rho^* - \rho_0}{Q}.$$  \(\text{Equation (5):}\)

So, Equation (2) can be written as:

$$\rho(Q_1) = \text{FCR} = \rho_0 + \frac{\rho^* - \rho_0}{Q} \cdot Q_1.$$  \(\text{Equation (6):}\)

The Equation (5) indicates the linear relationship between FCR and the load the vehicle carry where the intersection point is at $\rho_0$ and slope is $\frac{\rho^* - \rho_0}{Q}$. Consider, $C_0$ – cost of unit amount of fuel; $\rho_j$ – FCR on the path from $i$ to $j$; $d_{ij}$ – distance between $i$ and $j$; $r$ – the count of the customers on the path; $C_{\text{fuel}}$ – cost of fuel for one vehicle:

$$C_{\text{fuel}} = \sum_{i=1}^r \sum_{j=1}^r C_{\text{fuel}} \cdot x_{ij} =$$

$$\sum_{i=1}^r \sum_{j=1}^r C_{\text{fuel}} \cdot (\rho_j \cdot d_{ij} \cdot x_{ij}),$$

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):

$$\rho_j = \rho_0 + \alpha \cdot y_{ij}, \quad i, j = 1, \ldots, n.$$  \(\text{Equation (7):}\)

Let $\rho_{ijk}$ is the FCR on the path from $i$ to $j$ for $k$th vehicle.

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

$$\text{min } Z_2 = \sum_{i=0}^N \sum_{j=0}^N \sum_{k=1}^M d_{ij} \cdot \rho_{ijk} \cdot x_{ijk} =$$

$$\sum_{i=0}^N \sum_{j=0}^N \sum_{k=1}^M d_{ij} \cdot (\rho_0 + \alpha \cdot y_{ijk}) \cdot x_{ijk},$$

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, $\delta_{kw}$ will be 1 if $k$th vehicle consumes the fuel of category $w$ and $e_f{CO}_2.w$ be the factor for CO$_2$ emission that is the quantity of CO$_2$ released per unit of $w$ category fuel burned.

Now,

$$\min Z_2 = \sum_{i=0}^N \sum_{j=0}^N \sum_{k=1}^M \delta_{kw} \cdot e_f{CO}_2.w \cdot d_{ij} \cdot (\rho_0 + \alpha \cdot y_{ijk}) \cdot x_{ijk}.$$  \(\text{Equation (8):}\)

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:

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

$$\min Z_2 = \sum_{i=0}^N \sum_{j=0}^N \sum_{k=1}^M \delta_{kw} \cdot e_f{CO}_2.w \cdot d_{ij} \cdot (\rho_0 + \alpha \cdot y_{ijk}) \cdot x_{ijk},$$

subject to:

$$\sum_{k=1}^M x_{ijk} = 1, \quad j = 1, 2, \ldots, N;$$

$$\sum_{k=1}^M x_{ijk} = 1, \quad k = 1, 2, \ldots, M;$$

$$\sum_{i=1}^N x_{ijk} = 1, \quad k = 1, 2, \ldots, P;$$

$$\sum_{j=1}^N x_{ijk} = 1, \quad i = 1, 2, \ldots, N;$$

$$\sum_{i=1}^N x_{ijk} = 1, \quad j = 1, 2, \ldots, N;$$

$$\sum_{i=1}^N x_{ijk} = 1, \quad k = 1, 2, \ldots, M;$$

$$\sum_{j=1}^N x_{ijk} \leq Q, \quad k = 1, 2, \ldots, M;$$

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

$$\sum_{k=1}^M \sum_{i \in S} \sum_{j \in S} x_{ijk} \leq |S| - 1, \quad \forall S \subseteq V \setminus \{0\}.$$  \(\text{Equation (15):}\)

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 the demand for city $k$ 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: $q_j^3 \leq q_j^1 < q_j^2 \leq q_j^4$.

