A Memetic Algorithm to Solve the Two-Echelon Collaborative Multi-Centre Multi-Periodic Vehicle Routing Problem with Specific Constraints

Camelia Snoussi, Abdellah El Fallahi, Sarir Hicham
MaCS-DM Laboratory, National School of Applied Sciences
University AbdelMaleek Essaadi
Tetuan, Morocco

***Abstract*—The collaboration between distribution companies is gaining a great interest in the last years due to the benefit provided to reduce the cost of deliveries. In this work we study the centralized two-echelon collaborative multi-center multi-periodic vehicle routing problem with a specific constraints. In which each distribution center conserves its VIP customers, and each partner keep their delivery scheduling unchangeable. The problem is modelled as a MILP, and to solve it a hybrid algorithm is proposed. This algorithm combines a multi-population memetic algorithm (MPMA) and a variable neighbourhood search algorithm that integrates a tabu search list (VNS-T). The results obtained are compared with those obtained by CPLEX solver and the best known solution of the multi-depot vehicle routing problem (MDVRP).**

Keywords*—Collaborative vehicle routing problem; two-echelon networks; memetic algorithm; Variable neighbourhood serach

I. Introduction

The significant growth in the delivery of small volumes of goods generated by the increase in e-commerce sales [1] and domestic freight, particularly during the Covid-19 pandemic [2], creates major challenges for distribution companies operating in the urban sector. It's well known that the urban transport faces a major problem of empty runs with more than 40% of unloaded trips. The empty running of trucks generates multiple challenges like higher delivery costs [3], congestion of distribution networks [4], and increased CO2 emissions [5]. To face these challenges, distribution companies are driven to explore new distribution strategies.

Recently, centralized collaborative strategies have been gaining considerable attention due to their positive impact on the reduction of distribution costs. These strategies generate coalitions involving multiple independent members, in which the organization of the collaborative process can be outsourced to a third-party (TP). This collaboration is often described by the collaborative multi-center vehicle routing problem (CMCVRP) [6]. The maximum performance of a collaborative process is obtained through total information sharing between its members [7]. Nonetheless, the formation of new coalitions faces several challenges [8], especially in establishing the necessary level of trust between partners. The most common problem resides in the lack of background in the field of collaborative practices as well as an incomplete legislative framework [9]. Moreover, Companies are not willing to risk losing their Very Important (VIP) customers in favour of other coalition members. On the other hand, to prevent a possible deterioration of their service quality, companies try to keep their delivery schedules unchangeable.

To the best of our knowledge, there are no studies that tackle the centralized CMCVRP where the information related to VIP customers is concealed and the delivery schedule of each member of the coalition is kept unchanged. To fill this gap, this paper studies a new extension of the two-echelon collaborative multi-center vehicle routing problem (2E-CMCVRP) by considering constraints of VIP customers and inflexible delivery schedules [10]. The problem is formulated as a MILP, and a multi-phase solving approach (MPSA) is proposed to solve it. The MPSA integrates a multi-population memetic algorithm (MPMA) and a modified VNS algorithm.
The remainder of this paper is organized as follows. In Section II, the literature is reviewed. Then in Section III, we describe the problem and we formulate its corresponding mathematical model. In Section IV, a detailed description of the proposed multi-phase solving approach is presented. The numerical results are presented in the Section V. Finally, the conclusions and future research suggestions are presented in the Section VI.

II. Literature Review

A. Collaborative Two-echelon Periodic MCVRP

The underlying problem of this paper (CMCVRP) is an extension of the MDVRP. Several approaches to solve the MDVRP have been examined in the literature. In 2012 Vidal et al. proposed a hybrid genetic algorithm with an adaptive diversity control metaheuristic to solve the periodic MDVRP [11]. In 2015, Rahimi et al. introduced a new modular heuristic algorithm (MHA) to manage the periodic MDVRP with capacity, duration, and maximum budget constraints [12]. Recently, an extensive review of different formulations and solving approaches for the MDVRP was published by Ramos, Shara et al. [13], [14].

To deal with the different challenges, distribution companies are constrained to treat their competitors differently by introducing new forms of interaction. Therefore, various forms of collaboration are emerging in this sector that show an important potential benefits [15], [16], [17], [18], [19]. Moreover, different variants of the routing problem in a collaborative setting have been explored. In [20] the authors developed an adaptive large neighborhood search iterative algorithm to solve a pickup and delivery problem with time window (PDPTW) that considers the outsourcing and exchange of requests between collaborators in a centralized collaborative configuration. In 2016, Soysal et al. studied the impact of horizontal collaboration on perishable products, logistics costs, and CO2 emissions for the inventory routing problem (IRP) [21].

Generally, the urban distribution is a periodic VRP (PVRP) for which several studies focused on implementing collaborative scenarios are presented. In [22] an empirical study is conducted to evaluate the influence of three companies' characteristics (e.g., the number of orders to transport, the order size and the ability of a company to delay its orders) which operate in a periodic scenario on the total profit. In 2017, Smilowitz et al. developed an adaptive large neighborhood search algorithm to solve the periodic location routing problem in the collaborative recycling sector [23]. They concluded that increasing the flexibility of delivery schedules impacts positively the reduction of expenses, especially when the maximum capacity constraint is very stringent.

The two-echelon vehicle routing problem (2E-VRP) is a variant of the multi-echelon vehicle routing problem (MEVRP) where the delivery of goods to customers is done by various intermediate plants. The urban distribution is one of the sectors where the 2E-VRP is often implemented [24]. In [25] Wang et al. introduced the two-echelon collaborative multi-center vehicle routing problem (2E-CMCVRP) as a combination of a multi-center VRP (MCVRP) and a profit allocation problem. The authors evaluated the economic and environmental impact of such collaboration and they proposed a two-phase algorithm based on a clustering method and a non-dominated sorting genetic algorithm to solve it.

In 2020, Wang et al. [26] proposed a collaborative and resource-sharing strategy to solve the multi-depot multi-period vehicle routing problem with pickup and delivery (MD-PVRPPD). The authors concluded that combining collaborative and resource-sharing mechanisms improve the multi-depot multi-period logistics network with pickup and delivery.

