Hybrid resolution approaches for dynamic assignment problem of reusable containers in close loop supply chain

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Abstract

We address in this study the dynamic assignment problem of reusable containers. The objective is optimizing the collect, exploitation, storage and redistribution operations under a carbon emission constraint over a finite planning horizon. We present a new generic mathematical model, which describes the mentioned problem. A Mixed Integer Programming (MIP) model was developed to solve the problem, the model which is very time consuming, was tested on Cplex (Software optimizer). We then adapted two hybrid approaches based on a genetic algorithm to solve the problem at a reduced time cost. The second configuration of the proposed hybrid method is enhanced with a local search procedure based on the Variable Neighborhood Search (VNS). The numerical results have shown that both developed hybrid approaches generate high-quality solutions in a moderate computational time, especially the second hybrid method.

Keywords

Reverse logistics; collect; return flow; hybrid algorithm; reusable container.

1. Introduction

In order to meet environmental and economic requirements, supply chain management (SCM) is no longer limited to direct flow management but it also works on returns flow, which resulted in reverse logistics. Reverse logistics is a quite vast field, indeed the returned products assist to several types of recovery such as remanufacturing, recycling, reuse…etc (Hanafi et al., 2008). In this study, we are interested in reuse activity that describes the fact of using a product more than once. The product concerned by our research is the reusable container by raison of the economic and environmental importance of their use (Bhattacharjya and Kleine-Moellhoff, 2013). the container require normally certain treatments before they are redistributed again, thus reusing containers addressed in our work is not limited only to a simple recovery and transportation; it is a return logistic system that involves also the cleaning and maintenance of containers, as well as their storage and redistribution. In this study we propose a model that helps firms to optimize transportation, storage, containers exploitation and investment under a carbon emission constraint, and resolve this model thereafter with an exact method and meta-heuristic approaches.

Managing reverse flow is becoming a crucial element of supply chain. Rogers and Tibben-Lembke (1998) discuss the reverse logistics activities and management methodologies, their benefits and barriers to successful implementation. Producers in several countries are facing increasing market pressures to use returnable containers. Castillo and Cochran (1996) present a formulation of an optimal configuration for the reusable bottle production and distribution activities of a large soft drink manufacturer located in Mexico City. Goudenege et al. (2013) proposes a generic model for reverse logistics management focused on reusable containers. The authors adapt the model to the specific requirements of companies. Atamer et al. (2013) present a study that focus on pricing and production decisions in utilizing reusable containers with stochastic customer demand. Accorsi et al. (2014) propose an original conceptual frame work for the integrated design of a food packaging and distribution network. 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). In the same sense, evaluating the environmental impact is one of the aims of the green supply chain. The signed Kyoto protocol will engage many countries and companies as a consequence to a carbon emission quota. Several methodologies are used to calculate carbon emissions (RetelHelmrich et al., 2015). 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 and adapted to several cases. In this paper, we discuss an integrated planning for the distribution, exploitation and collection of the reusable containers under carbon emission constraints.

2. Problem definition and mathematical model

2.1 Problem definition

In this study, 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 with the storage option within warehouses and customers. The model holds a carbon emissions constraint for the distribution and collection activities.

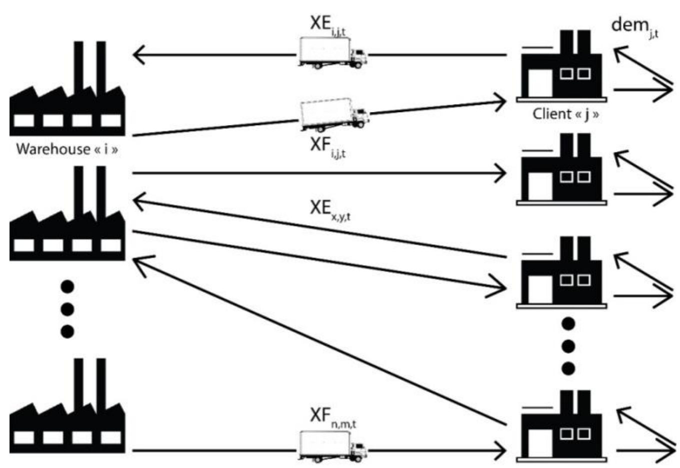

Figure 1 Generic Model scheme

We supposed in this configuration (Figure 1) that the client demands are deterministic over a finite planning horizon; also we assume that each warehouse or store has its own holding cost for full and empty containers. In other hand the transportation cost is constituted from a fixed cost and variable cost per unit.