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

$$\text{Tr} \left( \sum_{i=0}^{N} \sum_{j=1}^{N} q_j^i \cdot x_{ij} \leq Q \right) \geq \beta,$$

where: $\beta$ is the trust value.

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

$$\sum_{i=0}^{N} \sum_{j=0}^{N} x_{ij} \cdot \left( 1 - 2 \cdot \beta \right) \cdot q_j^1 + 2 \cdot \beta \cdot q_j^4 \leq Q,$$

when $\beta \leq \frac{q_j^1 - q_j^3}{2 \cdot (q_j^4 - q_j^3)}$;                              \hspace{1cm} (18a)

$$\sum_{i=0}^{N} \sum_{j=0}^{N} x_{ij} \cdot \left( (1 - \beta) \cdot q_j^3 + (2 \cdot \beta - 1) \cdot q_j^4 \right) \leq Q,$$

when $\beta \leq \frac{q_j^3 + q_j^4 - 2q_j^3}{2 \cdot (q_j^4 - q_j^3)}$; \hspace{1cm} (18b)

$$\sum_{i=0}^{N} \sum_{j=0}^{N} \left( q_j^3 - q_j^4 \right) + \left( q_j^4 - q_j^3 \right) \leq Q, \text{ otherwise},$$

where:

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

$$2 \cdot \beta \cdot \left( q_j^3 - q_j^4 \right) \cdot \left( q_j^4 - q_j^3 \right).$$

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 meta-heuristic 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 fronts, 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 $(0 \rightarrow 4 \rightarrow 7 \rightarrow 0), (0 \rightarrow 5 \rightarrow 3 \rightarrow 9 \rightarrow 0), (0 \rightarrow 1 \rightarrow 3 \rightarrow 6 \rightarrow 8 \rightarrow 0)$ and $(0 \rightarrow 2)$. Now each sub-routes may end in 0 or not. Here 0 indicates 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 $(0 \rightarrow 4 \rightarrow 7 \rightarrow 0), (0 \rightarrow 5 \rightarrow 3 \rightarrow 9 \rightarrow 0), (0 \rightarrow 1 \rightarrow 3 \rightarrow 6 \rightarrow 8)$ and $(0 \rightarrow 2).$ 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 abovementioned 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 $\beta$ (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, CO₂ 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                  |         |
|          |            |                           |                      |                 | 456.634535                 | 2363.712891                  |         |
| 2        | P-n40-k5   | 5                         | 5                    | 140             | 445.661011                 | 2445.344727                  | 17.69812 |
|          |            |                           |                      |                 | 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                  |         |
| 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                  |         |
| 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, CO₂ 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                  |         |
### 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, CO2 emission [kg] | Time [s] |
|----------|----------|----------------------------|----------------------|-----------------|---------------------------|--------------------------------|---------|
| 5        | P-n51-k10| 10                         | 0                    | 80              | 744.487000                | 4897.581055                    | 26.40236 |
| 6        | P-n55-k10| 10                         | 0                    | 115             | 602.078735                | 3579.873779                    | 35.99121 |
| 7        | P-n60-k15| 15                         | 0                    | 80              | 812.449097                | 4540.724609                    | 44.39017 |
| 8        | P-n70-k10| 10                         | 0                    | 135             | 861.279053                | 4836.739258                    | 51.00678 |
| 9        | P-n76-k5 | 5                          | 0                    | 280             | 807.335510                | 4598.143555                    | 61.91205 |
| 10       | P-n101-k4| 4                          | 0                    | 400             | 1102.859741               | 5867.583008                    | 75.82014 |

