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A multi-objective optimization model for cooperative supply chain planning

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Abstract: Generally, each member of a supply chain (SC) optimizes his own individual objective and accordingly, plans his activities (e.g. production operations, inventories) without considering a global perspective. The goal of this work is the development of a multi-objective optimization model for cooperative planning between different manufacturing plants belonging to the same SC. The model aims at minimizing simultaneously the total production cost and the average of inventory level for several items and over a multi-period horizon. To solve this problem, a non-dominated sorting elitist genetic algorithm (NSGA-II) is developed to derive the Pareto front solutions. Several tests are developed to show the performance of the solution method and the behavior of the cooperative planning model with respect to different demand patterns. The proposed model shows high performance in the tested cases with comparison to the literature.

Keywords: Multi-objective optimization model; cooperative planning; supply chain management; elitist genetic algorithm; NSGA-II

1 Introduction

Planning the operations across supply chains (SC) is considered in the literature as a major task of supply chain management (SCM). Christopher (1998) defined the SC as "*the network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services in the eyes of the ultimate consumer*". In other words, a SC is composed of two or more organizations that are linked by materials, information and financial flows, with the aim to fulfil customer request /demand. According to Stadtler (2005), "*Supply chain management (SCM) is the task of integrating organizational units along a SC and coordinating materials, information and financial flows in order to fulfil (ultimate) customer demands with the aim of improving competitiveness of the SC as a whole*". SCM is turning into one of the major activities of the management, which has great importance in competitive markets (Ganjavi et al., 2015).

Planning tasks are classified into three planning levels, depending on the corresponding planning horizon: strategic, tactical and operational levels. In this work, the tactical planning (mid-term planning), that is concerned with the productions decisions, the resources utilization and the material flows management, is considered.
Many works addressed the issue of coordination between partners and its impact on SC performances ((Xu & Meng, 2014), (Shukla et al., 2014), (Chan & Zhang, 2011), Lyu et al. (2010), Li & Wang, (2007) , Dudek & Stadtler (2005, 2007), Schneeweiss & Zimmer (2004), Ertogral & Wu, (2000)). The collaboration between partners and the ability to exchange information are important entities that can be adopted by SC to enhance their competitiveness (Mishra et al., 2014). Coordination in SCs depends on the decision-making nature, which can be either centralized or decentralized. Independent decisions characterizing decentralized planning benefit some parties of the SC, while the aligned decisions benefit all parties and maximize the profits ((Cárdenas-Barrón & Treviño-Garza 2014), (Cárdenas-Barrón et al., 2012). To ensure good coordination, one approach is the implementation of centralized decision-making ((Hu et al. 2010), (Kumar et al., 2014)). Li & Wang (2007) provided a review of coordination mechanisms of SC systems based on the demand nature and the SC decision structure. To improve the SC performances, cooperative planning is one of the important levers of action. In this case, the decision makers planning tasks are interconnected to achieve a global objective. Centralization occurs by considering the whole system as one entity, while coordination appears from the information exchange between the planning domains: information on demand as well as manufacturing and inventory capacities are provided to each others. Erengüç, et al. (1999) and Jaber & Zolfaghari (2008) provided a review of mathematical programming planning models within centralized SCs. According to Axsater & Rosling (1993), Lee & Billington (1993), Haehling von Lanzenauer & Pilz-Glombik (2002), and Rudberg (2004), centralized management offers better cost-effectiveness, possibilities of higher resources utilization and avoidance of duplication of activities, due to a better coordination than in decentralized management.

According to Sobhani & Wong (2013), in SCM, a series of organizations integrate and cooperate in order to improve the competitive capabilities of the whole chain. In this context, they developed a mono-objective model, which aims to minimize the transportation cost and inventory holding cost, in order to optimize the distribution quantity of products in a three-stage SC system. They developed a robust elitist genetic algorithm (GA), which outperforms the EXCEL SOLVER. Timpe & Kallrath (2000), Berning et al. (2002) and Schröpfer et al. (2009) presented different models and algorithms for centralized master planning in chemical industry SC that show the advantages of cooperation between partners in SC. All these proposed models aimed at minimizing a total cost function, which is composed of production costs, shipping costs, and holding costs. Manimaran & Selladurai (2014) developed a mixed integer programming model, which aims to minimize the total distribution cost of the multi-stage SC network by selecting the optimum numbers, locations and capacities of plants and distribution centers to open in order to satisfy all customer demand. In considering total profit maximization, Alemany et al. (2010) developed a deterministic mixed-integer linear programming, for multi-period centralized planning problem of SCs in the ceramic sector. The objective of the model is to maximize the total net profit. Kim et al. (2009) developed an equitable mechanism of sharing the profits achieved due to cooperation between a single manufacturer and a single retailer in a SC.

From a technical perspective, the problem considered in this paper is the deterministic multi-period, multi-level, multi-item capacitated lot-sizing problem (MLCLSP). According to Ertogral & Wu (2000), MLCLSP in a multiple tier SC context can be defined as follows: Given external demand for end items over a time horizon, a bill-of-material structure for each end item where the production of sub-assemblies may be spread across multiple facilities, the problem is to find a production plan over multiple facilities that optimizes specific objectives. The MLCLSP represents a major decision in production planning by defining the appropriate lot sizes under capacity restriction constraints (Jans & Degraeve, 2008). The MLCLSP belongs to the production management area and it can represent real situations or scenarios in different industries (Toledo et al. 2013). Maes (1991) proved that the MLCLSP is NP-complete problem. Sahling et al. (2009) proposed a dynamic multi-level capacitated lot sizing problem with setup carry-overs, which aims to minimize the sum of overtime costs, setup costs and inventory holding costs. They solved the problem via an iterative heuristic called the fix-and-optimize algorithm. To solve the same problem, Goren et al. (2012) developed a hybrid approach by combining GAs and a fix-and-optimize heuristic. Furlan & Santos (2015) addressed the MLCLSP to find a production plan that satisfies the demand on time and minimizes the sum of inventory holding costs, setup costs and overtime costs. To solve the problem, they proposed a hybrid heuristic based on the bees' algorithm combined with the fix-and-optimize heuristic. Taghipour & Frayret (2013) proposed a dynamic mutual adjustment search heuristic, in order to coordinate the operations plans of two independent SC partners, linked by material and non-strategic information flows. Each partner solves a local MLCLSP taking into account the local capacity constraints of his partners. Almeder (2010) combined an ant colony optimization algorithm with the exact solver CPLEX, to solve the MLCLSP based on the formulation proposed by Stadtler (1996). The metaheuristic fixes the binary variables, and the mixed-integer programming finds the continuous variables. The objective is to minimize the total cost, which consists of the sum of the setup, inventory and overtime costs. Reiß & Buer (2014) proposed a coordination mechanism based on a negotiation approach to enable collaborative planning in the context of an n-tier SC, where agents jointly solve a distributed MLCLSP in order to minimize the joint total cost. Kim & Shin (2015) proposed a production planning algorithm for the MLCLSP in a SC that takes back order into account, aiming to minimize the sum of the inventory holding, setup, and back-order costs. They developed a hybrid heuristic algorithm named greedy rolling horizon search to solve the problem.

