

12-31-2004

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## Recommended Citation

Finnie, Gavin and Barker, Jeffrey, "Learning Agents for Dynamic Supply Network Management" (2004). *AMCIS 2004 Proceedings*. Paper 209.  
<http://aisel.aisnet.org/amcis2004/209>

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# Learning Agents for Dynamic Supply Network Management

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## ABSTRACT

Supply networks rely increasingly on dynamic information flow between organisations. Providing intelligent automated collaboration requires learning capability i.e. an agent should be capable of adapting behaviour as conditions change. This paper proposes a scalable multi-agent system which uses case-based reasoning as a framework for part of its intelligence. Agents operate at two levels: an inter-enterprise level and a product/logistics level. Tests with a simulated system for buyer side operations show that such a buyer agent is capable of learning the best supplier and of adapting if supply conditions change e.g. if average delivery times deteriorate or a new supplier enters the market.

## KEYWORDS

Agents, Case-Based Reasoning, Supply Chain Management.

## INTRODUCTION

Supply chains/networks can be of arbitrary size and complexity. In electronic business, information flows at high speed and organisations must be capable of rapid reaction and reorganisation in response to dynamic information relating to any changes in constraints or conditions (McClellan, 2003).

This paper describes an agent-based approach for intelligent automation of inter-organisational interaction in the supply chain. Any organisation will have some history of dealing with problems relating to orders, perturbations in the supply chain and the solutions applied, as well as formal processes for dealing with these. To automate the response to any stochastic event, software must be capable of reacting as one would expect a human agent to do. Humans often respond by working from and possibly adapting solutions to previously encountered situations similar to the problem i.e. a process of reasoning from prior cases or Case-Based Reasoning (CBR). A model is proposed where the interface between an organisation and the outside world is controlled by a number of agents, each of which acquires at least part of its intelligence by applying CBR.

## PRIOR WORK

Agents for the management of scheduling and supply chains have been discussed for a number of years, with most work being intra-organisational rather than inter-organisational. Early research by Beck and Fox (1994) uses a mediating agent with a global perspective and gathers information on commitments from other agents when there is any event which disrupts supply. More recent work (Fox, Barbuceanu and Teigen, 2000) defines an agent based framework which simulates the supply chain with agents at each station. Huhns and Stephens (2001) describe a multi-agent system where each agent manages a part of the B2B supply-chain for the company. Sycara and Zeng (1999) describe an agent-based approach to optimizing an inventory model under cost and lead-time constraints. The AARIA project (Parunak, Baker and Clark 2001) has been a major investigation of agents in supply chain management. MASCOT (Sadeh-Konieczpol, Hildum, Kjenstad and Tseng, 2001) is a multi-agent system (MAS) for dynamic information processing in supply chains. The current research is focused on inter-organisational supply network issues and differs from prior work by attempting to incorporate a dynamic learning capability. Earlier work in this field used more static approaches e.g. rule based reasoning.

Several learning approaches have been considered in MAS e.g. reinforcement learning (Arai, Sycara and Payne, 2000) and neural networks (Wermter, Arevian and Panchev, 2000). This research proposes using case-based reasoning as a learning paradigm so that agents can learn and respond dynamically to environmental changes.

Case based reasoning (CBR) has been used in a variety of intra-organisational scheduling problems, particularly for reactive scheduling where there is a need to adapt schedules. Dorn (1999) used case based reasoning supported by fuzzy reasoning to adapt old schedule models. Cunningham and Smyth (1996) devised an approach that reuses components of known good schedules which are stored in a case base. The current research looks at scheduling within the entire supply network.