The study aims to propose an exploitation planning of reusable containers between warehouses and clients. The objective is to determine on each period, the deliveries of each warehouse for each client, and the collected quantities from each clients and their destinations. In this configuration, we assume also that each warehouse serve many clients on each period, the returnable containers quantities split is allowed for each client. Transportation costs are fixed per unit and per client. We suppose also 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 collect operations and for recapturing the empty containers. The delay of the consumption and the reloaded is fixed and determined respectively by the stores and the warehouses. We note also that warehouses and stores possess a limited storage capacity.

2.2 Model description

The model adapted is shown in the following:

N : Number of warehouses.
M : Number of clients.
T : Number of periods.
$dem_{j,t}$: Demand of client j at theperiod t.
vehC : Vehicle capacity.
$s\_c\_w_i$: Warehouse stock capacity.
$s\_c\_c_j$: Client stock capacity.
$d_{j,i}$: Distance between a warehousei and a client j.
co2 : Carbon emissions per unit per kilometer.
Emax : maximum average emission per unit.
$IOFC_j$: Full containers initial inventory in the client i.
$IOEC_j$: Empty containers initial inventory in the client i.
H : an arbitrarily large number
$trans_{i,j}$: Transportation cost of a container from/to client/ warehouse per distance unit.
$h\_f\_w_i$: Holding cost of full reusable container of warehouse i.
$h\_e\_w_i$: Holding cost of empty reusable containers of warehouse i.
$h\_f\_C_j$: Holding cost of full reusable containers of clients i.
$h\_e\_C_j$: Holding cost of empty reusable containers of clients i.
$pur_{i,j}$: Ordering cost of a client i from a warehouse j.
$recov_{i,j}$: Recover cost from a client i to a warehouse j.
$XF_{i,j,t}$: Full containers delivered quantity from a warehouse i to a client j in the period t.
$XE_{i,j,t}$: Empty containers delivered quantity from a warehouse i to a client j in the period t.
$IFW_{i,t}$: Full containers inventory in a warehouse i in the period t.
$IEW_{i,t}$: Empty containers inventory in a warehouse i in the period t.
$IFC_{j,t}$: Full containers inventory in a client i in the period t.
$IEC_{j,t}$: Empty containers inventory in a client i in the period t.
$IOFW_i$: Full containers initial inventory in a warehouse i.
$IOEW_i$: Empty containers initial inventory in a warehouse i.
$Q_{i,t}$: Number of full containers reproduced by a warehouse i in period t.
$Z_{i,j,t}$: Binary variable indicating if a client purchases full containers from a warehouse on period t
$Y_{i,j,t}$: Binary variable indicating if a warehouse j recovers empty containers from a client i in a period t
TransC : Delivery and collect transport cost between the warehouses and clients over the planning horizon

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

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.

$$\mathrm{HoldC} = \sum_{i=1}^{N}\sum_{t=1}^{T}\left(\left(\mathrm{IFW}_{i,t} * h_{f_{w\,i}}\right) + \left(\mathrm{IEW}_{i,t} * h_{e_{w\,i}}\right)\right) + \sum_{j=1}^{M}\sum_{t=1}^{T}\left(\left(\mathrm{IFC}_{j,t} * h_{f_{C\,j}}\right) + \left(\mathrm{IEC}_{j,t} * h_{e_{C\,j}}\right)\right) + \sum_{i=1}^{N}\left(\left(\mathrm{IOEW}_{i} * h_{e_{w\,i}}\right) + \left(\mathrm{IOFW}_{i} * h_{f_{w\,i}}\right)\right)$$

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

$$\mathrm{ProdC} = \sum_{i=1}^{N}\sum_{t=1}^{T}\left(Q_{i,t} * \mathrm{Prod\_cost}_{i}\right)$$

The integrated planning model is shown in the following:

