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A novel Dynamic programming approach for Two-Echelon Capacitated Vehicle Routing Problem in City Logistics with Environmental considerations

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Abstract

The paper proposes a Two-Echelon Capacitated Vehicle Routing Problem with Environmental consideration, intended for managing urban freight distribution in City Logistics. It presents a novel Dynamic programming approach that divides the main problem into several ones and uses an exact algorithm to obtain optimal route paths. The approach applies Fuzzy C-Means Clustering for assigning a group of customers to a satellite. The initial solution is improved with roulette selection, 2-opt, and Or-opt exchange heuristics. The approach was tested on benchmark instances, and obtained results are satisfactory. Moreover, the proposed method highlights the environmental improvement we can obtain in managing urban freight transportation.

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Keywords: Two-Echelon Capacitated Vehicle Routing; Dynamic Programming; Fuzzy C-Means Clustering; Environmental impact;

1. Introduction

During the last decades, the worldwide globalization and process of rapid urbanization have been estimated as one of the key threats for sustainable development. Population growth and development of cities cause higher traffic and transportation volumes, which lead to negative impacts on road infrastructure such as traffic jam and congestion, air pollution, etc. (Ananda et al., 2012). In addition, freight carriers are more concerned with high market requirements

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and economy, reduction of costs and number of vehicles, improvement of delivery service, etc. As a result, sustainable development of urban areas faces two emerging conflicting interests - public authorities, concerned with environmental issues, and private companies who seek to satisfy high market requirements (Schliwa et al., 2015). The main encouragement for solving aforesaid issues was demonstrated through different approaches Vehicle Routing Problem in City Logistics (CL).

This work considers a Two-Echelon Capacitated Vehicle Routing Problem with Environmental consideration (2E-CVRP-E) in CL. The paper aims at finding the optimal route paths regarding the number of customers and satellites, load weights, transportation costs and emissions. We propose a novel Dynamic programming approach that uses Fuzzy C-Means Clustering (FCM) to relax the main problem into smaller sub-problems. The main task is the assignment of customers a specific satellite. The initial solution of each assignment has been obtained with exact solver. Then, three improvement heuristics are used: roulette selection, 2-opt and Or-opt.

The paper is structured as follows. Section 2 summarizes the literature review on different approaches of 2E-CVRP. Section 3 emphasizes the problem description and mathematical formulation. Section 4 presents the novel Dynamic solution approach. Section 5 reports the results. Section 6 present the conclusion.

2. Literature review

The concept of CL was introduced in literature through different variations and formulations of Vehicle Routing Problem approaches related to the: number of echelons, number of depots, time-windows dependence, pick-up deliveries (Cattaruzza et al., 2017). During the last years, the recent literature proposes different 2E-CVRP solution approaches, considering heuristic, metaheuristic and exact algorithms (Cuda et al., 2015; Wang et al., 2015). Crainic et al. (2010) proposed one of the first paper that pointed out the significant result of using two-echelon system instead of single-echelon. They used the fast clustering heuristic to minimize total distribution costs in 2E-CVRP. Most of the papers in literature that considered exact approaches for 2E-CVRP are based on branch-and-cut and branch-and-cut-price algorithm (Jepsen et al., 2012; Santos et al., 2014). Instead, Baldacci et al. (2013) introduced an exact algorithm for 2E-CVRP and a new bounding procedure based on dynamic programming approach. However, we intended to highlight the influence of environmental aspect in CL.

This paper focuses on exact method and dynamic programming approach for 2E-CVRP-E. During the last years, some works proposed different 2E-CVRP approaches, considering environmental issues such as fuel consumption and CO_2 emissions (Wanga et al., 2017; Soysal et al., 2015; Hongqi et al., 2016). Crainic et al. (2012) introduced one of the first studies that considered environmental issues in 2E-CVRP. Wanga et al. (2017) solved the 2E-CVRP-E with a matheuristic approach which combines variable neighbourhood search algorithm and the integer programming in CL with environmental considerations. However, all these papers evaluated the emissions without stressing out the environmental impact of the final solutions. Hence, the contribution of this paper first lies in evaluating the environmental impact of the solutions and comparing them with 2E-CVRP formulation. Moreover, we propose a novel dynamic programming approach for 2E-CVRP-E in CL.

