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Supply Chain Planning under Uncertainty using Genetic Algorithms

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Abstract

The solution of a mixed integer linear programming (MILP) model describing the main characteristics of the basic Supply Chain Management (SCM) problem is attained using different procedures. The use of genetic algorithms is proposed as a computing efficient alternative to deal with the combinatorial explosion of alternatives associated to the consideration of different production scenarios, which is a requirement if, as usual, the basic planning information is just estimated with a significant degree of uncertainty.

Keywords: Supply Chain Management, Planning, Stochastic programming, Genetic algorithm.

1. Introduction

For the last decades, different solution strategies have been proposed to solve supply chain planning problems, proposing alternative ways to decide on the procurement of raw materials, production and inventory levels, distribution to the final consumers, etc. These decisions making in the supply chain management scenario become more complex when the consideration of different sources of uncertainty in the models (process, distribution, inventory, demand, competence behavior, etc.) is essential to ensure solution quality or even its practical feasibility.

Previous approaches usually include the separate solution of the master planning, transport planning and distribution planning problems. Nowadays different integrated supply chain planning models can be found to determine the planning actions across the whole supply chain, having as a goal different complex functions related, for example, with the customer satisfaction, cost in a given time period, etc. Also some models have been developed to consider the supply chain planning problem under uncertainty (demand, markets, competition, etc.), most of them in the form of a two stage stochastic programming problem.

Since 1980 there is an important increase of optimization applications in the study of the uncertainty behavior in the chemical systems, production planning and scheduling systems. Dolgui et al 2002, identify different sources of uncertainties along the supply chain (supplying reliability, assembly and manufacturing random lead times; random level and customers demand), the oldest fashion solutions for this problems was the use of safety stocks. Due to this, the academy focuses its efforts to solve the demand uncertainty in the production problems.

Sahinidis 2004, makes an exhaustive revision of the state of the art of the optimization under uncertainty setting as a principal recourse the two stage stochastic programming; the first stage variables are those that have to be decided before known the uncertainty parameters, subsequently, the random scenarios have presented the policy of the model selects the values of the second stage variables.

The use of heuristics/metaheuristics to optimize the decisions associated to the SCM has been widely proposed in recent years, as a way to manage the complexity and size of the resulting problem, which lead to large computational efforts or even to the practical intractability of the resulting models. Some examples are the works of Jayaraman et al 2000 (ant colony optimization ACO), Arnaout et al 2010 (also ACO), Li and Ierapetritou 2007 (simulated annealing - SA), etc. But up to now, the use of metaheuristics has not been exploited to deal with more complex systems, as the ones resulting from the introduction of nonlinearities in the model.

This work analyzes the effect of considering multiple sources of uncertainty (internal and external) to be faced during the decision making associated to this type of two stage stochastic programming model. As usual, the production levels and raw materials procurement needs will be the first stage variables and the transportation and inventory levels will be the second stage variables. The resulting mixed integer linear programming (MILP) model is then solved through different combinations of mathematical programming and metaheuristic procedures. The solutions are compared in order to identify the strategies able to enhance the overall efficiency of the resulting decision making systems, both in terms of solution quality and computational effort.

2. Problem statement

The typical scope of a SC planning problem is to determine the optimal production, inventory and distribution levels in the organization network (production centres, distribution equipments, storage centres, and market places), taking care of the constraints of the raw materials, production and distribution limits. These problems are typically formulated as MILP problems and are solved using mathematical programming tools, heuristics rules, metaheuristics, etc.

This work considers the concourse of several SC's (production sites, storage centres and distribution options) that should face the same market competition for multiple time periods. Limits on the availability of equipment, utilities and manpower are considered and there is also a limited capacity to distribute the products to the nodes of the network. Fixed and variable costs are also associated to the production, distribution and the storage of the products.

2.1. Supply Chain Planning under uncertainties

The model originally proposed by Zamarripa et al 2011 (this model introduce the use of game theory as a decision technique to determine the optimal SC production, inventory and distribution levels in a competitive planning scenario, and model the competition behavior of several SC's as an uncertainty source) has been adopted as a basis for the formulation presented in this paper, and consists in a two stage stochastic programming. Also this work considers as organization network; several SC's (production sites, storage centers and distribution options) that should face the same market competition for multiple time periods, there are some availability of machine and man hours to limit the production and there is a fixed capacity to distribute the products to the nodes of the network, also there are some fixed cost associated to the production, distribution and the storage of the products.

So the problem statement can be summarized as follows

Parameters under uncertainty

Demand. As mentioned before, different scenarios (sc) for the satisfaction of the consumers are usually defined to take into account the overall effect of all exogenous sources of uncertainty. This is usually modeled as a normal probability distribution curve in the products demand. Since all the exogenous sources of uncertainty are considered to be included in the “Demand uncertainty” model, only the Total Cost of the Supply Chain under consideration (*z1*) is needed to optimize the SC behavior.

To minimize the total cost of the Supply Chain under consideration (production, inventory, distribution and backorder costs)

$$\begin{aligned} Min\ z1(g) = & \sum_{i\in I\_G(i,g)} \sum_{n} \sum_{h} a_{in} Q_{inh} (1+e_b)^h \\ & + \sum_{sc} \frac{1}{sc} \sum_{i\in I\_G(i,g)} \sum_{n} \sum_{h} c_{in} W_{scinh} (1+e_b)^h \\ & + \sum_{i\in I\_G(i,g)} \sum_{n} \sum_{h} d_{in} E_{scinh} (1+e_b)^h \\ & + \sum_{i\in I\_G(i,g)} \sum_{n} \sum_{h} \sum_{j} k_{inj} T_{scinhj} (1+e_b)^h \end{aligned}$$

This model approach sets the production as first stage variable, being the second stage variables the storage and distribution levels, to be fixed/optimized once the uncertain parameters (supplying reliability, assembly and manufacturing random lead times; random level and customers demand, etc.) are revealed.

