

## Dynamic Planning of Reusable Containers in a Close-loop Supply Chain under Carbon Emission Constraint

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### Abstract

Nowadays, companies need to collect and deliver goods from and to their depots and their customers. Reusable containers are considered as a greener choice and a cost saving strategy. This paper addresses a dynamic management of reusable containers (e.g. gases bottles, wood pallets, maritime containers, etc.) in a closed-loop supply chain. The aim of the study is to find an optimal lot sizing and assignment strategy that minimizes the cost of reusable container management under the environmental constraints. In this study, a new integer-linear-programming model and two hybrid approaches based on the genetic algorithm are proposed to solve the problem. The second hybrid method is enhanced within a local search based on variable neighborhood search (VNS). The numerical results show the performance of the two hybrid approaches in terms of solution quality and response time.

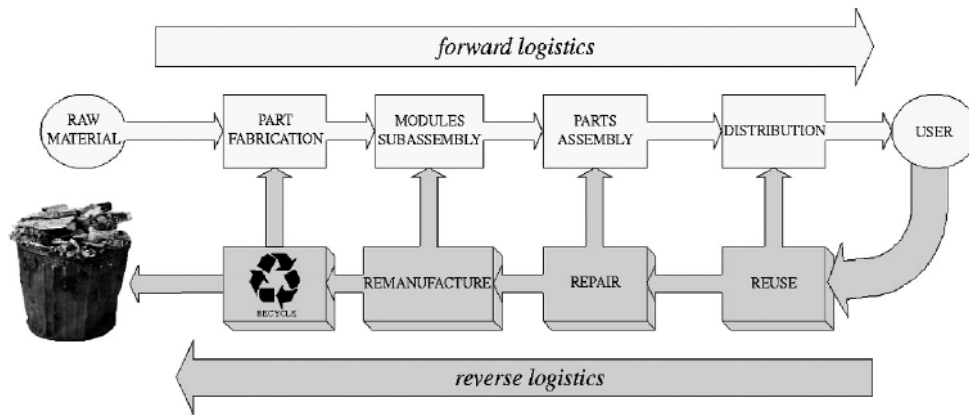
**Keywords:** Reverse logistics; Collect; Return flow; Hybrid algorithm; Reusable container; Lot-sizing.

### 1. Introduction

Reverse logistics, as defined by Rogers and Tibben-Lembke (1998), is “the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal”. However, there are several other terms designating reverse logistics (e.g. green logistics, the reverse distribution, etc.)

Reverse logistics is a quite vast field of study. The returned products assist several types of recovery such as recondition, refurbishing, remanufacturing, recycling, reuse, etc. (Hanafi et al., 2008) (see Figure 1). In this study, we are interested in reuse activity that describes the fact of using a product more than once, either for the same or different purpose. The products concerned in our research are the reusable containers by reason of the economic and environmental importance of their use (Bhattacharjya and Kleine-Moellhoff, 2013). Based on the definition of secondary packaging given by Stock (1992), Kroom and Vergin (1995) defined a reusable container as any packaging like wooden pallets, gauze boxes, beverages, maritime containers, etc. that can be used multiple times. In this paper, we discussed an integrated planning for the distribution and collection of the reusable containers. The aim of this study is first to propose a model that helps firms to optimize transportation, item storage, container reloading, and investment, under a carbon emission constraint from multi-producer to multi-retailer, and then to propose meta-heuristic approaches for the resolution of the problem in the complex networks cases.

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**Figure 1.** Reverse logistics strategies for end-of-life products (Hanafi et al., 2008)

The mathematical modeling proposed for the container management problem under investigation considers two combinatorial optimization classes, i.e. the dynamic batch sizing problem and the assignment problem. Moreover, the approaches proposed for solving the problem present a new adaptation of the genetic algorithm (with three-dimensional coding) and the VNS (Variable Neighborhood Search) approach.

The paper is organized as follows: In section 2, the review of the related literature is presented. The problem definition and the mathematical model are elaborated in section 3. Then, the developed hybrid algorithms are explained respectively in sections 4. Finally, the results are discussed in section 5. In the last section, the conclusions are presented. .

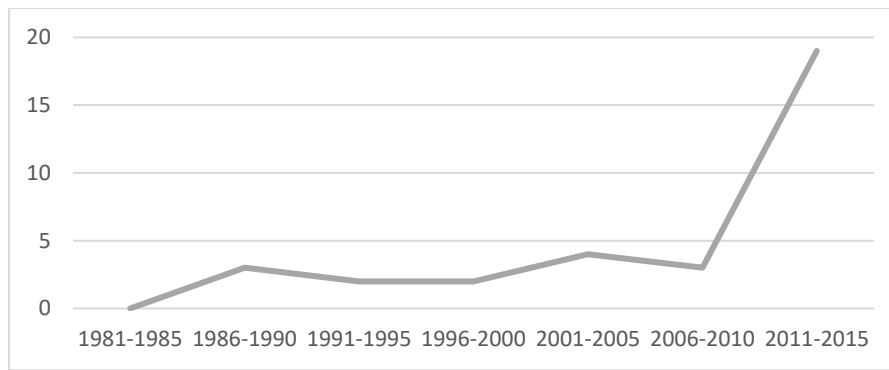
## 2. Review of the related literature

Supply Chain Management refers to the material, information, and financial flow management among the suppliers, vendors, manufacturing and assembly plants, distribution centers, and the others components of the supply chain. Lambert and Cooper (2000) discussed the supply chain success factors presented a framework for supply chain management as well as questions on how it might be implemented, and suggested relevant research trends (perspectives) for future researches.

Managing reverse flow is becoming a crucial element of supply chain management and, in some cases, a profit generating function. Rogers and Tibben-Lembke (1998) discussed the reverse logistics activities and management methodologies, their benefits, and the barriers to their successful implementation. In addition, Tavana et al. (2016a, b) focus on the delegation of the reverse logistic process to a 3PRLPs (Third-Party Reverse Logistics Providers). Some recently published state-of-the-art articles have addressed reverse logistics and the closed-loop logistics chain (see Lambert and Riopel, 2003, Sasikumar and Kannan, 2008a, 2008b, 2008c, Chanintrakul 2009, Govindan et al. 2015, Govindan and Soleimani, 2017).

Many studies discuss the integrated supply chain planning. For instance, Sheu et al. (2005) presented an optimization-based model that deals with integrated operational problems in the green-supply chain management. In this study, the researchers presented a formulation of a linear multi-objective programming model that optimizes the operations of both integrated logistics and corresponding used-product. Moon et al. (2002) proposed an integrated process planning and scheduling model for the multi-plant supply chain, which behaves like a single company through strong coordination and cooperation toward mutual goals. Park (2005) presented a model for integrated production and distribution planning and investigated the effectiveness of their integration in a multi-plant, multi-retailer, multi-item, and multi-period logistic environment, where the objective is to maximize the total net profit. You can find more examples of multi-objective models in Keyvanshokoo et al. (2013), Kumar et al. (2017), and John et al. (2017).

Producers in several countries are facing increasing market pressures to use returnable containers. According to Glock (2017), the number of published articles on using returnable containers has increased obviously, which is an indicator of the increasing relevance of their effective management (see Figure 2).



**Figure 2.** Number of studies on ITRs (Glock, 2017)

This particular interest of researchers in the reusable containers management reflects the extent of the economic and environmental benefit of using this type of packaging.