3. Problem description

Basically, the concept of 2E-CVRP is addressed to determining first and second level routes for fulfilling demand, starting from and ending at the depot, while traversing the set of satellites and customers assigned to satellites. Therefore, the first level routes decisions (first echelon level) determine the set of routes from the depot to satellites, while the decisions for the second level routes (second echelon level) refer to assigning customers to a specific satellite (Wanga et al., 2017). The first echelon comprises a set of homogenous vehicles, located at a depot. The total number of vehicles used for delivering goods to a set of satellites cannot exceed the number of the vehicles located at the depot. Also, the number of used homogenous vehicles must satisfy the demand at satellites. Concurrently, another group of homogenous vehicles in the second echelon is assigned to each satellite, intended for delivering freight to a set of customers. The demand of each customer is known in advance and should not be split into different vehicles. At the same time, each vehicle delivers the demand for more than one customer, in such a way that total demand assigned to the vehicle cannot exceed its capacity. The problem is related to find the optimal set of first and second level routes among satellites, customers and depot, including environmental and distance costs. The objective function minimizes total costs, in accordance with demand and number of customers assigned at each satellite.

However, two-echelon level routing problems are proved as more cost-efficient than single-level distribution systems. In this case, satellites are perceived as a cross-docking between origin and destination. New approaches consider multi-echelon level problems between origin and destinations using intermediate satellites. At each level, these satellites could be interpreted as warehouses in which goods could be stored for more days. 2E-CVRP is a special case of the multi-echelon vehicle routing problem in which the number of levels is equal to 2.

Especially in CL, the choices of optimal route are influenced by different traffic conditions, including traffic density, number of traffic lanes, number of traffic lights, parking availability, etc. (Behnke and Kirschstein, 2017). Due to these factors, the estimation of total travel time and route cost is quite difficult. Moreover, increased number of small-sized vans and large trucks have the main influence on traffic congestions in cities, and therefore on fuel consumption, CO_2 and GHG emissions. For these reasons, we included an environmental impact model in the 2E-CVRP which considers costs related to the difference of fuel consumption between empty and full load vehicles, as well as among different type of vehicles. In the following, we introduce the basic formulation and, then, the proposed formulation for the 2E-CVRP-E.

3.1. Mathematical formulation

In the basic formulation, the 2E-CVRP is defined on a graph $G=\{V, A\}$, where the set of nodes is $V = \{N \cup C \cup D_0\}$: $N = \{1, 2,..., n_s\}$ is the set of satellites; $C = \{n_s+1, n_s+2,..., n_c\}$ is a set of customers and depot $D_0 = \{0\}$, as illustrated in Fig 1. The set A consists of two subsets: a set of links among the satellites and customers $A_{NC} =\{(i, j) \mid i,j \in N \cup C\}$ in the second level; the set A_{DN} of links among satellites and depot $A_{DN} = \{(i, j) \mid i,j \in D_0 \cup N\}$ in the first level, where d_{ij} is the distance on arc (i, j) and c_{ij} is the transportation cost per distance unit. We assumed that depot D_0 has no demand. A homogenous group of first-echelon level vehicles with capacity Q_m, located at the depot, is assigned to a set of links defined on A_{DN}. The number of required vehicles m is calculated according to sum of demands at each satellite D_j^{sat} and the capacity of a vehicle Q_m, as $m = \sum_{j \in N} D_j^{sat} / Q_m$.