B. Information Sharing in Decentralized and Centralized Collaboration Configurations

The development of the collaborative process involving different partners requires certain level of information sharing. Generally, there are two information sharing strategies: partial sharing in decentralized collaborative configurations and total sharing in centralized configurations [27]. In both strategies, a third-party (A logistics service provider, online platform...etc) it's responsible for organizing the collaboration.

The decentralized collaborative VRP has been the focus of several studies that considered different mechanisms of information sharing. In [28] the authors suggested a request exchange mechanism based on the auction of a single request with limited information. In 2017, Huang et al. [29] developed an efficient auction-based mechanism for the carrier collaboration problem with bilateral exchange (CCPBE) where the carriers can only offer requests with the highest marginal costs and can bid on a bundle of lanes. Under this mechanism, the shared lanes' information is available to all carriers. In [30], the authors evaluated the impact of providing information about requests to the auction pool in an auction-based carrier collaboration problem where the requests are shared in an aggregated form. The aggregates are generated through grids that cover the geographical area of the requests.

Different types of central authorities have been considered in studies investigating the centralized collaborative VRP. The dynamic collaborative pickup and delivery problem which relies on a peer-to-peer platform that matches ad hoc drivers or backup vehicles to deliver tasks in real time is introduced in [1]. In [17], Maneengam et al. developed the centralized collaborative bidirectional multi-period vehicle routing problem under profit-sharing agreements, where the collection and integration of information and resources are done by a control tower. The tower establishes a collaborative transport planning respecting the profit-sharing agreements. The integration of tactical collaborative decisions has been raised in [32], in which the authors evaluated the economic and environmental impact of two collaborative scenarios in a centralized configuration: semi-cooperative and fully cooperative. In the first scenario, collaboration takes place at the operational level where all the customers and vehicle capacity information are shared to build the routing plan. In the second scenario, the collaboration occurs not only on an operational level but also tactical one. In this scenario, the routing and facility location decisions are taken jointly.

III. The Two-echelon Collaborative Multi-center Multi-periodic Vehicle Routing Problem

A. Problem Description and Assumptions

The 2E-CMCPVRP with VIP customers and inflexible delivery schedules is a distribution network with several independent distribution centers (DC), in which we suppose that one of the centers has the needed infrastructure to play the role of a logistics center (LC). Each center i serves a set of customers according to a specific schedule w_i of several periods t with a fleet of K_i vehicles, some of these customers can be shared with other centers except its VIP customers. Furthermore, we consider that a neutral third-party is in charge of the organization of the centralized collaborative process whose objective is to establish a collaborative network by a possible reassignment of non-VIP customers. The volumes of goods corresponding to the reassigned customers are initially stored in the LC. The presence of a LC transforms the initially independent distribution network into a collaborative two-echelon system where the routes between the LC and the DCs are covered by semi-trailers. The major assumptions of this study are:

- The LC has enough additional storage space,
- Each center DC has enough storage space to accommodate the reassigned goods from other centers,
- The customer's demand is deterministic and is known a priori,
- Each customer is visited only once during the consolidated delivery schedule,
- The fleet of vehicles is homogenous and each DC has a limited number of vehicles,

- Each vehicle starts and ends its route at the center in which it is parked within a limited time,
- The semitrailer starts and ends its route at the LC,
- The average speed of the roads (arcs) may differ from one road to another,
- The maintenance, leasing, and fuel costs of the vehicles may differ from one vehicle to another.
- Model formulation

The proposed MILP model for the 2E-CMCPVRP-VCIS is formulated as a two-echelon collaborative periodic VRP model. The objective is to minimize the total distribution costs considering the VIP customers' constraints and the inflexible delivery schedules. The parameters and related notations used in the 2E-CMCPVRP-VCIS model are detailed in the next section.

B. Parameters and Notations

The parameters and notations used in this work are presented in Table I, Table II and Table III. The best values of the parameters are obtained by testing various values of each parameter.

TABLE I. DATA SETS IN THE 2E-CMCPVRP-VCIS

Set	Definition
I	Set of centers (DC and LC)
J	Set of customers
K	Set of vehicles
T	Set of periods in w
K^i	Set of vehicles belonging to the center i, i∈ I
J^i	Set of customers initially assigned to center i, i∈ I

C. Modeling

a) Objective function: The objective function is defined as follows:

$$T_{total} = T_1 + T_2 + T_3 \tag{1}$$

where,T1 defines the sum of costs related to the semi-trailer's, T_2 is the sum of the dispatching, maintenance, leasing, and fixed costs and T_3 is the sum of delivery costs related to the fuel consumption during a consolidated delivery schedule.

$$T_1 = \sum_{t\in T}(T_{11}^t + T_{12}^t) \tag{2}$$

where, T_{11}^t and T_{12}^t are respectively the sum of the fuel costs and maintenance costs of the semi-trailer over a period *t* given by the Eq. (3) and Eq. (4).

$$T_{11}^t = \sum_{i,h\in I,h\neq i} H_{se} \times \rho \times d_{ih} \times o_{ih}^t \tag{3}$$

$$T_{12}^t = \sum_{(i,h\in I,h\neq i)} \frac{M \times o_{ih}^t \times d_{ih}}{K_a} \tag{4}$$