The common objective of the papers dealing with the MLCLSP is the minimization of a total cost function, with some differences in the considered assumptions or the structure of the SC system. According to Deb (2001), decomposing an original single-objective function into multiple, conflicting objectives gives more flexibility in exploring the solution space. Thus, unlike standard models, we consider in this paper the MLCLSP as a multi-objective model. In fact, inventory is crucial to the success of many activities and is a part of the effective management of a firm (Kumar et al., 2013). It is considered as one of the most important and essential issue in production and operations management (Elsayed, 2014). Moreover, the inventory level is a fundamental measure in SC planning and particularly in MLCLSP. In order to control the inventory more effectively, avoid diluting it in a total cost function and consider it with its adequate weight, we consider the inventory level as a separate measure to be minimized rather than a cost component from the total cost function as considered in the literature. The considered MLCLSP is so modelled as a bi-objective model, which aims to minimize the total production cost and the average inventory level.

The literature of SC planning presents some multi-objective models, but not in the context of MLCLSP. Cheng et al. (2009) proposed a multi-objective optimization model for the manufacturing of complex products in SC. The first objective is to minimize the total cost, which is the sum of the processing cost, linked cost between manufacturing units and penalty cost. The second one is to minimize the whole production load. They solved the problem using the non-dominated sorting elitist genetic algorithm (NSGA-II), which show its performance compared to three other GAs. Paksoy et al. (2010) proposed a mixed integer linear programming model composed of three objective functions. The first one aims to minimize the total transportation costs between partners, the second one aims to minimize holding and ordering costs in distribution centres (DCs), and the last objective function aims to minimize the unnecessary and unused capacity of plants and DCs. Kébé et al. (2012) modeled an industrial SC planning problem, which aims to determine the flows between DCs and the suppliers, while minimizing the total cost. A Lagrangean heuristic is developed to solve the problem. Bandyopadhyay & Bhattacharya (2013) proposed a modified version of NSGA-II to minimize first, the transportation and inventory holding costs and second, the bullwhip effect of a two echelon serial SC. Sazvar et al. (2014) developed a multi-objective model in a two-echelon centralized SC. The first objective is to minimize the total cost, which consists of the inventory holding costs, the purchasing costs, the ordering costs, the recycling costs, the transportation costs, the backordered costs and the lost sale costs minus revenues. The second objective aims to minimize the expected greenhouse gas produced in the SC. Ivanov et al. (2014) developed a multi-objective, multi-period planning model for a multi-stage centralized SC. The model aims to maximize the service level and minimize the total cost composed of the fixed, the transportation, the storage, the return and the sourcing costs. Ganjavi et al. (2015) developed a goal programming model, which aims to minimize the total deviation cost from the selected target. The purpose is to determine appropriate lot-size to procure in each period, which meets the total available periodic budget and the buyer's maximum acceptable quality, and minimizes the shortage. To solve the model, they developed a differential evolutionary algorithm, which outperforms GAMS software and the GA. For an overview of various mathematical programming models for SC production planning, one may refer to Mula et al. (2010), Steeneck & Sarin (2013) and Esmaeilikia et al., (2014).

We contribute to the literature on SC planning by developing and solving a multi-objective multi-level, multi-item, multi-period optimization model for cooperative planning. In fact, cooperation between partners can lead to the generation of a global optimal production plan. To solve the multi-objective model, we design and develop an elitist based on the non-dominated Sorting Genetic Algorithm -II (NSGA-II).

The paper is organized as follows. The MLCLSP in a cooperative scheme is modelled and formulated in section 2. The resolution methodology is presented in section 3, followed by the computational results in section 4. Section 5 provides a comparative study to evaluate the performance of the proposed model. Finally, a conclusion and discussion of future research directions close the paper.

2 Problem statement and proposed methodology

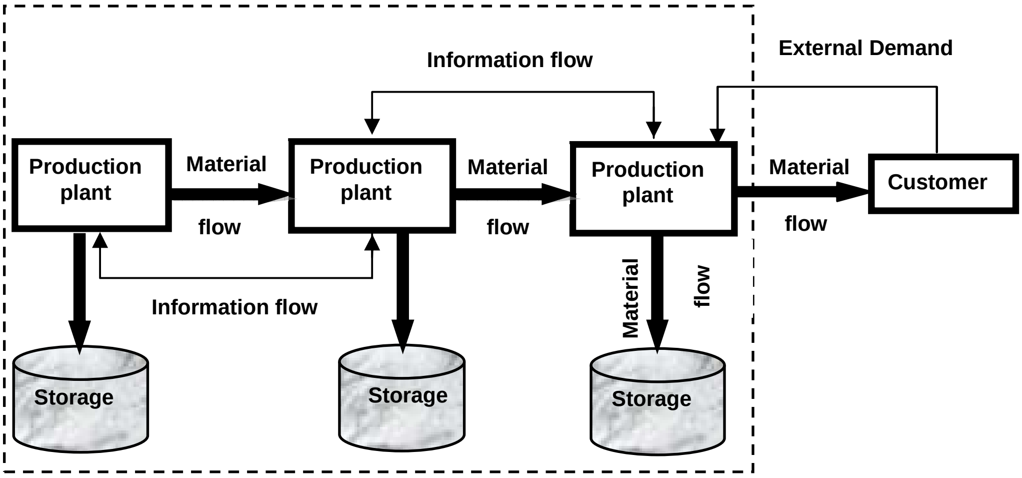
Consider a multi-echelon SC planning problem over a fixed number of periods with a finite capacity of personnel and machines. Products are interconnected by successor and predecessor operations according to the bill of materials and the sequences of operations that increase the problem complexity. The demand for every finished product or semi-finished product is assumed to be given and has to be fully met in time and quantity. The deadline to satisfy the customer’s demand corresponds to the end of the planning period.

The following assumptions are considered in the multi-objective optimisation problem:

- Raw materials are always available.
- Periodic external demand of each item is known.
- Inventories at the starting planning period are empty.
- Several resources, with limited availabilities, can process several items.
- The sequence of operations required to produce an item is fixed, and any alternative routing is forbidden.
- Overtime is allowed to extend the main production capacity availability.
- Setup time is neglected.
- Items can be only produced if all their predecessor components are available.
- Backlogging is not allowed.
- Inventory is calculated at the end of each planning period.