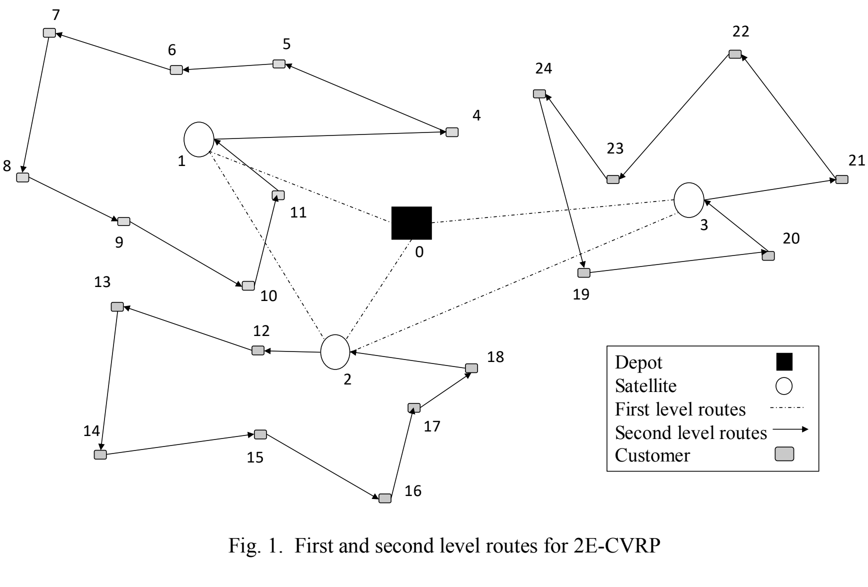

Fig. 1. First and second level routes for 2E-CVRP

Baldacci et al. (2004) proposed a two-index Vehicle Flow formulation based on the formulation by Laporte et al. (1985). Accordingly, for a given set N, we denote $R = \{S: S \subseteq N, |S| \geq 2\}$. We used the proposed formulation and developed the model for first level routes as follows:

$$Z = \min \sum_{i \in A_{DN}} \sum_{j \in A_{DN}} d_{ij} c_{ij} \cdot x_{ij} \tag{1}$$

s.t.

$$\sum_{\substack{j \in D_0 \cup N \\ i>j}} x_{ji} = 1, \forall i \in N \tag{2}$$

$$\sum_{\substack{j \in D_0 \cup N \\ i>j}} x_{ij} = 1, \forall i \in N \tag{3}$$

$$\sum_{i \in S} \sum_{\substack{j \in D_0 \cup N \setminus S \\ i<j}} x_{ij} \geq \sum_{j \in S} D_j^{sat} / Q_m, \forall S \in R \tag{4}$$

$$\sum_{i \in D_0 \cup N \setminus S} \sum_{\substack{j \in S \\ i<j}} x_{ij} \geq \sum_{j \in S} D_j^{sat} / Q_m, \forall S \in R \tag{5}$$

$$\sum_{j \in N} x_{0j} + \sum_{j \in N} x_{j0} = 2m \tag{6}$$

$$\sum_{i \in S} \sum_{\substack{j \in S \\ i<j}} x_{ij} \leq |S| - m, \forall S \in R \tag{7}$$

Decision variables

$$x_{ij} \in \{0,1\}, \forall (i,j) \in A_{DN} \setminus \{(0,j) : j \in N\} \tag{8}$$

$$x_{0j} \in \{0,1,2\}, \forall \{0,j\} \in A_{DN}, j \in N \tag{9}$$

The objective function (1) minimizes total transportation costs. Constraints (2) and (3) ensure that each satellite has one entering link and one exiting link. Constraints (4) and (5) are capacity constraints related to the number of vehicles needed to satisfy demand at satellites. The constraints are related to the number of vehicles entering at and leaving from each satellite. Accordingly, constraint (6) is related to a total number of vehicles leaving from and returning at depot. Constraint (7) is denoted as subtour elimination constraint. Constraints (8) and (9) are integrality constraints, where x_{ij} is equal to 1 if the arc (i, j) is selected in the solution, and 0 otherwise. The variable x_{oj} is equal to 2 if the selected route includes the single satellite.

3.2. The proposed formulation including environmental impact

In the literature, emission models showed that emission is not-linearly correlated with speed and traffic flows, depending on a time period with or without traffic congestion (Behnke and Kirschstein, 2017). In free-flow routes, the emission slowly increases as the vehicle's driving speed increase. Therefore, the payload capacity of vehicles is quite important, according to the fact that the increment of small-sized vehicles in cities causes significant emission. Moreover, the fuel emission varies among the diverse type of vehicles due to their technical specification, type of engine, aerodynamics, road gradient, rolling resistance. Consequently, to include the environmental impact into the 2E-CVRP, we used the emission function by Behnke and Kirschstein (2017) since it is a state-of-the-art model that fits our problem requirements. The emission function is defined as follows:

$$emis(l_{ij}) = e \cdot d_{ij} \cdot \left(c_{ij}^{fix} + c_{ij}^{load}\left(m^{tare} + l_{ij}\right)\right) \tag{10}$$

where:

- c_{ij}^{load} and c_{ij}^{fix} denote the load-dependent and load-independent emission factor on arc (i, j);
- m^{tare} denotes the tare weight of vehicles;
- e is the emission coefficient for diesel fuel;
- d_{ij} is the travel distance on arc (i, j);
- l_{ij} is the load of vehicles traversing arc (i, j).

