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Sustainable vehicle routing based on firefly algorithm and TOPSIS methodology

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ABSTRACT

In a sustainable management of logistics, transportation plays a crucial role. Traditionally, the main purpose was to solve the Vehicle Routing Problem minimizing the cost associated with the travelled distances. Nowadays, the economic profit cannot be the only driver for achieving sustainability and environmental issues have to be also considered. In this paper, to satisfy the intricate limits involved in real vehicle routing problem, the study has been structured considering different types of vehicles in terms of maximum capacity, velocity and emissions, asymmetric paths, vehicle-client constraints and delivery time windows. The firefly algorithm has been implemented to solve the vehicle routing problem and the TOPSIS technique has been applied to integrate economic and environmental factors. Finally, to prove the effectiveness of the proposed approach, a numerical example has been proposed using data provided by a logistic company located in Sicily.

1. Introduction

Transport causes a number of negative impacts that can affect sustainability targets from an economic, social and environmental point of view. Even if sustainable development is a major concern globally, it should be solved mainly locally [1]. Much scientific literature addressed the problem of transports at the county (or city) level, proposing measuring and monitoring systems for the three-dimensional aspects of transport sustainability [27,29].

Although some attempts have been made to develop indicators and to compare transport sustainability among various cities [1,9], only in recent years there has been a growing attention in the integration of environmental goals into traditional logistics operations.

The optimization of transport routes, based on algorithms can improve both economic and environmental performances [22,35–38]. In particular, with stricter carbon polices and ever-increasing fuel cost, many businesses focus on lowering the carbon emissions and fuel consumptions by improving vehicle routing choices. Vehicle Routing Problem (VRP) aims to find the optimal solution to satisfy the requests of a set of clients in the area of the distribution centre, towards a fleet of trucks with different volumes [2]. Green Vehicle Routing Problem (GVRP), is a recent alternative to standard traditional vehicle routing models in which the minimizing of fuel consumptions [12] or the reducing of carbon emissions [23,33], are also considered.

Moreover, in the real word situations, the mandatory company's requests about the daily planning tasks of deliveries must be taken into account in the formulation of the problem. For this purpose, the well-known conventional VRP [30] has been designed as a Rich Vehicle Routing Problem (R-VRP). Vidal et al. [31] and Lahyani et al. [20], show that R-VRP with multiple constraints and complex formulations is an NP-Hard (Non-deterministic Polynomial-time) problem and it has a great scientific interest because its solution represents a challenge. Moreover, the applicability of R-VRP to true-life cases is wider than the classic versions of routing problems. Recently, de Armas et al. [4] proposed the R-VRP with hard and soft time windows, heterogeneous fleet, customers' priorities and vehicle-customer constraints. Meta-heuristics approaches are most favorable methods for solving these kinds of problems are [3,14,28]. In order, to solve the R-VRP, in our study we have developed a method referring to a class of meta-heuristic methodologies proposed by Yang (2008) few years ago. This technique is the Firefly Algorithm (FA), a nature-inspired algorithm based on the conduct of fireflies. As recent surveys show [7,8], since it was proposed, the FA has been applied to many different optimization fields and problems with great success. Moreover, the current scientific community is still interested in it [18,21]; Zouache et al. 2015. However, the FA has never been employed in combination with a multi-criteria method to obtain sustainable solution to the R-VRP.

In this study we propose a Sustainable Vehicle Routing in which the optimal solution is selected, from a set of feasible solutions acquired by

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way of the FA, through the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) methodology [19]. Recently, Ebrahimi [5] proposed a multi objective approach to solve location routing problem for tire supply chain taking into consideration sustainability aspects.

The principal originalities and contributions of this paper can be synthetized as follow:

- the R-VRP proposed has been formulated selecting a combination of vehicles from an initial fleet.
- an elitist version of the FA has been presented to solve the proposed R-VRP. The move approach adopted by the fireflies is based on an additional elitism mechanism, which is described in following sections.
- the TOPSIS multi criteria approach is implemented to select the most suitable solution in terms od sustainability of vehicle routing decision.

