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Supply Chain Management through a combined simulation-optimisation approach

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Abstract

Supply Chain Management (SCM) involves the decision-making related to resources management through the entire Supply Chain (SC), from the initial suppliers to the final customers (Shapiro, 2001). Many of present SCM approaches consider operations research optimisation models, which often assume centralised management and are inadequate to efficiently undertake SC dynamics and uncertainty. On the contrary, simulation-based approaches are able to deal with these two issues but they are not appropriate to optimise the SC operation. In this work, a combined framework, which offers the advantages of simulation and optimisation, is proposed and a methodology is presented in order to explicitly include not only the traditional economic criteria, but also the other concerns: environment, safety, flexibility, customer satisfaction, etc. In this way, the simultaneous consideration of multiple criteria provides a way to further explore the necessary trade-offs upon which decision-making should be based. The results so far obtained are very promising.

Keywords: LCA, multiobjective optimisation, SCM.

1. Introduction

Within the Supply Chain Management (SCM) scope, it is possible to identify two kinds of managing modes: push systems or planning-based approaches, which are centralised approaches with global information sharing, and pull systems or demand-driven approaches that can be either centralised or decentralised with a variable degree of information sharing.

Many of present SCM approaches belong to the first group, considering operations research optimisation models and solving them through mathematical programming methods. Usually, these models assume centralised management and they are not able to efficiently deal with SC dynamics and uncertainty. Otherwise, within the second group, simulation-based approaches do recognise the role of uncertainties in SCM, but lack of optimisation aptitudes is their major shortcoming (Wan et al., 2003).

In this work, a combined framework, which offers the advantages of simulation and optimisation, is proposed. The simulation-optimisation procedure is aimed to support the decision-making process at a tactical level determining the policies to implement

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along the simulation time horizon. Additionally, the methodology presented is able to explicitly include not only the traditional economic criteria, but also other concerns such as environment, quality, customer service, demand satisfaction, etc. Particular emphasis has been placed on environmental considerations on the basis of Life-Cycle Assessment (LCA) principles, which consider environmental issues as an integral part of the SCM problem. On the contrary, most of environmental developments tend to reduce waste generation, without explicitly accounting for wastes associated with inputs to the process and emissions that occur during acquisition of natural resources, raw material production, and use and final disposal of the product. Under these circumstances, the simultaneous consideration of multiple criteria provides a way to further explore the necessary trade-offs upon which decision-making should be based (Hugo and Pistikopoulos, 2003). Validation of the proposed approach methodology has been done through a case study and results obtained are discussed.

2. Methodology

As it can be seen in Figure 1, in the core of the methodology there is an agent-based simulator module that acts as an execution system responding to uncertainties through local dispatching rules, invoking when necessary local optimisation modules, and solving conflicts through message exchange.

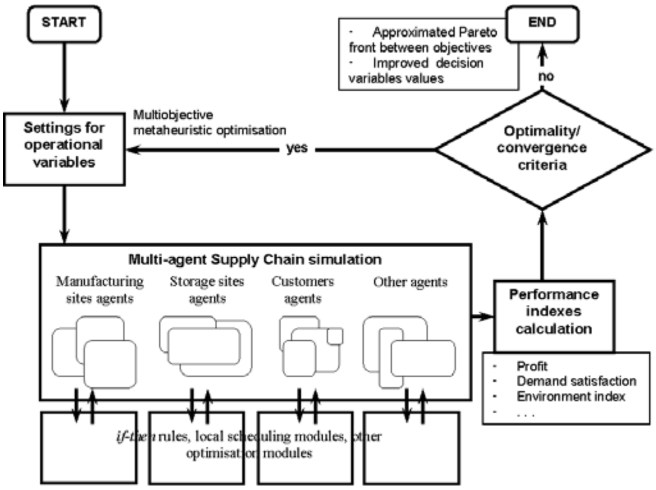

Figure 1. GA-based strategy

The simulator receives a set of input values (decision variables) and then, by emulating the system dynamics, provides valuable information (performance measures) to an external optimisation module. The optimisation, which in our case has been implemented based on genetic algorithms (GA), utilises the information from the simulator and proposes new trial solutions for the decision variables trying to improve the performance of the entire supply chain (SC). This loop goes on until the optimality/convergence criteria are reached. As a result, an approximation of the set of trade-off solutions, commonly referred to as the efficient, non-inferior or Pareto set of solutions, is obtained. A given value of the decision variables is Pareto optimal if and only if there exist no other feasible solution that yields better in all the objectives simultaneously. Therefore, the decision maker obtains not only one solution, but a set of alternatives from which he/she can then further explore interesting trade-offs.