The c_{ij}^{load} and c_{ij}^{fix} are defined as follows:

$$c_{ij}^{fix} = \frac{r^{idle}}{V_{ij}} + \frac{c^{air}}{3.6^3} \cdot \frac{1}{2000} \cdot \alpha_{ij} \cdot \rho \cdot A \cdot V_{ij}^2 \tag{11}$$

$$c_{ij}^{load} = \alpha_{ij} \cdot \left(\frac{c^{roll}}{3.6} \cdot g + \frac{0.504}{2 \cdot 3600 \cdot 3.6^2} \cdot n_{ij}^{acc} \cdot V_{ij}^2\right) \tag{12}$$

where:

- c^{air} is the air resistance coefficient;
- ρ is the density of air [kg/m^3];
- c^{roll} is the rolling resistance coefficient for vehicles;
- A is the front surface [m^2];
- n_{ij}^{acc} is the expected number of acceleration per km;
- V_{ij} is the driving speed of vehicle [km/h];
- r^{full} and r^{idle} are the vehicle's maximum and minimum fuel consumption rate [1/h];
- g is the gravity acceleration [9.81 m/s^2];
- α_{ij} is the amount of fuel consumed per hour to produce one kWh of output energy.

Finally, α_{ij} is calculated as in following equation:

$$\alpha_{ij} = \frac{r^{full} - r^{idle}}{P \cdot \left(0.88 - 0.72 \cdot \exp\left(-0.077 \cdot V_{ij}^{1.41}\right)\right)} \tag{13}$$

where P is the rated power of the engines in vehicles [kW].

We used the values of parameters given in Table 1. CO_2 emissions depend on the type of homogenous vehicles, related to the first and second level echelons. However, we considered only emissions of the class of small vehicles in second level routes, concerning the fact that their influence on the overall network optimization is the highest.

We included the emission model above in the basic formulation (Eq. 1) for the second level routes. As a result, we obtained the following formulation considering the environmental impact:

$$Z = \min \sum_{i \in A_{NC}} \sum_{j \in A_{NC}} e \cdot d_{ij} \cdot \left(c_{ij}^{fix} + c_{ij}^{load}\left(m^{tare} + 1\right)\right) \cdot x_{ij} \tag{14}$$

subject to constraints (2)-(9).

Table 1. Parameters on emission model

Notation	Description	Value
r^{full}	Vehicle's maximum fuel consumption rate [1/h];	30
r^{idle}	Vehicle's minimum fuel consumption rate [1/h];	1
c^{air}	Air resistance coefficient	0.64
ρ	Density of air [kg/m^3]	1.2
e	Emission coefficient for diesel fuel [kg CO_2e/l]	3.15
A	Front surface [m^2]	6
P	Engine's rated power	85
c^{rol}	Rolling resistance coefficient	0.008
m^{tare}	Empty weight [t]	3.5
n_{ij}^{acc}	Number of vehicle's acceleration processes per kilometer	3

4. Solution approach

The 2E-CVRP is considered as a complex optimization problem, which involves different solution approaches to find the optimum. The proposed method uses the Dynamic programming approach to divide the main problem into several sub problems using the FCM clustering. Through FCM, in the second level problem, we assigned each customer to a specific satellite. Then, we used an exact algorithm to obtain a first solution for each sub problem, through the minimization of the considered objective function. Afterwards, to improve the quality of the initial solution, we proposed a combination of the 2-opt and Or-opt exchange heuristic and the roulette selection to obtain a new assignment of customers to satellites. The selection probability is related to the membership degree of each customer to satellites obtained by FCM. We applied again the exact algorithm to each new sub problem to obtain the optimal routes at the second level. The first level problem is solved by an exact algorithm. We improve the solution applying iteratively the method described above.