To show the procedure of the proposed approach, a numerical example of vehicle routing problem is presented. The rest of the paper is structured as follows. In Section 2, the R-VRP proposed has been formulated. In Section 3, the developed FA is presented and in Section 4 the TOPSIS methodology and the evaluation criteria are discussed. After that, a numerical example is presented in Section 5. Finally, in Section 6 conclusions and future developments of this study are discussed.

2. Problem description

The proposed R-VRP refers to a medium distribution company in which several constraints have been taken into account with the objective of modelling the problem closer to true conditions:

1. *Asymmetry.* The delivery paths in the proposed R-VRP are asymmetric. This implies that the traveling distance from any i client to another j client is not the same as the reverse trip path. Asymmetric paths have been applied previously in the literature [11]. This characteristic is very common in true-life applications.
2. *Time windows.* The time window indicates to the range of time within which one customer can be served. If a vehicle gets to the destination before the start point of the customer's time window, it must wait. This characteristic has already been used in other contexts [25].
3. *Variable delivery times.* In true transportation, the trip between two clients depends on the type of vehicle and road [10]. Often, this time is subject to some external variables, such as the traffic or the weather. Moreover, the time required to unload the pallets in each distribution center has been also measured, considering an average unloading time for a single pallet. In order to make the problem more realistic, this time has been added in the delivery time formulated in this research.
4. *Vehicle dimension.* In the real world, it is not uncommon to find roads, where vehicles of big dimensions cannot go through. Each client, depending on its structural characteristics and on the position of the road in which it is located, can receive vehicles up to a certain size. This limit has not been used previously in the literature.

2.1. Mathematical formulation of the problem

The mathematical model is described as follows: we assume $V(v=1,2,\ldots,V)$ vehicles with $q_v(v=1,2,\ldots,V)$ capacity and D $(i=0,1,\ldots,D)$ clients; $i=0$ represents the distribution centre. The delivery distance between two clients i and j is d_{ij}. Due to the asymmetry property, $d_{ij} \neq d_{ji}$. The delivery time t_{ij} depends on the vehicle and road types and it can be computed on the basis of the distance and the average travel speed. This value takes into account also the unloading time. The eventual time window at client i is denotes as $[l_i, u_i]$. Where l_i is the start point of the time window and u_i is the end point. Besides the following variables are defined:

$$x_{ijv} = \begin{cases} 1 & vehicle\ v\ travel\ from\ client\ i\ to\ client\ j \\ 0 & otherwise \end{cases}$$

$$y_{iv} = \begin{cases} 1 & the\ request\ of\ client\ i\ is\ satisfied\ by\ the\ vehicle\ v \\ 0 & otherwise \end{cases}$$

$$z_{iv} = \begin{cases} 1 & client\ i\ can\ be\ served\ by\ vehicle\ v \\ 0 & otherwise \end{cases}$$

The main problem is to minimize:

$$min \sum_{i=0}^{D} \sum_{j=0}^{D} \sum_{v=1}^{V} d_{ij} \cdot x_{ijv} \tag{1}$$

This subject to the following constraints:

$$\sum_{i=1}^{D} g_i \cdot y_{iv} \leq q_v \quad \forall\ v \in V \tag{2}$$

$$\sum_{j=1}^{D} x_{ijv} \cdot t_{ij} \leq l_i \quad \forall\ i \in D,\ \forall\ v \in V \tag{3}$$

$$\sum_{j=1}^{D} x_{ijv} \cdot t_{ij} \geq u_i \quad \forall\ i \in D,\ \forall\ v \in V \tag{4}$$

$$y_{iv},\ z_{iv} \in (0,1)\ \forall\ i \in D,\ \forall\ v \in V \tag{5}$$

$$\sum_{v=1}^{V} y_{iv} \cdot z_{iv} = 1\ \forall\ i \in D,\ i \neq 0 \tag{6}$$

The constraint (2) ensures the capacity of each vehicle is sufficient to satisfy the requests of the served clients and it assures that the total capacity of the vehicles satisfies the total delivery demand. Constraints (3) and (4) are about time window restrictions. Constraint (6) is related to the vehicle dimension limits.

