A NOVEL AGENT-BASED APPROACH FOR SUPPLY CHAIN RETROFITTING

Fernando D. Mele, Gonzalo Guillén, Francisco Urbano, Antonio Espuña and Luis Puigjaner*
Universitat Politècnica de Catalunya
Diagonal 647, E-08028, Barcelona, Spain

Abstract

Supply Chain Management involves the material and information management through the entire supply chain (SC), from the initial suppliers to the end users, going through manufacturing and distribution facilities. The main objective is to achieve suitable economic performance taking into account the large amount of constraints featuring this kind of problems. In this work, decisions that have a long lasting effect on the firm such as the design and retrofit decisions have been considered. The decision variables are the storage sites capacities, and the flows and production rates of materials to be produced/transformed at each node, to meet the demand requirements. The retrofitting tasks are accomplished by using a SC agent-oriented simulation model, which includes each entity belonging to the SC as an independent agent and represents in a functional way the interactions between the components of the chain. This is a suitable tool for evaluating the impact that possible design decisions could have in the network. The starting point is a set of possible design options for the existing SC. For each design alternative a performance index is obtained through the agent-based system, which looks for the best value of the operational variables associated to the resulting network. This approach shows that similar configurations can lead to considerably different values of the SC performance index.

Keywords

Supply Chain Management, dynamic simulation, agent system, retrofitting.

Introduction

The objective of this work is to solve a strategic Supply Chain Management (SCM) problem without neglecting the existing relationships between the strategic variables and the operational ones.

Supply Chains (SCs) are made up of several elements whose behaviour affects the performance of the entire system (Perea-López et al., 2000) since the relationships that constitute this system are not simple at all. Then SCs, as many real-world systems, cannot be evaluated analytically using mathematical methods to obtain exact information on questions of interest, being therefore more appropriate to consider the SC by means of dynamic simulation.

Uncertainties also contribute to the complexity of the SCM. In addition to none stationary random demands at each retailer, equipment breakdown and processing time uncertainty greatly influence the SC operation. It should be obvious that a pure mathematical programming and pure simulation can not satisfactorily model and even less solve such a complex SC.

Simulation is one of the best means for analysing SCs because of its capability for handling variability. Although managers were able to try ‘what if’ scenarios with input data and simulation to obtain potential solutions, an optimisation procedure helps to eliminate the need for random trial and error (Wan et al., 2003).

* To whom all correspondence should be addressed.

This study presents an approach for SCM that considers the event-driven nature of real SCs through a dynamic simulation of a set of independent agents. Moreover, the agent-system includes a coordinator agent which manages the information between the other agents, allowing to study the impact of different strategic variable settings as well as other decisions currently taken by managers (Julka et al., 2002).

Once the value of the strategic variables is chosen, in order to avoid the exhaustive inspection of all the possible production scenarios to find the best one, this work presents Genetic Algorithms (GAs) as a useful tool to identify the operational parameter values that optimise the SC performance through an oriented search. GAs are a vast class of stochastic algorithms for optimisation that are based on the mechanisms of natural selection and genetics followed by living beings.

This procedure in two stages allows managers to make strategic decisions in a reliable manner because a systematic analysis has been done on the consequences previous to these decisions.

Motivating Example

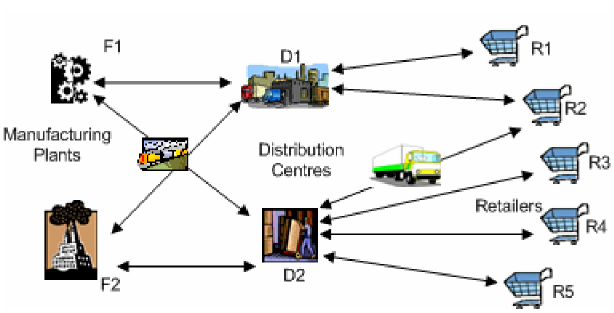

Figure 1. Supply chain motivating example.

Let us consider a SC system consisting of nine interconnected entities shown in Figure 1. There are two plants (F1 and F2), two distribution centres (D1 and D2) and five retailers (R1 to R5). Raw materials enter the plants and the three different products elaborated (A, B and C) are distributed by the rest of the chain. The plants supply the distribution centres whereas the distribution centres supplies the retailers. Therefore, the material flow will move from the plants to the customers and the information flow (ordering flow) will do in the opposite direction. Details about the operational scheduling at plants F1 and F2 are not considered because it is widely accepted that in practice these decisions are local and belong to a more detailed level of analysis.