In our approach, the main complexity is related to the number of satellites and customers in big sized problems. In general, the clustering method enumerates the subset of $\binom{n}{m}$ cluster alternatives, where n is the number of customers, and m is the number of satellites. According to Makhalova (2013), the FCM algorithm for the proposed problem is presented as follows: in the first step, we defined the number of clusters (c) as the number of satellites; in the next step, we measured the distance $\|x_i\text{-}c_j\|$ between a satellite j and customer i. So, the membership value u_{0j} at the first iteration is calculated, and the matrix $U_0 = [u_{0j}]$ is obtained. Then, membership values u_{ij} of the matrix U and clusters centres c_j are iteratively updated using the following formulas (15)-(16):

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\| x_i - c_j \|}{\| x_i - c_k \|}\right)^{\frac{2}{m-1}}} \tag{15}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{16}$$

where m is any real number greater than 1. In this work m is equal to 2.

At the end of the clustering procedure, FCM assigns a group of customers to each satellite obtaining an initial solution S^*. Cluster groups are formed in accordance with membership degree. During iterations, to ensure that clustering procedure generates the same assignments, we fixed a seed value in the FCM initialization to always obtain the random number sequence.

The pseudo-code of the proposed method is reported in Algorithm 1. We applied three different methods to improve the initial solution. First, the roulette selection is used to change the initial solution, according to the probability p_{ij} that the customer i is assigned to a satellite j, defined as follows (17):

$$p_{ij} = \frac{u_{ij}}{\sum_{j=1}^{n_s} u_{ij}} \tag{17}$$

Moreover, we applied 2-opt and Or-opt heuristics to improve the overall solution. 2-opt heuristics is more widely used for Traveling Salesman Problem, but also for constructing routes in Vehicle Routing Problems. The algorithm of 2-opt heuristic considers $k = 2$ routes and exchange the order between them, to obtain a better solution. For example, considering a set of nodes $N = \{a, b, c, d, e, f, g, h, i, j, k\}$, we can obtain the graph reported in Fig. 2.

We set up the value $p_r = 0.33$ related to the probability of choosing roulette selection. Accordingly, we set up the value $1 - p_r$ for choosing 2-opt and Or-opt heuristic. The method updates the best membership value for each iteration calculates the second level routes through an exact solver. This is also applied to the first level problem to find the best route among satellites and depot. The final solution provides the cost minimization of first and second level routes.

Algorithm 1. Solution improvement approach for 2E-CVRP

Initialization: Input parameters and data
S*, U* ← Generate the initial solution by applying FCM
repeat
    /* Solution improvement */
    if *rand* < p_r **then**
        S ← Roulette selection(U*)
    else if r > p_r and r < p_r+p_o **then**
        S ← 2-Opt Heuristic(S*)
    else
        S ← Or-opt Heuristic(S*)
    end
    update route set R_2 solving the CVRP(S) for each satellite at the 2nd level
    if f(S) < f(S*) **then**
        S*← S
until termination condition is satisfied
return S*

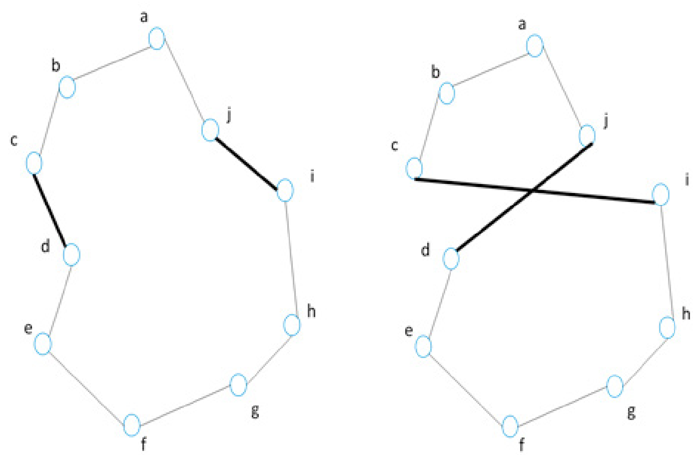

Fig. 2. Example of 2-opt exchange heuristic

5. Results

We applied the proposed algorithm to the 2E-CVRP instances introduced by Breunig et al. (2016) (http://www.univie.ac.atprolog/research/ TwoEVRP/) to test it and validate the results. These instances contain the data related to the maximum number of trucks located at the depot and satellites, total capacity of trucks, travel cost per distance, coordinates of a set of customers, satellites and depot, demand of each customer. We used *Set 2a* and *Set 2b* instances organized into three groups. In particular, the first group include 22 customers and 2 satellites; second group includes 33 customers and 2 satellites; the third group includes 50 customers and 4 satellites. The distances between depot and satellites as well as satellites and customers were calculated as Euclidian. The proposed algorithm was developed in Python using Gurobi as exact solver. The results were obtained on a workstation equipped with an Intel Xeon E5450 3.00GHz CPU, 4 GB RAM.