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

Subject to:

$$\mathrm{IFW}_{i,1} = \mathrm{IOFW}_{i} + Q_{i,1-\mathrm{Delay}} - \sum_{j=1}^{M}\left(\mathrm{XF}_{i,j,1}\right) \quad \forall i, (\forall \mathrm{Delay} < 1\, if\ not\ Q = 0) \tag{2}$$

$$\mathrm{IFW}_{i,t} = \mathrm{IFW}_{i,t-1} + Q_{i,t-\mathrm{Delay}} - \sum_{j=1}^{M}\left(\mathrm{XF}_{i,j,t}\right) \quad \forall i, (\forall t > Delay, \text{if not } Q = 0) \tag{3}$$

$$\mathrm{IEW}_{i,1} = \mathrm{IOEW}_{i} - Q_{i,1} + \sum_{j=1}^{M}\left(\mathrm{XE}_{i,j,1}\right) \quad \forall i \tag{4}$$

$$\mathrm{IEW}_{i,t} = \mathrm{IEW}_{i,t-1} - Q_{i,t} + \sum_{j=1}^{M}\left(\mathrm{XE}_{i,j,t}\right) \quad \forall i \tag{5}$$

$$\mathrm{IFC}_{j,1} = \mathrm{IOFC}_{j} - \mathrm{dem}_{j,1} + \sum_{i=1}^{N}\left(\mathrm{XF}_{i,j,1-d_{j,i}}\right) \quad \forall j, (\forall d_{j,i} < 1\, ifnot\ \ \mathrm{XF} = 0) \tag{6}$$

$$\mathrm{IFC}_{j,t} = \mathrm{IFC}_{j,t-1} + \sum_{i=1}^{N}\left(\mathrm{XF}_{i,j,t-d_{j,i}}\right) - \mathrm{dem}_{j,t} \quad \forall j, \forall t > 1, (\forall d_{j,i} < t \text{ else } \mathrm{XF} = 0) \tag{7}$$

$$\mathrm{IEC}_{j,1} = \mathrm{IOEC}_{j} - \sum_{i=1}^{N}\left(\mathrm{XE}_{i,j,1+d_{j,i}}\right) \quad \forall j, (\forall d_{j,i} < T \text{else } \mathrm{XE} = 0) \tag{8}$$

$$\mathrm{IEC}_{j,t} = \mathrm{IEC}_{j,t-1} - \sum_{i=1}^{N}\left(\mathrm{XE}_{i,j,t+d_{j,i}}\right) + \mathrm{dem}_{j,t-1} \quad \forall j,\ \forall t > 1, \left(\forall d_{j,i} \leq T - t \text{ else } \mathrm{XE} = 0\right) \tag{9}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{t=1}^{T}\left(\left(\mathrm{XF}_{ijt} + \mathrm{XE}_{i,j,t}\right) * \mathrm{CO2} * \mathrm{dist}_{i,j}\right) \leq \mathrm{Emax} * \sum_{j=1}^{M}\sum_{t=1}^{T}\mathrm{dem}_{j,t} \tag{10}$$

$$\mathrm{XF}_{ijt} \leq H * Z_{i,j,t} \quad \forall i, \forall j,\ \forall t \tag{11}$$

$$\mathrm{XE}_{ijt} \leq H * Y_{i,j,t} \quad \forall i, \forall j, \forall t \tag{12}$$

$$\mathrm{IFW}_{it} + \mathrm{IEW}_{it} \leq \mathrm{s\_c\_w}_{i} \quad \forall i,\ \forall t \tag{13}$$

$$\mathrm{IFC}_{jt} + \mathrm{IEC}_{jt} \leq \mathrm{s\_c\_c}_{j} \quad \forall j,\ \forall t \tag{14}$$

$$\mathrm{XE}_{ijt}, \mathrm{XF}_{ijt}, \mathrm{IFW}_{it}, \mathrm{IEW}_{it}, \mathrm{IFC}_{jt}, \mathrm{IEC}_{jt}, \mathrm{IOFW}_{i}, \mathrm{IOEW}_{i}, Q_{i,t} \geq 0 \tag{15}$$

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. We note that all variables are positive.

3. Solving approaches

3.1 Hybrid algorithm 1 (HA1)

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 within exact resolution based on mixed integer programming model.