TABLE II. INPUT PARAMETERS IN THE 2E-CMCPVRP-VCIS

Parameter	Definition
u_j^t	Equals 1 if the customer must be visited on period t, j∈J,t∈T
ρ	Fuel price
N_i	Number of vehicles belonging to the center i,i∈I
N_s	Number of semi-trailers
H_{se}	Average fuel consumption of the semi-trailer per 100km
h_k	Average fuel consumption of the vehicle k,k∈K per 100km
F	Average annual vehicle maintenance costs
L	Average annual vehicle rent or leasing costs
Q_{max}	Maximum capacity of a vehicle
N_{Tot}	Total number of available vehicles
K_a	Average annual distance covered by a semi-trailer (Km)
B	The capacity of the semi-trailer
T_{max}	Maximum working time per period
q_j	The demand of the customer j,j∈ J
M	Average annual semi-trailer maintenance costs
G_i	Fixed costs of center i per period. The third-party (TP) covers the fixed costs when the centre i agrees to cooperate, i∈I
P_i	CA's service costs for center i per period when cooperation is achieved, i∈I
τ	Number of consolidated delivery schedules per year
w_i	Delivery schedule of center i,i∈I
w	Consolidated delivery schedule of the coalition with $w = \cup_{i\in I} w_i$
d_{ij}	The distance between centers i and j, i,j∈ $J \cup I$
y_i	Coefficient of variable costs of center i, i∈I
vip_{ij}	If the customer j is a VIP customer of centre i, $vip_{ij} = 1$ else $vip_{ij} = 0$,j∈J, i∈I
v_{ij}	Average road speed between nodes i and j, (j,i)∈ $J \cup I$
V_{ik}	Assignment of a vehicle to a specific center, i∈I,k∈K
y_i	y_i=1 if centre i collaborates else y_i= 0, i∈I

TABLE III. DECISION VARIABLES

Variable	Definition
x_{ij}^{kt}	Equals 1 if vehicle k travels directly from i to j during the period t otherwise is equal to 0, (i,j)∈I∪J,k∈K,t∈T
o_{ij}^t	If the semi-trailer travels directly from center i to centre j on period t, $o_{ij}^t = 1$ else $o_{ij}^t = 0$, i,j∈I,t∈T
ϕ_{ik}	A variable used for the elimination of sub-turns in the second echelon. It is always positive, i∈I,k∈K
δ_{ik}	A variable used for the elimination of the sub-turns in the first echelon. It is always positive, i∈I,k∈K

T_2 gives the sum of the dispatching, maintenance, leasing, and fixed costs as in the Eq. (5).

$$T_2 = T_{21} + \sum_{t\in T} T_{22}^t. \tag{5}$$

where T_{21} Gives the total service costs required by the third-party plus the maintenance and leasing costs of the fleet, and T_{22}^t is the dispatching costs of the quantities delivered during a period *t*. where:

$$T_{21} = \sum_{i\in I}[(1-y_i)G_i + y_i P_i + (T_{23} \times (\frac{F+L}{\tau}))] \tag{6}$$

where T_{23} gives the needed number of vehicles to cover the customers' demands over the consolidated delivery schedule; it is equal to the highest number of vehicles used by all centers during a period *t*.

$$T_{22}^t = \sum_{i\in I}\sum_{k\in K^i}\sum_{p\in I\cup J}\sum_{j\in J} x_{ij}^{kt} \times u_j^t \times q_j \times \gamma_i. \tag{7}$$

T_3 is the sum of delivery costs related to the fuel consumption during a consolidated delivery schedule as in Eq. (8)

$$T_3 = \sum_{t \in T} \sum_{i,j \in I \cup J} \sum_{k \in K} \frac{d_{ij} \times x_{ij}^{kt} \times u_j^t \times \rho \times h_k}{100}. \quad (8)$$

First echelon constraints:

$$\sum_{j \in J, j \neq i} o_{ji}^t = 1, i \in I, t \in T (i = 1 \text{ corresponds to LC}) \quad (9)$$

$$\sum_{i \in J, j \neq i} o_{ij}^t = 1, j \in I, t \in T (j = 1 \text{ corresponds to LC}) \quad (10)$$

$$\sum_{j \in I} o_{ij}^t - \sum_{j \in I} o_{ji}^t = 0, i \in I, i \neq, t \in T \quad (11)$$

$$\sum_{i \in I} \sum_{k \in K_i} \sum_{l \in I \cup J, p \in J \setminus J^i, l \neq i)} x_{ij}^{kt} \times u_j^t \times q_p \leq B, t \in T \quad (12)$$

$$\phi_i - \phi_j + N_s \times o_{ij}^t \leq (N_s - 1), i, j \in I, i \neq 1, t \in T \quad (13)$$

$$\phi_i \geq 0, i \in I, i \neq 1 \quad (14)$$

Second echlon constraints:

$$\sum_{t \in T} \sum_{k \in K} \sum_{i \in I \cup J, i \neq j} x_{ij}^{kt} \times u_j^t = 1, j \in J \quad (15)$$

$$\sum_{j \in J} (q_j \times \sum_{i \in I \cup J} x_{ij}^{kt}) \leq Q_{max}, k \in K, t \in T \quad (16)$$

$$\delta_{ik} - \delta_{jk} + N_v \times x_{ij}^{kt} \leq N_{Tot} - 1, k \in K, i, j \in J, t \in T \quad (17)$$

$$\delta_{ik} \geq 0, k \in K, i \in J \quad (18)$$

$$\sum_{j \in I \cup J} x_{ij}^{kt} - \sum_{j \in I \cup J} x_{ji}^{kt} = 0, k \in K, i \in I \cup J, t \in T \quad (19)$$

$$\sum_{i,j \in I \cup J} x_{ij}^{kt} \times \frac{d_{ij}}{v_{ij}} \leq T_{max}, k \in K, t \in T \quad (20)$$

$$\sum_{t \in T} \sum_{K^p} \sum_{i \in I \cup J} x_{ij}^{kt} \geq vip_i j, p \in I, j \in J \quad (21)$$

$$\sum_{k \in K} \sum_{j \in J} x_{ij}^{kt} \leq N_i, i \in I, t \in T \quad (22)$$

$$\sum_{J \in J} x_{ij}^{kt} - V_{ik} = 0, i \in I, k \in K, t \in T \quad (23)$$

$$T_{23} \geq \sum_{k \in K} \sum_{i \in I, p \in J} x_{ij}^{kt} \quad (24)$$

$$x_{ij}^{kt} \in \{0, 1\}, i \in I \cup J, j \in J, k \in K, t \in T \quad (25)$$

