Multi-Objective Capacitated Disassembly Scheduling with Lost Sales

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Abstract: Disassembly scheduling is one of the important problems in reverse logistic decisions. This paper focuses on this problem with capacity restrictions on disassembly resources, lost sales, multiple products and without part commonality. A model with two objectives is developed and optimized by a multi-objective approach. The first objective is a sum of several costs to minimize: setup cost, inventory cost, and over capacity penalty cost. The second objective is a measure of the service level. Considering the complexity of this model, a genetic algorithm is developed (NSGA-II) to obtain a set of Pareto-optimal solutions, the results are compared with those calculated by a mixed integer programming model. Results of computational experiments on randomly generated test instances indicates that the genetic algorithm gives good quality solutions up to all problem sizes in a reasonable amount of computation time whereas linear programming solvers do not give solution in reasonable time.

1 INTRODUCTION

Nowadays, due to environmental and economic reasons, more and more companies acknowledge that reverse logistic is a part of the supply chain as important as production or distribution. Disassembly process consists in separating recovered products to generate components which can be reused or be conditioned safely for the environnement. Disassembly scheduling defines how many products to disassemble given the demands for components in each period of a finite horizon planning. In this paper we consider two-level product structure disassembly scheduling problem with setup times, lost sales, multi-products types and limited capacity. Part commonality between products is not considered in this paper.

The goal of this study is to develop a optimization tool for this problem with two objective: total cost and service level. To our knowledge, the disassembly scheduling problem with lost sales has not been studying in literature. Lost sales allow selecting demand to be satisfied and minimizing inventory surplus that is inherent to disassembly scheduling problem. In the following section, we start by a literature review of disassembling problems. In section 3, a mathematical formulation of the problem is introduced. In section 4, a meta-heuristic based on genetic algorithm NSGA-II is developped for large instance when CPLEX solver do not give solutions in reasonable time. Finally, section 5 explores the performances of the meta-heuristic and compares results with solutions given by solving the mixed integer programming model. Concluding remarks and future research goals will be given in section 6.

2 LITERATURE REVIEW

In this section we present various problems in disassembly system studied in literature. Gupta and Taleb (1994) defined and characterized the basic disassembly scheduling problem for a single product type, without explicit objective function and suggested an algorithm that is a reversed Material Requirement Planning (MRP). This problem was further extended to include commonality parts by Guta and Taleb (1997) for multiple product case. Disassembly scheduling can be classified into deterministic and non-deterministic problems which incorporate random factors in the models, Inderfurth and Langella (2006) developed two heuristics which take into consideration stochastic disassembly yields, with multiple product types, parts commonality, two-level product structure. Here we interested on deterministic problems. When set up costs is considered in the objective function, lost sizing decision have to be made. We note that methodologies for lot sizing in production and

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assembly scheduling cannot be applied to disassembly due to their divergence characteristic, see Kim et al. (2007) for more details of the divergence characteristic. Resource capacity restriction also complicate the problem. Lee et al. (2002) considered the capacitated problem, and proposed an integer programming model for the case of single product type. Lee and Xirouchakis (2004) and Kim et al. (2003) proposed integer programming models to determine the disassembly scheduling of used products in order to satisfy the demand of their parts over a planning horizon, considering various situations involving costs and capacity. Kim et al. (2006) developed a two-phase heuristic to minimize of set up, disassembly operation and inventory-holding costs. Lee et al. (2006) developed an integer programming model considering capacity restriction, a two stage solution approach is proposed. Barba et al (2008) present an algorithm for reverse MRP with various lot sizing heuristics. Kim et al. (2010) consider the problem that minimizes the total cost that is sum of setup cost and inventory holding cost, they suggested a branch and bound algorithm that incorporates Lagrangian relaxation technique to obtain good lower and upper bounds. In this study we test the model with their instances. Kim and Lee (2011) proposed a heuristic for multi-period disassembly leveling and scheduling. To out knowledge, there is no study on disassembly lot sizing with lost sales.

There are several references on production lot sizing with lost sales. Xiao Liu and Freng Chu (2004) address the capacitated lot sizing problem with lost sales, they developed a dynamic programming algorithm to solve the problem. Absi et al (2013) deals with the same problem, they proposed a non-myopic heuristic based on a probing strategy and refining procedure. Their approaches can not be applied in disassembly. Indeed, there is one supply product source for several component demands and hence when a component demand is satisfied and may be cause stockout or inventory surplus for others components.