3. Firefly algorithm

3.1. Firefly encoding

This study uses the real-coded schema, presented by Wu et al. [34]. Because there are V vehicles for distribution, at the most V routes can be taken into consideration. Every vehicle begins and finishes at the distribution centre. Considering D clients, the problem is coded in order to obtain fireflies whose dimension is $D+V$-1. For example, consider there are 5 clients, and 3 vehicles. The request of each client and the capacity of each vehicle are reported below:

$D=5$	$V=3$
$g_1=60$ pallet	$q_1=120$ pallet
$g_2=30$ pallet	$q_2=140$ pallet
$g_3=40$ pallet	$q_3=100$ pallet
$g_4=40$ pallet	
$g_5=90$ pallet	

Step 1

Generate a vector $A=(a_1 \ldots a_{D+V-1})$ of $D+V$-1 = 5 + 3–1 random number $\in]0,1[$:

$$A = \begin{bmatrix} 0.56 & 0.10 & 0.6 & 0.13 & 0.41 & 0.43 & 0.12 \end{bmatrix}$$

Step 2

Create an ordered vector = $(b_1 \ldots b_{D+V-1})$:

$$B = \begin{bmatrix} 0.10 & 0.12 & 0.13 & 0.41 & 0.43 & 0.56 & 0.6 \end{bmatrix}$$

Step 3

Create a $C=(c_1 \ldots c_{D+V-1})$ vector substituting each element of the B vector with a integer number $\in [1, D+V\text{-}1]$:

$$C = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 \end{bmatrix}$$

Step 4

Insert these numbers in a $D = (d_1 ... d_{D+V-1})$vector in the same position of the A vector:

$$D = [6 \quad 1 \quad 7 \quad 3 \quad 4 \quad 5 \quad 2]$$

Step 5

Generate an $E = (e_1 ... e_{D+V-1})$ vector in which each element is the position number in the D vector. For example in the D vector number 1 is in the second position then the first element of E will be 2:

$$E = [2 \quad 7 \quad 4 \quad 5 \quad 6 \quad 1 \quad 3]$$

Step 6

Create a $G = (g_1 ... g_{D+V-1})$ vector in which the elements from $D+1$are substituted with 0:

$$G = [2 \quad 0 \quad 4 \quad 5 \quad 0 \quad 1 \quad 3]$$

Step 7

Create a $F = (f_1 ... f_{D+V+1})$ vector (the firefly) in which in the G vector one 0 is added at first and one 0 at the end:

$$F = [0 \quad 2 \quad 0 \quad 4 \quad 5 \quad 0 \quad 1 \quad 3 \quad 0]$$

In this example the F vector represents the following routes:

- Vehicle 1 $0 \rightarrow 2 \rightarrow 0$
- Vehicle 2 $0 \rightarrow 4 \rightarrow 5 \rightarrow 0$
- Vehicle 3 $0 \rightarrow 1 \rightarrow 3 \rightarrow 0$

In this approach we have considered adjacent zeros (i.e. the number of routes can be less or equal to the number of vehicles). The code allows to choice the best combination of vehicles from an initial fleet.

3.2. Firefly algorithm with elitism procedure

In FA, variation of the light intensity and attractiveness are main concerns. This attractiveness is determined by brightness, which is associated with the objective function. After generating initial number of fireflies or solutions of the problem, the light intensity of firefly is updated. Assuming the absorption coefficient γ, the light intensity of the firefly varies with the square of the distance d, as in the following Eq. (7):

$$L = L_0 e^{-\gamma d^2} \tag{7}$$

Where L_0 denotes the light intensity of the source. The attractiveness of the fireflies is proportional to their light intensities L. Thus, Eq. (8) is given, so as to describe the attractiveness.