$$\theta_{ij}^t \in \{0, 1\}, i \in I, j \in J, t \in T \quad (26)$$

Constraints (15) ensure that each customer must be visited only once during the consolidated delivery schedule. Constraints (16) concern the vehicle's capacity. Constraints (17) and (18) are used for the vehicle's sub-tours elimination. Constraints (19) guarantee the flow conservation from/to each customer. Constraints (20) limit the vehicle travel time. Constraints (21) state that if j is a VIP customer it can be served only if there is a vehicle starting from its original center, otherwise, if it is not a VIP customer, it can be served by any available vehicle. Constraints (22) limit the number of vehicles starting from a center to the number of vehicles belonging to this center. Constraints (23) guarantee that any vehicle that starts from a center must belong to this center. Constraints (24) ensure that the number of vehicles to cover all the customer requests throughout the consolidated delivery schedule equals the sum of the maximum of vehicles used by each center in the busiest period. Constraints (25) and (26) ensure that the decision variables are binary.

IV. Multi-phase Solution Approach

The main objective of this approach is to determine the optimal coalition that minimizes the distribution cost and assures the best individual profit for its members. The approach is divided into two phases. In the first phase, we optimize the second echelon routes using a multi-population memetic algorithm (MPMA). And, in the second phase, to optimize the semi-trailer's routes we propose a variable neighbourhood search (VNS) algorithm that integrates a tabu list mechanism. These two phases are performed for each period of the delivery schedule.

Memetic algorithms are a hybridization of a genetic algorithm (GA) with local search heuristics. They are widely adopted in the resolution of routing problems [33], [34]. In the proposed MPMA, the chromosomes are encoded as a giant tour as presented in sub-section IV-A. The solutions are firstly evaluated using the clustering algorithm detailed in sub-section IV-B, and secondly by an improved splitting algorithm given by the pseudo-code 2. The MPMA uses three same-sized populations to avoid premature convergence [35]. Two populations are relaxed and may contain infeasible solutions P_{relax1} and P_{relax2} while the third one contains only feasible solutions$P_{feasible}$. To build the initial populations a clustering method is used as described in sub-section IV-C.

In P_{relax1} the fleet size N_i is relaxed according to the following equation $N_i = CR_v \times N_i, i \in I, CR_v \geq 1$ while in P_{relax2}, the maximum working time T_{max} and the maximum capacity Q_v are relaxed as follows $T_{max} = CR_t \times T_{max}$ and $Q_v = CR_l \times Q_v, CR_t \geq 1, CR_l \geq 1$ where CR_v is the vehicles number relaxation coefficient, CR_t is the maximum route duration relaxation coefficient and CR_l is the maximum load relaxation coefficient. During the search process, the populations remain sorted in ascending order according to their solutions' fitness values. In each generation, the algorithm selects two parent solutions from each population and then performs the crossover procedure presented in sub-section IV-D. The resulting offspring solutions are then evaluated using the modified Beasley-Bellman algorithm described in sub-section IV-G. If the new solution is feasible it is inserted in $P_{feasible}$ if it verifies the insertion conditions. Otherwise, the new solution will be inserted in one of the corresponding unfeasible populations if it checks the insertion conditions. The insertion conditions are: (1) the new solution should be different from all the existing solutions in the population and (2) the new solution should outperform the worst one in this population. To intensify the search around the newly generated solutions, a local search procedure, as presented in sub-section (e), is performed after each $n = Freq_{loc}$ generations. The algorithm then calculates the second echelon costs T_3 and based on the best feasible solution it calculates T_{22}. Then, the first echelon route optimization is performed as detailed in sub-section (g). When all the periods are processed the MPMA calculates T_{23} and T_{21}. Finally, the sub-coalition total cost is computed.

The pseudo-code of MPMA is shown in Algorithm 1.

Algorithm 1 Multi-phase solving approach

Load data
for <each sub-coalition Of industries> **do**
  Establish the consolidated schedule based on T
  for each period Of T **do**
    for each population **do**
      Choose the clustering parameters $N_{initial}, wf, wd,$ $Max_{deviation}$
      Create a giant tour for each DC
      Determine the intersection zones between DCs
      Relax T_{max} and split the giant tour into trips
      Perform the route sequencing
      for n fro 1 to n_{max} **do**
        Perform the intra-routes *Swap(1,1)*, inter-routes *Swap(i,i)*
        Insert the generated solutions into the current population
        $n = n + 1$
      end for
    end for
  end for
  for g→1 to g_{max} **do**
    if counter=Freqloc then **then**
      Perform the VNS-Tabu search algorithm
      Perform the diversification heuristic
    end if
    Perform the parents' selection procedure
    Perform the crossover procedure
    Perform the advanced split procedure
    if Is Feasible Population **then**
      if Is a Feasible Solution **then**
        Compute cost
        Insert offspring into the feasible population according to the cost order
        if Is New Best Solution **then**
          Update the new best solution
          Insert into the relaxed population according to the penalized cost order
        end if
      else
        Compute penalized cost
        Insert into the relaxed population according to the penalized cost order
        Remove the worst solution from the population
        $g = g + 1$
      end if
    end if
  end for
  With the best solution from the feasible population
  for g → 1 to g **do**
    Compute the second echelon routes costs
    Compute goods' exchange between collaborating DCs in period w
    Compute used vehicles per DC
    Improve semitrailer routes
    Compute semitrailer routes costs
    Determine necessary vehicles per DC
    Compute the maintenance and leasing vehicles' costs
    Compute the centers fixed and variables costs
    Return the total costs for each sub-coalition
  end for
end for

A. Chromosome encoding

The chromosome encoding is defined by a giant tour divided into routes by delimiters representing the center from which each route starts. The node numbering $(0, \ldots, i-1)$ represents the centres and the following numbers $(i, \ldots, n+i-1)$ represent the set of n customers. During the crossover, the route delimiters are removed and then reinserted later using the splitting algorithm as shown in Fig. 1.