The studies that have focused on reusable containers management are focusing on various dimensions. For example, Mollenkopf et al. (2005), Palsson et al. (2013) and Carrano et al. (2015) evaluate the use of reusable containers in comparison to disposable containers. Also, Goh and Varaprasad (1986), Kelle and Silver (1989), and Cobb (2016a, 2016b) worked on the prediction of returns and the purchase of new reusable containers. Kroon and Vrijens (1995) studied reusable containers management policy in a closed-loop supply chain. The authors proposed a model for the case, where a reusable containers agency is responsible for coordinating the system and a service provider collects used containers and sends them on demand to supply chain members. In the same way, Goudenege et al. (2013) propose a generic model for reverse logistics management that focused on reusable containers. The authors adapt the model to the specific requirements of the companies. The article focuses on a precise and real-life industrial application at a luxury goods company. Silva et al. (2013) discuss reverse logistics flow in which a returnable packaging is introduced, where the objective is to present a case study on direct and reverse flow of returnable packaging to replace a disposable packaging system. As a result, the returnable packaging model consumed 18% less material than the disposable packaging. Furthermore, the developed model provides greater protection to the exported products and minimizes waste generation. Accorsi et al. (2014) propose an original conceptual framework for a food packaging and distribution network. The paper considers fresh fruit and vegetable flow throughout a food catering chain, from vendors to final customers. The paper compares a multi-use system to traditional single-use packaging to quantify the economic returns and environmental impacts of the reusable plastic container (RPC). Along the same line, Singh et al. (2016) explore the economic advantages / disadvantages of RPCs in the fresh product transportation from growers to retailers. Atamer et al. (2013) focus on pricing and production decisions in utilizing reusable containers with stochastic customer demand. Mensendiek (2015) proposes a mathematical programming formulation of the single scheduling problem of a supplier producing jobs for several buyers. Hariga et al. (2016) propose a mixed-integer, non-linear program for the flow coordinating of the product and reusable containers in single-buyer and single-vendor supply chains.

Johansson and Hellström (2007) investigate the impact of the control strategies on the management of returnable transport Item (RTI). The paper proposes a simulation model based on an empirical case to explore different scenarios. The results suggest that the choice of control strategy has a significant impact on investments and operating costs and that RTI shrinkage can be controlled using tracking systems. Castillo and Cochran (1996) present a formulation of an optimal configuration of this type of system. The authors model the reusable bottle production and distribution activities of a large soft drink manufacturer located in Mexico City, Mexico. Kim et al. (2014) analyze the interdependencies between the inventory of finished products and the ITR inventory in two-stage supply chain, where RTIs are used to transport finished products from the supplier to the buyer.

Thoroe et al. (2009) considered a closed-loop supply chain as containers move between a single supplier and a single buyer. The authors studied the case where RFID tags can be used to track the return flow of containers. This work was extended by Kim & Glock (2014) who developed a mathematical planning model for a closed-loop supply chain that uses containers for transporting products from a supplier to a retailer. Martinez-Sala et al. (2009) present a study in collaboration with a Spanish firm that developed an innovative and ecological packaging and transport unit, called MT. The study shows how the firm can turn the MT into intelligent product platform by embedding Active RFID tags. Glock and Kim (2016) extend the work of Kim & Glock (2014) and introduce various security measures that the supply chain can adopt to protect against ruptures of RTI. In this regard, Cobb (2016b) presents a return rate estimate for RTI from

RFID data. Recently, Yang et al. (2018) analyze the value of the recovery information collected by sensors and integrated into the Internet of Things environment.

Product distribution and collection optimization in a closed-loop supply chain is one of the most frequent topics in transport optimization. The pickup delivery problem is one of the most studied problems in the literature (see Lin et al., 2014). Prive et al. (2006) discuss the vehicle-routing problem with the soft drinks delivery and the pickup of empty bottles and aluminum from stores. The deliveries were mandatory, while the pickup process at each point was optional. The problem considers the time window constraints and assumes that the vehicles are heterogeneous with a multiple type of products. A similar problem was examined by Gribkovskaia et al. (2007) in which each store was allowed to be visited twice. Aras et al. (2011) studied a selective multi-depot vehicle routing problem with pricing. The study assumes that split collection is not allowed. Soysal (2016) propose a new probabilistic mixed-integer linear programming model for the Closed-loop Inventory Routing Problem (CIRP) in order to enhance the traditional models proposed for CIRP and make them easy to use for the decision makers in closed-loop supply chains with multi-products and demand uncertainty. Iassinovskaia et al. (2017) propose a mixed-integer linear program for inventory-routing problem of RTI with time windows and simultaneous pickup and delivery in closed-loop supply chains with mono-producer, mono-product, and multi period.

By analyzing the literature, we found that the authors resort frequently to linear programming by working on RL / CLSC (as shown in Figure 3).

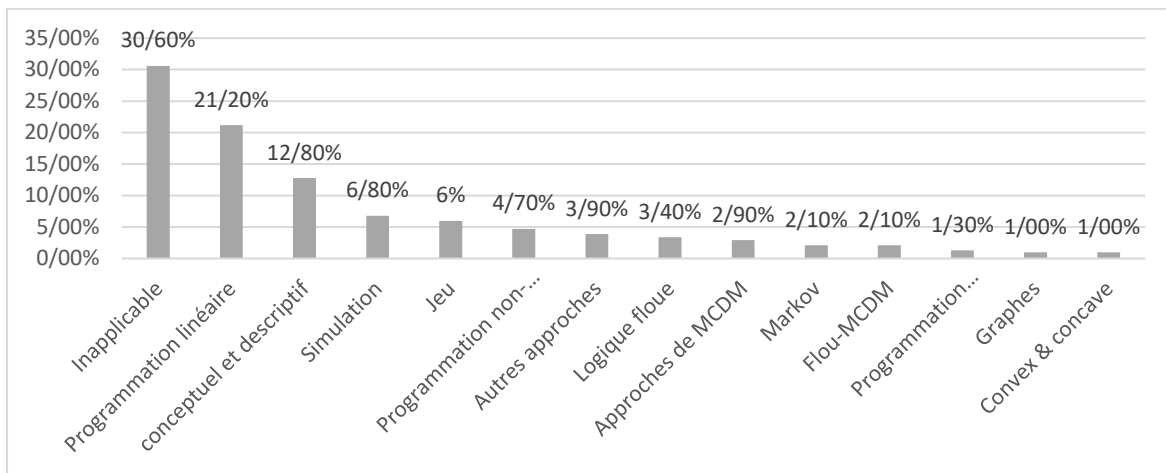


Figure 3. Modeling approaches (Govindan et al., 2015)

Otherwise?, evaluating the environmental impact of the distribution, production, and energy use in the supply chain activities is one of the aims of the green supply chain. However, the environmental constraints are still not involved in the current logistics activities. The signed Kyoto protocol engages many countries and companies to a carbon emission quota. These restrictions lead firms to monitor their carbon footprint (CF) and to evaluate the environmental impacts of their activities. Several methodologies are used to calculate carbon emissions (RetelHelmrich et al., 2014) and the greenhouse gas protocol is the commonly the most used one. In their study, Accorsi et al. (2014) investigate Life cycle assessment (LCA) methodology issued to evaluate the CF associated with the life cycle of packages in this distribution network. The integration of the carbon emission constraints can be considered in different supply chain activities and decision levels. Absi et al. (2013) propose four types of carbon emission constraints (Periodic, cumulative, global, and rolling) for the multi-sourcing lot-sizing problem which can be used in and adapted to several cases. Other studies have recently been conducted to examine the critical environmental problem. For instance, Bazan et al. (2017) examine three critical environmental issues, i.e. energy used in production processes (manufacturing and remanufacturing), greenhouse gas emissions from production and transportation activities (subject to a penalty), and the number of refurbishment. Similarly, Sarkar et al. (2017), focus on the environmental impacts of production and transportation operations and propose mixed-integer non-linear programming model for a multi-echelon closed-loop supply chain.