$$\beta = \beta_0 e^{-\gamma d^2} \tag{8}$$

Where, β_0 is the attractiveness at $d=0$. The distance between any two fireflies p_i and p_j is taken as Euclidean distance. Considering each firefly as a sequence of $D+V$-1 routes, the distance between two fireflies can be formulated as follows:

$$d_{ij} = \left\| p_i - p_j \right\| = \sqrt{\sum_{k=1}^{D+V-1} \left(p_{i,k} - p_{j,k}\right)^2} \tag{9}$$

The i th firefly is attracted to another brighter firefly j. The movement of the firefly from one position to another is expressed by the following equation:

$$p_{inew} = p_{iold} + \beta\left(p_j - p_{iold}\right) + \alpha\varepsilon \tag{10}$$

in which α=0.2 and ε is a random number in the range [0,1].

The parameter γ has an essential effect on the convergence speed of algorithm. The value of this parameter is based on the problem to be optimized. Normally, its value ranges from 0.1 to 10 [32]. Three parameters control the FA: the randomization parameter, the attractiveness, and the absorption coefficient. By adjusting these parameters we can obtain good results of an optimization problem. The flowchart of FA is shown in Fig. 1:

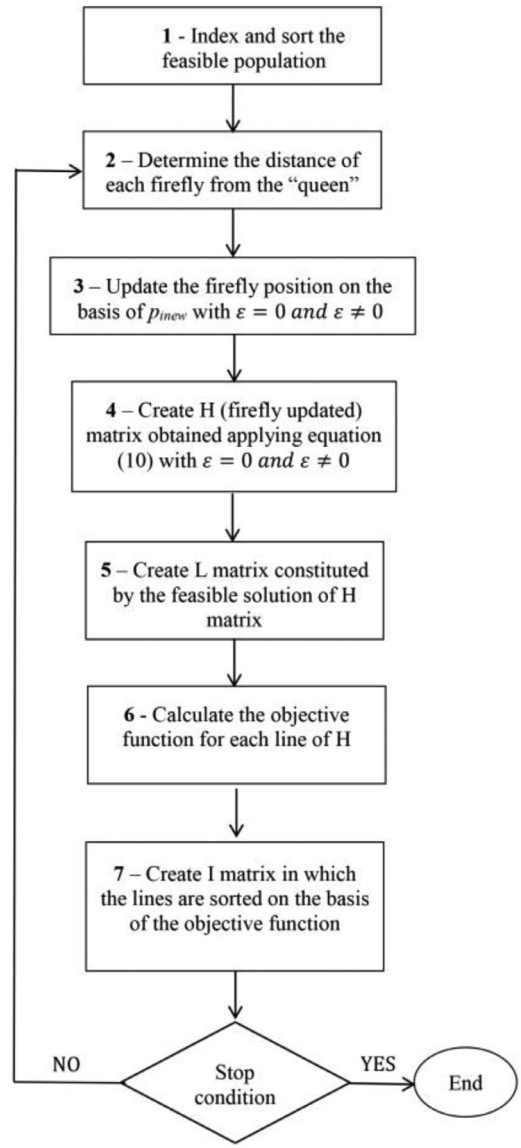

Fig. 1. Flow chart of FA optimization procedure.

In the phase **1** the vectors $F = (f_1 ... f_{D+V+1})$ corresponding to the feasible routes (fireflies) are sorted on the basis of the objective function and then matrix $F' = \begin{pmatrix} f_{11} & \cdots & f_{1j} \\ \vdots & \vdots & \vdots \\ f_{z1} & \cdots & f_{zj} \end{pmatrix}$ is build. The first line corresponds to the firefly with the best objective function and it is considered as a "Firefly Queen" (FQ) of the initial population.

In the phase **2** the distance of each firefly from the best (FQ) is calculated using Eq. (9).

In the phase **3** the position of the fireflies is updated by putting the distance and intensity values in Eq. (10). In this phase an elitism mechanism is introduced in order to avoid losing the FQ obtained in the first phase and the eventual solutions near by the global optimum. This condition is obtained considering ε=0 and $\varepsilon \neq 0$.