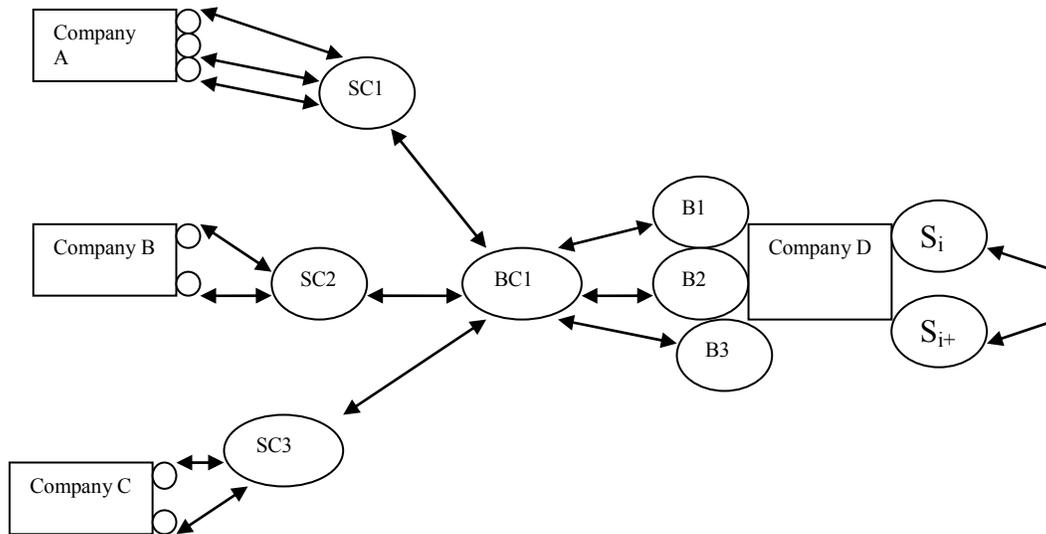


Figure1: The Multi-Agent Model

Corchado and co-researchers (2001) have proposed the use of CBR to allow agents to replan their intentions in real time, using the BDI (Belief-Desires-Intentions) framework for the agents. Olivia, Chang, Enguix and Ghose (1999) propose the use of CBR for BDI agents for intelligent search on the web. Finnie and Sun (2003) have considered a MAS in which only those agents that require learning have CBR capability. We are building on earlier work by considering supply network applications.

### THE AGENT MODEL

The model proposes two level of operation. The first is at a transaction/enterprise level (the buyer and supplier control agents) which requires dynamic CRM information, user profiling and will eventually need a bargaining capability. The second is at a logistics/manufacturing level (the buyer and supplier agents) which deals with product transfer and requires learning cost-effective buyer/supplier dealings for specific products. Agents operating at the top level are middle agents (Decker, Sycara and Williamson, 1997) which “support the flow of information in electronic commerce, assisting in locating and connecting the ultimate information provider with the ultimate information requester.”

The interface between an organisation and its suppliers will be controlled by a number of buyer agents, each of which will have access to CBR to provide intelligent processing of supply needs on the basis of prior experience. Coordinating and controlling the activation and operation of the buyer agents is a buyer interface control agent which again uses CBR to select a suitable strategy for finding all components required for a particular product i.e. it will review the bill of materials, decide on suitable suppliers and set up agents to control the interaction with each supplier. There is one buyer interface agent for each organisation. It will also have responsibility for ensuring that all components are suitably sourced i.e. a failure procedure must be in place to backtrack if a specific supplier fails to ensure supply.

At the supplier interface, there will be one seller agent for each product type. A request to purchase may itself trigger adaptations in the internal schedule and in turn cause its buyer agents to negotiate with its suppliers. To coordinate the actions of supplier agents there is a supplier interface control agent for each supplier. This has responsibility for checking whether the product can be supplied. A model is given in Figure 1 where agents  $SC_i$  are supplier interface agents, agents  $B_i$  are buyer or procurement agents while  $BC1$  is the buyer interface agent for company D. Each buyer agent has a local case base. The supplier interface agents will check on the impact of an order which may in turn generate a procurement need.

### TEST IMPLEMENTATION

To test the case based approach a simple scenario was set up and a buyer agent modelled. The buyer agent has its own case base implemented using a relational database and a simple nearest-neighbour search strategy. The buyer agent goal is to

minimize expected cost. Cases simply record information on order size, order time (in days), previous delays and a price for the order type. In this case the nearest neighbour was measured as difference in days and difference in order size (over 10). The buyer control agent would have provided the list of suppliers i.e. this is operating at the lower agent level.