### 3. Problem definition and mathematical model

#### 3.1. Problem definition

In this study, the proposed model is related to the firms that integrate reusable containers to their network. The model proposes a flow management of the reusable containers between the warehouses and the stores. The full delivered

containers are consumed by the stores and recuperated empty thereafter by the warehouses to be reloaded and redistributed again to the stores on a finite planning horizon. The model holds a carbon emissions constraint for the distribution and collection activities. The model could be beneficial for the companies that manage reusable containers like wooden pallet distributor, reusable gas, soda, water bottles, reusable plastic containers, etc.

In this configuration (Figure 4), we suppose that the client demands are deterministic over a finite planning horizon. We also assume that each warehouse or store has its own holding cost for full and empty containers. On the other hand, the transportation cost constituted of a fixed cost and variable cost per unit.

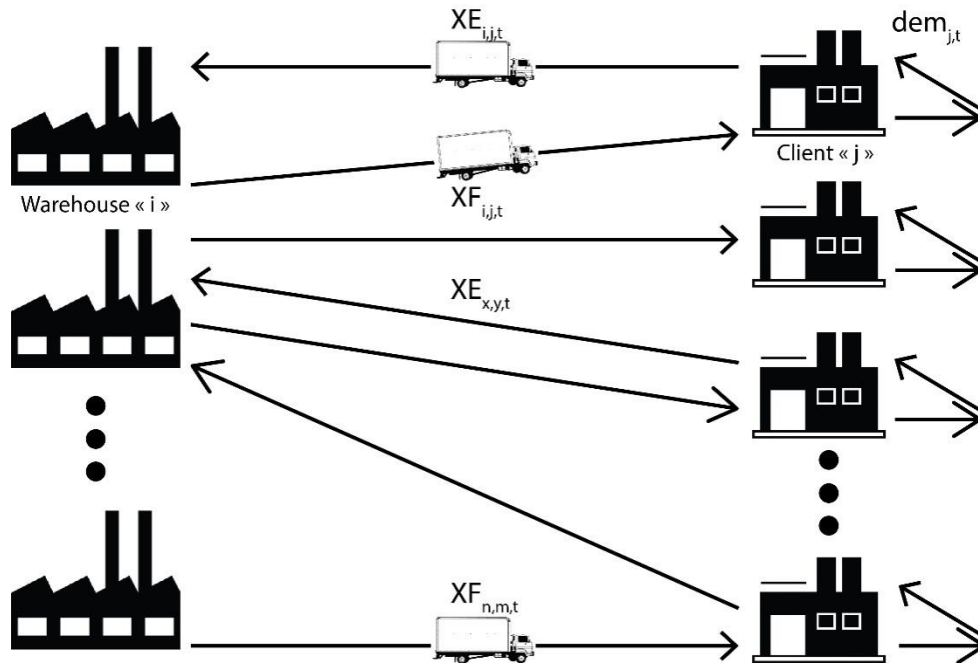


Figure 4. Generic model scheme

The study aims to propose an exploitation planning of reusable containers between warehouses and clients. The objective is to determine in each period, the deliveries of each warehouse for each client, and the collected quantities from each clients and their destinations. In this configuration, we also assume that each warehouse serves many clients in each period, the returnable containers quantities split is allowed for each client. Transportation costs are fixed per unit and per client. We also suppose that each warehouse has its own returnable containers maintenance cost. It is important to note that the vehicle routing problem optimization is beyond the scope of this study and the model.

The distribution and the collect phase are considered in this configuration. They are carried out by a limited capacity vehicle. Also, we consider a set up cost for launching the distribution and collection operations and for recapturing the empty containers. The delay of the consumption and the reloaded...? Fixed and determined respectively by the stores and the warehouses. We also note that warehouses and stores possess a limited storage capacity.

The objective of this research is to propose a containers exploitation policy that would minimize the holding and transportation costs for the warehouses and the stores, reduce the procurement of new containers, satisfy the customer's need, and respect the carbon emission restrictions.

### 3.2. Model description

The proposed model integrated two decision levels. The first level concentrates on the initial stock of reusable containers and the procurement phase along the finite planning horizon. The second one deals with the distribution and the collection phase. The initial stocks, procurement, distribution, and collection decisions are considered in this model as decision variables.

The model considered minimizes the holding, transportation, and procurement cost with satisfying the client's needs under several constraints. We note that the proposed model presents an integrated supply chain planning that aims to enforce coordination and collaboration. The proposed model has been discussed in international conferences (Ech-charrat and Amechnoue, 2016; Ech-charrat et al., 2017a, b).

The model is shown in the following:

- N : Number of warehouses  
 M : Number of clients  
 T : Number of periods  
 dem<sub>j,t</sub> : Demand of client j in period t  
 vehC : Vehicle capacity  
 s\_c\_w<sub>i</sub> : Warehouse stock capacity  
 s\_c\_c<sub>j</sub> : Client stock capacity  
 d<sub>j,i</sub> : Distance between warehouse i and client j  
 co2 : Carbon emissions per unit per kilometer  
 Emax : maximum average emission per unit  
 IOFC<sub>j</sub> : Full containers initial inventory in client i  
 IOEC<sub>j</sub> : Empty containers initial inventory in client i  
 H : an arbitrarily large number  
 trans<sub>i,j</sub> : Transportation cost of a container from/to client/ warehouse per distance unit  
 h\_f\_w<sub>i</sub> : Holding cost of full reusable container of warehouse i  
 h\_e\_w<sub>i</sub> : Holding cost of empty reusable containers of warehouse i  
 h\_f\_C<sub>j</sub> : Holding cost of full reusable containers of clients i  
 h\_e\_C<sub>j</sub> : Holding cost of empty reusable containers of clients i  
 pur<sub>i,j</sub> : Ordering cost of a client i from warehouse j  
 recov<sub>i,j</sub> : Recover cost from a client i to warehouse j  
 XF<sub>i,j,t</sub> : Full containers delivered quantity from warehouse i to client j in period t  
 XE<sub>i,j,t</sub> : Empty containers delivered quantity from warehouse i to client j in period t  
 IFW<sub>i,t</sub> : Full containers inventory in warehouse i in period t  
 IEW<sub>i,t</sub> : Empty container inventory in warehouse i in period t  
 IFC<sub>j,t</sub> : Full container inventory in client i in period t  
 IEC<sub>j,t</sub> : Empty container inventory in client i in period t  
 IOFW<sub>i</sub> : Full containers initial inventory in a warehouse i  
 IOEW<sub>i</sub> : Empty containers initial inventory in a warehouse i  
 Q<sub>i,t</sub> : Number of full containers reproduced by a warehouse i in period t  
 Z<sub>i,j,t</sub> : Binary variable indicating if a client purchases full containers from a warehouse in period t  
 Y<sub>i,j,t</sub> : Binary variable indicating if a warehouse j recovers empty containers from client i in period t  
 TransC : Delivery and collect transport cost between the warehouses and clients over the planning horizon

$$TransC = \sum_{i=1}^N \sum_{j=1}^M \sum_{t=1}^T \left( (Z_{i,j,t} * pur_{i,j}) + (Y_{i,j,t} * recov_{i,j}) + ((XF_{i,j,t} + XE_{i,j,t}) * trans_{i,j} * dist_{i,j}) \right)$$

HoldC: Holding cost of the empty and full reusable containers in the warehouses and clients over the planning horizon. The cost englobes the initial stock investment.