First, the mentioned instances were used without considering environmental impact to evaluate the results obtained by our proposed method. We used the main benchmarks existing in the literature as reported in Table 2. The column “Final solution” summarizes the results we obtained for *Set 2a* and *Set 2b* instances. The column “gap” refers to the gap percentage between our results and the best-known solution (BKS) in the literature. The column “Comp. Time” refers to the computational time after 200 iterations, while the column “No. iterations to best” refers to the number of iteration to reach the best solution. As a result, we obtained the optimal and near-optimal results for small and medium sized instances, with the highest gap of 1.79%, and improved the BKS for the instance Set2a_E-n33-k4-s2-13 with a gap of -0.58%. The results are obtained in low computational times (15 seconds on average). Moreover, for some instances, the proposed approach was able to find the optimal solution at the first iteration. For bigger instances, the proposed algorithm found a good solution with an acceptable gap in few seconds.

Second, we attempt to solve the 2E-CVRP instances concerning environmental impact (2E-CVRP-E). In the literature, some researchers considered environmental impact for 2E-CVRP and reported the total route and environmental costs (Wanga et al., 2017). In this work, we highlighted the differences between non-environmental and environmental considerations in the total routing cost. We used the basic 2E-CVRP formulation (Eq. 1) and calculated the environmental impact by using Eq. 10 on the obtained results. Then, we solved the 2E-CVRP-E using Eq. 14. At this point, we carried out a comparison between 2E-CVRP and 2E-CVRP-E. The speed was randomly generated in the range 20-60 [km/h] for each link. Fig. 3 illustrates the resulting comparison of the obtained routes on the Set2a_E-n22-k4-s6-17 instance. It is observed that considering the environmental impact we obtained a different clustering and routing, but a decrease of total environmental costs of 8.42% on average as reported in Table 3. In this way, we quantified the cost improvement and stressed out the importance of introducing environmental impact in CL.

Table 2. Results and benchmarks of 2E-CVRP instances

Instances	n_c	n_s	The main BKSs in the literature for 2E-CVRP		**Proposed approach**			
			Matheuristic *Wanga et al. (2017)*	LNS heuristic *Hemmelmayr et al. (2012)*	**Final solution**	**Gap (%)**	**Comp. Time (s)**	**No. iterations to best**
Set2a_E-n22-k4-s6-17	21	2	417.07	417.07	**417.07**	0.00%	26	15
Set2a_E-n22-k4-s8-14	21	2	384.96	384.96	**384.96**	0.00%	37	14
Set2a_E-n22-k4-s9-19	21	2	470.60	470.60	**470.60**	0.00%	35	45
Set2a_E-n22-k4-s10-14	21	2	371.50	371.50	**371.50**	0.00%	34	27
Set2a_E-n22-k4-s11-12	21	2	427.22	427.22	432.31	1.19%	36	-
Set2a_E-n22-k4-s12-16	21	2	392.78	392.78	393.09	0.08%	31	-
Set2a_E-n33-k4-s1-9	32	2	730.16	730.16	743.22	1.79%	50	-
Set2a_E-n33-k4-s2-13	32	2	714.63	714.63	**710.48**	-0.58%	53	52
Set2a_E-n33-k4-s7-25	32	2	756.85	756.85	**756.84**	0.00%	55	1
Set2b_E-n51-k5-s2-4-17-46	50	4	530.76	530.76	577.16	8.74%	63	-
Set2b_E-n51-k5-s6-12-32-37	50	4	531.92	531.92	581.52	9.33%	65	-
Set2b_E-n51-k5-s11-19-27-47	50	4	527.63	531.12	607.30	15.10%	70	-