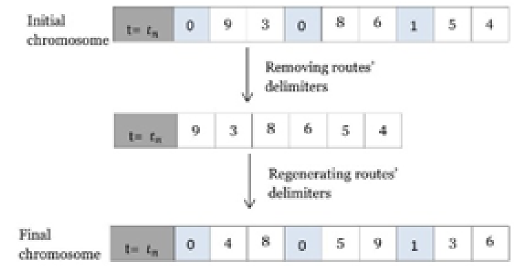

Fig. 1. Chromosome encoding in the MPMA.

B. Chromosome Evaluation

To build the solution corresponding to each chromosome, we apply the splitting procedure described in Algorithm 2. This algorithm is inspired by Vidal's adapted version of the Beasley-Bellman method [36] and integrates specific constraints of our model. During the splitting process, we perform an extraction of intermediate solutions while updating the set of the needed vehicles for each centre. The feasible sub-sequences of customers $T_{ts} = (T_t, \ldots, T_s), t \in [0, n], s \in [t + 1, n]$ are evaluated using two nested loops as shown in Algorithm 2. The duration of the route $(dc, \sigma T_{ts}, dc)$, where σT_{ts} is a circular permutation of T_{ts}, is calculated by choosing the dc having available free vehicles and offering minimal service time. If among the customers belonging to sub-sequence Tts there is a VIP customer of a centre i then this centre must be the starting and ending node of the route.

C. Generation of Initial Population

To generate the initial population, we use the Split Middle Line Clustering (SMLC) method, which is a variant of the route-first cluster-second method. The SMLC method takes into consideration the collaborative and periodic aspects of the problem.

a) Step1: Initial clustering: This procedure creates a giant tour or a cluster cl_{it} for each pair center-period (i, t), which includes the centers' VIP customers and closest customers as shown in Fig. 2(b). After that, it creates shared zones between each pair of clusters cl_{it} and cl_{jt} which include non-VIP customers for whom the distance to the nearest customers belonging to the other cluster is smaller than the distance to the nearest customers of their own cluster (see Fig. 2(b)).

b) Step2: Route splitting: The splitting procedure divides the giant tour into routes, respecting the problem's constraints, by assigning customers from the center's giant tour and shared areas to the routes as follows:

- Place the center dc_i as the first element of each route r_i^m starting from dc_i where m is the index of the route and i is the number of the centre.
- Add the closest node n_i to dc_i as the second element of r_i^m and determine the barycentre z of (dc_i, n_i).
- Add the closest node n_2 to the barycentre and determine the new barycentre of (dc_i, n_1, n_2). Repeat this

Algorithm 2 : Splitting algorithm

Non-splitted chromosome
/*Initialize relaxation coefficients CRv=vehicles, CRt=route duration, CRl=load*/
if the Current population= Pfeasiblethen **then**
CRv←1 State CRt←1
CRl←1
else
CRv←crv /*Vehicles number relaxation coefficient */
CRt←crt /*Maximum route duration relaxation coefficient */
CRl←crl /*Maximum load relaxation coefficient */
end if
Q←Vehicle capacity × CRl
H←Maximum route duration ×CRt
Fc←Fleet per center × CRv
i←Number of centres
n←Number of nodes in the current period
Tour=(S1,S2,...,Sn) ←Giant tour of chromosome
$V_{1...n} \longleftarrow \infty$ /*Initial costs of arcs */
$P_{1...n} \longleftarrow \emptyset$ /*List of predecessors */
for v ⟵ 1 to n **do**
/*Single node case*/
load ⟵ Request Of (S_v)
/*Add the node t to path*/
path ⟵(S_v)
/*Choose the nearest centre dc to node v */
/*If v corresponds to a VIP customer, choose its original centre */
dc ⟵ Nearest Center (S_v)
route ⟵ (dc, S_v, dc)
time ⟵ Duration Of(route)
s ⟵ v+1
end for
while s≤ n and time¡H and load+RequestOf $(S_s) \leq Q$ **do**
load⟵ load+Request Of (S_s)
/* Add the nodes to the path */
Add Node(path, Ss)
/* Choose the centres that have enough vehicles (used vehicles ¡ Fc) */
/* Compute, for each centre with s in the best placement, the route duration */
/* Choose the centre dc with the minimal route duration */
dc⟵ Best Center For (path)
route ⟵ (dc, path, dc)
time ⟵ Duration Of (route)
if time≤ V_s **then**
Vs ⟵ time
P_s ⟵ s-1
s ⟵ s+1
end if
end while
/* Using route and the list P to update the partial solutions */
Return Splitted chromosome

operation until reaching the parametrized number of nodes $N_{initial}$.These nodes are used to determine the first slope of the line connecting dc_i to the barycentre z of $(dc_i, n_{1,2} ..., n_{N_initial})$.

- Determine the slope $\Delta_c = \frac{y_2-y_1}{x_2-x_1}$ of the line connecting the center dc_i to z where (y_1, y_2) are the coordinates of dc_i and (x_1, x_2) are the coordinates of z.
- Add the node p which minimizes the value of D. Given the new slope Δ_t and the length l_p of the arc $N_{(initial,p)}$: $D = w_f|(\Delta_t - \Delta_c)/\Delta_c| + w_d \times l_p$. Where w_f= *shape weight*, w_d= *distance weight*, with $|\frac{\Delta_t-\Delta_c)}{\Delta_c}| \leq Max_{deviation}$
- Add the following nodes according to the same principle while respecting the non-relaxed constraints. If the deviation of the resulting slope Δ_c engendered by adding the node p' to the route is greater than $Max_{deviation}$, then the node p' will not be considered.
- Place the center dc_i as the last node of the route.
- Merge the routes of not fully loaded vehicles if the non-relaxed constraints allow it.

c) Step3: Route sequencing:

- Project the nodes coordinates of each route on a plane and divide it into two sub-routes by a split middle line (SML).
- Project the nodes of the first sub-route on the SML and reorder them in ascending order according to the resulting coordinates as shown in (see Fig. 2(a)).
- Project the nodes of the second sub-route on the SML and reorder them in descending order according to the resulting coordinates as shown in (see Fig. 2(a)).
- Reconstruct the route by connecting the two sub-routes considering dc_i as the starting and ending node of the route (see Fig. 2(a)).

d) Step4: Initial improvement:

- Perform inter-route improvement using a $swap(n1, n2)$ move by exchanging $n1$ successive customers of one route with $n2$ successive customers of another route while respecting the route's constraints.
- Perform intra-route improvement using an iterative $swap(1, 1)$ move.

