

Research Article

Research on Genetic Optimization for Multinational Food Companies with Random Lead Time

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Abstract: This study aims to investigate the inventory optimization problems for multinational food companies with random lead time. Multinational organizations play an increasingly important role in the world economy. The majority of their activities seem to be driven by market-seeking considerations. In this study we considered a multinational organization in which lead times are stochastic. There is a determined due date that if demands are not prepared for delivery in that day, backlogging cost would happen. In contrast to most of studies in this field that consider sum of these cost, this study attempts to make a tradeoff between these objectives' affects using multi-objective approach based on genetic algorithm. Furthermore, effectiveness of our proposed method is compared against an adapted non-dominated sorting genetic algorithm which has been presented for this problem.

Keywords: Genetic algorithm, inventory optimization, multinational food company, random lead time

INTRODUCTION

Traditional companies tend to be older firms or been in existence for quite some time and the firms' age reveals the level of experience that the firm holds. The age of a firm can also indicate how flexible or inflexible a company might be. Younger companies tend to be more responsive because those organizations are still developing their internal systems and those younger firms tend to be less risk adverse. However, today, younger firms have been found entering the international world much earlier in their organizational development than what has been witnessed traditionally in the past (Yamaguchi *et al.*, 2006).

The new international firms are exhibiting an accelerated pattern of internationalization allowing for them to grow at a faster rate than what was seen previously under the traditional pattern of internationalization. As a result, new firms from around the globe have become major global players at an accelerated pace. The internationalization theory suggests factors such as a firm's technological level; degree of maturity, type of process and its degree of concentration all play a role within internationalization (Peral and Fusun, 2011). The paths to market expansion for these new firms include alliances or joint ventures and subsidiaries or Foreign Direct Investment (FDI). The new firms are moving through the traditional stages very quickly, giving the impression of beginning their

internationalization within the traditional final stage. From 1991 to 1996, 64% of global FDI inflows were received by the developed countries, while 33% were received by the developing countries. From 1975 to 1980, these percentages were 77 and 23, respectively, which demonstrates the changes within these regions. As a result, new firms have become key global players within a global economy and they operate on some form of competitive advantage (Chou *et al.*, 2008). New firms tend to invest abroad in order to explore country-specific ownership advantages, whereas traditional firms were built from firm-specific advantages. New firms begin with country specific and work their way to firm-specific advantages during the course of building their organizations on a global basis.

There are also many works in multinational organization research that considered uncertainty to have more reality in their researches. Grasso and Taylor used safety stock in their problem which had stochastic quantity and lead time (Deng, 1982). Stochastic processing time is also considered in Li *et al.* (2006). Mula, Poler, Garcia-Sabater and Lario also worked on production planning with uncertain demand (Ou and Chou, 2009). In relative research there are some studies that solve some control problem with more than one objective (Polkowski and Skowron, 1998). Hnaien *et al.* (2008) solved the same problem as their previous work but for minimizing holding cost and maximizing the customer service level. However, little work has been

done to address the optimization problem for multinational food companies with random lead time.

In order to optimize the food products order management, this study try to apply an evolutionary algorithm to find non-dominated solutions for stochastic multinational food companies in a multi-objective context. For this reason we reinforce the genetic algorithm with a developed evolutionary algorithm and compared it with former method.

MATERIALS AND METHODS

The multinational food company we discussed in this study is shown in Fig. 1.

We assume that demand and due date for the finished products are known. Optimization is for one-period demand. Each component has known unit inventory cost and unit backlogging cost for the finished product. Whenever all the components of each level become available, process would start in that level.