There are two reasons for using metaheuristics (GA in this work) in the optimisation tasks. Firstly, this class of methods clearly shows that they are appropriate to address a problem of such combinatorial complexity in which the model is very difficult to be described through explicit differential or algebraic equations. Secondly, metaheuristic multiobjective algorithms have the advantage that they can potentially obtain Pareto optimal solutions also from the non-concave parts of the Pareto front in one single run, most of times clearly outperforming the strategies using mathematical programming techniques.

In the specific case to be presented in this paper, the multiobjective GA works as follows. An initial population consisting of a number of chromosomes or individuals is created and evaluated in all the objectives through the corresponding simulation runs. Each individual encodes all the decisions variables for the problem. From the initial population, the initial Pareto-optimal set of solutions is isolated. Then a fitness value is assigned to each solution in the current population on the basis of its non-dominance level. Pairs of solutions are selected according their fitness value and then recombined and mutated. New individuals are inserted in the old population and the Pareto-optimal set is updated. The procedure is repeated until the maximum number of generations is reached. The GA strategy has been considerably improved on the basis of elitism mechanisms and the utilisation of neural networks metamodels which discard the low-performance individuals avoiding unnecessary simulation runs.

The performance measures include a traditional economic indicator, the total profit, and a set of environmental impact indicators calculated according to the LCA principles. The total profit measures the operational profit of the SC over the simulation time horizon. It basically considers revenues, and storage, manufacturing and transport costs. With regard to the environmental impact indexes, they are based on the third phase of the LCA methodology, Life-Cycle Impact Assessment, as defined in the ISO 14042. Taken from Heijungs (1992), the indicators incorporated in the model are: enhancement of the greenhouse effect (GHE), acidification (Ac) and biochemical demand of oxygen (BDO).

In general, the methodology enables to deal with many objective functions, then, the multiobjective problem can be posed as:

$$\min U \quad \left\{ \begin{array}{l} f_1(x) = -profit \\ f_2(x) = environmental\ index \\ \qquad \dots \\ f_i(x) = \dots \\ \qquad \dots \end{array} \right\}$$

where U is the set of objective functions and $f_i(x)$ is the i-th objective function depending on the vector of decision variables x.

3. Case study

3.1. Scenario description

Let us consider the SC system consisting of nine interconnected entities shown in Figure 2. 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 through the rest of the chain. Therefore, the material flow will move from the plants to the customers and the ordering flow will do in the opposite direction. Production and transportation times are defined as random parameters. Details about the operational scheduling at plants are not considered because it is accepted that in practice these decisions are local and belong to a more detailed level of analysis.

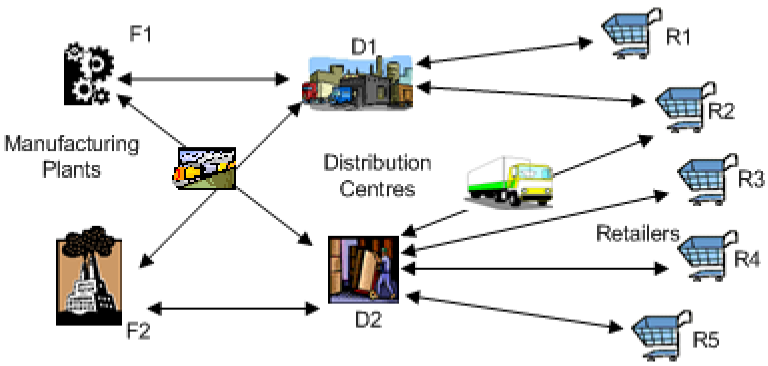

Figure 2.SC motivating case study.

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. For this example, the material quantity of each demand event has been selected according to a normal distribution law. Instead, a Poisson process has been used to emulate the inter-arrival times between orders, as it is usually accepted (Law and Kelton, 1991).

An important issue that determines the system behaviour is the implemented inventory control law. In this case, a periodic revision strategy has been implemented at the factories and 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 adapted.