The cooperative SC structure considered is represented in Figure 1, where different production sections or manufacturing plants cooperate together in order to generate a global optimal production plan, which satisfies all the concerned parts. The plant that produces the finished product requested by the customer receives orders from his customers and transmits them to the other plants. Besides the inherent nature of SC actors, these plants share different information with each other, such as production capacity and production costs. Products are moved from an upstream plant to the downstream one until reaching the last plant, where the finished products are stored and delivered to the customer. To generate the production plans, within the whole SC, the mathematical programming of the MLCLSP is used. This choice is motivated by the fact that it is a standard problem which is well known and documented in the literature. In fact, it depicts the important decision in production planning of determining adequate lot-sizes from final products onward, to subassemblies, parts and raw materials. Moreover, it captures the essential planning issues presented above: several final products, a multi-level process structure, limited capacities, and discrete setup decisions.

Figure 1 Cooperative supply chain planning structure



The following notations are considered:

- Indexes sets

T set of planning periods

J set of operations

R set of resources

S_j set of direct successor operations of *j*

- Indices

t planning period, $t= l,..., T$.

j, k operation, $j = 1,. . . , J; k= 1,. . . , J$.

r resource, $r = 1,. . . , R$.

- Data

cv_j unit cost of operation *j*

cf_i fix setup cost of operation j

co_r unit cost of overtime (capacity expansion) at resource r

$D_{j,t}$ (external) demand for operation j in period t

$C_{r,t}$ Capacity at resource r in period t

$L_{j,t}$ Large constant

$a_{r,j}$ Unit requirement of resource r by operation j

$r_{j,k}$ Unit requirement of operation j by successor operation k

- Decision variables

C total production cost

I_{moy} average of inventory level for all operations

$x_{j,t}$ output level of operation j in period t (lot size)

$i_{j,t}$ inventory level of operation j at the end of period t

$y_{j,t}$ setup variable of operation j in period t

($y_{j,t}$ =1 if operation j is set up in period t; $y_{j,t}$ =0 otherwise)

$o_{r,t}$ overtime at resource r in period t

- Formulation

$$Min(C, \mathrm{I}moy) \quad (1)$$

$$St \quad C = \sum_{t=1}^{T}\sum_{j\in J}[(cv_j.x_{j,t}) + (cf_j.y_{j,t})] + \sum_{t=1}^{T}\sum_{r\in R} co_r.o_{r,t} \quad (2)$$

$$\mathrm{I}moy = \frac{1}{T}\sum_{t=1}^{T}\sum_{j\in J} i_{j,t} \quad (3)$$

$$i_{j,t-1} + x_{j,t} = D_{j,t} + r_{j,k}x_{k,t} + i_{j,t} \qquad \forall j\in J, \forall t \quad (4)$$

$$\sum_j a_{r,j}.x_{j,t} \le C_{r,t} + o_{r,t} \qquad \forall j\in J, \forall t, \forall r\in R \quad (5)$$

$$x_{j,t} \le L_{j,t}.y_{j,t} \qquad \forall j\in J, \forall t \quad (6)$$

$$x_{j,t} \ge 0, \qquad i_{j,t} \ge 0 \qquad \forall j\in J, \forall t \quad (7)$$

$$o_{r,t} \ge 0 \qquad \forall t, \forall r\in R \quad (8)$$

$$y_{j,t} \in \{0,1\} \qquad \forall j\in J, \forall t \quad (9)$$

The purpose of this model is to determine the adequate production plan, which minimizes simultaneously the total production cost and the average inventory level of the whole SC. The objective functions are represented by equations (2) and (3). The first objective function considered is the total production cost as the sum of operations costs, setup costs, and overtime costs. The second function is the average inventory level with respect to the number of planning periods. The second objective gives to the inventory level its importance as a fundamental measure by considering it as a separate quantity to be minimized and not as a component of a total cost function. This formulation favours the inventory level optimization, especially in the case where the storage cost is low or negligible. The first decision variable consists of the operations levels ($x_{j,t}$), which presents the units of operation *j* to be produced at period *t*; in other words the lot-size to be produced in order to fully satisfy the external demand. The second decision variable is the inventory levels ($i_{j,t}$) for all operations considered, which represents the units of operation j in the inventory at period t (Any amount exceeding the demand is stored for future use). The third decision variable is the setup binary variable, which indicates whether a setup for the operation j occurs in period t. Finally, the last model output is the expansions of resource capacity through overtime ($o_{r,t}$), which presents the overtime needed for resource *r* during the period *t* to finish production. Operations represent production or other value-adding activities. Equation (4) provides the constraints capturing the flow balance between output, inventory and consumption by external demand or successor operations. In fact, external demand has to be fulfilled at any stage and any time using the items either produced at that period or stored. The constraint (5) ensures the capacity restrictions in using the resources to produce the different items. This limitation in capacity is a representation of real-life SC situations, where overtime could be used as a means to extend the capacity of a plant at any period. The setup constraints are expressed in (6), forcing the binary setup variable ($y_{j,t}$) to be set to 1 when the operation j is performed in period t. The domains of the different decision variables are specified in the constraints (7), (8) and (9).

Formulating the MLCLSP with a bi-objective representation fosters the innovation and presents the advantage of considering the inventory level as a dissociated objective function. This allows giving the inventory level its real importance rather than artificially converting it into a cost component within a total cost function. The developed bi-objective optimization model allows finding a compromise between two contradictory phenomena, which are the inventory level and the total production cost.

3 The resolution method

The original MLCLSP is a NP-hard mixed integer programming (MIP) problem with binary and integer variables, which means that it is hard to solve. In this paper this problem is transformed to a multi-objective problem, which increases the complexity of the resolution.

In multi-objective optimization problems, the objective functions conflict with each other. In other words, improving one of the objectives leads to sacrifice on another. Unlike mono-objective problems, there is no single optimal solution that can optimise all objective functions simultaneously. But rather, there exist a set of trade-off solutions, called the Pareto-optimal solutions. To solve such multi-objective optimization problems, some researchers transformed the objective problems into a series of mono-objective problems. For this purpose, an order of importance on the objectives could be given, and the objectives are optimized separately without degrading the values already obtained for the priority objectives. Another approach in optimizing a linear aggregation target, each objective may have a weight representing its importance. However, in a real multi-objective context, it is not always possible to find an order of importance of the criteria. It is then necessary to look for best compromise between the objectives solutions.