$$HoldC = \sum_{i=1}^N \sum_{t=1}^T \left( (IFW_{i,t} * h_{f_{w_i}}) + (IEW_{i,t} * h_{e_{w_i}}) \right) + \sum_{j=1}^M \sum_{t=1}^T \left( (IFC_{j,t} * h_{f_{c_j}}) + (IEC_{j,t} * h_{e_{c_j}}) \right) + \sum_{i=1}^N \left( (IOEW_i * h_{e_{w_i}}) + (IOFW_i * h_{f_{w_i}}) \right)$$

ProdC: the cost represents the cost of washing, maintaining, filling, and capping of the empty reusable containers.

$$ProdC = \sum_{i=1}^N \sum_{t=1}^T (Q_{i,t} * Prod\_cost_i)$$

The integrated planning model

$$Min (TransC+HoldC + ProdC) \tag{1}$$

Subject to:

$$IFW_{i,1} = IOFW_i + Q_{i,1-Delay} - \sum_{j=1}^M (XF_{i,j,1}) \quad \forall i, (\forall Delay < 1 \text{ if not } Q = 0) \quad (2)$$

$$IFW_{i,t} = IFW_{i,t-1} + Q_{i,t-Delay} - \sum_{j=1}^M (XF_{i,j,t}) \quad \forall i, (\forall t > Delay, \text{ if not } Q = 0) \quad (3)$$

$$IEW_{i,1} = IOEW_i - Q_{i,1} + \sum_{j=1}^M (XE_{i,j,1}) \quad \forall i \quad (4)$$

$$IEW_{i,t} = IEW_{i,t-1} - Q_{i,t} + \sum_{j=1}^M (XE_{i,j,t}) \quad \forall i \quad (5)$$

$$IFC_{j,1} = IOFC_j - dem_{j,1} + \sum_{i=1}^N (XF_{i,j,1-d_{j,i}}) \quad \forall j, (\forall d_{j,i} < 1 \text{ if not } XF = 0) \quad (6)$$

$$IFC_{j,t} = IFC_{j,t-1} + \sum_{i=1}^N (XF_{i,j,t-d_{j,i}}) - dem_{j,t} \quad \forall j, \forall t > 1, (\forall d_{j,i} < t \text{ else } XF = 0) \quad (7)$$

$$IEC_{j,1} = IOEC_j - \sum_{i=1}^N (XE_{i,j,1+d_{j,i}}) \quad \forall j, (\forall d_{j,i} < T \text{ else } XE = 0) \quad (8)$$

$$IEC_{j,t} = IEC_{j,t-1} - \sum_{i=1}^N (XE_{i,j,t+d_{j,i}}) + dem_{j,t-1} \quad \forall j, \forall t > 1, (\forall d_{j,i} \leq T - t \text{ else } XE = 0) \quad (9)$$

$$\sum_{i=1}^N \sum_{j=1}^M \sum_{t=1}^T ((XF_{ijt} + XE_{i,j,t}) * CO2 * dist_{i,j}) \leq Emax * \sum_{j=1}^M \sum_{t=1}^T dem_{j,t} \quad (10)$$

$$XF_{ijt} \leq H * Z_{i,j,t} \quad \forall i, \forall j, \forall t \quad (11)$$

$$XE_{ijt} \leq H * Y_{i,j,t} \quad \forall i, \forall j, \forall t \quad (12)$$

$$IFW_{it} + IEW_{it} \leq s\_c\_w_i \quad \forall i, \forall t \quad (13)$$

$$IFC_{jt} + IEC_{jt} \leq s\_c\_c_j \quad \forall j, \forall t \quad (14)$$

$$XE_{ijt}, XF_{ijt}, IFW_{it}, IEW_{it}, IFC_{jt}, IEC_{jt}, IOFW_i, IOEW_i, Q_{i,t} \geq 0 \quad (15)$$

The objective function (1) computes the solution fitness. It minimizes the transportation, maintenance, filling, and holding cost of reusable containers between warehouses and stores. Constraints (2 & 3) and (4 & 5) are respectively the inventory flow conservation equations for full and empty reusable containers in the warehouses. Constraints (6 & 7) and (8 & 9) are respectively the inventory flow conservation equations for full and empty reusable containers in the stores. Constraint (10) presents the unitary carbon emission over the whole horizon that cannot be larger than the maximum unitary environmental impact allowed. Constraints (11) and (12) guarantee respectively the cancellation of full and empty reusable containers deliveries when no delivery is programmed. Constraints (13) and (14) guarantee respectively the respect of the inventory capacity of the warehouses and clients or stores. Constraint (15) ensures the variables positivity.

#### 4. Resolution approaches

##### 4.1. Hybrid algorithm (HA1)

Recently, evolutionary algorithms have received an increased interest from researchers due to their simplicity and the flexibility, and for their capacity for solving difficult optimization problems in a moderate computational time. Researchers use several technics and heuristics/metaheuristics to improve the general efficiency of the evolutionary algorithm. Some approaches use the hybrid architectures like

- Hybridization between evolutionary algorithms and mixed integer programming
- Neural network or fuzzy logic-assisted evolutionary algorithms
- Particle swarm optimization (PSO) assisted evolutionary algorithm
- Hybridization between two evolutionary algorithms
- Ant colony optimization (ACO)-assisted evolutionary algorithm
- Hybridization between evolutionary algorithm and other heuristics (such as tabu? search, simulated annealing, hill climbing, VNS, GRASP, etc.)

Several hybrid architectures are implemented to solve difficult optimization problems. Vidal et al. (2011) proposes a hybrid Genetic Algorithm for Multi-depot and Periodic Vehicle Routing Problems. The study combines the population-based evolutionary search breadth, the neighborhood-based metaheuristics aggressive-improvement capabilities, and advanced population-diversity management schemes. Puchinger and Raidl (2005) review the literature on the hybrid

algorithms combining metaheuristics and exact algorithms in combinatorial optimization. Zouadi et al. (2015) proposed a hybrid method for the lot-sizing problem in the hybrid manufacturing/remanufacturing system. The authors report that the obtained results were satisfactory. Similarly, Frazzon et al. (2017) proposed a hybrid approach combining mixed linear programming and a genetic algorithm for the integrated planning of production and transport processes within SC.

In this section, we propose a hybridization approach between an evolutionary algorithm and a mixed integer programming to solve the problem. The evolutionary algorithm used in this study is the genetic algorithm combined with an exact resolution based on mixed integer programming model proposed in section 3.

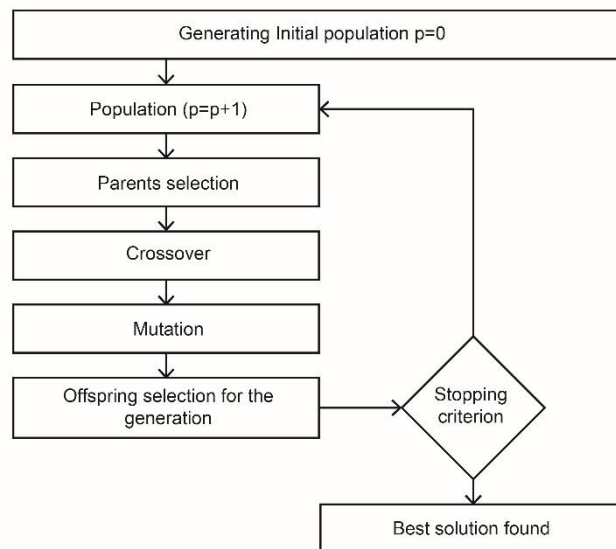
The proposed genetic algorithm (GA) determines the binary decision variable values of full and empty reusable container deliveries or collects while the mixed integer programming model is solved to determine the integer variables (full and empty reusable containers deliveries or collects quantities decisions).