In this approach, the demand has been modelled as a set of events distributed over the time horizon of the study, each of these events having an associated amount of material and time of occurrence. Both parameters, the amounts and the inter-arrival intervals between events, are time-variant. The material quantity of each demand event follows either a uniform or a normal distribution law. Instead, a Poisson process has been used to model the inter-arrival times between orders, as it is usually accepted (Law and Kelton, 1991). However, other models could have been used.

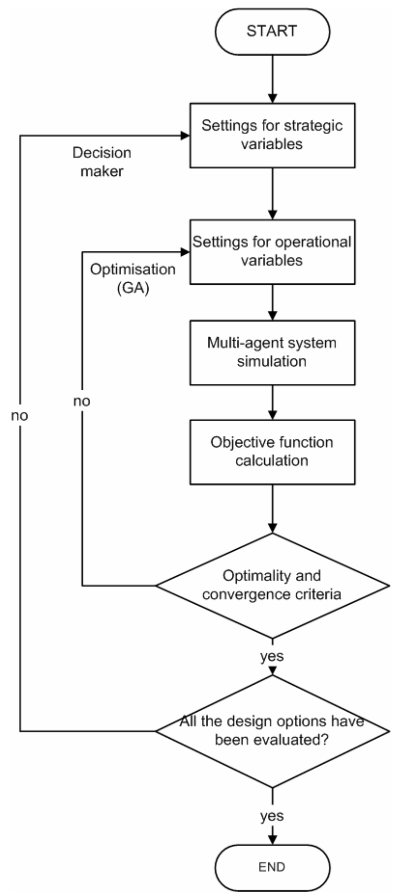

Figure 2. Decision-making procedure.

An important issue that determines the system behaviour is the implemented inventory control law. An inventory policy is a set of rules that states when should a replenishment order be placed and/or how large should the replenishment order be. There are a number of possible inventory control systems (Silver, Pyke and Peterson, 1998). In this case, a periodic revision strategy has been implemented at the distribution centres, being R the time period between two consecutive inventory reviews. Every R time units, the inventory position Inv is checked. If Inv is below the reorder point s, a replenishment quantity $u = S - Inv$ is ordered to raise the stock level to S. If the position is above s, nothing is done until the next review. Thus, the strategy has three parameters whose values have to be determined: R, S and s. For the retailers, a similar but continuous revision strategy has been applied.

Proposed Approach

So as to analyse the behaviour of the system and make comparisons between the strategies utilised, a performance index has been defined: total profit (*profit*). This index measures the operational cost of the SC over the simulation time horizon. It basically considers revenues, and storage, manufacturing and transportation costs.

The revenues (*revenues*) are calculated according to:

$$revenues = \sum_t \sum_k U_{k,t} S_{k,t} \tag{1}$$

where t represents each simulation step, $S_{k,t}$ is the unit price at retailer node k and time t, and $U_{k,t}$ is the amount sold at retailer entity k and time t.

The storage cost IC accounts for the opportunity cost related to the value of the inventoried material, the expenses incurred in running a warehouse, handling and accounting costs, the costs of special storage requirements, and so on:

$$IC = \sum_t \sum_k I_{k,t} IC_{k,t} \tag{2}$$

where $IC_{k,t}$ is the unit holding inventory cost at entity k and time t, and $I_{k,t}$ is the inventory level at the entity k in the SC and at time t.

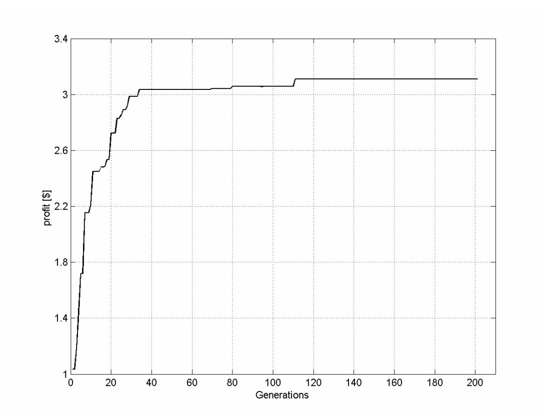

Figure 3. Average objective function evolution during the GA run.

The manufacturing cost MC is calculated as:

$$MC = \sum_t \sum_k U_{k,t} MC_{k,t} \tag{3}$$

where $MC_{k,t}$ is the unit manufacturing cost at entity k and time t, and $U_{k,t}$ is the amount produced at a manufacturer entity k and time t.

The transportation cost TrC is calculated as:

$$TrC = \sum_t \sum_k U_{k,t} TrC_{k,t} \tag{4}$$

where $TrC_{k,t}$ is the unit transportation cost at entity k and time t, and $U_{k,t}$ is the material delivery quantity at every entity k and time t.