According to Vanchipura & Sridharan (2014), it is difficult to get an optimal solution for even small size NP hard problems; thus, Metaheuristics, and more specifically GAs represent suitable solution approaches in such situations. According to (Bandyopadhyay & Bhattacharya, 2013) the mathematical techniques have limited search ability to find optimal solutions for SC planning compared to biological methods such as GAs. GAs have a high potential in solving varieties of NP-hard multi-objective problems and show good performances in finding near-optimal solutions for multi-level lot sizing ((Dellaert et al., 2000), (Dellaert & Jeunet, 2000), (Xie & Dong, 2002), (Guner Goren et al., 2010)). In the case of multi-objective problem, no single optimal solution can optimize all the objectives, especially when the objectives are conflicting. GAs are able to provide a set of compromised solutions called Pareto optimal solution (Coello et al., 2007) that answer to the optimization model. For this reason, we slightly modified the well established NSGA-II (Non-dominated Sorting Algorithm II), initially developed by (Deb & Agrawal, 2002), to make it suitable for use in cooperative SC planning with integer decision variables. This algorithm is chosen for the following reasons:

- The use of elitism: A comparison made by Zitzler et al. (2001) on a set of test problems shows that elitism is an important factor to consider in evolutionary multi-objective optimization.

- The low computational complexity: According to (Deb & Agrawal, 2002), NSGA-II has a computational complexity equal to $O(MN^2)$ (M is the number of objectives and N is the population size). Compared to other Multi-objective Evolutionary Algorithms (MOEAs), where the computational complexity is equal to $O(MN^3)$, NSGA-II is an efficient algorithm.

- Its wide use: NSGA-II is one of the contemporary multi-objective evolutionary algorithms that demonstrates high performance. The algorithm was successfully used in various problems (see for instance (Bekele & Nicklow, 2007), (Kanagarajan et al., 2007), Cheng et al. (2009), (Bensmaine et al., 2011), (Lingxiao & Liangyou, 2013), (Bandyopadhyay & Bhattacharya, 2013), (Pasandideh et al., 2015)).

- Its good convergence features: Deb (2001) shows the ability of NSGA-II to maintain a better spread of solutions and to converge better than two other elitist MOEAs: Pareto Archived Evolution Strategy and Strength Pareto Evolutionary Algorithm.

A population in NSGA-II is a set of possible solutions that may produce Pareto fronts (set of optimal solutions with equal performances). Firstly, a random parent population P_0 is created, the population is formed by different feasible and infeasible solutions called individuals. From N parents, N new individuals (offspring) are generated in every generation by the use of the Simulated Binary Crossover (SBX) and Polynomial mutation (Agrawal & Deb, 1995). The selection is made using tournament between two individuals. Both parents and offspring compete with each others, which ensures the elitism and forms a population of 2N individuals. The population is then sorted based on the concepts of domination and the crowding distance. An individual x_1 dominates another individual x_2, if all the objective functions of x_1 are better than those of x_2, or at least x_1 is strictly better than x_2 for one objective function. Each solution is assigned a fitness value (or rank) equal to its non-domination level. Individuals in the first front are given a fitness value of 1, individuals in the second front are assigned a fitness value of 2, and so on. In addition, the crowding distance parameter is calculated for each individual. This parameter allows estimating the density of solutions surrounding a particular individual in the population. The solution located in a lesser crowded region is selected. Finally, if the stopping criterion (which can be the generation number) is reached, the first front obtained represents the Pareto optimal solutions. Otherwise, a new population is formed and the procedure is repeated.

Relying on the features of the considered problem, the proposed algorithm operates with two fitness functions: the total production cost and the average of inventory level. The decision variables representing the genes in the algorithm are $x_{j,t}$, $y_{j,t}$, $o_{r,t}$, and $i_{j,t}$. All the genes represent integer variables. To ensure elitism, the best chromosome obtained, corresponding to the current optimal solution is included in the population of the next generation.

In the proposed model, there are J*T equality constraints and (2*R*T+4*J*T) inequality constraints as well. To generate the Pareto optimal solutions, the constrained-domination principle, proposed in Deb & Agrawal (2002), is used. All the constraints are then normalized, and the equality constraints are transformed into two inequality constraints. Hence, all the resulting constraint functions are $f\ (x_i) \geq 0$. In the initiation phase of the algorithm, the difficulty is to obtain a feasible solution. The initial generated solution must at least satisfy the non-negativity constraint. After that the constraints violation is calculated for each constraint. If the sum of the constraints violation is null, so the constraints are satisfied and the solution is feasible. Otherwise, if the solutions are infeasible, the solution that has a smaller overall constraint violation is chosen to be included in the new population. After the selection of the feasible solutions, they are ranked in accordance to their non-domination level based on the fitness function values. Finally, the solutions that belong to the first non-dominated front are chosen.

4 Experimental results

4.1. Test description

Consider a linear SC constituted of two production units (2R). The demand is given and has to be fulfilled, while the SC is facing finite capacities of personnel and machines. Three types of items necessitating three types of operations (3J) are produced: product 1 made from one unit of operation 1, product 2 made from one unit of operations 1 and 2, and product 3 made from one unit of operations 1, 2 and 3. Two tests are designed, where the objective is to find the optimal production plan. The first test considers a planning horizon constituted of two periods (2T), whereas the second test considers three periods (3T).

The genetic parameters shown in Table 1 are selected using trial and error methodology, to solve the proposed model. The algorithm is run several times with different parameters combinations. They correspond to the best combination that is selected for running the different tests.

Table 1 Genetic parameters

NSGA-II (parameters)	N, Population size	G, generation number	P_c, crossover probability	P_m, mutation probability	η_c, Crossover Index	η_m, Mutation Index	r, controlled elitism
Parameter values	150	1000	0.99	1/n (n=number of variables)	50	100	0.123

In the first test “2R.3J.2T”, two examples are studied with two different demand trends. As shown in table 2, in the first example, the external demand increases from the first to the second period, to exceed the main production capacity. For the second example, the very high demand in the first period decreases in the second period. The demand profile of the second test “2R.3J.3T”, dealing with three planning period horizon, is presented in table 3. Three cases are generated. In the first case, the demand is triangular: low in the first and the third period and very high in the second period until exceeding the main available capacity. In another words the external demand has triangular shape. In the second case, the demand increases from the first period to exceed the main available capacity in the third period. In the last case, the demand follows a “V” shape (inverted triangular), thus overtime is only expected to occur in the first and the third period.

Table 2 Customer demand features in the first test “2R.3J.2T”

	Example 1		Example 2	
Demand of	T1	T2	T1	T2
Product 1	20	140	90	15
Product 2	15	70	40	5
Product 3	10	70	50	5

Table 3 Customer demand features in the second test “2R.3J.3T”

	Example 1			Example 2			Example 3		
Demand of	T1	T2	T3	T1	T2	T3	T1	T2	T3
Product 1	5	140	15	5	35	140	90	15	140
Product 2	15	70	10	15	25	70	40	10	70
Product 3	10	70	10	10	20	70	50	10	70

4.2 Test results

The developments of NSGA-II algorithm for the different designed tests are coded in C-language. The execution time does not exceed 5 minutes for all the examples tested. The results of tests are shown in Table 4 and Table 5. One can notice that at the convergence of the algorithm, only one compromise solution is provided at the Pareto front. In particular, the problem presents many equality constraints and integer decision variables, which imply discontinuities in the solution domain and limit the search space for the algorithm.