### 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, CO2 emission [kg] | Time [s] |
|----------|----------|----------------------------|----------------------|-----------------|---------------------------|--------------------------------|---------|
| 1        | P-n23-k8 | 8                          | 4                    | 40              | 386.759003                | 1995.323031                    | 9.72660 |
| 2        | P-n40-k5 | 5                          | 3                    | 140             | 443.188782                | 2342.624893                    | 16.49023 |
| 3        | P-n45-k5 | 5                          | 2                    | 150             | 533.550781                | 2799.590088                    | 19.94491 |
| 4        | P-n50-k10| 10                         | 5                    | 100             | 695.228455                | 3719.603271                    | 30.60901 |
| 5        | P-n51-k10| 10                         | 5                    | 80              | 894.975525                | 5345.306152                    | 32.98000 |
| 6        | P-n55-k10| 10                         | 5                    | 115             | 688.032349                | 3852.808838                    | 45.11901 |
| 7        | P-n60-k15| 15                         | 8                    | 80              | 959.418091                | 4968.879883                    | 55.95671 |
| 8        | P-n70-k10| 10                         | 5                    | 135             | 1017.865417               | 5343.324707                    | 59.70112 |
| 9        | P-n76-k5 | 5                          | 3                    | 280             | 874.226929                | 4875.469727                    | 66.27169 |
| 10       | P-n101-k4| 4                          | 2                    | 400             | 1100.233521               | 5733.073242                    | 78.50237 |

End of Table 2
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              |                         |

**Result of rough model**

For the different trust values of $\beta$ 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 $\beta = 0.7$ |                         |
| P-n45-k5 | 484.481689  2337.624268 |                         |
|          | 482.118500  2359.121094 |                         |
|          | 483.143982  2342.926270 |                         |
| P-n50-k10| 501.937195  2397.32510  |                         |
|          | 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 |                         |
|          | 1109.19263  5322.774902 |                         |
|          | 1087.434692 5326.059918 |                         |
|          | 1081.279053 5336.755859 |                         |
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 a 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 CO₂ 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 NO₂ emissions. This work can be an excellent reference to further research on G-VRP with multi-objectives.
Granada-Echeverri, M.; Toro, E. M.; Santa, J. J. 2019. A mixed integer linear programming formulation for the vehicle routing problem with backhauls, *International Journal of Industrial Engineering Computations* 10(2): 295–308. https://doi.org/10.5267/j.ijiec.2018.6.003

Huang, J.; Jin, L.; Zhang, C. 2017. Mathematical modeling and a hybrid NSGA-II algorithm for process planning problem considering machining cost and carbon emission, *Sustainability* 9(10): 1769. https://doi.org/10.3390/su9101769

Jabir, E.; Panicker, V. V.; Sridharan, R. 2015. Multi-objective optimization model for a green vehicle routing problem, *Procedia – Social and Behavioral Sciences* 189: 33–39. https://doi.org/10.1016/j.sbspro.2015.03.189

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. https://doi.org/10.1016/j.ejor.2007.06.065

Jozefowiez, N.; Semet, F.; Talbi, E.-G. 2008. Multi-objective vehicle routing problems, *European Journal of Operational Research* 189(2): 293–309. https://doi.org/10.1016/j.ejor.2007.05.055

Kancharia, S. R.; Ramadurai, G. 2018. Incorporating driving cycle based fuel consumption estimation in green vehicle routing problems, *Sustainable Cities and Society* 40: 214–221. https://doi.org/10.1016/j.scs.2018.04.016

Knowles, J.; Corne, D. 1999. The Pareto archived evolution strategy: a new baseline algorithm for Pareto multiobjective optimisation, in *Proceedings of the 1999 Congress on Evolutionary Computation* – CEC99, 6–9 July 1999, Washington, DC, US, 98–105. https://doi.org/10.1109/CEC.1999.781913

Kundu, P.; Kar, M. B.; Kar, S.; Pal, T.; Maiti, M. 2017. A solid transportation model with product blending and parameters as rough variables, *Soft Computing* 21(9): 2297–2306. https://doi.org/10.1007/s00500-015-1941-9

Lawler, E. L.; Lenstra, J. K.; Kan, A. H. G. R.; Shmoys, D. B. 1985. *The Traveling Salesman Problem: a Guided Tour of Combinatorial Optimization*. Wiley. 476 p.

