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An agent-based approach for supply chain retrofitting under uncertainty

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Abstract

In this work, decisions that have a long lasting effect on the SC such as the design and retrofit of a production/distribution network are considered. The retrofitting tasks are accomplished by using a SC agent-oriented simulation system, which model each entity belonging to the SC as an independent agent and represents in a functional way the interactions between the components of the SC. 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 framework, which is coupled with a genetic algorithm (GA) that looks for the best value of the operational variables associated to the resulting network.

Keywords: Retrofit, SCM, agent, discrete-event simulation

1. Introduction

The concept of Supply Chain Management (SCM), which appeared in the early 90s, has recently raised a lot of interest. A lot of attempts have been made to model and optimise the SC behaviour, currently existing a big amount of deterministic and stochastic derived approaches.
Supply Chains (SCs) are made up of several elements whose behaviour affects the performance of the entire system (Perea-López et al., 2000) being the relationships that constitute this system 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 substantially contribute to the complexity of the SCM. In addition to none stationary random demands at each retailer, equipment breakdowns and uncertainty in processing times greatly influence the SC operation.

1.1 Simulation approaches for SCM

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

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data and simulation to obtain potential solutions, an optimisation procedure helps to eliminate the need for random trial and error (Wan et al., 2003).
In distributed artificial intelligence (DAI), an agent is defined as a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives. SCM problems are both distributive in nature, and require extensive intelligent decision-making. Thus, in the last few years, multi-agent systems have been a preferred tool for solving SC problems, and several approaches using multi-agent systems have been proposed (Julka et al., 2002). Such architectures are particularly recommended for modelling complex networks which are driven by a combination of heuristics rules and mathematical programming tools. Moreover, this kind of systems can also handle the perturbations caused by stochastic events in the supply chain.
This study presents an approach for SC design and retrofit that considers the event-driven nature of real SCs through a dynamic simulation of a set of independent agents. Each agent represents one SC entity or node. The agents store the real-world SC data and emulate the behaviour of the entities by means of a set of specific algorithms based on a state-transition description that they have implemented. The system includes a "central" agent that coordinates the activities among the rest of the agents and manages the information between them. The multi-agent system able to carry out the discrete-event simulations of the SC is coupled with Genetic Algorithms (GAs) as a useful tool that identifies better values for the operational variables associated to a given network. This procedure in two stages allows managers to make strategic decisions in a reliable manner. The main contribution of such approach in comparison with previous methodologies is the combination of the multi-agent system (discrete-event simulation) with an optimization algorithm. The former allows a realistic modelling of the SC and also handles uncertainty, while the latter improves the performance of the overall network regarding inventory control policies, transport and production decisions.

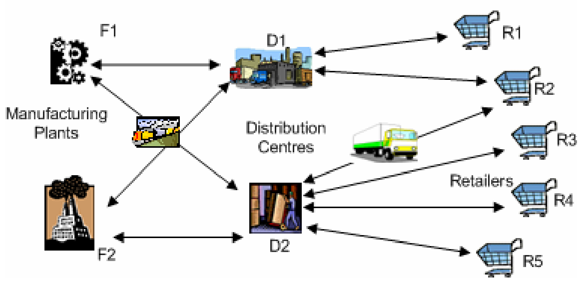

Figure 1. Structure of the case study

2. Motivating example

Let us consider a SC consisting of nine interconnected entities as the one shown in Figure 1. The network comprises two plants (F1 and F2), two distribution centres (D1 and D2) and five retailers (R1 to R5). The plants manufacture final products A, B and C from raw materials provided by external suppliers. Final products are transported from plants to warehouses and from warehouses to retailers where they become available to customers. In such SC, there is a material flow that moves from the plants to the

customers and an information flow (ordering flow) which does it in the opposite direction.
It is supposed that the demand of the system can be modelled as a set of events distributed over the time horizon under study, each of them involving an associated amount of material and time of occurrence. Both parameters, the amounts and the inter-arrival intervals between events, are assumed to be time-variant. The material quantity of each demand event follows either a uniform or a normal distribution law, while a Poisson probability distribution is used to model the inter-arrival times between orders (Law and Kelton, 1991). Moreover, processing and transport times are also assumed to follow normal probability distributions.
A periodic revision strategy is 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 the value of 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 is considered.
The retrofit of the above described SC could be in principle addressed by means of mathematical programming tools. However, this would lead to high computation times owing to the scale and complexity of the resulting formulation. On the one hand, a global optimisation approach, which requires an extensive computation effort, would be necessary for optimizing the inventory control policies applied in the warehouses. On the other hand, a complex multi-stage stochastic formulation requiring also high computation times, should be applied to provide a 'walk through the timeline' concerning the decisions to be taken under uncertainty in the demand, the processing and the transport times.

3. Proposed Approach

The overall SC design problem is hierarchically-decomposed into two levels, a higher strategic level and a lower tactic/operational one. This leads to tractable problems and avoids monolithic formulations that require an extensive computation time and become impossible to solve in the case of large-scale SC problems. At the strategic level, the capacities of the plants and storage sites are considered. At the lower level, which comprises tactical and operational decisions, the quantities manufactured in the factories, transported between nodes, and the values for the parameters of the inventory control policies, are computed by applying a genetic GA on the multi-agent system.
The overall algorithm is depicted in Figure 2. In first place, it is necessary to provide a set of design candidates from which the final configuration should be selected. A Monte Carlo sampling is next performed over the probability distributions that characterise the uncertain parameters (demand, processing and transport times), thus generating a set of scenarios with given probability of occurrence. For each SC alternative a GA, that provides an oriented search mechanism that decreases the computation effort required by rigorous optimization techniques, is applied for optimizing the operational variables associated to the selected configuration. Therefore, the fitness function is obtained by running for each scenario generated by Monte Carlo sampling, i.e. for each set of values

of the uncertain parameters, a discrete-event simulation and computing the average value of the objective function, in this case profit, over the entire range of them. The different configurations are finally compared in terms of the expected total profit (*profit*) associated to the best set of their operative variables computed by the GA.