GA is widely discussed and implemented in the literature to solve several resolution problems because it is easy to implement and very often it provides adequate solutions compared to other optimization techniques. Some interesting applications of GA are presented by Supithak et al. (2010), Rezaei and Davoodi (2011), and Zouadi et al. (2015, 2016)

The flow chart of a GA therefore relies on three features:

- The selection allows to foster individuals who have a better fitness. For our problem, the fitness is the sum of the preparation cost, the setup cost, and the holding cost
- The crossover combines two parents to form one or two children (offspring), while trying to keep the good features of parents
- Mutation is a genetic operator used to preserve genetic diversity

In a GA, a population of candidate solutions is created which is formed from several solutions called offspring. By using and applying crossover or reproduction operators, new solutions are created. The fitness of the resulting solutions is evaluated and then the best solutions are maintained in the next generation after applying a suitable selection strategy. The procedure is then iterated until a stopping criterion. Thus, we will use this type of algorithm with a standard overall scheme presented in Figure 5.



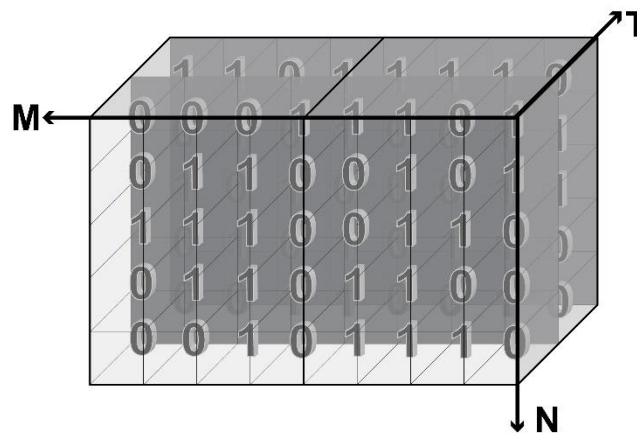
**Figure 5.** Genetic algorithm scheme (Zouadi et al., 2015)

#### 4.1.1. Solution encoding

The problem resolution relies heavily on the encoding. The encoding phase is considered crucial in the GA implementation. Binary encoding is one of the most common forms of encoding. In this encoding, each chromosome is represented using a binary string. In the binary encoding, every chromosome is a string of bits, 0 or 1.

In this study, we use a binary encoding for the developed GA. The Figure 6 show the proposed encoding.





**Figure 6.** Solution encoding (Ech-charrat and Amechnoue, 2016, Ech-charrat et al., 2017a, 2017b).

The proposed binary encoding presents a three-dimensional vector which is the period of the planning horizon  $T$ , warehouses number  $N$ , and a double of the clients number  $2 \times M$ . In the first part of the vector, we find the reusable containers deliveries binary decisions between the warehouses and clients over the planning horizon. While in the second part of the vector, we have the reusable containers collection binary decisions between the clients and the warehouses over the planning horizon.

#### 4.1.2. Crossover

The population individuals are three-dimensional vectors. Following the nature of the solutions for encoding the solutions, we need a crossover operator able to cross two three-dimensional vectors. The proposed crossover is presented in the Figure 7.

The proposed crossover operator consists of splitting the three-dimensional vectors into  $T$  matrix (two-dimensional vectors) in such a way that each matrix presents the full reusable containers deliveries and the empty reusable container collection binary decisions. The crossover operator consists of crossing randomly two matrices issued from two parents using one of the crossing operators proposed by Toledo et al. (2013) and shown in the Figure 8.

In the example presented in the Figure 7, each of the two three-dimensional vectors (Parent A, Parent B) are divided into two matrices  $\{(PA1, PA2); (PB1, PB2)\}$  representing the deliveries and collection launching decisions of the two period of the planning horizon ( $T$ ). The crossover operator consists of crossing the first half of the matrix  $PA1$  (presenting the delivery quantities decisions launching) with the first half of the matrix  $PB1$ , and the second half of the  $PA1$  (presenting the collection quantities decisions launching) with the second half of the  $PB1$  to have the offspring 1 presenting the first period matrix decision crossing. The same procedure is launched to cross the  $PA2$  and  $PB2$  to have the offspring 2. The two offspring 1 and 2 are assembled in a three-dimensional vector presenting the resulted offspring.

#### 4.1.3. Mutation

Mutation prevents forming a uniform population or tapping trapped in a local optimum. This procedure modifies the selected chromosome genes with a mutation probability. In this paper, we propose the implementation of a total of four mutation operators proposed by Toledo et al. (2013). (See Figure 9).

In this study, a total of four mutation operators are used. The first operator (Figure 9) consists of changing a randomly chosen value. For the second operator, two values are randomly chosen and inverted from the same column. In case of the third operator, two values are randomly chosen and inverted from the same row. The last operator consists of applying the first mutation operator twice. One of these four mutations is randomly selected.

#### 4.1.4. Exact resolution to determine collected and delivered quantities

At each iteration level of the Hybrid algorithm, the generated offspring determine the binary decisions variable values of full and empty reusable container deliveries or collects. These propositions generated by the offspring are integrated in the mathematical model which is then solved by CPLEX. The solution returned by CPLEX defines optimal reusable container quantities to deliver or to collect according to the binary decisions proposed by the offspring structure resulting from the crossover and mutation operator.