Lin, C.; Choy, K. L.; Ho, G. T. S.; Chung, S. H.; Lam, H. Y. 2014. Survey of green vehicle routing problem: past and future trends, *Expert Systems with Applications* 41(4): 1118–1138. https://doi.org/10.1016/j.eswa.2013.07.107

Liu, R.; Jiang, Z. 2012. The close–open mixed vehicle routing problem, *European Journal of Operational Research* 220(2): 349–360. https://doi.org/10.1016/j.ejor.2012.01.061

Mardani, A.; Zavadskas, E. K.; Govindan, K.; Senin, A. A.; Jusoh, A. 2016. VIKOR technique: a systematic review of the state of the art literature on methodologies and applications, *Sustainability* 8(1): 37. https://doi.org/10.3390/su8010037

Matl, P.; Hartl, R. F.; Vidal, T. 2018. Workload equity in vehicle routing problems: a survey and analysis, *Transportation Science* 52(2): 239–260. https://doi.org/10.1287/trsc.2017.0744

Matl, P.; Hartl, R. F.; Vidal, T. 2019a. Leveraging single-objective heuristics to solve bi-objective problems: heuristic box splitting and its application to vehicle routing, *Networks: an International Journal* 73(4): 382–400. https://doi.org/10.1002/net.21876

Matl, P.; Hartl, R. F.; Vidal, T. 2019b. Workload equity in vehicle routing: the impact of alternative workload resources, *Computers & Operations Research* 110: 116–129. https://doi.org/10.1016/j.cor.2019.05.016

Mohammed, M. A.; Abd Ghani, M. K.; Hamed, R. I.; Mostafa, S. A.; Ibrahim, D. A.; Jameel, H. K.; Allallah, A. H. 2017. Solving vehicle routing problem by using improved k-nearest neighbor algorithm for best solution, *Journal of Computational Science* 21: 232–240. https://doi.org/10.1016/j.jocs.2017.04.012

Molina, J. C.; Eguía, I.; Racero, J.; Guerrero, F. 2014. Multi-objective vehicle routing problem with cost and emission functions, *Procedia – Social and Behavioral Sciences* 160: 254–263. https://doi.org/10.1016/j.sbspro.2014.12.137

Montoya, A.; Guéret, C.; Mendoza, J. E.; Villegas, J. G. 2016. A multi-space sampling heuristic for the green vehicle routing problem, *Transportation Research Part C: Emerging Technologies* 70: 113–128. https://doi.org/10.1016/j.trc.2015.09.009

Murata, T.; Itai, R. 2007. Local search in two-fold EMO algorithm to enhance solution similarity for multi-objective vehicle routing problems, *Lecture Notes in Computer Science* 4403: 201–215. https://doi.org/10.1007/978-3-540-70928-2_18
Murata, T.; Itai, R. 2005. Multi-objective vehicle routing problems using two-fold EMO algorithms to enhance solution similarity on non-dominated solutions, Lecture Notes in Computer Science 3410: 885–896. 
https://doi.org/10.1007/978-3-540-31880-4_61

NEO. 2013. Capacitated VRP Instances. Networking and Emerging Optimization (NEO), Malaga, Spain. Available from Internet: https://neo.lcc.uma.es/vrp/vrp-instances/capacitated-vrp-instances

Ombuki, B.; Ross, B. J.; Hanshar, F. 2006. Multi-objective genetic algorithms for vehicle routing problem with time windows, Applied Intelligence 24(1): 17–30. https://doi.org/10.1007/s10489-006-6926-z

Pacheco, J.; Martí, R. 2006. Tabu search for a multi-objective routing problem, Journal of the Operational Research Society 57(1): 29–37. https://doi.org/10.1057/palgrave.jors.2601917

Poonthalir, G.; Nadarajan, R. 2018. A fuel efficient green vehicle routing problem with varying speed constraint (F-GVRP), Expert Systems with Applications 100: 131–144. https://doi.org/10.1016/j.eswa.2018.01.052