The notations of our study are as following:

- T : Due date for the finished product
- D : Demand (known) for finished product for the date T
- $c_{i,j}$: Component i of level j ($j = 1$ or 2) of Bill of Material (BOM)
- N_j : Number of types of components of level j ($j=1$ or 2)
- $P_{i,j}$: Set off the ‘sons’ of $c_{i,j}$ in a BOM tree
- $L_{i,j}$: Random lead time for component $c_{i,j}$
- $h_{i,j}$: Unit holding cost for component $c_{i,j}$ per unit of time
- b : Unit backlogging cost for finished product per unit of time
- $x_{i,j}$: Planned lead time for component $c_{i,j}$
- $X_{i,2}$: Release date for component $c_{i,2}$ (this type of variable is defined only for level 2)
- $d_{i,2}$: Number of components $c_{i,2}$ required to assemble one unit of finished product
- $Q_{i,j} = d_{i,2} * D$: The quantity of component $c_{i,2}$ ordered
- $n_{i,1}$: Number of components $c_{k,2} \in P_{i,1}$ required to assemble one unit of $c_{i,1}$, $i = 1, 2, \dots, N_1$
- $F_{i,j}(\cdot)$: Cumulative distribution function of $L_{i,j}$
- $u_{i,j}$: Maximum value of $L_{i,j}$; each $L_{i,j}$ varies in $[1, u_{i,j}]$
- $U_{k,2} = u_{k,2} + u_{i,1}$: Maximum value of $L_{k,2} + L_{i,1}$, $c_{k,2} \in P_{i,1}$; $(L_{k,2} + L_{i,1})$ varies in $[2, U_{k,2}]$

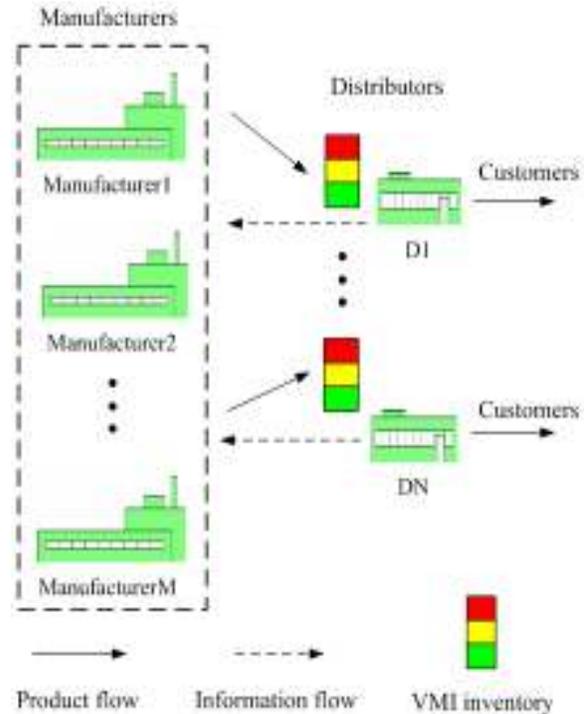


Fig. 1: A food production-distribution supply chain system

$$U : \text{Max } (U_{k,2}), k = 1, 2, \dots, N_2$$

$$H = b + \sum_{i=1}^{N_1} Q_{i,1} h_{i,1} : \text{Sum of unit backlogging cost for finished product and holding cost of components at level 1}$$

Let $T = 0$ and $D = 1$. Orders are given from customer to level 1, from level 1 to level 2. Components (semi finished products) should be delivered from level 2 to level 1 within random discrete lead time. And then finished product should meet customer demand.

Considering more than one objective in optimization problem in field of inventory control has been studied for long time. These objectives are often conflicting and no single solution would simultaneously optimize all objectives. So an optimization approach searches for a set of solutions that are acceptable for all objectives of problem.

Here we consider q objectives and p decision variables (which is equal to the number of component in level 2, N_2) to show the multi objective optimization in general. Goal is finding vector $t^* = (t_1^*, t_2^*, \dots, t_p^*)$ that minimizes objective vector $f(t) = (f_1(t), f_2(t), \dots, f_q(t))$ where $t = (t_1, t_2, \dots, t_p)$ is the vector of decision variables.

Different approaches have been used to solve multi-objective problems. Most of them use various methods to combine multiple objectives to a single objective but a more desirable approach is Pareto which

creates set of non-dominated solutions instead of single solution. Here we use the concept of Pareto approach via a meta-heuristic method.

Also a general definition of dominant solution is as follows.