Various objectives can be considered in lot sizing problems. Jafar and Mansoor (2011) addressed the lot-sizing problem with supplier selection, they developed two multi-objective mixed integer non-linear models for multi-period lot-sizing problems with multiple products and multiple suppliers, three objectives are considered cost, quality and service level. Ayyuce et al. (2013) deals with multi-objective optimization of a stochastic disassembly line balancing problem, they proposed a genetic algorithm which generates Pareto-optimal solutions considering two different fitness evaluation approaches.

To the best of the authors' knowledge, no one has addressed the optimization of capacitated disassembly scheduling with lost sales and multi-objective approach. In this paper we compare an exact method for mono-objective and a meta-heuristic for multi-objective.

3 MODEL FORMULATION

In this section we present the mixed integer programming model of the problem. Before formulating the mathematical model, the disassembly process is described first.

A parent (root) item can be disassembled to produce a specific number of child (leaf) items. Given a set of root items, the demand of each leaf items of all roots is given over a time horizon. Each period has a normal production capacity, exceeding this capacity will result a penalty cost. If the demand of a leaf item is not met in a period it will be considered as lost sales. The problem is to determine the quantity and timing of disassembling all root items to satisfying demand of their leaf items over the planning horizon subject to capacity restrictions in each period, respecting a particular service level.

In this paper we consider two objectives: total cost and service level. The first objective is to minimize the sum of purchase, inventory holding, and disassembly costs. The second one is to maximize the service level. The cost of not satisfied demand is difficult to assess and we cannot combine cost and quantity in the same objective function, thus we consider in this model one objective (Total cost) and we include the second (Service level) as a constraint.

A. Model parameters and decision variables

The notations used are summarized below.

Indices:

r Index for root items, $r=1,2,\dots, R$

i Index for leaf items, $i=1,2,\dots,N$

t Index for periods, $t=1,2,\dots,T$

Parameters

s_r Setup cost of parent item r.

C_t Capacity available, in time, in period t.

φ_i Parent of leaf item i.

g_r Disassembly operation time of root item r.

h_i Inventory holding cost of item i.

p_t Penalty cost disassembly time in period t.

d_{it} Demand of item i in period t.

a_{ri} Number of unit of items i obtained by disassembly of one unit of its parent item r.
I_{i0} Initial inventory of item i.
M Large Number.
$LMax$ Maximal lost sales level *(%)*.

Decision variables
Y_{rt} = *1* if there is a setup for root item r in period t, 0 otherwise.
X_{rt} Disassembly quantity of root item r through period t.
OT_t Disassembly over-time in period t.
I_{it} Inventory level of leaf item i at the end of period t.
L_{it} Lost sales for each leaf item I in period t.

B. Model assumptions

Assumptions made in this model are summarized as follows:
(a) Demands for leaf items are given and deterministic;
(b) Lost sales is allowed, hence demand can be not satisfied;
(c) The disassembly process is perfect, all parts are in perfect quality, no defective are considered;
(d) Disassembly operation times are given and deterministic;

C. Mathematical formulation

In this study we solve the problem using two approaches.

The first case is a mixed integer program (MIP) where the first objective is the objective function and the second objective is a constraint. The constraint level is varying it to obtain different solutions for the same instance.

We note that in this model we consider the total lost sales level which can be calculated as:

$$\mathrm{TotalLostSalesLevel} = \sum_{t}^{T}\sum_{i}^{N} \mathrm{L_{it}} / \sum_{t}^{T}\sum_{i}^{N} \mathrm{d_{it}}$$

and then total service level can be deducted :

$$TotalService\ level = 1 - TotalLostSalesLevel$$

With above parameters and decision variables, the MIP is given bellow.

$$Minimize\ z = \sum_t^T \sum_r^R Y_{rt} * s[r] + \sum_t^T \sum_i^N I_{it} * h_i + \sum_t^T OT_t * p_t \quad (1)$$