Table 3. Comparison between environmental costs of 2E-CVRP and 2E-CVRP-E

Instances	2E-CVRP (kg CO_2)	2E-CVRP-E (kg CO_2)	Improvement (%)
Set2a_E-n22-k4-s6-17	252.09	237.41	6.18
Set2a_E-n22-k4-s8-14	214.40	189.32	13.25
Set2a_E-n22-k4-s9-19	274.28	256.54	6.92
Set2a_E-n22-k4-s10-14	201.52	177.51	13.53
Set2a_E-n22-k4-s11-12	221.52	211.48	4.75
Set2a_E-n22-k4-s12-16	203.29	188.75	7.70
Set2a_E-n33-k4-s1-9	485.97	472.84	2.78
Set2a_E-n33-k4-s2-13	476.47	436.67	9.11
Set2a_E-n33-k4-s7-25	530.32	503.94	5.23
Set2b_E-n51-k5-s2-4-17-46	295.45	285.69	3.42
Set2b_E-n51-k5-s6-12-32-37	289.76	237.70	21.90
Set2b_E-n51-k5-s11-19-27-47	320.19	301.40	6.23

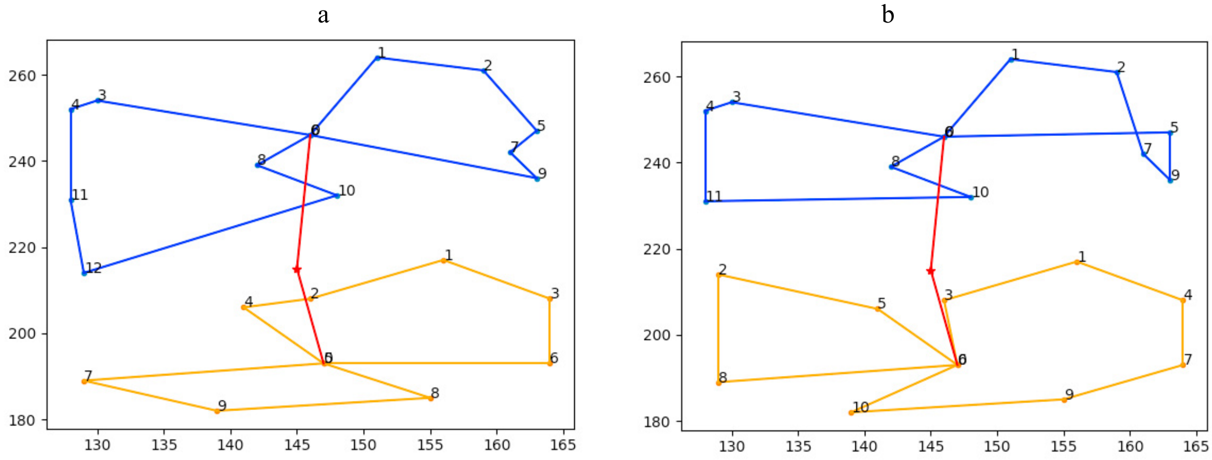

Fig. 3. Resulting comparison of routes obtained for (a) 2E-CVRP and (b) 2E-CVRP-E on Set2a_E-n22-k4-s6-17 instance

6. Conclusion

In this work, we introduced a Dynamic programming approach for the two-echelon capacitated vehicle routing problem (2E-CVRP). To evaluate the environmental impact, we introduced the emission model by Behnke and Kirschstein (2017) in the basic 2E-CVRP to obtain our 2E-CVRP-E formulation. The Dynamic programming approach is implemented using Fuzzy C-Mean clustering (FCM) in order to divide the main problem into smaller sub problems. Moreover, we introduced a solution improvement algorithm combining roulette selection, 2-opt and Or-opt heuristics. We tested the proposed method on main instances by Breunig et al. (2016) and carried out a comparison between 2E-CVRP and 2E-CVRP-E regarding environmental impact.

The contribution of this work can be summarized as follows. Obtained results, as shown in Table 2, highlight the effectiveness of proposed method in approaching the best-known solution in the literature with an average gap of 3.24%. The computational results highlighted the high performances of the proposed algorithm. Moreover, we quantified the emission improvement obtained with 2E-CVRP-E when compared to 2E-CVRP, with an average decrease of 8.42%. Finally, the proposed method could serve as a useful tool for logistic companies to plan "green" routes taking into account not only travel costs, but also considering traffic congestion and emission costs.

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