The three populations $p_{feasible}$, p_{relax1} and p_{relax2} are filled using the intermediate solutions generated in Step 4.

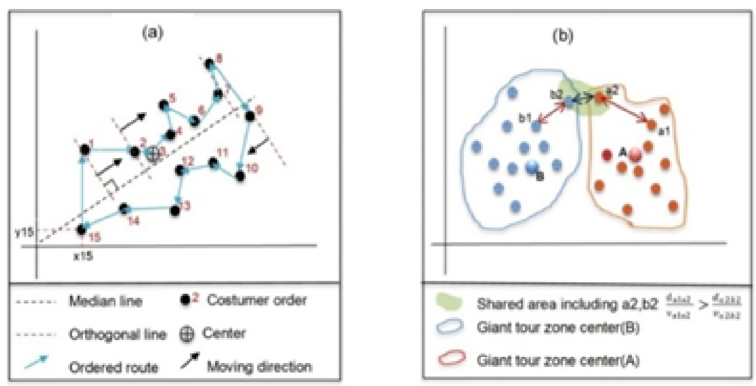

Fig. 2. (a) Route splitting and (b) The initial clustering

D. Selection and Crossover Mutation

In the selection procedure, the first parent is randomly selected from the first half of the population which is always sorted according to the fitness value, and the second parent is randomly chosen from the other half of the population. The proposed genetic operator performs three types of transpositions with different frequencies. To perform the crossover, two cutting points are defined randomly as shown in Fig. 3:

- A typical crossover consists of placing the genes between the cutting point of the second parent in the same position in the first offspring and the rest of its genes are copied from the first parent circularly. The same operation is performed for the second offspring by changing the roles of parents 1 and 2 as shown in (see Fig. 3).

- A transposition similar to the first one, but in this case the exchanged portions are partially or fully rotated (see Fig. 4).
- A transposition with position shifting in which the position of the exchanged portions is shifted when placed in the offspring chromosomes (see Fig. 5).

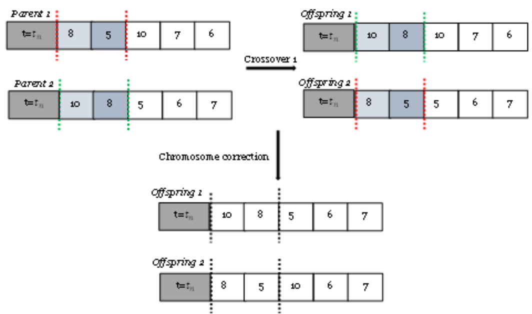

Fig. 3. First transposition method of the genetic operator.

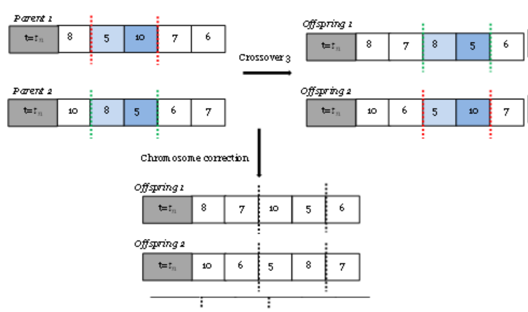

Fig. 4. Second transposition method of the genetic operator.

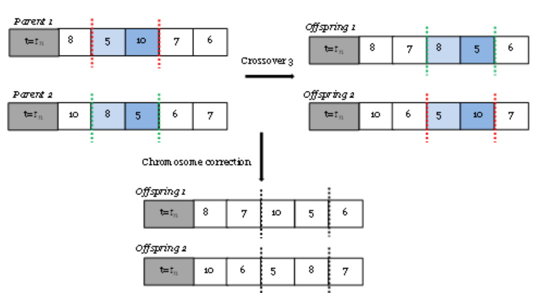

Fig. 5. Third transposition method of the genetic operator.

E. Local Variable Neighbourhood Tabu Search

The proposed VNS-Tabu algorithm (VNS-T) is a modified version of the Skewed Variable Neighbourhood Search algorithm proposed by Hansen et al. in 2020 [36], [37], it integrates a Tabu list and a variable acceptance margin α. The VNS-Tabu algorithm uses a list of neighbourhoods $k = (k_1, k_2, \ldots, k_n)$ corresponding to a sequence of intra-route and inter-route swap moves and shift moves applied on a current solution s. The local search (*LocalImprovement*) performs 2-opt and 3-opt heuristics moves. A new solution $S_i^{'}$ is accepted only if the cost quotient $\frac{f(s_i^{'})}{f(s)}$ is inferior to $1+\alpha$ where $\alpha = \beta \times \frac{i}{Maxreps}$ and β is a scale parameter. To avoid a local optimum, a ***Tabulist*** that stores the solution s and the move k_j performed on it is used. This list is emptied for each new value of α. The pseudo-code of **VNS-T** is presented in Algorithm 3.

Algorithm 3 : VNS-Tabu algorithm

S_{best} ← Splitted chromosome
s← S_{best}
$k = (k_1, k_2, ..., k_n)$ ← Set of neighbourhoods
j← 1
I←1
α ←0
while $i \leq Maxreps$ **do**
  while $j \leq n$ **do**
    if $(s, k_j) \notin Tabulist$ **then**
      $s' \leftarrow$ Shake(s,k_j)
      $s'' \leftarrow LocalImprovements'$
      if $\frac{f(s")}{f(s)} \leq (1+\alpha)$ **then**
        Tabulist.Add(s,k_j)
      end if
      if f(s")≤ f(s) **then**
        $S_{best} \rightarrow s"$
        $s \leftarrow s''$
      else
        $j \leftarrow j+1$
      end if
    else$j \leftarrow j+1$
    end if
  end while
  Tabulist.Empty()
  $i \leftarrow i+1$
  $\alpha \leftarrow \beta \times \frac{1}{Maxreps}$
end while
Return

a) No results found by CPLEX within the time limit. b) The time limit for the small and medium sized instances was set to 3600s. For the large-scale instances (≥150 customers) the time limit is 7200s.