4.2.1. The "2R.3J.2T" test results

The first example of the "2R.3J.2T" test considers high demand during the second period that exceeds the main capacity. If the plants produce the items needed (to fulfil the demand) in the same period, the first plant requires 1600 minutes of overtime and the second plant requires 620 minutes of overtime. Therefore, a solution as given in Table 4 is to produce in advance the products needed and to store them in the first period. Consequently, there is no need for overtime to meet the demand, since overtime is more expensive compared to nominal capacity utilisation costs. Besides, at the end of the planning period, the inventory level is null. Normally, to meet the exact demand in every period, the plants have to achieve 45 operations of operation 1 in the first period, 35 units of the operation 2 and 10 units of the operation 3. But in the solution provided by the algorithm, the production exceeds the needs by 68 units for the product 1, 50 units for the product 2 and 48 units for the product 3. Thus, the plants have to complete the products needed to satisfy the customer's demand in the second period. The total production cost for this plan is about 2669 [MU] and the average inventory level is equal to 34 units.

In the second example, the demand increases starting from the first period. To meet the demand of that period, the first plant needs 60 minutes of overtime, whereas, the main capacity of the second plant is sufficient. Despite using the same genetic parameters, the algorithm does not provide good solutions as expected. In fact, the solution provided by the algorithm proposes that the production plants produce the exact quantities needed to satisfy the demand of the first period and use the needed overtime only in that period. Hence, there is no storage at that period. At the second period, the production quantities are higher than the demand. This explains the needs for storage of the second and the third operation at the end of the planning horizon. The total production cost of this example is equal to 3130 [MU] and the average level of inventory is equal to 33.

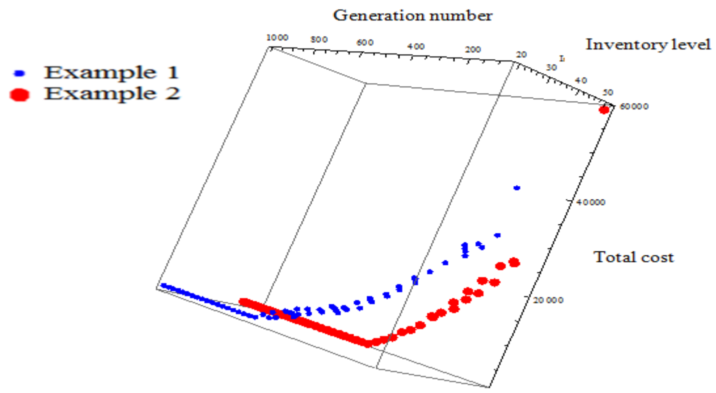
Table 4 Results of the first developed test "2R.3J.2T"

	Example1	Example 2
$x_{1,1}$	113	180
$x_{2,1}$	85	90
$x_{3,1}$	58	50
$x_{1,2}$	212	91
$x_{2,2}$	80	76
$x_{3,2}$	22	36
$o_{1,1}$	0	60
$o_{2,1}$	0	0
$o_{1,2}$	0	0
$o_{2,2}$	0	0
$i_{1,1}$	8	0
$i_{2,1}$	12	0
$i_{3,1}$	48	0
$i_{1,2}$	0	0
$i_{2,2}$	0	35

$i_{3,2}$	0	31
C	2669	3130
I_{moy}	34	33

Figure 2 shows the optimisation process from the first generation until the convergence of the two examples of 2R.3J.2T. For both examples, at least 75 generations are necessary to find feasible solutions. During the first 300 generations, both objective functions are simultaneously optimized, where the solutions Pareto contains up to five solutions. Afterwards, the curve shows that the inventory level stabilizes around a certain value. In the last generations, only the total cost is minimized, by minimizing the use of overtime, until its convergence to a unique optimal solution. During the optimization process, the total cost is reduced by more than 90%, whereas the reduction of the average inventory levels does not exceed 50%.

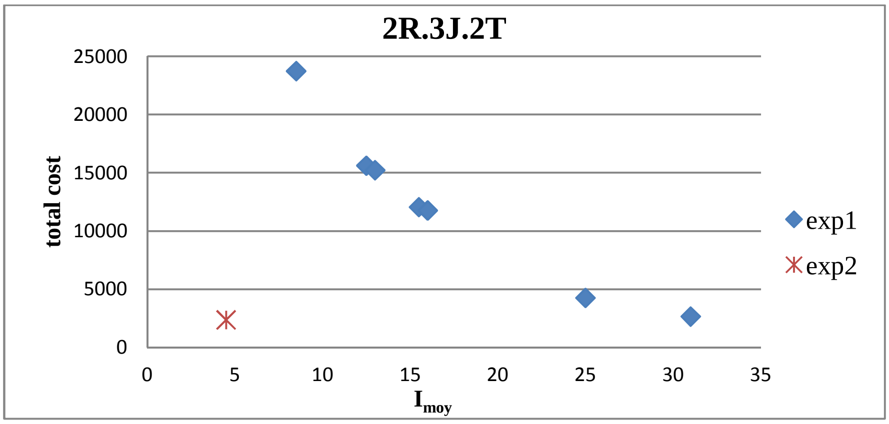
Figure 2 The optimization evolution for example 1 and example 2 for “2R.3J.2T”



In the case of the proposed model, to find a Pareto of multiple optimal solutions the NSGA-II parameters must be varied. Thus, the algorithm is run several times with different parameters combinations and the Pareto optimal solution is obtained with respect to the non-domination concepts.

The search strategies of the examples are different. In the first example, the solutions region is larger and conflict between the considered objectives occurs especially in this case. In fact, for an increasing demand case, in order minimize the total production cost; the use of the overtime must be avoided. However, the production must be made in advance because the demand exceeds the available capacity, which will increase the average inventory level. The contradictory phenomenon allows obtaining a Pareto of multiple optimal solutions, as shown in Figure 3. The Pareto contains seven solutions. The decision maker can choose the suitable production plan according to his preferences. Moreover, we notice that, NSGA-II provides multiple production plans for the same objective functions, which gives a wider range of choice to the planners. However, for the second example, the demand has a decreasing pattern, which does not exceed the available production capacity of the planning period. Therefore, there is no need for storage and the objective functions are not conflicting. The NSGA-II provides one global optimal solution as shown in Figure 3. Finally, the choice of the most suitable production plan is made by the partners according to their preferences.