Three suppliers of a particular product exist i.e. S1, S2 and S3. S1 is a low cost supplier (\$10) but has a number of problems with delivery delays and inability to meet order requests. S2 has a better record but charges a higher price (\$15) while S3 can meet all deadlines but has a high price (\$22). The delays were modelled as follows:

- S1 and S2 can meet a new request for an order 80% of the time while S3 can always meet an order.
- If there is a delay in meeting an order, S1 has a 60% chance of a one day delay, 20% chance of two days and 20% chance of three. S2 has a 50% chance of a one day delay and a 50% chance of a two day delay.
- On order delivery, S1 has a 40% chance of delivery on schedule, 40% chance of a one day delay and 20% chance of a two day delay. S2 has an 80% chance of no delay and a 20% chance of a one day delay.
- Delays are assumed to cost a fixed amount per day (modelled as \$4 per unit)

Calculating the expected values for these distributions gives an expected cost per unit for S1 of \$14.10, for S2 of \$17.00 and \$22.00 for S3.

The simulation was run for 400 random cases. If a case was judged to be sufficiently different from a case in the case base, it was added to the set of cases. If it was reasonably similar to an existing case, the existing case had its price for the order adjusted as the average of the new price and two times the existing price (this has the effect of giving significant weight to the most recent case). 59 new cases were added overall.

Figure 2 shows the frequency of use of the supplier data for each case i.e. S1 shows the number of times a case for supplier one is used as the basis for the new order. Under this scenario, the average price per unit rapidly converges to close to the expected price of \$14.10. It is apparent that S1 is by far the preferred supplier. S3 does not enter the reasoning as its price is too high.