In the phase **4** the software creates a matrix $H = \begin{pmatrix} f_{11} & \cdots & f_{1j} \\ \vdots & \vdots & \vdots \\ h_{z'1} & \cdots & h_{z'j} \end{pmatrix}$, where $z' = 2 \cdot z$, that memorizes the new values obtained applying twice Eq. (10) with and without the last factor.

In the phase **5** the software creates a matrix L constituted by the feasible solutions of the H matrix. The maximum number of rows is set equal to 20 fireflies.

The phase **6** computes the objective function for each line of the H matrix.

Finally in the phase **7** a matrix $I=\begin{pmatrix} i_{11} & \cdots & i_{1j} \\ \vdots & \vdots & \vdots \\ i_{2z1} & \cdots & i_{2zj} \end{pmatrix}$ sorted on the basis of the objective function, is created. The first line represents the new FQ that could (or not) coincide with the old one.

The procedure is repeated from step 2 until the stop condition (maximum number of iteration) is reached.

4. TOPSIS methodology

TOPSIS is among the most well-known classical Multi-Criteria Decision Making (MCDM) approaches, and was first presented by Hwang and Yoon [13]. The fundamental aim of the TOPSIS method is that the best alternative should have both the shortest distance from the positive ideal solution and should also be the most distant from the negative one. The TOPSIS method and its applications have often been used in literature, recently even to evaluate alternative vehicle technologies [24].

The use of this methodology involves the definition of a decision matrix. The decision matrix is a chart in which the m rows represent the routes and the n columns represent the selected criteria. A point found at the junction of row and column in the table represents the performance of a decision alternative according to a specific criterion. The first step of the TOPSIS procedure consists of defining a set of criteria that take into account the different aspects of the problem. The criteria used in this paper are reported below.

4.1. Evaluation criteria

4.1.1. Total distances

This criterion coincides with the value of the Objective Function (FO).

The same results, in terms of total distances can be obtained with different routes and considering diverse scenarios in terms of vehicle fleets engaged.

4.1.2. Utilization coefficient

This criterion is one of the most significant parameters to define the efficiency of a transportation system. Let q the capacity of a vehicle and defined k its space used, the utilization coefficient represents the percentage of vehicle space occupied by the items:

$$U = \frac{k}{q} \tag{11}$$

Considering a fleet of V vehicles the average Utilization Coefficient (UC) can be calculated as:

$$UC = \frac{\sum_{v=1}^{V} U_v}{V} \tag{12}$$

4.1.3. Carbon footprint

The carbon footprint may be defined as, "the quantity of Greenhouse Gases (GHGs) expressed in terms of equivalent carbon dioxide, emitted into the atmosphere by an individual, organization, process, product, or event from within a specified boundary". The set of considered GHGs and boundaries are defined according to the adopted methods and the scope of footprinting [26].

In the present study the emissions produced by the fleet of vehicles have been considered to evaluate the environmental impact. The Carbon Footprint (CF) has been calculated according to the Guidelines e Good Practice Guidance IPCC [15–17] in which the Emission (E) of CO_2 equivalent (CO_2eq) are:

$$\mathrm{E}(\mathrm{CO_2eq}) = \mathrm{E}(\mathrm{CO_2}) + \mathrm{E}(\mathrm{CO_2eq})\text{from } \mathrm{CH_4} + \mathrm{E}(\mathrm{CO_2eq})\text{from } \mathrm{N_2O} \tag{13}$$

where

$$\mathrm{E}(\mathrm{CO_2}) = \text{Distances} \cdot \text{Emission factor } (\mathrm{CO_2}) \cdot \mathrm{GWP}(\mathrm{CO_2}) \tag{14}$$

$$\mathrm{E}(\mathrm{CO_2eq})\text{from } \mathrm{CH_4} = \text{Distances} \cdot \text{Emission factor } (\mathrm{CH_4}) \cdot \mathrm{GWP}(\mathrm{CH_4}) \tag{15}$$

$$\mathrm{E}(\mathrm{CO_2eq})\text{from } \mathrm{N_2O} = \text{Distances} \cdot \text{Emission factor } (\mathrm{N_2O}) \cdot \mathrm{GWP}(\mathrm{N_2O}) \tag{16}$$

The emission factor [g/km] for each pollutant emission is a function of route typology, the fuel and vehicle used. A different fleet with the same routes can produce different value of CO_2eq.