A vector $w = (w_1, w_2, \dots, w_q)$ is said to dominate $v = (v_1, v_2, \dots, v_q)$ if and only if w is partially less than v , i.e.:

$$\forall i \in \{1, 2, \dots, q\}, w_i \leq v_i \wedge \exists i \in \{1, 2, \dots, q\} \quad w_i < v_i \tag{1}$$

In former research the mathematical expectation of cost function is proved to be objective function which is the summation of holding and backlogging costs. Since these are two conflicting costs that decrease in one of them would lead to the other ones increasing, we divide it into two separate objectives which should be optimized synchronously.

We would obtain stocks at both levels which lead to holding cost, when components arrive before beginning of the assembly at each level:

$$\begin{aligned} ECH(X) = & \sum_{i=1}^{N1} h_{i,1} Q_{i,1} * \sum_{s \in N} \left(1 - \prod_{i=1}^{N1} \left(\sum_{o_1, o_2 \in Z | o_1 + o_2 = s} \left(pr(L_{i,1} = o_1) * \prod_{c_{k,2} \in P_{i,1}} F_{i,2}(X_{i,2} + o_2) \right) \right) \right) \\ & + \sum_{i=1}^{N1} H_{i,1} Q_{i,1} * \left(\sum_{s \in N} \left(1 - \prod_{c_{k,2} \in P_{i,1}} F_{i,2}(X_{i,2} + s) \right) \right) \\ & - \sum_{i=1}^{N1} H_{i,1} Q_{i,1} * \left(\sum_{s \in N} \left(1 - \prod_{c_{k,2} \in P_{i,1}} (1 - F_{k,2}(X_{k,2} - s - 1)) \right) \right) - \\ & \sum_{i=1}^{N1} \left(\sum_{c_{k,2} \in P_{i,1}} h_{k,1} Q_{k,1} \{ E(L_{k,2} - X_{k,2}) \} \right) - \sum_{i=1}^{N1} h_{i,1} Q_{i,1} E(L_{i,1}) \end{aligned} \tag{2}$$

where,

$$X = (X_{1,2}, \dots, X_{k,2}, \dots, X_{N2,2}), \quad H_{i,1} = -h_{i,1} + \sum_{c_{k,2} \in P_{i,1}} h_{k,2}$$

N is the set of natural numbers and Z is the set of integer numbers.

Backlogging cost may occur if customers' demand do not satisfied at due dates:

$$ECB(X) = b * \sum_{s \in N} \left(1 - \prod_{i=1}^{N1} \left(\sum_{o_1, o_2 \in Z | o_1 + o_2 = s} \left(pr(L_{i,1} = o_1) * \prod_{c_{k,2} \in P_{i,1}} F_{i,2}(X_{i,2} + o_2) \right) \right) \right) \tag{3}$$

RESULTS AND DISCUSSION

In order to show the competitiveness of our proposed algorithm, we do comparison on NSGA-II which applied the meta-heuristic on the same problem as Hnaien's previous work but for minimizing holding cost and maximizing the customer service level.

Required data for the problem consist of distribution function of lead times, unit components holding costs and unit finished product backlogging cost and number of component types. The distribution function of lead times is considered geometric here. Unit components holding costs, unit finished product backlogging cost and number of component types used at level 1 and level 2 are given to the algorithm as an input. Different problems are generated by these assumptions: the number of components in level 2 varies in (10, 20, 30, 40, 50, 60, 70, 80, 90, 100). Ten different instances are created for each number of components. Assumptions of the algorithm which are estimated via experiments are as follows: Population size is equal to 50, maximum iteration is equal to 100, the probability of crossover is equal to 0.80 and the probability of mutation is equal to 0.15.

Four comparison metrics are taking in to account to evaluate the performance of the algorithm.