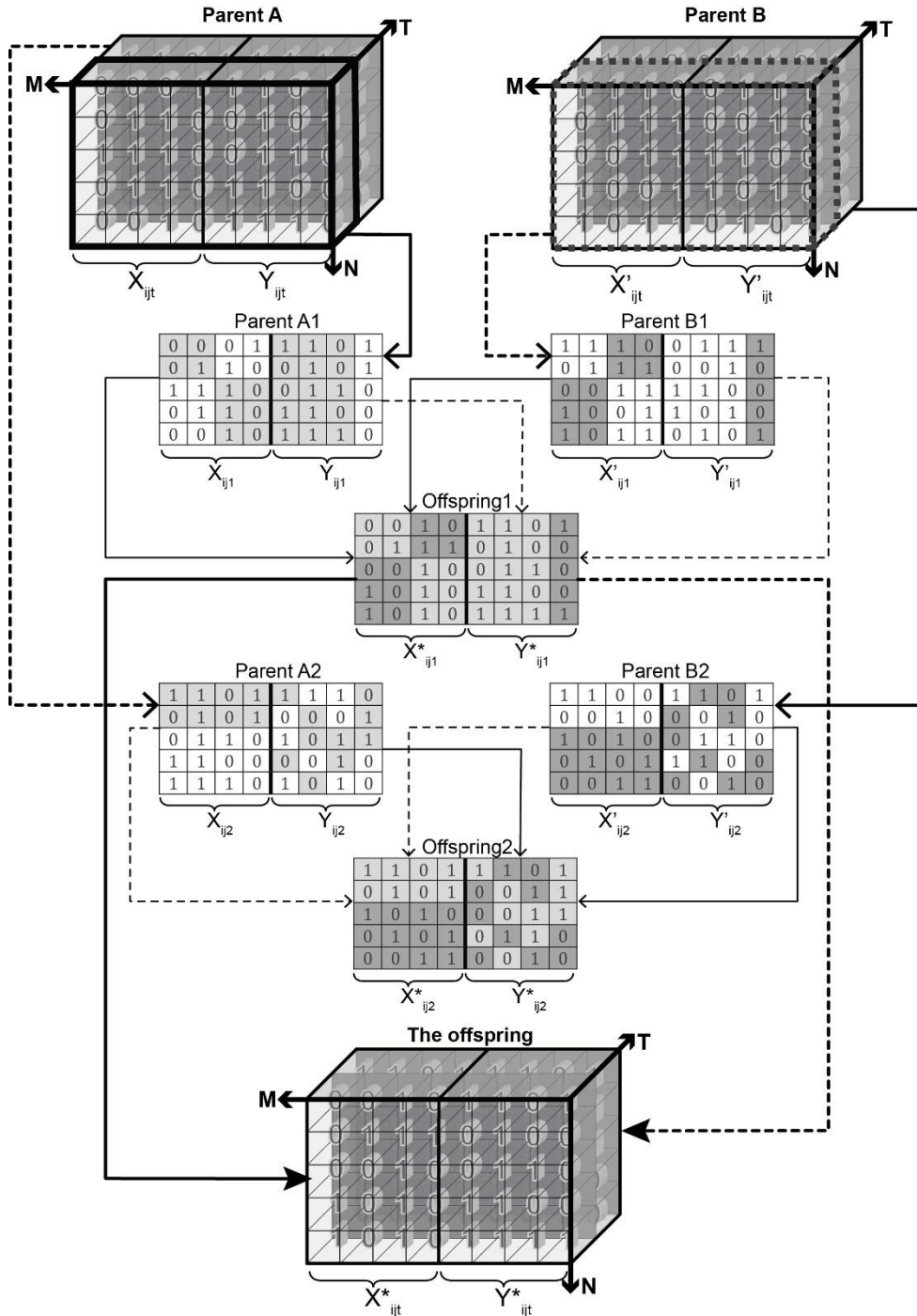


Figure 7. crossover operator (Ech-charrat and Amechnoue, 2016, Ech-charrat et al., 2017a, 2017b).

**4.1.5. Correction function**

The new solutions issued from the crossover and mutation operators are not always feasible. For this reason, a correction function is developed to correct the unfeasible solution.

**4.2. Hybrid algorithm (HA2)**

In this section, we propose similar hybridization architecture by using a memetic algorithm instead of the genetic algorithm used in the HA1. As the first hybridization structure, the second formulation consists of a memetic algorithm (MA) with exactly the same resolution of the hybrid algorithm 1. The exact resolution was mainly based on mixed integer programming model proposed in section 3.

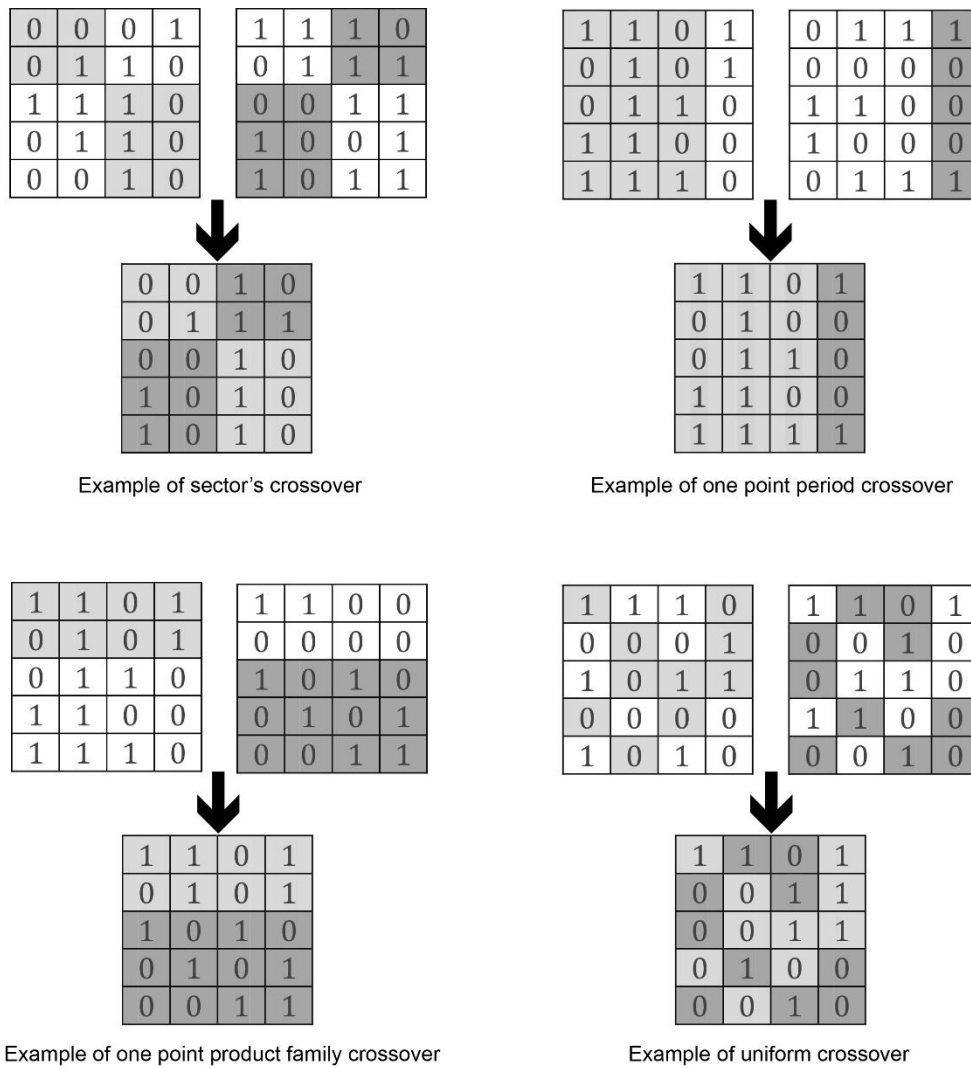


Figure 8. Matrix crossing (Toledo et al., 2013)

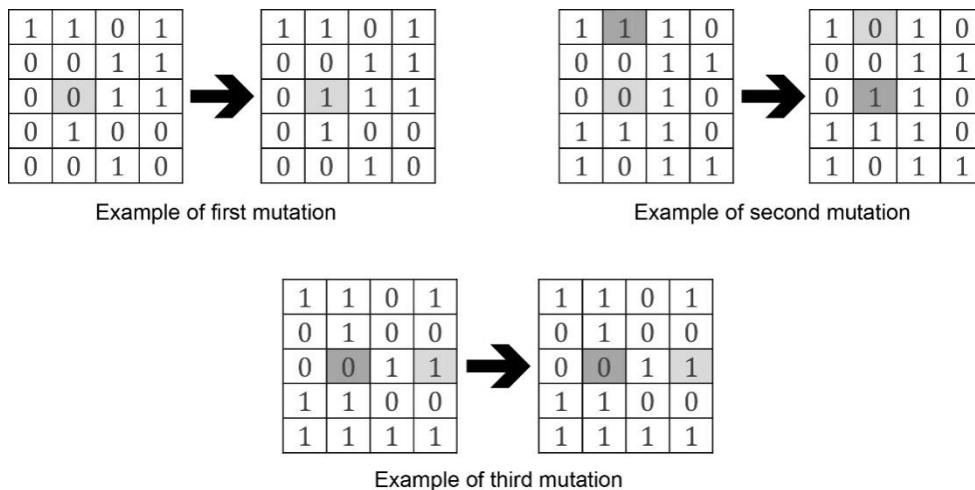


Figure 9. The used mutation operators (Toledo et al. 2013)

Memetic algorithm is considered as one of the ideal metaheuristic to solve a wide range of combinatorial optimization problems. The Memetic Algorithm is an extension of the traditional GA. It uses a local search technic to reduce the likelihood of the premature convergence. Goren et al. (2010) provide a survey on the use of the Memetic Algorithm.