A number of input parameters have been also set to apply the economic and environmental model. For instance, for profit calculation, unit product prices as well as unit costs for raw materials, utilities, production, storage and transportation, have been defined. Regarding the environmental indexes calculations, utilities and raw material consumption and emissions for each process and product have been used.

After setting the value of all the input parameters for the multi-agent simulator, the GA-based strategy properly designed and tuned has been applied to find those decision variables values that optimise simultaneously all the objectives posed. The planning horizon has been set to one week with precision of ½ hour for each simulation run. In this work, the GA handles 22 decision variables that characterise the inventory replenishment strategy: the *s*, *S* and *R* inventory parameters at the factories and distribution centres (12 variables), and the *s* and *S* parameters at the retailers (10 variables). Real-valued encoding for the variables and maximum number of generations as termination criterion have been used.

3.2. Results

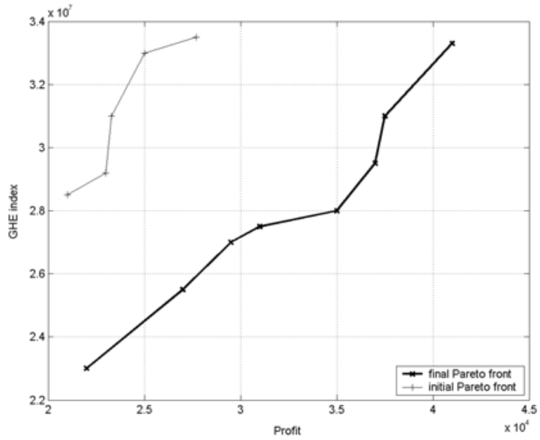

Figure 3.Pareto front for two objectives

In Figure 3, an approximation of the Pareto-front involving the total profit and the GHE environmental index is depicted.
Figure 4 shows the inventory level evolution at distribution centre D1 for two different points on the Pareto front, as it appears in the graphical user interface of the multi-agent system.
The CPU time required for the algorithm execution varies from 20 minutes to 2 hours in the cases tested. Although the quality of the solutions may be improved by increasing the iterations number, the algorithms are able to give a feasible and acceptable solution set in a fair period of time. It is important to notice that this time depends on the number of simulation runs to be made during each algorithm execution, and then on the tuning parameters of the GA-based strategy. 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*®.

4. Conclusions

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 a GA-based method as improving/optimisation technique.
The most relevant contribution of this study is the methodology employed. The GA application coupled with the use of metamodels clearly shows that other optimisation techniques would be difficult to use in solving a problem of such combinatorial

complexity. Moreover, the proposed approach obtains high quality solutions with reasonable computation effort even if optimality can not be guaranteed. Perhaps the main drawback on using GAs is the need of a sensitivity analysis to study the influence of the tuning parameters.

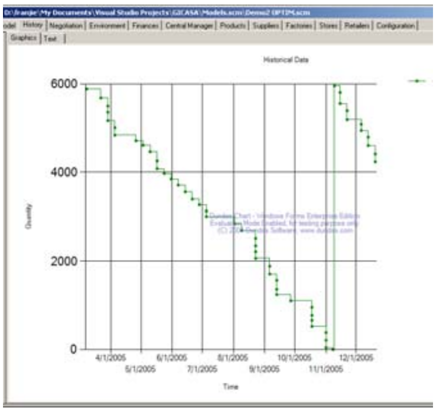

Figure 4. Inventory level at D1 for one point on the Pareto front.

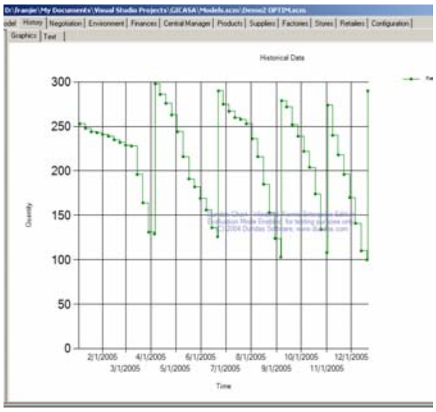

Figure 5. Inventory level at D1 for another point on the Pareto front..

On the other hand, the methodology provides a good platform for exploring the inherent conflicts between the traditional economics objectives and other important socio-economic factors. The consideration of environmental issues into the optimisation-simulation framework at a tactical level is a novel and promising contribution to the SCM state-of-the-art.

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