F. Results of the MPMA for the MDVRP Instances

To measure the efficiency of the MPMA, a comparative study is performed between the results of Vidal's HGA [31] and Juan's ILS [12] and those obtained by our algorithm with the best-known solutions (BKS) in the literature for 20 MDVRP instances of Cordeaux & al. Table V shows that the solutions obtained by the MPMA are close to the BKS with an average gap of 0.33%. Also, we observe that our method outperforms the ILS algorithm. Furthermore, MPMA was able to match 13 BKS within relatively small processing times. These experiments prove the efficiency of the proposed algorithm and its adaptability to solve the MDVR problem.

G. Fitness Evaluation

In the second echelon, the fitness evaluation for a given period t and a given population is based on the objective sub-function $T_3^t = \sum_{i,j \in I \cup J_t} \sum_{k \in K} \frac{d_{ij} \times x_{ij}^{kt} \times u_j^t \times \rho \times h_k}{100}$. For $p_{feasible}$, the fitness is equal to T_3^t. For p_{relax1} and p_{relax2}, the fitness is equal to $\frac{T_3^t}{Cf_v} \times Cf_l \times Cf_t$ where Cf_v is the percentage of centres respecting the fleet constraint,Cf_t is the percentage of routes respecting the duration constraint and Cf_l is the percentage of routes respecting the load constraint. For the first echelon, we use the objective function T_{total}.

TABLE IV. COMPARISON BETWEEN THE MILP AND MPMA RESULTS

Instances				MILP					MPMA			
Instance	Cst.	DCs.	Prds.	BI(1)	Gap(1-2)	LB(2)	Time(s)b	Stat.	Avg.(3)	Time(s)	Gap(3-2)(%)	Gap(3-1)(%)
C-PVip-1	20	4	2	10619	10.04	9553	3600	Int	9591	5	0.4	-10.72
C-PVip-2	20	4	2	10842	0.03	10838	336	Opt	10841	1	0.03	-0.01
C-PVip-3	30	4	2	11053	12.49	9673	3600	Int	9713	3	0.41	-13.8
C-PVip-4	30	4	2	11317	2.19	11069	3600	Int	11233	3	1.46	-0.75
C-PVip-5	30	2	3	8886	0.04	8882	3600	Int	8886	2	0.05	0
C-PVip-6	50	2	3	10746	8.64	9818	3600	Int	10097	3	2.76	-6.43
C-PVip-7	75	5	3	20224	4.28	19359	3600	Int	19451	17	0.47	-3.97
C-PVip-8	80	2	3	27384	11.19	24320	3600	Int	25146	9	3.28	-8.9
C-PVip-9	95	3	3	58096	2.11	56871	3600	Int	57711	15	1.46	-0.67
C-PVip-10	97	2	3	-a	-	12465	3600	-	13281	10	6.14	-
C-PVip-11	100	2	3	14604	23.38	11189	3600	Int	11510	17	2.79	-26.88
C-PVip-12	100	4	4	61560	2.31	60138	3600	OM	60661	10	0.86	-1.48
C-PVip-13	100	4	4	60207	5.55	56868	3600	Int	56952	47	0.15	-5.72
C-PVip-14	150	4	4	76222	14.91	64859	5405	OM	67327	13	3.67	-13.21
C-PVip-15	150	2	3	-	-	32355	7200	-	33909	13	4.58	-
C-PVip-16	200	4	4	-	-	69175	7200	-	71423	54	3.15	-
C-PVip-17	249	4	4	-	-	73482	2100	OM	79206	49	7.23	-
C-PVip-18	249	2	3	-	-	-	-	OM	50989	54	-	-
C-PVip-19	249	3	3	-	-	-	-	OM	31918	57	-	-

H. First Echelon Optimization using the Local Variable Neighbourhood Tabu Search Algorithm

The first phase of the MPMA generates the second echelon routes for each period t, then based on the best second echelon feasible solution S_{best}, the demands of the reassigned customers are calculated. These demands represent the quantities of goods to be delivered by the LC to each DC each period t. Additionally, the algorithm optimizes the semi-trailer route by performing the above-mentioned VNS-T algorithm.

V. NUMERICAL RESULTS

In this section, we present the results obtained by MPMA by solving 19 new instances built for the 2E-CMCPVRP-VCIS with IBM Ilog CPLEX Optimization Studio 20.1. After that, we compare the efficiency of our MPMA with Vidal's HGA and Juan's ILS based on Cordeaux's MDVRP benchmark instances. Three different scenarios are considered: non-collaborative, collaborative with VIP customers, and collaborative without VIP customers.

A. Description of Data Instances

19 new instances of different sizes and complexity are considered by adapting Cordeaux's MDVRP benchmark instances. For each instance, we add the following information related to the first and second echelon: semi-trailer's fuel consumption and annual maintenance costs, vehicles assignment to the centers, maintenance, annual leasing costs of each vehicle, centers' fixed and variable costs, the variable cost coefficient, customers' initial assignment to the centers, centers' delivery schedules, centers' VIP customers and third-party service costs. In these instances, the number of customers (Cst.) varies between 20 and 498, the number of centers (Dc) ranges from 2 to 6, the number of periods varies between 2 and 4, and the average speed of the arcs ranges between 70km/h and 110km/h. Moreover, the input parameter settings are: $H_{se} = 98l/100$km, H_{sl}=410l/100km,$h_(k)$ ∈[19,25]l/100km, F_v ∈[123 800,138000],L_v ∈[216000,288000], K_a = 190720km, M = 380000, B =2000, $\rho = 9.8$, $G_i \in [586, 645]$, P_i ∈[605,935], $y_i = 1.5$.