Figure 3 Pareto optimal solution of "2R.3J.2T"



4.2.2. The "2R.3J.3T" test results

The results of the different examples of the "2R.3J.3T" test are shown in Table 5. In the first example, the demand is very important in the second period. So the production of the first and the second operation is done in advance. Instead of producing 30 units of the first operation, which is the necessary quantity that satisfies the demand, the solution provided by the algorithm is to produce 135 units without use of overtime in the first period. So, taking the two first periods, the algorithm reacts in the same way as in the last test of the first example. The production of the units needed to fulfil the second period's demand is completed in that period. Overtime is then used by 802 minutes for the first resource and 18 minutes for the second one. However, if in every period the production is done to satisfy the demand of that period, the first plant would need in the second period 1600 minutes of overtime and the second plant would need 620 minutes of overtime. But in this case, storage is required at the end of the second period. In the third period, there is no need of overtime. At the end of the planning horizon, there are only 14 units in the inventory, 7 units each of product 3 and 2. The total production cost of this example is equal to 11400 [MU] and the average level of inventory is equal to 44.33 units.

For the second example the demand increases starting from the first to the last period. There is no need to use overtime at the two first periods. But, at the third period, the first plant will need 2060 minutes of overtime and the second plant will need 1990 minutes of overtime, if they produce the quantity asked at that period. However in the proposed compromise solution, shown in column 2 of Table 5, the third plant uses only 878 minutes of overtime and the second plant uses only 64 minutes of overtime. In this case, the solution optimizes the SC production cost by minimizing the use of overtime. The produced quantities in the first and the second period exceed the quantities needed to satisfy the external demand. For the second operation, the SC produces 46 items instead of 25 items at the first period, and 53 items instead of 45 items. At the end of the planning horizon, the inventory level of all products is null. The total production cost of this example is equal to 13043 [MU] and the average level of inventory is equal to 25 units.

Considering the third example, the solution is shown in the third column of Table 5. The demand has an inverted triangular shape. The demand of the first period exceeds the main capacity only of the first plant by 60 minutes. To satisfy the demand of the third period at that period, both plants will need overtime; 1600 minutes for the first plant and 620 minutes for the second one. To minimize the use of overtime, which is very expansive, the demand size has to be fulfilled at an earlier period. But, to satisfy the second objective, which is minimizing the average of inventory level, does not allow a high minimization of overtime. In the first period, instead of producing 180 units of the first operation, the plants produced 230 units and 45 units more for the second operation. There are then 5 units of the first operation stored, 45 units of the second operation and no inventory of the third operation. At the second period, only 38 units of the second operation and 12 units of the third operation are stored. At the end of the planning horizon, there are only 6 units of the third operation in the storage. For this example, the proposed compromise solution consists on a total production cost equals to 21876 [MU] and an average level of inventory equals to 35 units.

One can note that when the demand is important in the second or the third period and exceeds the available main capacity, the algorithm minimizes the total production cost by the minimization of the use of overtime because of its high cost. The average of inventory level then increases as production is done in advance. At the end of the planning horizon, the inventory level is very low or null. Generally, it is noticed that when the number of planning periods horizon increases, a better customer service is provided with high cost saving. The generated solutions consist on compromise between the both contradictory objectives.

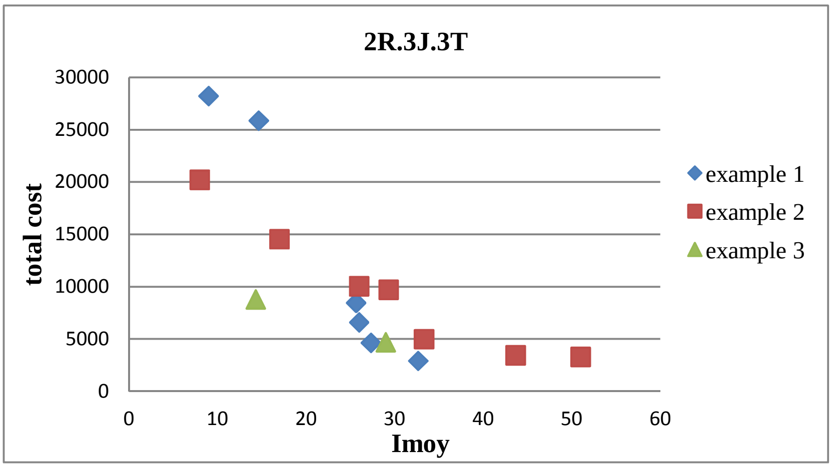
Table 5 Results of the second developed test “2R.3J.3T”

	Example 1	Example 2	Example 3
$x_{1,1}$	135	51	230
$x_{2,1}$	32	46	135
$x_{3,1}$	10	10	50
$x_{1,2}$	189	113	35
$x_{2,2}$	133	53	25
$x_{3,2}$	70	20	22
$x_{1,3}$	35	226	236
$x_{2,3}$	34	111	96
$x_{3,3}$	17	70	64
$o_{1,1}$	0	0	910
$o_{1,2}$	802	0	0
$o_{1,3}$	0	878	736
$o_{2,1}$	0	0	80
$o_{2,2}$	18	0	0
$o_{2,3}$	0	64	0
$i_{1,1}$	98	0	5
$i_{1,2}$	14	25	0

$i_{1,3}$	0	0	0
$i_{2,1}$	7	21	45
$i_{2,2}$	0	29	38
$i_{2,3}$	7	0	0
$i_{3,1}$	0	0	0
$i_{3,2}$	0	0	12
$i_{3,3}$	7	0	6
C	11400	13043	21876
I_{moy}	44.33	25	35.33

In order to generate the Pareto of multiple optimal solutions of the developed examples, the NSGA-II is run several times with different parameters combinations. The Pareto optimal solutions are obtained with respect to the non-domination concepts, as shown in figure 4. The Pareto optimal set contains six optimal solutions, for the first examples, where the demand has a triangular shape during the planning horizon. For the second example, where the demand is increasing during the planning horizon, the algorithm provides seven optimal solutions. In this case, there is the highest number of compromise solutions due to the contradictory objectives. But, for the third example where the demand has a "V" shape, only two optimal solutions are found. The three extracted Pareto have different shapes, which shows different impacts of the demand pattern on the evolution of the objective functions. In fact, in all studied examples the demand shape influences the optimization process behavior. In the case of an increasing external demand, the contradictory phenomena between objectives functions rises, the algorithm provides more optimal solutions. Finally, the partners could choose the appropriate production plan to follow according to their preferences.