Qian, J.; Eglese, R. 2014. Finding least fuel emission paths in a network with time-varying speeds, Networks: an International Journal 63(1): 96–106. https://doi.org/10.1002/net.21524

Qian, J.; Eglese, R. 2016. Fuel emissions optimization in vehicle routing problems with time-varying speeds, European Journal of Operational Research 248(3): 840–848. https://doi.org/10.1016/j.ejor.2015.09.009

Ralphs, T. 2003. Vehicle Routing Data Sets. Lehigh University, Bethlehem, PA, US. Available from Internet: https://www.coin-or.org/SYMPHONY/branchandcut/VRP/data/index.htm.old

Ribeiro, R.; Lourenço, H. R. D. 2001. A Multi-Objective Model for a Multi-Period Distribution Management Problem. Social Science Research Network (SSRN). 22 p. https://doi.org/10.2139/ssrn.273419

Schrijver, A. 2002. On the history of combinatorial optimization (till 1960), Handbooks in Operations Research and Management Science 12: 1–68. https://doi.org/10.1016/S0927-0507(05)12001-5

Siu, W. S. H.; Chan, C.-K.; Chan, H. C. B. 2012. Green cargo routing using genetic algorithms, in International MultiConference of Engineers and Computer Scientists, IMECS 2012, 14–16 March 2012, Kowloon, Hong Kong, 1: 170–175.

Tan, K. C.; Chew, Y. H.; Lee, L. H. 2006. A hybrid multiobjective evolutionary algorithm for solving vehicle routing problem with time windows, Computational Optimization and Applications 34(1): 115–151. https://doi.org/10.1007/s10589-005-3070-3

Toro, E. M.; Franco, J. F.; Granada-Echeverri, M.; Guimarães, F. G. 2017a. A multi-objective model for the green capacitated location-routing problem considering environmental impact, Computers & Industrial Engineering 110: 114–125. https://doi.org/10.1016/j.cie.2017.05.013

Toro, E. M.; Franco, J. F.; Granada-Echeverri, M.; Guimarães, F. G.; Rendón, R. A. G. 2017b. Green open location-routing problem considering economic and environmental costs, International Journal of Industrial Engineering Computations 8(2): 203–216. https://doi.org/10.5267/j.ijiec.2016.10.001

Turkson, R. F.; Yan, F.; Ali, M. K. A.; Liu, B.; Hu, J. 2016. Modeling and multi-objective optimization of engine performance and hydrocarbon emissions via the use of a computer aided engineering code and the NSGA-II genetic algorithm, Sustainability 8(1): 72. https://doi.org/10.3390/su8010072

VRP-REP. 2018. Datasets. Vehicle Routing Problem Repository (VRP-REP). Available from Internet: http://www.vrp-rep.org/datasets.html

Wen, L.; Eglese, R. 2016. Minimizing CO₂e emissions by setting a road toll, Transportation Research Part D: Transport and Environment 44: 1–13. https://doi.org/10.1016/j.trd.2015.12.019

Xiao, Y.; Zhao, Q.; Kaku, I.; Xu, Y. 2012. Development of a fuel consumption optimization model for the capacitated vehicle routing problem, Computers & Operations Research 39(7): 1419–1431. https://doi.org/10.1016/j.cor.2011.08.013

Zhou, J.; Wang, C.; Zhu, J. 2016. Multi-objective optimization of a spring diaphragm clutch on an automobile based on the non-dominated sorting genetic algorithm (NSGA-II), Mathematical and Computational Applications 21(4): 47. https://doi.org/10.3390/mca21040047

Zitzler, E.; Laumanns, M.; Thiele, L. 2001. SPEA2: Improving the Strength Pareto Evolutionary Algorithm. TIK-Report 103. Computer Engineering and Networks Laboratory (TIK), Swiss Federal Institute of Technology (ETH) Zurich, Switzerland. 21 p.