Subject to

$$I_{it} = I_{i,t-1} + a_{\varphi_i,i} * X_{t\varphi_i} + L_{it} - d_{it} \text{ for all t=2,...T and i=1,...N} \quad (2)$$

$$X_{rt} \le M * Y_{rt} \quad \text{for all t=1,...T and r=1,...R} \quad (3)$$

$$\left(\sum_r^R \mathrm{g_r} * X_{rt}\right) - \mathrm{C_t} <= OT_t \quad \text{for all t=1,...T} \quad (4)$$

$$L_{it} \le d_{it} \quad \text{for all t=1,...T and i=1,...N} \quad (5)$$

$$\sum_\mathrm{t}^\mathrm{T} \sum_\mathrm{i}^\mathrm{N} \mathrm{L_{it}} / \sum_\mathrm{t}^\mathrm{T} \sum_\mathrm{i}^\mathrm{N} \mathrm{d_{it}} \le LMax \quad (6)$$

$$X_{rt}, I_{it} \ge 0 \quad (7)$$

Objective function (1) is the Total cost which is the sum of setup cost, expected inventory holding and penalty costs, production costs are not considered in this study.

The constraint are the following :

- (2) define the inventory flow conservation of leaf items at the end of each period ($I_{i,0}$) is an input data.
- (4) Ensure that a setup is performed in a period when disassembly operation is performed.
- (5) Enforces the capacity feasibility.
- (7) State the upper bound available of lost sales level; we note that maximizing the total service level equivalent minimizing the total lost sales level.
- (8) Defines the domain of variables.

The second case we solve the problem by using the NSGA-II algorithm that considers multiple objectives:

$$Minimize\ z_1 = \sum_t^T \sum_r^R Y_{rt} * s[r] + \sum_t^T \sum_i^N I_{it} * h_i + \sum_t^T OT_t * p_t \quad Minimize\ z_2 = \sum_t^T \sum_i^N L_{it}$$

Subject to : Constraints (1) to (6) and (8).

4 MULTI-OBJECTIVE GENETIC ALGORITHM

Generally, based on a population search Multi-Objective Evolutionary Algorithm (MOEA) can present a set of non-dominated or Pareto optimal solutions. In this study we consider two objectives, total cost and service level. To solve the model in this paper we use Non-dominated Sorting Genetic Algorithm II (NSGA-II), one of the MOEAs frequently used in many optimization problems as the best technique to generate Pareto frontiers, which has been proposed by Deb et al. (2000). Moreover, the NSGA-II has been consistently uses in several research articles which deals with supply chain problems see Godichaud et al., D. Sanchez et al. and Li et al.

D. NSGA-II Principle

This algorithm uses a fixed-sized population. We start by initializing the population then the population is sorted based on non-domination criteria into several fronts. The first front is a completely non-dominated set in the current population and the second front being dominated by the individuals in the first front only and so on. Each individual in each front is assigned fitness value. We said that solution p is dominated by solution q if only q is better than p with regard to all objectives, or q is better than p with regard to other objectives. This process is continues until all fronts are identified. In addition to fitness value we calculate the crowding distance which is a measure of how close an individual is to its neighbors, we used it in order to maintain diversity in the population.

E. NSGA-II algorithm

Create initial population P_0*, of size n;*
Create child population Q_0 *using binary tournament selection, recombination and mutation;*
While *(stopping criterion)*
    We create a new population R_t *which combine* P_t *(parent) and* Q_t*(child)*
    Sort R_t *by non-domination*
    Assign a fitness equal to its non-domination level for each solution, identify levels $F_i, i = 1,2,\ldots$
    Computed the crowding distance of each solution
    Set new population P_{t+1}
    Set i=1
    While $|P_{t+1}| + |F_i| \leq n$ ***do***
        Add F_i *to* P_{t+1}
        Set i=i+1
    end while
    Set $Diff = n - |P_{t+1}|$
    If $diff \neq 0$
        Sort solutions by descending crowding distance
        for $j = 1$ *to* $diff$ ***do***
            Add $Solution_i$ *of* F_i *to* P_{t+1}
        end for
    end if
end while

F. Encoding

In this study, the decisions variables are $Y_{rt}, X_{rt}, OT_t, I_{it}$ and L_{it}, among which Y_{rt} is a binary variable (0-1), and the others are positive variables of integer numbers. Generally, in literature, setup variables are used to encode solutions and integer variables are deduced based of the properties of the model. These properties are not sufficient for the problem with with lost sales and integer varaibles can not be computed from Y_{rt}, and thus, we encode X_{rt} as chromosomes.

G. Initial population

In this study, population of candidate solution P_0 is randomly generated according to an uniform distribution. We use a random integer generator for X_{rt} with respect to the bounding conditions.

H. Selection and Evaluation

Capacity constrains and objective functions are used to evaluate the objectives of each chromosome, we note that there are two objective function values for each one. We use the constrained tournament method because of its ability to satisfy constraints and at the same time perform selection based on fitness.