Finally, the total profit over the time horizon is:

$$profit = revenues - (IC + MC + TrC) \tag{5}$$

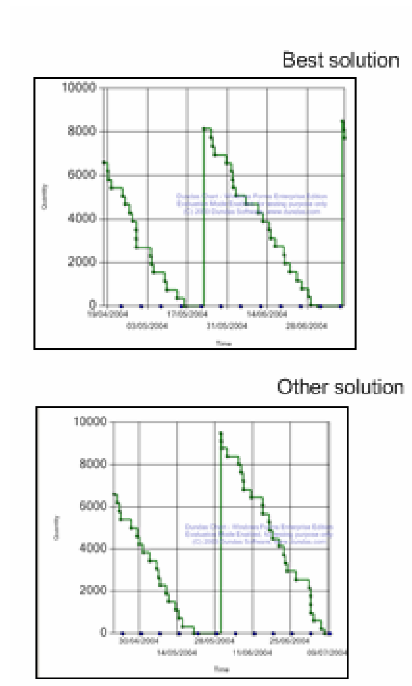

Figure 4. Inventory level evolution at D1 during the agent-system simulation.

As already commented, two kinds of variables have been taken into account: at strategic level, the variables are the capacities of the storage sites, whose values define the design alternatives; the second group of variables belongs to the tactical and operational level and include the quantities manufactured in the factories or transported between nodes, as well as the values for the inventory policy parameters, being these parameters the variables manipulated by the optimisation system, GA. Therefore, the decision-making procedure is as follows (Figure 2): Given a number of possible design options for an existing SC, for each alternative, by using GA, the system looks for those values of the operational variables that produce the best profit values associated to the resulting network. GAs provide an oriented search mechanism avoiding resource consuming exhaustive exploration.

Results

In this case, three sets of different capacity values for the distribution centres have been considered, which define three different strategic decisions or, in other words, three configurations to analyse. By assigning the value of one configuration to the multi-agent system, a GA properly designed and tuned has been run. The GA handles 27 variables: the *s* and *R* inventory parameters at the distribution centres (12 variables), and the *s* parameters at the retailers (15 variables). Real-valued encoding and maximum number of generations as termination criterion have been used. Figure 3 shows the evolution of the objective function *profit* through 200 generations. The curve represents the average value of *profit* for about ten GA runs and a variable number of sampled scenarios that has been considered at each generation in order to face uncertainty. Repeating the same procedure for each of the remaining configurations, the decision maker can determine which the best strategic decision is, depending on the maximum value of expected *profit* in the time horizon of the analysis. Figure 4 shows the inventory level evolution at distribution centre D1 for the best solution and for a solution found using other configuration, as it appears in the graphical user interface of the multi-agent system.

The planning horizon has been set in one year with daily precision for each simulation run. The multi-agent system has been developed in C# language and operates in an AMDK6 computer, 2.16 GHz, 512 MB, and the GA has been coded using *MATLAB*® (Chipperfield et al., 1994). The CPU time required for each configuration has been a few hours in all the cases tested. It is important to notice that this time depends on the number of simulation runs to be made, and then on certain tuning parameters of the GA such as the number of generations and the number of individuals in each population.

Conclusions

In this work, strategic decisions have been made taking into account their impact at a lower level. The SC operational behaviour has been simulated by using a dynamic multi-agent model. Some of the parameters that feature this behaviour have been obtained by using GAs as improving/optimisation technique. This approach has shown that different configurations, apparently similar between them, lead to considerably different values of the SC performance indexes.

The most relevant contribution of this study is the methodology employed. The GA application clearly shows that other optimisation techniques would be difficult to use in solving a problem of such combinatorial complexity. Perhaps the main drawback on using GAs is the need of a sensitivity analysis to study the influence of the tuning parameters. This procedure obtains high quality solutions in reasonable amount of time even if they are not the optimal solutions in general. This combined strategy greatly enhances the usefulness of the simulation approach. Finally, the exhaustive enumeration of different configurations is a first step to develop a cleverer optimisation strategy in the future.

The computational cost associated to the proposed approach depends on the problem dimension and its level of complexity. The total number of model simulations is a function of the population size and the number of iterations required in the optimisation. However, the time requirement is reasonable for such a long-term decision.

On the other hand, the use of multi-agent systems allows modelling SCs in a very realistic manner particularly taking into account important aspects such as uncertainty.

Acknowledgements

Financial support received from the Spanish “Ministerio de Educación, Cultura y Deporte” (FPU programs), “Generalitat de Catalunya” (FI programs) and European Community (project VIP-NET-G1RDT-CT-2000-00318) is fully appreciated. Besides, financial support from GICASA-D (I0353) and OCCASION (DPI2002-00856) projects is gratefully acknowledged.

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