4.1.4. Fuel consumption

This is an economic criterion, which depends on the route and vehicle used. The cost of Fuel Consumption (FC) can be calculated with the following equation:

$$\boldsymbol{FC = C \cdot \sum_{i=0}^{D} \sum_{j=0}^{D} \sum_{v=1}^{V} d_{ij} \cdot x_{ijv} \cdot f_v} \tag{17}$$

where

C [€/l] is the fuel cost while f_v [l/km] is the average fuel consumption of each vehicle.

4.2. Mathematical procedure

Once the decision matrix is defined, the weighted normalized decision matrix V, multiplying each element of the normalized decision matrix R by the weights w_j of the corresponding criteria, has to be built. The generic element of the R matrix is obtained with the following equation:

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}}, \forall i = 1..m,\ \forall j = 1..n$$

where a_{ij} is the score of the alternative i with respect to the j criterion. The generic element of the V matrix is hence obtained by the following equation:

$$v_{ij} = w_j \cdot r_{ij}, \forall i = 1..m,\ \forall j = 1..n \tag{18}$$

and

$$\sum_{j=1}^{n} w_j = 1.$$

Afterward, on the basis of the TOPSIS methodology, the positive ideal solution Azimuth (A^*) and negative ideal solutions Nadir (A^-), have been found:

$$A^* = \{v_1^*, \ldots, v_n^*\} = \left\{ \left[\max_{\forall i} v_{ij} \,|j \in I' \right] \right\}, \left\{ \left[\min_{\forall i} v_{ij} \,|j \in I'' \right] \right\}, \tag{19}$$

$$A^- = \{v_1^-, \ldots, v_n^-\} = \left\{ \left[\min_{\forall i} v_{ij} \,|j \in I' \right] \right\}, \left\{ \left[\max_{\forall i} v_{ij} \,|j \in I'' \right] \right\} \tag{20}$$

where I' and I" are associated with benefit and cost criteria respectively.

The third step of the methodology is calculating the relative distances.

$$S_i^* = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^*\right)^2},\ \forall i = 1..m \tag{21}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2},\ \forall i = 1..m \tag{22}$$

The final step combines the two distances so as to acquire the relative coefficient nearness by the following equation:

$$C_i^* = S_i^- / \left(S_i^- + S_i^*\right) \quad 0 \le C_i^* \le 1 \tag{23}$$

The alternatives are ranked according to C_i^* in descending order.

Fig. 2. Location of the clients.

Table 1
Fleet composition.

Vehicle	Quantity	Capacity (pallet)
Truck 1	6	16
Truck 2	2	18
Truck 3	6	22
Semitrailer	1	32

Table 2
Vehicle limit, TDA and clients' demand.

ID	Vehicle limit (max)	TDA	Demand	
1	Semitrailer	**8- 12**	16	
2	Truck 3	**8 - 13**	6	
3	Semitrailer	**8- 13**	20	
4	Truck 3	**8- 13**	10	
5	Truck 3	**8- 13**	7	
6	Truck 3	**8- 13**	9	
7	Truck 3	**8- 13**	10	
8	Truck 3	**8– 11/12–13**	18	
9	Truck 2	**8 - 13**	11	
10	Truck 3	**8- 13**	5	**112**

5. Numerical example

A numerical example is given in this paper to show the proposed approach. More specifically, this study refers to a medium-sized distribution company located in Sicily. The company covers a provincial area, which means that the it serves a set of customers geographically distributed in various towns and cities. For instance, in Fig. 2 the location of 10 clients served on a Monday morning is reported.

The fleet composition of the company in terms of quantity and maximum capacity of each vehicle is reported in Table 1.

Vehicle limit dimension, Time Delivery Availability (TDA) and demand (pallet) of each customer are known values, as shown in Table 2.