Figure 4 The Pareto optimal solution of "2R.3J.3T"



5 Model Performance analysis

To evaluate the proposed model and the solution quality provided by NSGA-II, a benchmark is created with respect to a mono-objective model of MLCLSP in a cooperative SC. The latter is a well known and established model (cf. (Dudek & Stadtler (2005), (Stadtler, 2003), (Almeder, 2010)). The objective function of the mono-objective model is to minimize the total costs, composed of the operations cost, the inventory holding cost, the setup cost and the overtime cost, as presented in Equation (10). Inventory levels are transformed into costs and incorporated in the objective function. Hence, for this model, the average inventory level is indirectly optimized using the flow balance constraint presented in Equation (4). However, in the proposed model, the inventory is not treated as cost but kept as a quantity to be minimized. In order to obtain the same total cost function for a comparison purpose, we assume that the inventory holding cost is neglected in the mono-objective model. The other constraints of both models are the same. Two tests are designed and run using NSGA-II.

$$C = \sum_{t=1}^{T} \sum_{j \in J} [(cv_j.x_{j,t}) + (ch_j.i_{j,t}) + (cf_j.y_{j,t})] + \sum_{t=1}^{T} \sum_{r \in R} co_r.o_{r,t} \qquad (10)$$

5.1 *First set of tests: 2R.3J.2T*

In these tests, the notation 2R.3J.2T indicates that the SC consists of two manufacturing Plants (2R) and the planning is done over two periods (2T) for three types of products that require three kinds of operations (3J). The first product requires one unit of operation 1. The second product needs one unit of operations 1 & 2. And the third product needs one unit of operations 1, 2 & 3. The external demand $D_{j,t}$ of each product is represented in Table 6.

Table 6 External demand of different items

$D_{1,1}$	$D_{2,1}$	$D_{3,1}$	$D_{1,2}$	$D_{2,2}$	$D_{3,2}$
90	40	50	80	60	70

To satisfy the external demand for each period over the same period, the first plant needs 60 minutes in the first period, and 940 minutes of overtime in the second period; whereas the second plant does not need any overtime.

To solve the standard mono-objective model as well the multi-objective MLCLSP, the NSGA-II algorithm is used. In each test, the population size N varies, while keeping the other NSGA-II parameters unchanged. In terms of convergence, the proposed multi-objective model needs only 1000 iterations to converge to the optimal solution, whereas the mono-objective model needs about 2000 generations. Consequently, in order to objectively compare the models in their best conditions, the maximum generation number used in the tests is limited to 2500 generations. The results are visualized in Table 7 that contains the quantities produced, the binary setup variable, the overtime used, the inventory levels and the objective functions, for both the mono-objective model and the proposed multi-objective model.

Table 7 Results of 2R.3J.2T test for the proposed model and the mono-objective model

N	60		100		150		200		300	
Model	The mono-objective model	The proposed model	The mono-objective model	The proposed model	The mono-objective model	The proposed model	The mono-objective model	The proposed model	The mono-objective model	The proposed model
$y_{j,t}$	1	1	1	1	1	1	1	1	1	1
$x_{1,1}$	302	300	227	231	244	236	235	233	283	282
$x_{2,1}$	158	157	127	137	117	117	114	114	134	134
$x_{3,1}$	101	101	67	65	60	60	64	64	88	88
$x_{1,2}$	138	135	265	199	176	178	250	210	170	168
$x_{2,2}$	108	108	150	123	133	127	159	159	149	146
$x_{3,2}$	40	40	71	65	60	60	96	96	85	85
$o_{1,1}$	2328	2303	1010	1118	962	898	908	892	1780	1772
$o_{2,1}$	600	580	0	0	0	0	0	0	242	236
$o_{1,2}$	0	0	1608	722	578	534	1862	1542	990	944
$o_{2,2}$	0	0	206	0	0	0	276	36	0	0
$i_{1,1}$	54	53	10	4	37	29	31	29	59	58
$i_{2,1}$	17	16	20	32	17	17	10	10	6	6
$i_{3,1}$	51	51	17	15	10	10	14	14	38	38
$i_{1,2}$	4	0	45	8	0	0	42	0	1	0
$i_{2,2}$	25	24	39	30	30	24	13	13	10	7
$i_{3,2}$	21	21	18	10	0	0	40	40	53	53
C	*36372.9*	*35799.7*	*33585.7*	*22343.4*	*19178.4*	*18043.2*	*36269*	*29162*	*35798.9*	*35141.3*
I_{moy}	*86*	*82.5*	*74.5*	*45.5*	*47*	*40*	*75*	*53*	*83.5*	*81*

From these results, one can note as an important issue, that the production level of the mono-objective model is higher than the production level of the proposed model by 100%. This difference between the produced quantities reflects the fact of adding the inventory level as a separate objective. For different population sizes, the performances reached by the proposed model are better than those of the mono-objective model in all the tested cases. For example, for a population size equal to 60, we save 573.2 [MU] in the production costs compared to the mono-objective model. Moreover, the inventory level (82.5) is lower than the mono-objective model (86). Besides, for a population size equal to 100, the total production cost is equal to 33585.7 [MU] in the mono-objective model, whereas the proposed model solution provides 22343.4 [MU]. This difference is due to the high use of overtime during the second period for the mono-objective model. In fact, for the mono-objective model, the first resource uses 1608 units of time compared to only 722 units of time in our case, and the second resource uses 206 minutes, while no overtime is used in the proposed model.

One can note that the average of inventory level in the proposed model is always lower than that in the mono-objective model. For instance, for a population size equals to 100, the average inventory level is equal to only 45.5 units, for the proposed model, compared to 74.5 units in the mono-objective model case. Consequently, considering the inventory level as an objective function and not as a constraint clearly improves the results.

At the last planning period, the inventory level of the first operation is null in 80% of the tested cases of the proposed model. For the second operation, the inventory level is always higher in the case of the mono-objective model. Finally, for the third operation, one can note that the inventory levels for both models are almost the same in 80% of the tests. The best result is found using a population size equal to 150. For the proposed model, the total production cost is equal to 18043.2 [MU] (respectively vs. 19178.4 [MU] for the mono-objective model). And, the average inventory level is equal to 40 units, for the proposed model, compared to 47 units provided for the mono-objective model.

5.2 Second set of tests: 3R.2J.3T

In these tests 3R.2J.3T, the cooperative SC consists of three manufacturing Plants (3R) planning over three time Periods (3T) to provide two types of Products requiring two kinds of operations (2J). The production starts in the first plant, followed by the second plant where parts are manufactured and transmitted to the third plant from where the finished products are stored and delivered to the ultimate customers. In these tests, the production plan is optimized over three periods, where the demand for products is known and has to be fulfilled while facing finite capacities of personnel and machines. The product 1 requires one unit of operation 1 to be produced. The product 2 requires one unit of operations 1 &2. The demand $D_{j,t}$ is visualized in Table 8.

Table 8 *External demand for different items for the 3R.2J.3T test*

$D_{1,1}$	$D_{2,1}$	$D_{1,2}$	$D_{2,2}$	$D_{1,3}$	$D_{2,3}$
40	50	60	30	55	55

For this test, the external demand of each period doesn't exceed the main available capacity of each planning period and for the three planners. Thus, there is no need of overtime. The generation number used for the tests is equal to 1300 and the population size N varies. Both models are coded and solved with NSGA-II algorithm. The results are shown in Table 9; the produced quantities, the binary setup variable, the used overtime, the inventory level and the objective functions for both the mono-objective model and the proposed model.