This operator involves running several tournaments among a few individuals chosen at random from the population and the one with best fitness (winner) is selected for crossover.

I. Crossover and Mutation

One crossover point is used. Genes from beginning of chromosome to the crossover point is copied from one parent, and the rest is copied from the second parent, at the end we obtained two children. After this we mutate on chromosome by changing one more variable in some way by random. Crossover and mutation are performed with a given probability. Values are mentioned in the next section.

5 COMPUTATION EXPERIMENTS

The NSGA-II algorithm tested in this paper was coded in Java and run on a personal computer with a five processors operating at 2.60 GHz clock speed.

J. Test instances

For the test, instances are generated as in (H.-J. Kim and P. Xirouchakis, 2010). U(a,b) is the discrete uniform distribution with a range of [a,b].

- We generated 10 instances for each number of root items (10,20,30), three number of children generated from a discrete uniform distribution with a rang U(1,10), U(10,100), and U(100,1000) for low, medium, and large respectively ,and three number of periods (10,20,30);
- s_r : Setup cost for each root was generated from U(1000,5000);
- a_i : For each root the number of child were generated from U(1,5);
- d_{it} :Demand was generated from U(50,200);
- h_i : Inventory holding costs were generated from U(1,10);
- p_t : Penalty costs for overtime were generated from U(5,15);

- g_r : Disassembly time was generated from U(1,3);
- I_0 : Initial inventory was generated from (20,100).
- C_t : Available aggregate capacity in each period is set to 540,480 and 400 with probabilities, 0.3,0.5,0.2

K. *Parameters setting*

Different tests with different parameters were made to choose the efficient parameters for the algorithm. The following control parameters for genetic algorithm are the ones we used in our case study:

- Maximum generation $NbrIttr = 1500$.
- Population size $NbPop = 100$.
- Mutation probability $\text{Coef}_m = 0{,}2$.
- Crossover probability $\text{Coef}_c = 0{,}9$.

L. *Computational Results*

In this section, we apply the GA discussed earlier to solve the model proposed and to show the effectiveness of our GA meta-heuristic firstly we compare the NSGA-II performances with those of Cplex 12.5 software, in terms of computation time and solution quality to solve the small-sized problem and after we present the strength of the NSGA-II to solve all sizes instances.

The figure 1 present Pareto front obtained with NSGA-II for the first instance (10 periods, 10 roots, low number of children), the Pareto contains 100 solutions. We present also 11 exact algorithm solutions solved with mono-objective for 11 different percentages of lost sales level. We note that each solution obtained is a point of the optimal Pareto front.

To show the quality of our results we will compare the two fronts: the first obtained by Cplex (optimal pareto solution) and the second obtained by NSGA-II.

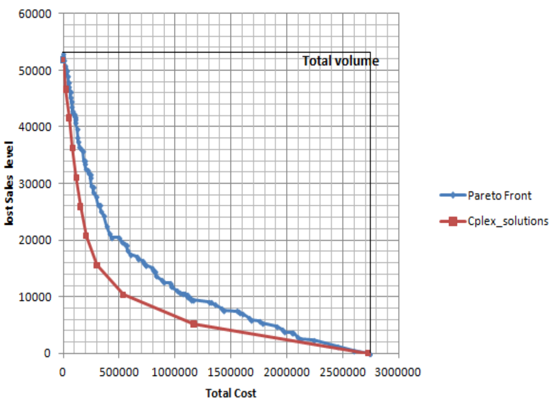

Figure 1: Example of Pareto front obtained with GA (100 solutions) and some exact algortihm solutons (11 solutions).

To compare our curves we use the Hyper Volume indicator. Readers wishing more detailed description of the algorithm can be referred to Deb.

Table 1 present the hyper volume values:

Table 1: Hyper volume values for Cplex and NSGA-II.

	Hyper Volume
Cplex	0.829
NSGA-II	0.826

$$Gap = \frac{HyperVolume_{Cplex} - HyperVolume_{NSGA-II}}{HyperVolume_{Cplex}}$$

$$Gap = 0.36\%$$

The gap indicates that the front solutions of NSGA-II is 99,64% close to the optimal front obtained by Cplex. Moreover the decision maker has several choices in terms of solutions (100 by NSGA-II against 11 by Cplex).