The flow chart of a memetic algorithm (MA) therefore relies on many features. We use this type of algorithm with the standard overall scheme:

The flow chart of a GA therefore relies on three features:

- **The selection** allows to foster individuals who have a better fitness. For our problem, the fitness is the sum of the preparation cost, the setup cost, and the holding cost.
- **The crossover** combines two parents to form one or two children (offspring), while trying to keep the good features of parents
- **Mutation** is a genetic operator used to preserve genetic diversity
- **Local search** allows making moves from solution to another one in the space of candidate solutions by applying local changes up to a stopping criterion

The proposed memetic algorithm keeps the same GA architecture (The same solution presentation, crossover and mutation operators, and the exact resolution). In addition to genetic features, the memetic algorithm uses a local search to enhance the solutions quality. In this paper, a local routine search metaheuristic is applied to improve solution's quality. We call this approach Variable Neighborhood Search (VNS) (Hansen and Mladenovic, 1997, 1999, 2002, 2003; Hansen et al., 2001) The VNS metaheuristic exploits systematically the idea of neighborhood change.

The VNS in this configuration exploits a total of three local search. The metaheuristic logic is to explore distant neighborhoods of the current solution (offspring) up to a stopping criterion, and move from solution to another and from a local search procedure to another only if an improvement was made. In the case where no improvement is made, the metaheuristic passes to the second local search exploitation with the best found solution to reach the stopping criterion. If no improvement is made, the same strategy is followed by launching the third local search. In the case of finding a better solution in the second or in the third local search, the VNS starts from the beginning by exploring the first local search using the best found solution. Algorithm 1 summarizes the structure of this improvement strategy.

---

**Algorithm 1:** proposed VNS configuration

---

*// Cost(): Solution evaluation function*

S ← Initial\_Solution

i ← 0

S3 ← Local\_search\_3(S)

While ( Cost(S3) < Cost(S) Or i < 1)

    S ← S3

    S1 ← Local\_search\_1(S)

        While ( Cost(S1) < Cost(S))

            S ← S1

            S1 ← Local\_search\_1(S)

        End while

    S2 ← Local\_search\_2(S)

    While ( Cost(S2) < Cost(S))

        S ← S2

        S1 ← Local\_search\_1(S)

        While ( Cost(S1) < Cost(S) )

    S ← S1

    S1 ← Local\_search\_1(S)

        End while

    S2 ← Local\_search\_2(S)

    End while

    S3 ← Local\_search\_3(S)

i ← 1

End While

S\* ← S

*// When the stopping criterion is reached, the loops are closed with the break function*

---

We propose three local search movements. The first local search consists of permuting the matrices presenting the full and empty reusable container deliveries or collect decisions in each period  $T_i$ . The move A in Figure 10 shows an example of the used operator. The second local search consists of permuting the lines of the matrix  $T_i$  presenting the full and empty reusable containers deliveries or collets decisions of the period  $i$ . The move B in the Figure 10 shows an example of the used operator. While the third local search consists of inverting the bit's value?, one by one of each line in the matrix  $T_i$  presenting the full and empty reusable containers deliveries or collets decisions on the period  $i$  until a stopping criterion. The move C in Figure 10 shows an example of the used local search.

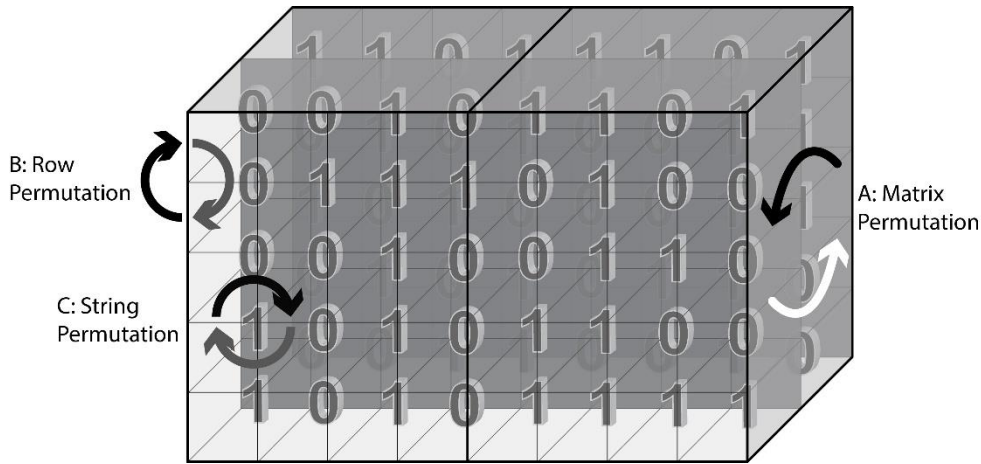


Figure 10. The used local search procedure

## 5. Result and discussion

To prove the proposed algorithms performance, we summarize in this section the numerical experiments performed on these approaches. The obtained results by the first Hybrid method 1 (HA1) and the second Hybrid method (HA2) were compared with those obtained by CPLEX.

To tune the parameters of the proposed approaches, many tests have been performed. The best configuration of each algorithm was found by varying the following parameters:

- Number of iterations
- Population size
- The maximum number of non-improving iterations
- The probability of crossover
- The probability of mutation

The hybrid methods employ a set of parameters that requires fine tuning. In Table 1, these parameters are listed and explained. Based on a large number of runs, the following set of parameters was finally selected  $(\beta ; \mu ; \alpha ; \Gamma ; \mathcal{E}) = (500 ; 50 ; 0,7 ; 0,3 ; 50)$ .

Table 1. Parameters of the hybrid method

$\beta$ : The number of crossing
$\mu$ : Number of individuals in the initial population
$\alpha$ : The probability of crossover
$\mathcal{E}$ : The maximum number of non-improving iterations in the genetic algorithm
$\Gamma$ : The probability of mutation
$\mathcal{E}$ : The maximum number of non-improving iterations in the local search

The instances are derived from the article of Teunter et al. (2006), Zouadi et al. (2015) and Absi et al. (2013). Five different types of demand and return patterns (stationary, linearly increasing, linearly decreasing, seasonal (peak in the middle), and seasonal (valley in the middle), 6 horizon lengths, 4 set of warehouses, and 8 sets of clients are considered.

Tests are performed on 960 instances grouped in 5 sets, each set containing 192 instances. The obtained results are given in Tables 2 to Table 4. The notations used are listed below:

- AS: average solution
- AT (s): average time
- HA1: Hybrid algorithm 1
- HA2: Hybrid algorithm 2
- GHA1C: gap between Hybrid method 1 and CPLEX.
- GHA2C: gap between Hybrid method 2 and CPLEX.
- MaxG: The maximum gap found.

The obtained results of all the approaches are compared following two different instances classifications:

- Grouped according to the number of periods of the planning horizon
- Grouped according to the number of warehouses and clients
- Grouped according to the type of demand

For all the instances, the proposed approaches are compared with the optimal value returned by CPLEX, but when CPLEX can't prove optimality, we compare with the lower bound. The results of HA1 have been discussed in Ech-charrat and Amechnoue, 2016, Ech-Charrat et al., (2017a, b).

**5.1. Grouped according to the number of periods of the planning horizon**

The instances have a planning horizon up to 30 periods. The obtained results are given in tables 2.