B. Parameter tuning

To tune the parameters of the proposed algorithm, multiple iterative computational treatments are performed on a set of MDVRP benchmark instances following an experimental methodology inspired by the design of experiments (DOE) approach. Firstly, we determine the three parameters that most significantly impact the performance of our MPMA and their levels through extensive testing. The parameters that obtained, and their respective levels are: $Maxreps \in \{10, 20, 40\}$, $Freq_{loc} \in \{2, 7, 14\}$, $P_{feasible} \in \{30, 50, 100\}$. In the second phase, 10 runs of the algorithm are performed on the instances set for each of the following twenty-seven parameter configurations: $\{10, 20, 40\} \times \{2, 7, 14\} \times \{30, 50, 100\}$. Then, the average of all the iterations' results for each instance is compared to the corresponding BKS. Next; the average gap and the standard deviation for each configuration is computed. The experiments indicate that the optimal parameter settings are: $maxreps = 40, freq_{loc} = 7, P_{feasible} = 30$.

C. Results of the MILP and MPMA for the 2E-CMCPVRP-VCIS Instances

The comparison between the MILP and MPMA results based on the values of the fitness function T_{total} are presented in Table IV. In the first four columns, the parameters of the 2E-CMCPVRP-VCIS instances are described in the following order: name of the instance, number of customers, number of centers, and number of periods. The second part of Table IV, from column 5 to column 9, summarizes the MILP results obtained by the CPLEX solver. BI refers to the best integer solution found by CPLEX, LB refers to the lower bound and column Stat describes the CPLEX status (Opt: CPLEX found

TABLE V. MPMA RESULTS VS BEST KNOWNS SOLUTIONS OF THE MDVRP

Instance	Cst.	DCs	Vehicles	BKS{1}	HGA{2}	ILS{3}	MPMA{4}	Gap(%) $\{4-1\}$	Gap(%) $\{4-2\}$	Gap(%) $\{4-3\}$	Time(s) (MPMA)
1	50	4	4	576.87	576.87	576.87	**576.87**	0	0	0	5
2	50	4	2	473.53	473.53	473.87	**473.53**	0	0	-0.07	3
3	75	5	3	641.19	641.19	641.19	**641.19**	0	0	0	5
4	100	2	8	1001.04	1001.04	1003.45	1003.86	0.28	0.28	0.04	43
5	100	2	5	750.03	750.03	751.9	**750.03**	0	0	-0.25	16
6	100	3	6	876.5	876.5	876.5	**876.5**	0	0	0	16
7	100	4	4	881.97	881.97	885.19	**881.97**	0	0	-0.36	50
8	249	2	14	4372.78	4372.78	4409.23	4400.36	0.63	0.63	-0.2	273
9	249	3	12	3858.66	3858.66	3882.58	3882.11	0.61	0.61	-0.01	296
10	249	4	8	3629.6	3631.11	3646.67	3634.74	0.14	0.1	-0.33	257
11	249	5	6	3545.48	3546.06	3547.09	3546.06	0.02	0	-0.03	426
12	80	2	5	1318.95	1318.95	1318.95	**1318.95**	0	0	0	25
13	80	2	5	1318.95	1318.95	1318.95	**1318.95**	0	0	0	9
14	80	2	5	1360.12	1360.12	1360.12	**1360.12**	0	0	0	25
15	160	4	5	2505.42	2505.42	2511.92	**2505.42**	0	0	-0.26	78
16	160	4	5	2572.23	2572.23	2573.78	**2572.23**	0	0	-0.06	58
17	160	4	5	2709.09	2709.09	2709.09	**2709.09**	0	0	0	17
18	240	6	5	3702.85	3702.85	3702.85	3708.7	0.16	0.16	0.16	364
19	240	6	5	3827.06	3827.06	3840.91	**3827.06**	0	0	-0.36	213
20	240	6	5	4058.07	4058.07	4063.64	4091.78	0.83	0.83	0.69	278

the optimal solution, OM: CPLEX goes out of memory, Int: The best solution was found by CPLEX within the time limit). The results obtained show that CPLEX was able to find an optimal solution only for the small-sized instance C-PVip-2 within 336 seconds. For sixteen instances, CPLEX was able to find a feasible solution within the set time limit and with an average gap between BI and LB of 7.7%. For two instances, the solver found a feasible solution but went out of memory before the time limit. For the large-scale instances, CPLEX went out of memory before finding any solution or LB. The third-party of Table IV, from columns 10 to 13, presents the average results of the MPMA on 10 runs for each one of the 19 instances, the computational time of the MPMA and the gaps between the MPMA results and the LB and BI respectively. The results revealed that the MPMA was able to find good quality solutions for all the instances with an average gap of 2.01% with the LB and -6.59% with the BI and within a relatively short average computational time of 43.23 seconds. Moreover, the gap between the MPMA and CPLEX for the instance C-PVip-2 for which the MILP optimal solution was found is negligible. The computational results validate the MILP model and prove the efficiency of the MPMA.

VI. CONCLUSION

In this paper, we have introduced the two-echelon collaborative multi-center multi-periodic vehicle routing problem with VIP customers and inflexible delivery schedules (2E-CMCPVRP-VCIS). To solve the proposed model, an efficient multi-phase solving approach (MPSA) based on a multi-population memetic algorithm (MPMA) and a variable neighborhood search method is proposed. The performance of the MPSA is evaluated on benchmark MDVRP instances as well as newly created instances for our case of study. The numerical results on the benchmark instances show that the MPMA outperforms Juan's ILS and can find high-quality solutions with an average gap of 0.33% to the BKS. Furthermore, the results on the new instances prove the performance of our algorithm and its superiority compared to the upper bounds obtained by solving the MILP model on CPLEX. This research underscores the effectiveness of the proposed MPSA in tackling the 2E-CMCPVRP-VCIS.

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