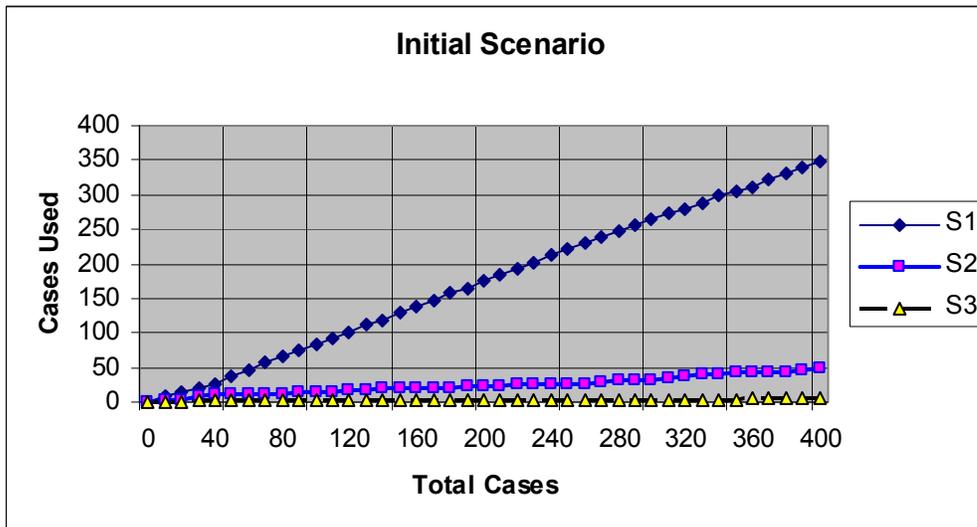


Figure 2: Use of Cases

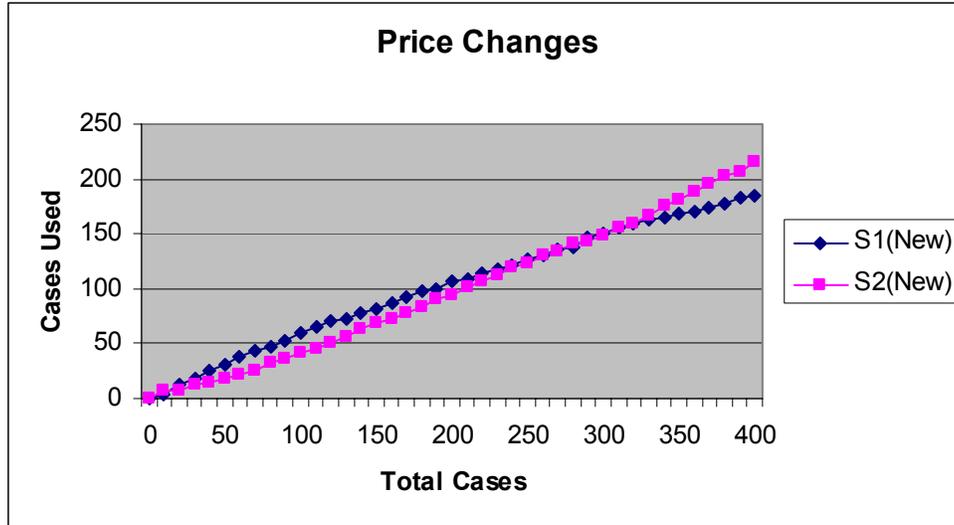


Figure 3: Scenario 2 after price changes

To determine whether the CBR system is capable of learning to change, the scenario was altered by assuming that after 100 cases had been processed, S1 has shown a decline in being able to meet orders from 80% to 50%. S1’s unit price has also increased from \$10.00 to \$12.00. S2 has been able to improve its ability to meet orders to 90% and to cut its price to \$14.00.

Figure 3 shows the relative use of S1 and S2 as the basis for new ordering decisions (S1 New and S2 New). Although S1 is initially the major basis for decisions, S2 steadily replaces it as the preferred supplier. Learning here is fairly slow but in this simple implementation there are only two attributes– in a real world scenario many more factors would be taken into account. The average price per unit moves steadily towards the new expected price of \$15.40.

Although it would be expected that once the system has learned that S1 is the best supplier, it will not adapt unless S2 comes in with a lower price. In this model, there are cases where the expected cost from S1, due to an inability to deliver because of other commitments, will be higher than that of S2. The expected cost of S1 is also adapted over time due to any additional delays. As a result there will be a steady move to S2. However, given that the only publicly known discriminator between suppliers in this model is the expected price, suppliers above this price will never enter the selection and will be unable to

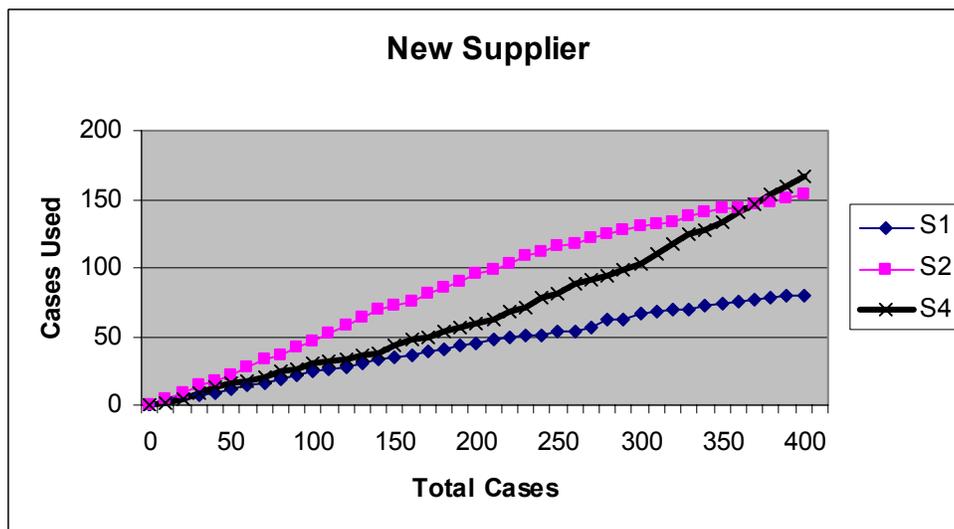


Figure 4: Scenario 3 with new supplier

compete e.g. on higher quality. The research of Plaza and Ontanon (2003) provides a possible general approach to cooperation between agents to learn from each other which suppliers have the best overall range.

To extend the scenario, a new supplier S4 enters the market. This is a low cost supplier with a good delivery schedule. Again there is a steady movement towards favouring S4 as the preferred supplier (Figure 4)

## CONCLUSIONS

To use dynamic information effectively in inter-enterprise supply chain management, decisions will need to be made automatically and effectively. The multi-agent system approach proposed here provides a suitable architecture for rapid and agile response. It is scalable as there is no overall controller – each organisation in the chain or network will have its own agent management structure.

An agent in this environment must be capable of intelligent reasoning and learning. The CBR approach provides a possible framework for at least part of the intelligence, and is capable of learning dynamically i.e. as a new case is encountered it will be added to the case base for that specific product in a specific company. The CBR system adapts if the conditions change.

The framework proposed here requires further development and testing both in simulated and real environments. The initial results are encouraging and suggest that an MAS approach with CBR could be a useful tool for further automating supply chain management.

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