Competence behavior. Actually, the demand to be covered is the result of the uncertain market demand and the demand covered by the competitor SCs, which will depend on the uncertain competitors’ behavior. One way to consider this competition is to assume that the markets get the products from the cheaper SC; then, the second criteria above (“minimize the expenses of the buyers”) can be included in the model as a second objective to be optimized.

Minimize the expenses of the buyers.

$$\begin{aligned} \mathrm{Min\ CST(g)} = & \sum_{\mathrm{i\in I\_G(i,g)}} \sum_{\mathrm{n}} \sum_{\mathrm{h}} \sum_{\mathrm{j}} \mathrm{Ps_{inj} T_{scinhj}\ Prate} \\ & + \sum_{\mathrm{sc}} \frac{1}{\mathrm{sc}} \sum_{\mathrm{i\in I\_G(i,g)}} \sum_{\mathrm{n}} \sum_{\mathrm{h}} \sum_{\mathrm{j}} \mathrm{Ps_{inj} T_{scinhj}\ Disc_{sc}} \end{aligned}$$

The two stage stochastic programming model consists: the first stage variables which are the production, raw materials and the price rate for SC1, and the second stage variables are the inventory, production and distribution tasks for the competitors SCs. In order to manage this specific source of uncertainty, the eventual discount in the price of the products has been introduced as a new “first stage” variable to be optimized and this variable represents the bilinear term in the equation.

Obviously a new challenge appears, related to the evaluation of uncertain behavior of the competitor SCs.
The models are subjected to a series of constraints, some of them are characteristics of the problem itself, and are usually considered linear by nature, even in some cases the need to consider losses, efficiencies, etc. may force the introduction of non-linear terms: material balances (summarize the product shipped from each node of the network to the distribution centres and the final consumers), production capacity (limits for each production site, as associated to the time and resources required to produce the products), storage capacity,

2.2. Genetic Algorithm

Genetic algorithms are adaptive methods generally used to improve (optimize) a fitness function depending of certain number of variables defined in a discontinuous domain. The genetic algorithm implementation used for this work is the one included in the Matlab GA toolbox which only considers linear equality and inequality constraints.

3. Case study

An industrial network (production sites, storage centres and final consumers) is considered as case study to show the results of the proposed model. The factory's strategy is to maintain a constant work force level over the planning horizon, and supply as much product as possible (demanded), playing with inventories and backorders. Two products are considered (P1 and P2) with a market demand of 3 months horizon demanded from 4 distribution centres (Distr1 to Distr4). The information about the considered scenarios, production, etc. and the rest of problem conditions (initial storage levels, transport capacities, etc.) can be found at http://cepima.upc.edu/papers/CompetitiveGA_SCs.pdf (Tables 3-6).

3.1. GA solutions

The genetic algorithm is solved in the demand uncertainty case 20 times, obtaining solutions in 18 of them. In the other 2, initial conditions were not found. In the case of the nonlinear model (competence behavior), 16 solutions were found. The detailed solutions for the stochastic model are given in the web page http://cepima.upc.edu/papers/CompetitiveGA_SCs.pdf (Tables 3-5).

This paper considers 3 different scenarios for the product demand. The solutions for the case related to the demand uncertainty are shown in Table 1. In addition, Table 2 shows the summary solutions obtained for the nonlinear model that is solved under competitive uncertainty. In the competitive case the solution obtained for the discount rate is 0.3 % of discount for the products of SC1, to compete with the scenarios of the discount rate of SC2 (0.1, 0.2 and 03 %).

Table 1. Solutions for the demand uncertainty problem.

	Scenario 1		Scenario 2		Scenario 3	
	SC1	SC2	SC1	SC2	SC1	SC2
Cost	382 081	210 663	532941	269 572	649 097	363 342
Total cost	592 744		802 513		1 012 439	
Benefit	1 744 418	1 036 129	2 384 058	1 311 079	2 894 902	1 714 612

Table 2. Solutions for the competitive case.

	Scenario 1		Scenario 2		Scenario 3	
	SC1	SC2	SC1		SC1	SC2
Cost	518 697	533 140	519 813	538 819	519 745	543 649
Total cost	1 051 838		1 058 633		1 063 393	
Benefit	2 071 424	2 062 671	2 218 113	2 202 954	2 321 976	2 264 234

The performance of the results are dominated by the most important constrain in the model that is the budget capacity, also is important to remark that the same quantity demanded for each scenario is considered.

4. Conclusions

Genetic algorithms have increasingly been applied in engineering in the past decade, due to it is considered as tool for optimization in engineering design. This work introduces the use of genetic algorithms to solve complex optimization problems, manage the uncertainty in typical industrial scenarios. In this context, this work uses the GA as an optimization tool for decision making to determine the optimal production, inventory level and distribution in the Supply Chain planning problem under uncertainty. A MILP stochastic approach has been solved using a generic genetic algorithm of Matlab obtaining improved solutions.

Since the solution obtained has a good performance in time/quality of the results for the proposed model. This work determines that new schemes of genetic algorithms are an opportunity for future extensions of its capability for more complex models as recursive stochastic approaches and nonlinear models.

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