Here, the heuristic solutions are compared with Cplex solutions to assess the benefits of increasing the CPU time limit. Concerning the exact method (case 1), we solve the problem on mono-objective. This table summarizes the computation time of one instance with 10 periods, 10 roots and low number of children. As mentioned in mathematical model there is a constraint of lost sales level: *LMax*, in this experiment we change the *LMax* value and we evaluate the objective function. In this test we used Cplex software to obtain solutions.

For this instance for each lost sales level value we allowed Cplex to run for maximum 3000sec to avoid excessive computation times and we fixed the absolute tolerance on the gap between the best integer objective and the objective of the best node remaining at 0.01.

Table 2: CPU time for different lost Sales level.

Lost Sales level (%)	Objective CPU(sec)
0	1.71
10	5.89
20	49.30
30	1138.43
40	1804.52
50	466.61
60	98.88
70	59.77
80	21.39
90	6.19
100	0
Total time	3652,69

We reported CPU time in second for the instance example in table 2, the total time to compute solutions for each percentage of lost sales level (11 solutions) is:

$$Total_{Exact} = \sum_{Percentage} TObjective$$

$$Total_{Exact} = 3652{,}69sec$$

On the other side the total time to obtain the Pareto front which provides 100 solutions with the NSGA-II algorithm (considering mathematical model case 2) for the same instance is: $\mathrm{Total}_{\mathrm{NSGA-II}} = 4\mathrm{sec}$ (see the table 2 in the next section). We kept a large number of solution to analyse the behaviour of the algorithm. In practice, decision makers have to choose only one solution based on its preferences. Multi criteria decision making can be used to this end with the NSGA-II solutions as an input.

$$\mathrm{Total}_{\mathrm{NSGA-II}} \ll \mathrm{Total}_{\mathrm{Exact}}$$
(4sec<<3652,69sec)

Table 3: CPU time in seconds of Kim problem instances.

Number of root items	*Number of children*	*Number of periods*	*CPU(sec)*
10	Low	10	4
		20	7
		30	10
	Medium	10	19
		20	37
		30	66
	Large	10	299
		20	414
		30	741
20	Low	10	7
		20	11
		30	15
	Medium	10	47
		20	86
		30	115
	Large	10	618
		20	776
		30	1271
30	Low	10	11
		20	20
		30	26
	Medium	10	80
		20	121
		30	171
	Large	10	973
		20	2278
		30	3317

Genetic algorithm is much faster than Cplex, without taking into consideration the number of solution found. Genetic algorithm gives solutions that are very close to optimal ones within very short computational time. Hence the efficiency of the genetic algorithm provides the decision maker a huge choice in terms of solution quality and in short time. Before presenting results we note that from 30 periods with medium number of children Cplex could not give solutions. In this section the table 3 summarize the computation time of the GA for all instances.

We observe that the computation time increases quickly as the number of the periods, on the other side it does not increase apparently as the numbers of root items increase.

6 CONCLUSIONS

In this paper, we addressed the multi-products capacitated disassembly scheduling with setup times and lost sales. To our knowledge, it the first time that disassembly scheduling problem with lost sales is investigated. We formulated a multi-objective optimization model, and propose a genetic algorithm NSGA-II for solving the problem. The objectives considered are (1) Minimizing the total cost and (2) Maximizing the service level. The performance of NSGA-II is investigated by comparing its results with those obtained by exact method on mono-objective sample (270 test problems) randomly generated (Kim et al.-2009- instances). This comparison shows that the NSGA-II give solution with good quality in reasonable time while Cplex software does not. This research can be extended in several ways. New mathematical formulation approaches can be developed considering multi level product structure and parts commonality constraints. Uncertainties such as stochastic demands or stochastic disassembly times have to be considered. The method can also be improved by using other dominance criterion to reduce the number of solution and be developing hybridization. Properties of the model should also be investigated to improve encoding of solutions.

REFERENCES

S. M. Gupta and K. N. Taleb, “Scheduling disassembly,” International Journal of Production Research, vol. 32, no. 8, pp. 1857–1866, 1994.

H.-J. Kim, D.-H. Lee, and P. Xirouchakis, “Disassembly scheduling: literature review and future research directions,” International Journal of Production Research, vol. 45, no. 18–19, pp. 4465–4484, 2007.

K. N. Taleb and S. M. Gupta, “Disassembly of multiple product structures,” Computers & Industrial Engineering, vol. 32, no. 4, pp. 949–961, Sep. 1997.