The profit index computed for each configuration measures the operational cost of the SC achieved over the simulation time horizon and basically considers revenues, storage, manufacturing, and transportation costs. Unlike other works in the literature, we assume that some of the demand can actually be left unsatisfied because of limited production capacity.

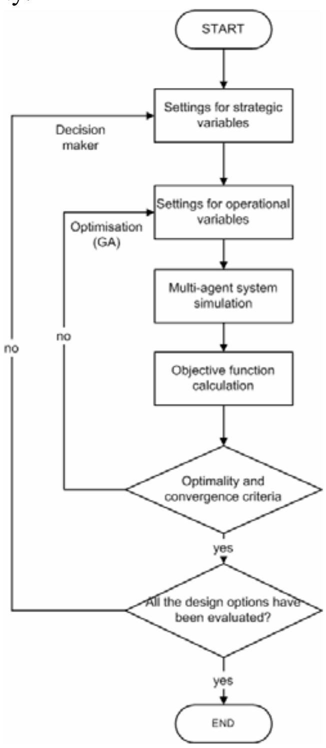

Figure 2. Decision-making procedure

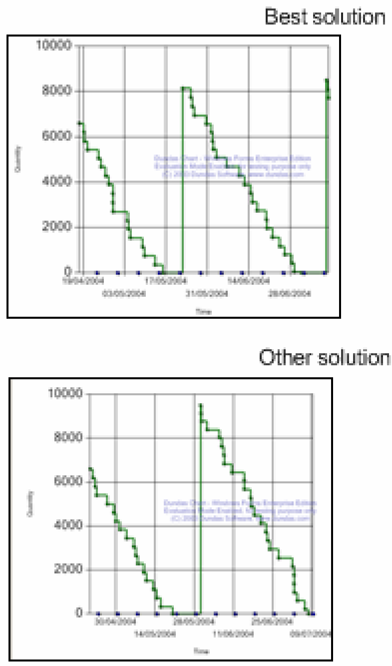

Figure 3. Inventory level evolution at D1

The revenues (*revenues*) are computed from the sales of products:

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

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 and also for the expenses incurred in running a warehouse:

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

In this equation, $IC_{k,t}$ 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.

The manufacturing cost MC is calculated by means of equation (3):

$$MC = \sum_t \sum_k U_{k,t} MC_{k,t} \quad (3)$$

where $MC_{k,t}$ represents 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.
Regarding the transportation cost (TrC), these are computed by applying equation (4):

$$TrC = \sum_t \sum_k U_{k,t} TrC_{k,t} \quad (4)$$

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 given by:

$$profit = revenues - (IC + MC + TrC) \quad (5)$$

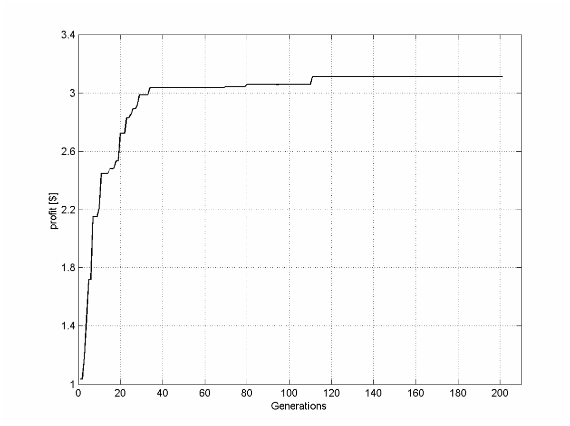

Figure 4. Average objective function evolution during the GA run.

4. Results

The case study presented before is solved by applying the proposed strategy. Three sets of different capacity values for the distribution centres are evaluated. For each value of the design variables, a GA properly designed and tuned is run over the discrete-event simulator. 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 are used. A one year horizon of time is considered with daily precision for each simulation run. The multi-agent system has been developed in C# language and has been operated in an AMDK6 computer, 2.16 GHz, 512 MB. Concerning the implementation of the GA applied in this work, it should be mention that this has been coded using *MATLAB*® (Chipperfield et al., 1994). With regard to the CPU time, for each configuration only a few hours are required to evaluate the expected profit. It is also important to notice that this time depends on the number of simulation runs to be made, which is given by certain tuning parameters of the GA such as the number of generations and the number of individuals in each population.
Figure 3 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. Figure 4 shows the evolution of the objective function (expected *profit*) through 200 generations. The curve represents the average value of *profit* for about ten GA runs. Repeating the same procedure for each of the remaining configurations, the decision maker can determine the best strategic decision to be implemented in the network in terms of the resulting expected *profit* achieved within the time horizon of the analysis.

5. Conclusions

In this work, the SC design and retrofit problem has been addressed. Strategic decisions have been made taking into account their impact at a lower level. The performance of each SC configuration has been assessed through a dynamic multi-agent model that has been coupled with GAs in order to optimise the operation variables associated to each design candidate.
The computation cost of the proposed approach depends on the problem dimension and its level of complexity. However, the time requirement is reasonable for such a long-term decision. On the other hand, the use of multi-agent systems allows modelling in a very realistic manner complex SCs, particularly those which imply the combined use of heuristic rules and mathematical programming tools and operate under uncertainty.

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