**Table 2.** The results obtained according to the number of periods

Periods	Cplex		HA1				HA2			
	AS	AT(s)	AS	GHA1C	AT(s)	MaxG	AS	GHA2C	AT(s)	MaxG
5	80889.34	66	81989,44	1,36%	73	7,00%	81876,19	1.22%	75	3,45%
10	193663,88	332	198931,54	2,72%	211	17,27%	198428,01	2.46%	233	5,76%
15	315144,58	3425	324977,09	3,12%	396	8,10%	321857,16	2.13%	424	8,10%
20	433879,89	8409	447156,61	3,06%	501	13,38%	443078,14	2.12%	779	11.91%
25	577111,09	13353	592923,93	2,74%	779	9,10%	586864,27	1,69%	1054	9,10%
30	747121,18	24438	764529,10	2,33%	968	11,80%	757431,45	1,38%	1634	9,80%

In table 2, the first column shows the number of periods in each set. Columns 2 and 3 present respectively the average solution found by Cplex and its average computational time for the instances of each set. The columns 4, 5, 6 and 7 give respectively the average solution cost obtained by the Hybrid algorithm 1 (HA1) for each set, the percentage gap between the results of HA1 and Cplex, the average computational time, and the maximum solution cost obtained by the Hybrid method 1 (HA1). The last four columns present the same information for the Hybrid Algorithm 2.

Compared to CPLEX solutions, when the optimum is achieved, the HA2 (1.83 %) gives near optimal solutions while the HA1 (2.56 %) is less efficient. On the other hand, the computational time of the HA2 is greater than the HA1 due to the used local search performed by VNS.

The quality of solutions depends on the length of the planning horizon. For small horizons (5 periods), both methods give near optimal solutions with an advantage for the HA2 specially when the number of client and warehouses is small, while for long horizons, the solution is pretty far from being close to optimal. Regarding the computational time, CPLEX is rather efficient to prove optimality for small size instances, but on larger ones, the computational time becomes more important and exceeds half an hour on many instances without finding an optimal solution. As far as the results obtained by CPLEX are concerned, the optimality is no more achieved in the big data instances. For all the instances, the proposed approaches are compared with the optimal value returned by CPLEX, but when CPLEX can't prove optimality, we compare with the lower bound.

**5.2. Grouped according to the number of warehouses and clients**

In Table 3, the results are grouped according to the number of warehouses and clients. The rows present the number of clients, while the columns present the number of warehouses. For each set of columns, the first and the second columns present respectively the percentage gap between the results of HA1 and Cplex, and the percentage gap between the results of HA2 and Cplex.

Table 3. The results obtained according to the number of warehouses and clients

Warehouses	2		4		8		12	
Clients	GHA1C	GHA2C	GHA1C	GHA2C	GHA1C	GHA2C	GHA1C	GHA2C
2	0.11%	0,03%	0,92%	0,53%	2,53%	0,91%	3,12%	1,37%
4	1.17%	0,89%	1,68%	0,91%	1,93%	0,99%	2,98%	1,76%
6	1,43%	1,11%	1,90%	1,21%	2,27%	1,87%	3,29%	1,97%
8	1,37%	1,01%	2,73%	1,89%	2,19%	1,99%	3,34%	2,38%
10	1,96%	1,37%	2,36%	2,03%	2,62%	2,28%	3,89%	2,47%
20	2,43%	1,76%	2,97%	2,12%	3,21%	2,45%	3,68%	2,61%
30	2,34%	1,98%	3,23%	2,30%	3,47%	2,82%	4,27%	2,81%
40	2,86%	2,12%	3,22%	2,65%	3,82%	2,96%	4,07%	2,98%

The numerical results show that when the number of the client or the warehouses increases, the gap between the two hybrids approaches and Cplex increases. Under most of the configurations, the hybrid algorithm 2 gives best computational results in comparison to hybrid algorithm 1.

### 5.3. Grouped according to the type of demand

In Table 4, the results are grouped according to the type of demand, i.e. stationary, positive and negative trend, seasonal with peak or valley in the middle. For the table, the first column shows the type of the demand. Columns 2 and 3 present respectively the average solution found by Cplex and its average computational time for the instances of each set. The columns 4, 5, and 6 give respectively the average solution cost obtained by the Hybrid algorithm 1 (HA1) for each set, the percentage. In Table 3, the results are grouped according to the type of demand: stationary, positive and negative trend, seasonal with peak or valley in the middle, and the average computational time. The last three columns present the same information for the Hybrid Algorithm 2.

Table 4. the obtained results according to the type of demand

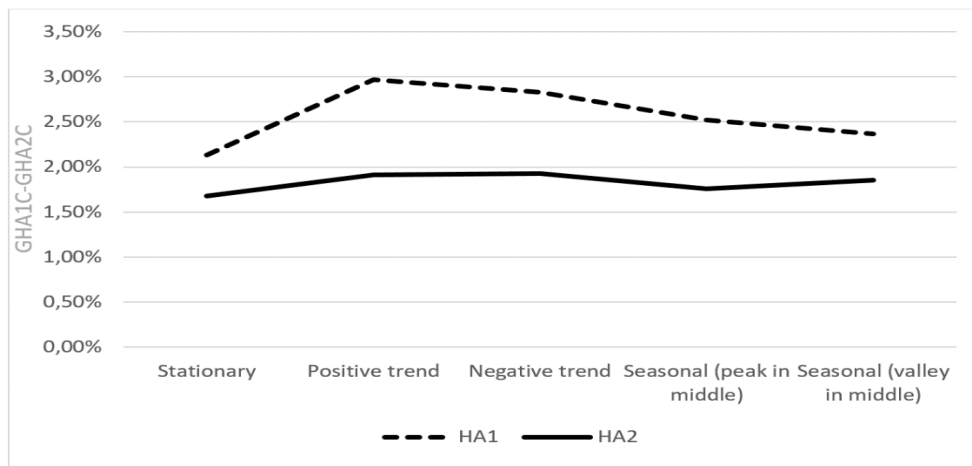
Type of Demands	CPLEX		HA1			HA2		
	A.S	A.T	A.S	GHA1C	A.T	A.S	GHA2C	A.T
Stationary	289630,48	7371	295799,609	2,13%	319	294496,272	1,68%	511
Positive trend	506910,9	8964	521966,154	2,97%	573	516592,898	1,91%	707
Negativetrend	472475,81	8563	485846,875	2,83%	597	481594,593	1,93%	895
Seasonal (peakin middle)	356277,15	6931	365255,334	2,52%	517	362547,628	1,76%	699
Seasonal (valleyin middle)	331213,96	6024	339063,731	2,37%	434	337341,418	1,85%	688

Table 4 shows the average gap between the Hybrid Algorithms and the optimal solutions when they are reached or with the lower bound for each set. This analysis shows that the HA1 and HA2 perform better when the demand is constant. However when the demand follows a positive or negative trend, the approaches are less efficient. When demands are seasonal peak in middle and seasonal valley in middle, a small gap is noticed.

Although the HA1 approach gives good quality results (average deviation of 2.56%), it is strongly dependent on the type of demand which has a considerable influence on the gap which tends towards 3% with positive trend demand type. This point constitutes the major limit of HA1 motivating the proposal of HA2 weakly dependent on the types of demand (Figure 11) that presents good results.

### 6. Conclusion

In this contribution, a distribution and collection network planning problem is presented. The objective is to determine respectively the delivery and collection of full and empty reusable containers quantities. A mixed integer programming model and two hybrid algorithms were developed to solve the problem. The proposed hybrid algorithms use an exact resolution based on the developed MIP stands for...? Model to find the optimal delivered and collected quantities following the binary decision of the GA solutions. The second configuration of the hybrid approaches is enhanced with a local search based on the VNS. This contribution presents a base to develop more generic models by considering several aspects (such as the number of products, vehicle routing, time window, etc.). Concerning the proposed resolution approaches, we are working to further reduce the dependence of the algorithms on the functional data of the problem (e.g. demand type dependency).



**Figure 11.** Stability of HA2 with different types of demand

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