The distances between clients and the delivery times are reported in Tables 3 and 4

Distances have been calculated by means of the Google map application while the delivery time has been determined as sum of the travelling time, measured considering an average velocity for three different type of road (city street, interstate and highway) and the unloading time.

Five fleet configurations have been defined complying with the maximum daily request and the vehicle-client constraint.

As reported in Table 5, for each configuration the total capacity of the fleet is grater than the clients' total request (112 pallets). Moreover, all the scenarios include at least a truck 1 or 2, considering that the client 9 can be served only by this kind of trucks.

5.1. Results and discussion

Computations have been performed using the Matlab software running under Intel core i7-3940XM 3.2 GHz CPU, 16GB Ram and Windows 10 operating system. The principal parameters of the Firefly algorithm are set accordingly:

- Initial population of fireflies: 5
- Degree of light attenuation γ=1
- Step factor α =0.2
- Iteration times:500

After the iterations of 500 times, FA converged for each configuration to the optimal solutions reported in Table 6. For each solution the routes associated and the corresponding trucks are also evaluated.

In Table 6 the other criteria (i.e. utilization coefficient, carbon footprint and fuel consumption) have been also reported. In this paper the weights of the criteria were assessed by means of the Delphi technique [6]. In particular, the panel of experts has been iteratively queried by means of questionnaires until the agreement was achieved. Table 7 reports the weights obtained for each criterion.

At this point the weighted normalized matrix was calculated and the values of Azimuth and Nadir were determined as reported in Tables 8.

Finally, the relative distances were calculated according with equations 24 and 25 so as find the coefficient closeness (eq.26). The final ranking is reported in Table 9.

Results show that the best configuration is the last one in which the objective function is comparable with the others but the values related to the economic and environmental aspects (CF and FC) are significantly better than others. These results are strictly correlated with the initial vehicles configuration in which there is a homogeneous vehicle distribution. Moreover, starting from a configuration of 9 vehicles, the proposed

Table 3
Distances between clients [km].

	0	1	2	3	4	5	6	7	8	9	10
0	–	88.3	83.8	89.9	93.6	97.6	89	75.9	120	79.7	66.6
1	90	–	27.5	81	2	2.1	0.75	19.7	30.2	23.5	29.9
2	83.8	28.5	–	33	31.6	35.6	27.1	13.6	36.4	4.6	7.7
3	92	76	33	–	84.8	88.8	80.3	67.2	20.3	45.1	36.9
4	93.6	7	31.6	84.8	–	0.6	1.6	24.4	29.5	28.1	34.6
5	97.6	4.5	35.6	92	0.6	–	2.6	24.9	28.9	28.6	35
6	89	2	29	27	1.6	3.5	–	20.7	30.7	24.5	30.9
7	75.9	23.2	13.6	72.5	24.4	24.9	23.7	–	49.9	9.6	16.1
8	125	30.2	37.8	38.8	32.6	28.9	30.7	49.9	–	58.5	64.9
9	79.7	25.6	5.2	45.1	28.1	29.6	24.5	11	58.5	–	9.3
10	66.6	29.9	9.2	36.9	35.8	35	32.8	16.1	65.8	9.3	–

Table 4
Delivery time [minutes].

	0	1	2	3	4	5	6	7	8	9	10
0	–	111	81	125	100	91	95	83	142	96	75
1	63	–	48	118	39	30	30	50	84	60	50
2	63	78	–	100	65	56	62	50	94	43	31
3	65	106	58	–	93	83.5	87	80	99	83	55
4	70	53	57	123	–	24	33	55	81	68	55
5	70	57	53	122.5	33	–	34	54	79	68	55
6	68	51	53	120	36	28	–	52	82	62	50
7	53	68	38	110	55	45	49	–	94	51	37
8	88	78	58	105	57	46	55	70	–	88	75
9	63	75	28	110	65	56	56	48	109	–	33
10	60	85	34	100	70	61	62	52	114	51	–

Table 5
Fleet configurations.