Table 9 *Results of 3R.2J.3T test for the proposed model and the mono-objective model*

N	100		150		200		300	
Model	the mono-objective model	The proposed model	the mono-objective model	The proposed model	the mono-objective model	The proposed model	the mono-objective model	The proposed model
$y_{j,t}$	1	1	1	1	1	1	1	1
$x_{1,1}$	144	152	106	100	137	135	136	128
$x_{2,1}$	53	66	54	50	65	60	68	60
$x_{1,2}$	70	50	87	103	90	98	117	81

$x_{2,2}$	46	36	27	41	37	53	44	36
$x_{1,3}$	113	117	99	102	75	57	72	81
$x_{2,3}$	63	62	56	59	33	22	58	39
$o_{1,1}$	0	0	0	0	0	0	0	0
$o_{1,2}$	0	0	0	0	0	0	0	0
$o_{1,3}$	0	0	0	0	0	0	0	0
$o_{2,1}$	0	0	0	0	0	0	0	0
$o_{2,2}$	0	0	0	0	0	0	0	0
$o_{2,3}$	0	0	0	0	0	0	0	0
$o_{3,1}$	0	0	0	0	0	0	0	0
$o_{3,2}$	12	0	0	0	0	0	0	0
$o_{3,3}$	0	0	0	0	0	0	0	0
$i_{1,1}$	51	46	12	10	32	35	28	28
$i_{1,2}$	3	0	12	12	15	20	18	13
$i_{1,3}$	15	0	0	0	25	0	41	0
$i_{2,1}$	19	16	4	0	22	10	32	10
$i_{2,2}$	10	22	1	11	12	33	0	16
$i_{2,3}$	27	29	2	15	0	0	35	0
C	***3086.7***	***3056.1***	***2699.7***	***2871.3***	***2741.7***	***2673.3***	***3135.3***	***2673.3***
$\boldsymbol{I_{moy}}$	***41.66***	***37.66***	***10.33***	***16***	***35.33***	***32.66***	***51.33***	***22.33***

For the different population sizes, the performances of the proposed model are better by 75% than those provided by the mono-objective model. For instance, for a population size equals to 200 the proposed model saves 68.4 [MU] compared to the mono-objective model. Additionally, the average of inventory level (35.3 units) in the mono-objective model is higher compared to the proposed model (32.6 units). Besides, for a population size equal to 300, the total production cost is equal to 3135.3 [MU] in the mono-objective model, whereas for the proposed model it is equal to 2673.3 [MU]. The cost difference of 462 [MU] is due to the high production level in the mono-objective model. The mono-objective model provides an inventory level of 51.3 units compared to the proposed model where it is equal to 22.3 units, a reduction of 29 units, which shows the influence of addressing the inventory level as a second objective function on the performance improving. Both models do not use overtime to fulfill customer demand, except once for the mono-objective model.

At the last planning period, the inventory of the first operation is empty in 100% of the tested cases for the proposed model. For the mono-objective model, the inventory is empty only in 25% of the tested cases. For the second operation, the inventory level is null in 50% of the tested cases of the proposed model and 25% of the cases using the mono-objective model.

In running both tests, the proposed model is faster than the mono-objective model despite of its complexity. The time needed to provide a solution by the proposed model does not exceed 5 minutes, whereas the mono-objective model needs about 10 minutes to converge and a very large number of iterations (generations).

6 Conclusion and future work

The main contribution of this paper consists on developing a cooperative tactical planning framework for a multi-objective deterministic multi-period, multi-level, multi-item capacitated lot-sizing problem in SC. Unlike, the standard MLCLP, the developed optimization model is a bi-objective model, which aims at minimizing simultaneously the total production cost and the average inventory level, taking into account capacities and demand constraints. The developed formulation considers the case of several production plants are planning together in order to generate a global optimal production plan. The proposed model shows different advantages over those discussed in the literature. Indeed, compared to simplistic mono-objective models, the bi-objective model considers not only costs but also inventory levels as separate measure to be optimized. This represents an interesting issue since inventory optimization is a fundamental concern in SCM and its consideration as a cost component as in the literature can neglect it, especially when it is characterized by lower costs than other considered cost components. Therefore, it allows assessing the real needs of inventories in each period with respect to the demand.

The developed model gives to the inventory level its importance, especially in the case of low or negligible inventory holding cost. The model is solved using the developed NSGA-II, coded with C language. The advantage of using such multi-objective method is avoiding aggregation and transformation of the original multi-objective problem into a mono-objective one. Actually, this method seeks to define compromise between the considered objectives rather than choosing an alternative over another, it provides a set of efficient solutions.

The proposed model is tested on several examples with different demand patterns. Results show that when the number of planning periods increases, the planning task becomes easier, balancing the workload between different periods, and the use of overtime decreases. At the convergence, the Pareto front surprisingly contains only one optimal solution. This is due to the complexity of the problem and particularly to the flow equality constraints between SC tiers. The main limitation of using NSGA-II, is the presence of large number of integer variables and equality constraints simultaneously. In fact, it is hard to handle efficiently integer restrictions on decision variables and satisfy equality constraints. Thereby, it is hard to maintain solutions on the Pareto optimal front. Indeed, equality constraints severely restrict the search space; each equality constraint absorbs one degree of freedom. In addition, the equality constraint becomes harder when considering the connection between manufacturing operations (successors and predecessors). Thus, to obtain a Pareto of multiple solutions, the NSGA-II parameters are varied during optimization, and the optimal solutions are kept with respect to the non-domination concept. The demand shape shows its influence on the optimization process, especially in the case of the increasing demand. In fact, in that case the contradictory phenomena between objectives functions rises, and the number of optimal solutions increases.

To evaluate the performances of the proposed model and the solution quality provided by NSGA-II, the model is compared to a mono-objective model of MLCLSP for several cases. The results show that the total production cost and the average inventory level are lower in all the cases tested in the setting “2R.3J.2T” and in 75% of the cases tested for the setting “3R.2J.3T”. The results show how considering the inventory level as an additional performance measure, decreases better its level and offer better production plans that satisfy the SC planners. Furthermore, computational time is significantly reduced at least by a factor of two, which proves the efficiency of the proposed approach.

The proposed model is used in the case of cooperative SC, where partners are sharing pertinent information, e.g. production costs. In most real-world cases, this access cannot be accepted by all partners. Thus, in the future, the model proposed can be further developed for SC with decentralized decision-making. In this case, the approach is useful to coordinate SCs, particularly when asymmetric information is shared and opportunistic behaviours take place. In such a situation, modelling the negotiation process between echelons using a decentralized planning system is considered as an interesting future research topic.

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