The Number of Pareto Solutions (NPS) shows the number of Pareto optimal solutions that each algorithm can find. Error Ratio (ER) measures the non-convergence of algorithm toward the Pareto optimal frontier:

Table 1: Character comparison of the algorithm

N_2	NPS		ER		G		QM	
	Hybrid GA	NSGA-II						
10	3.80	3.6	0.033	0.0878	65.764	93.46	62.30	37.70
20	6.00	1.3	0.078	0.3500	73.220	85.88	72.13	27.88
30	5.00	1.0	0.230	0.5600	256.600	309.60	58.45	41.54
40	10.00	6.3	0.500	0.6000	401.100	574.70	72.00	26.00
50	9.00	2.3	0.570	0.7200	466.600	824.92	68.80	31.20
60	9.33	4.2	0.600	0.7800	647.440	1023.30	59.22	40.78
70	8.00	3.4	0.673	0.6400	755.880	1219.50	80.35	19.67
80	7.33	4.0	0.750	0.8400	834.200	1345.80	79.53	20.45
90	10.20	4.2	0.700	0.8800	900.200	1424.30	70.11	29.89
100	9.80	3.7	0.800	0.9100	1023.100	1542.10	80.30	197.00

Table 2: Time comparison of the algorithm

N_2	Hybrid GA	NSGA-II
10	12.35	10.55
20	13.83	15.57
30	21.45	30.98
40	33.35	41.55
50	49.34	62.36
60	73.63	98.69
70	85.63	104.62
80	100.22	131.62
90	112.44	140.23
100	131.22	169.34

$$ER = \frac{\sum_{i=1}^m e_i}{m} \tag{4}$$

where, m is the number of Pareto optimal solutions and:

$$e_i = \begin{cases} 0 & \text{if solution } i \in \text{Pareto - optimal frontier} \\ 1 & \text{otherwise} \end{cases} \tag{5}$$

Generational Distance (GD): The distance between the Pareto optimal front and the set of solution can be calculated using this metric:

$$G = \frac{\sum_{i=1}^m d_i}{m} \tag{6}$$

where, d_i is a Euclidean distance between solution i and the closest solution of Pareto optimal front.

Quality Metric (QM) is measured by combining the Pareto optimal solutions of two algorithms. If P_1 and P_2 are Pareto optimal solutions of algorithms A_1 and A_2 , respectively, combined Pareto front have P Pareto optimal solutions which is greater than P_1 and P_2 and less than $P_1 + P_2$. Quality metric of algorithms A_1 and A_2 are represented as P_1/P_2 and P_2/P_1 , respectively.

Table 1 addresses the comparisons between algorithms with respect to four mentioned performance metrics in different instances. It also illustrates the behavior of the algorithms versus problem size. The values shown in the table are average values gained from each instance replications.

Despite NSGA-II's successful application in wide range of optimization problems, it yields inferior results than our algorithm. To further analyze the results, we study the interaction between quality of the algorithms and size of the problem. The presented comparison with NSGA-II proved that our proposed algorithm has the better performance, especially in larger problems than NSGA-II. As illustrated in Table 2, it can be observed that given the same stopping criterion (number of iterations), the bigger the values of N_2 , the more noticeable difference between algorithms values is.

CONCLUSION

There have been many studies in field of inventory problems for multinational food companies, but seldom focused on the uncertain parameter. In this study, a mathematical model that had been presented for this problem was improved here through multi-objective optimization in contrast to most of studies that tries to optimize sum of costs of inventory control systems. We proposed the previous model with two objectives, inventory holding cost and backlogging cost. A hybridized approach of genetic algorithm and electromagnetism-like mechanism was proposed to minimize both costs at the same time. Reinforcing GA with electromagnetism-like mechanism as local search in the algorithm is noteworthy because it creates a good pattern for finding neighborhoods in the algorithm. Through numerical experiments using four different mentioned metrics we've investigated the efficiency our proposed algorithm. Comparison was done against an outstanding meta-heuristic approach which was adapted to this problem, NSGA-II. Outperformance of proposed algorithm than NSGA-II revealed its efficiency and absolute superiority. In our future research, different type of distribution function can be considered for parameters. Lead time can be considered as continues variable. The model can be extended to more than two-level multinational food companies. Other heuristics may produce better results. It is interesting to apply the GAEM on other inventory problems or to the mentioned problem in this study with other objectives.

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