K. Inderfurth and I. M. Langella, “Heuristics for solving disassemble-to-order problems with stochastic yields,” OR Spectrum, vol. 28, no. 1, pp. 73–99, Jan. 2006.

D.-H. Lee, P. Xirouchakis, and R. Zust, “Disassembly Scheduling with Capacity Constraints,” CIRP Annals - Manufacturing Technology, vol. 51, no. 1, pp. 387–390, 2002.

D.-H. Lee and P. Xirouchakis, “A two-stage heuristic for disassembly scheduling with assembly product structure,” J Oper Res Soc, vol. 55, no. 3, pp. 287–297, 2004.

H.-J. Kim, D.-H. Lee, P. Xirouchakis, and R. Züst, “Disassembly Scheduling with Multiple Product Types,” CIRP Annals - Manufacturing Technology, vol. 52, no. 1, pp. 403–406, 2003.

H.-J. Kim, D.-H. Lee, and P. Xirouchakis, “Two-phase heuristic for disassembly scheduling with multiple product types and parts commonality,” International Journal of Production Research, vol. 44, no. 1, pp. 195–212, 2006.

H.-J. Kim, D.-H. Lee, and P. Xirouchakis, “Two-phase heuristic for disassembly scheduling with multiple product types and parts commonality,” International Journal of Production Research, vol. 44, no. 1, pp. 195–212, 2006.

Y. Barba-Gutiérrez, B. Adenso-Díaz, and S. M. Gupta, “Lot sizing in reverse MRP for scheduling disassembly,” International Journal of Production Economics, vol. 111, no. 2, pp. 741–751, Feb. 2008.

H.-J. Kim and P. Xirouchakis, “Capacitated disassembly scheduling with random demand,” International Journal of Production Research, vol. 48, no. 23, pp. 7177–7194, 2010.

B. Adenso-Diaz, S. Carbajal, and S. Lozano, “Disassembly scheduling of complex products using parallel heuristic approaches,” in 2010 IEEE/ACS International Conference on Computer Systems and Applications (AICCSA), 2010, pp. 1–4.

X. Liu, C. Wang, F. Chu, and C. Chu, “A forward algorithm for capacitated lot sizing problem with lost sales,” in Fifth World Congress on Intelligent Control and Automation, 2004. WCICA 2004, 2004, vol. 4, pp. 3192–3196 Vol.4.

N. Absi, B. Detienne, and S. Dauzère-Pérès, “Heuristics for the multi-item capacitated lot-sizing problem with lost sales,” Computers & Operations Research, vol. 40, no. 1, pp. 264–272, Jan. 2013.

J. Rezaei and M. Davoodi, “Multi-objective models for lot-sizing with supplier selection,” International Journal of Production Economics, vol. 130, no. 1, pp. 77–86, Mar. 2011.

D.-H. Kim and D.-H. Lee, “A heuristic for multi-period disassembly leveling and scheduling,” in 2011 IEEE/SICE International Symposium on System Integration (SII), 2011, pp. 762–767.

A. Aydemir-Karadag and O. Turkbey, “Multi-objective optimization of stochastic disassembly line balancing with station paralleling,” Computers & Industrial Engineering, vol. 65, no. 3, pp. 413–425, Jul. 2013.

M. Schoenauer, K. Deb, G. Rudolph, X. Yao, E. Lutton, J. J. Merelo, and H.-P. Schwefel, Eds., Parallel Problem Solving from Nature PPSN VI, vol. 1917. Berlin, Heidelberg: Springer Berlin Heidelberg, 2000.

M. Godichaud, Amodeo L., Multi-objective Optimization of Supply Chains with Returns, International Conference on Metaheuristics and Nature Inspired Computing, META 2012, Sousse, Tunisia, 27-31 October 2012.

D. Sánchez, L. Amodeo, and C. Prins, “Meta-heuristic Approaches for Multi-objective Simulation-based Optimization in Supply Chain Inventory Management,” in Artificial Intelligence Techniques for Networked Manufacturing Enterprises Management, L. Benyoucef and B. Grabot, Eds. Springer London, 2010, pp. 249–269.

Li X., Yalaoui F., Amodeo L., Chehade H., Metaheuristics and exact methods to solve a multiobjective parallel machines scheduling problem, Special Issue on Advanced Metaheuristics For Integrated Supply Chain Management, Journal of Intelligent Manufacturing (ISI), Vol 23, pp 1179-194, 2012.