The proposed genetic algorithm (GA) determines the binary decisions variable values of full and empty reusable containers deliveries or collects while the mixed integer programming model is solved to determine the integer variables (full and empty reusable containers deliveries, collects quantities decisions…). Some interesting applications of GA are presented by Supithak et al. (2010), Rezaei and Davoodi (2011), and Zouadi et al. (2015). Thus, we use this type of algorithm with a standard overall scheme presented in the Figure 2.

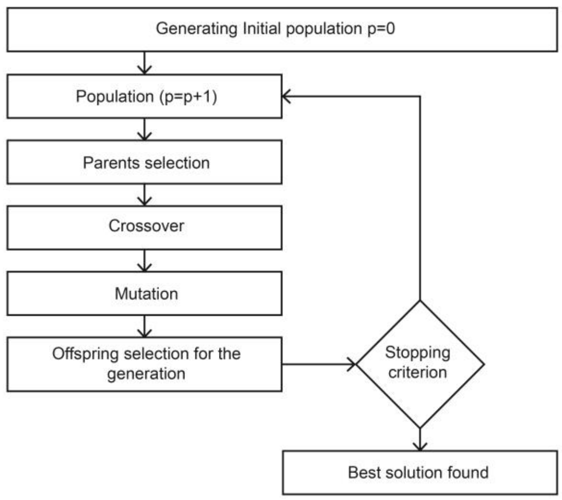

Figure 2 Genetic algorithm scheme (Zouadi et al., 2015)

3.1.1 Solution presentation

The encoding phase is considered crucial in the genetic algorithm implementation. In this encoding each chromosome is represented using a binary string. The proposed binary encoding in Fig 3 presents 3-dimensional vectors which are: 1) the period of the planning horizon T; 2) warehouses number N; 3) and a double of the clients number 2×M to present the distribution and the collection of the containers between the customers and the warehouse, in fact each warehouse has two decision for each customer a decision for the distribution (Zijt) and one for the collection (Yijt) that is why we have 2XM. In other words the vector consists of two parts, 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.

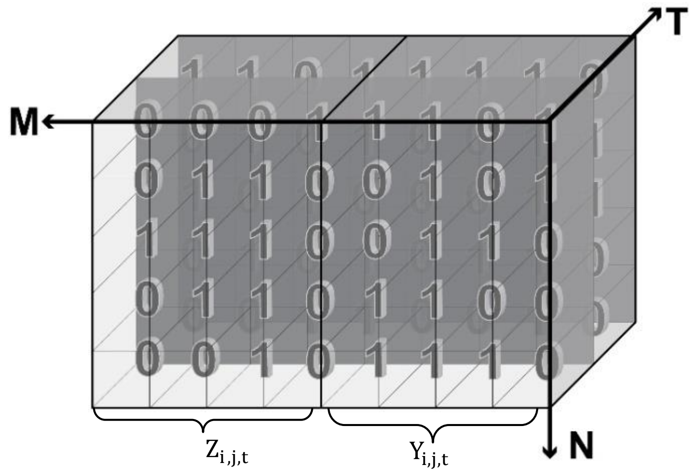

Figure 3 Solution presentation

3.1.2 Crossover

Following the nature of the solutions encoding the solutions, we need a crossover operator able to cross two 3-dimensional vectors. The proposed crossover is presented in the Fig 4.