	Configuration 1	Configuration 2	Configuration 3	Configuration 4	Configuration 5
	3 Truck 1 5 Truck 3 1 Semitrailer	2 Truck 1 2 Truck 2 5 Truck 3	5 Truck 1 4 Truck 3 –	1 Truck 1 7 Truck 2 1 Semitrailer	2 Truck 1 5 Truck 2 2 Truck 3
Total capacity	**190**	**178**	**168**	**174**	**166**

Table 6
Results obtained for the different fleet configurations.

Con	FO	UC	CF	FC	Fleet	Routes						
1	1303.7	81.2%	678,263.1	505.2	3 Truck 1 4 Truck 3	0=>6=>0 [T1]	0=>7=>0 [T1]	0=>10=>9=>0 [T1]	0=>5=>4=>0 [T3]	0=>8=>0 [T3]	0=>3=>0 [T3]	0=>1=>2=>0 [T3]
2	1302.8	82.7%	479,992.0	357.5	2 Truck 1 2 Truck 2 3 Truck 3	0=>10=>0 [T1]	0=>1=>0 [T1]	0=>2=>7=>0 [T2]	0=>9=>5=>0 [T2]	0=>8=>0 [T3]	0=>4=>6=>0 [T3]	0=>3=>0 [T3]
3	1303.9	86.6%	678,367.2	505.3	4 Truck 1 3 Truck 3	0=>6=>0 [T1]	0=>9=>10=>0 [T1]	0=>2=>7=>0 [T1]	0=>1=>0 [T1]	0=>5=>4=>0 [T3]	0=>8=>0 [T3]	0=>3=>0 [T3]
4	1303.9	82.8%	611,201.6	455.2	1 Truck 1 5 Truck 2 1 Semitrailer	0=>6=>0 [T1]	0=>9=>10=>0 [T2]	0=>1=>0 [T2]	0=>7=>2=>0 [T2]	0=>5=>4=>0 [T2]	0=>8=>0 [T2]	0=>3=>0 [S]
5	1298.9	81.1%	368,084.0	274.2	2 Truck 1 3 Truck 2 2 Truck 3	0=>6=>0 [T1]	0=>7=>0 [T1]	0=>1=>0 [T2]	0=>2=>9=>0 [T2]	0=>8=>0 [T2]	0=>3=>0[T3]	0=>4=>5=>10 =>0 [T3]

Table 7
Weights for each criterion.

FO	UC	CF	FC
0.35	0.25	0.15	0.25

Table 8
Weighted normalized matrix and ideal solutions.

	FO	UC	CF	FC
1	0.1567	0.1095	0.0790	0.1316
2	0.1565	0.1115	0.0559	0.0931
3	0.1567	0.1168	0.0790	0.1316
4	0.1567	0.1117	0.0712	0.1186
5.	0.1561	0.1094	0.0429	0.0714
A*	0.1561	0.1168	0.0429	0.0714
A-	0.1567	0.1094	0.0790	0.1316

Table 9
Final ranking.

	Ranking
1	0.002
2	0.635
3	0.096
4	0.218
5	**0.904**

approach allows selecting a reduced fleet (i.e. 7 vehicles) through the optimization procedure.

6. Conclusions

The vehicle routing problem is a main problem in logistics distribution. In this work, a rich vehicle routing problem with simultaneous economic and environmental aspects has been tackled in order to obtain a sustainable vehicle routing decision. To prove the effectiveness of the proposed approach a numerical example has been also reported, using information provided by a medium size company. To deal with such a complex problem, a new approach based on the Firefly algorithm and the TOPSIS methodology has been developed. Results show that the choice of the best route is strictly related to the fleet of vehicles due to their economic and environmental impact. The minimization of the total distance travelled cannot be the only target for solving this kind of problem. Further researches are needed to evaluate the economic saving, considering that the routes made by the same type of vehicle could be travelled by a single vehicle if within the established working time. Moreover, future developments should also include in the TOPSIS set of criteria different environmental/ecological variables, including water resources consumption and depletion, or loss of energy, to conduct an optimization through an holistic approach to sustainability.

Declaration of Competing Interest

None.

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