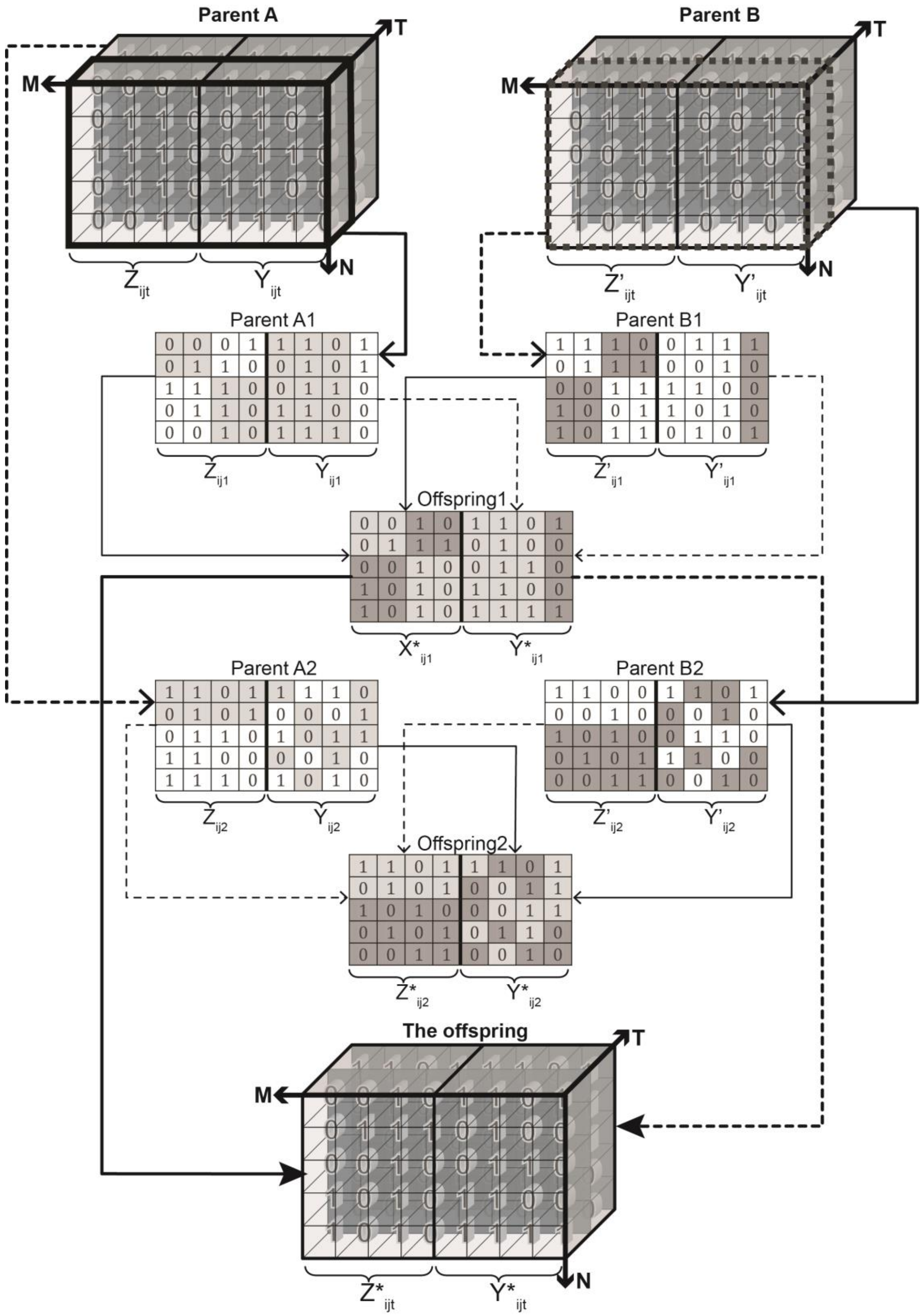

Figure 4 Crossover operator

The proposed crossover operator consists of splitting the 3-dimensional vectors into T matrix (2-dimensional vectors), in such a way that each matrix presents the full reusable containers deliveries and the empty reusable containers collection binary decisions. The crossover operator consists on crossing randomly two matrixes issued from two parents using one of the crossing operators proposed by Toledo et al. (2013).

In the example presented in the Fig 4, each of the two 3-dimensional vectors (Parent A, Parent B) are divided into two matrixes {(PA1, PA2) ;(PB1, PB2)} representing the deliveries and collection launching decisions of the two period of the planning horizon (T). The crossover operator consists on crossing the first half of the matrix PA1 (presenting the deliveries 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 3-dimensional vector presenting the resulted offspring.

3.1.3 Mutation

In this paper, we propose the implementation of a total of four mutation operators proposed by Teledo et al. (2013). The first operator consists on changing a value randomly chosen. The second operator two values are randomly chosen and inverted from the same column. In the third operator, two values are randomly chosen and inverted from the same row. The last operator consists on applying the first mutation operator twice. One of these four mutations is randomly selected.

3.1.4 Exact resolution to determine collected and delivered quantities

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

4.2 Hybrid algorithm 2 (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 a same exact resolution of the hybrid algorithm 1.

The proposed memetic algorithm keeps the same genetic algorithm 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. We call this approach Variable Neighborhood Search (VNS) (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 searches. The metaheuristic logic is to explore distant neighborhoods of the current solution (offspring) until a stopping criterion, and moves 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 pass to the second local search exploitation with the best found solution found until a 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 start from the beginning by exploring the first the local search using the best solution found. Algorithm 1 summarizes the structure of this improvement strategy.

Algorithm 1: Local search

```
// 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 on permuting the matrixes presenting the full and empty reusable containers deliveries or collets decisions on each period T_i. The move A in the Fig8 shows an example of the used operator. In the second local search consists on 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 Fig 8 shows an example of the used operator. While the third local search consists on 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 the Fig8 shows an example of the used local search.

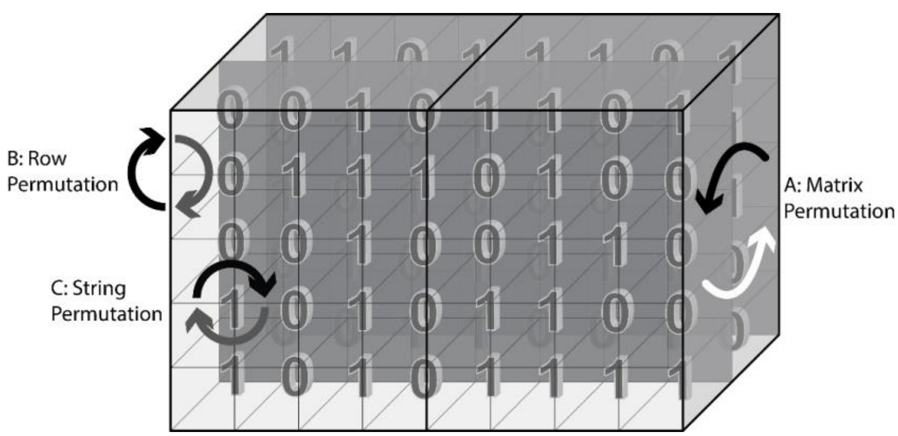

Figure 5 The used local search procedure

4. 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.

The hybrid methods employ a set of parameters (listed in Table 1) that requires fine tuning. Based on a large number of runs, the following set of parameters was finally selected (β ; μ ; α ; Γ ;£) = (500 ; 50 ; 0,7; 0,3 ; 50).

Table 1 Parameters of the hybrid method

β : The number of crossing.
μ: Number of individuals in the initial population.
α : The probability of crossover
£ : The maximum number of non-improving iterations in the genetic algorithm
Γ : The probability of mutation
Ɛ : 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. The obtained results are given in Tables 2 to 4. The notations used are: AS (average solution), AT (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) and MaxG (The maximum gap found).

For all the instances, the proposed approach is compared with the optimal value returned by CPLEX, but when CPLEX can't prove optimality, we compare with the lower bound.

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

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%

Compared to CPLEX solutions, the HA2 (1,83 %) gives near optimal solutions while the HA1 (2,56 %) is less efficient. The computational time of the HA2 is greater than the HA1 due to the used local search.

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 small number of client and warehouses, 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.

4.2. Grouped according to the number of warehouses and clients

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 configuration, the hybrid algorithm 2 gives best computational results in comparison with hybrid algorithm 1.

4.3. Grouped according to the type of demand

Table 4 the obtained results according to the type of demand

Type of Demands	CPLEX		HA1			HA2		
	A.S	**A.T**	**A.S**	**G.H1.C**	**A.T**	**A.S**	**G.H2.C**	**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
Negative trend	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

This analysis shows that the HA1 and HA2 perform better when the demand is constant. However when the demand is 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.

5. Conclusion

In this contribution, a distribution and collection network planning problem is presented. The objective is to determine respectively the delivered and collected of full and empty reusable containers quantities. A generic model is proposed and solved with MIP and two hybrid algorithms. The proposed hybrid algorithms use an exact resolution based on the developed MIP to find the optimal delivered and collected quantities following the binary decision of the hybrid algorithms solutions. The numerical results of the developed approach were very close to those obtained with the method of MIP, and time related to the MIP method was effectively reduced by these new hybrid approaches.

This contribution presents a base to develop more generic models by considering several constraints such as the number of products, multi-level structures, etc.

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