ADAPTIVE AGENTS FOR SUPPLY NETWORKS

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Abstract: Dynamic information flow in esupply networks requires that buyers and suppliers have the ability to react rapidly when needed. Using intelligent agents to automate the process of buyer/seller interaction has been proposed by a number of researchers. One problem in providing intelligent automated collaboration is incorporating learning capability i.e. an agent should be capable of adapting it's behaviour as conditions change. This paper proposes a scalable multi-agent system which uses case-based reasoning as a framework for at least part of its intelligence. Tests with a simulated system show that such an agent is capable of learning the best supplier and also capable of adapting if supply conditions change.

1 INTRODUCTION

Supply chain and supply networks can be of arbitrary size and complexity. In an electronic business environment, 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 will describe 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 and perturbations in the supply chain and the solutions applied, as well as some formal processes for dealing with these. In order to automate the response to any stochastic event, software must be capable of reacting as one would expect a human agent to do. In many cases, a human agent responds by working from and possibly adapting solutions to previously encountered situations similar to the present problem i.e. a process of reasoning from prior cases or Case-Based Reasoning (CBR). A model is proposed in which 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.

2 OVERVIEW OF CBR

Case based reasoning (CBR) solves new problems by adapting previously successful solutions to similar problems. The appeal of CBR as a problem solving approach lies in its familiarity - in many problem solving situations a solution will be based on a similar problem solved by us in the past. As an example, doctors would not usually start all diagnoses from first principles. They would in most cases recall similar cases of patients with the same symptoms and also recall what treatments have worked in the past. Treatments may be modified for the specific circumstances of this patient eg difference in ages, sex, weight, medical history, etc. might all suggest some need for adaptation of a past solution.

A new problem (the target case) is matched against cases in the case-base. The importance attached by the user to various features (indexes) of the case may be used to guide the matching process. One or more similar cases are retrieved from the case base. A solution suggested by these cases is reused and tested for success. If necessary, the retrieved case(s) will probably be revised to produce a new case which can then be retained in the case base.

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3 THE CASE AT THE INTERFACE

CBR has been primarily used in scheduling as an aid to creating and adapting specific schedules, usually within the organisation. This paper proposes the use of CBR for intelligence at each stage of a schedule within a specific supply chain. 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 utilises 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. The buyer (and the supplier) interface agents are “middle agents” which act as brokers between buyers and seller (Wong and Sycara, 2000). 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 per transaction. These are relatively short-lived agents responsible for monitoring the progress of a specific request for materials. A request to purchase from an organisation may itself trigger adaptations in the internal schedule for that organisation 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, also using CBR, whether the product can be supplied. The supplier interface agents will check on the impact of an order i.e. can it be realistically scheduled and processed. This may in turn generate a procurement need, causing a spreading activation of agents.

The supplier agent will also retain a base of prior cases i.e. what did we do last time. Agents will also need to have fall back positions i.e. if there is no suitable information in the case base, there must still be a response – either by appealing for human intervention or going to other forms of reasoning e.g. rule-based.

The Buyer Agent Cycle

Cases relate to specific products and suppliers and the basic cases will be indexed by product (or product class). There may need to be some form of generic or template cases which provide basic reasoning.

The Buyer interface Agent cycle will be:

1. An order is received
2. The case base is checked for previous suppliers of the product
3. An agent is initiated to control the buyer cycle.
4. A message is broadcast to the “web” looking for prospective suppliers. This assumes a standardised structure to define suppliers.
5. Prospective suppliers are ordered in terms of some priority scheme and either:
   (a) the order is sent to the supplier
   (b) there is a call for quotes

3.2 The Supplier Interface Agent Cycle

A supplier agent will receive a request for an order or a quote and will need to initiate a process to determine if and when the order could be filled. This may require rescheduling of production and ordering of new inputs. Each supplier interface agent will also maintain a case history of prior dealings with buyers.

On the basis of history (if it exists) and any other intelligence provided, the agent will decide to:

(a) Decline the order or quote
(b) Agree to fill the order/quote without adjusting existing schedules
(c) Revise schedules on a priority basis to meet an order or estimate impact if a quote is required. In this case a supplier watch agent is initiated to monitor the progress.

If (c) is selected, there may be a need to initiate a purchase cycle for input materials. This will require the company buyer agents to initiate PO’s or RFQ’s and any response by the supplier agent will be delayed until the necessary information is available.

Once an order is shipped and payment received and processed, the case base for the supplier agent will be updated.

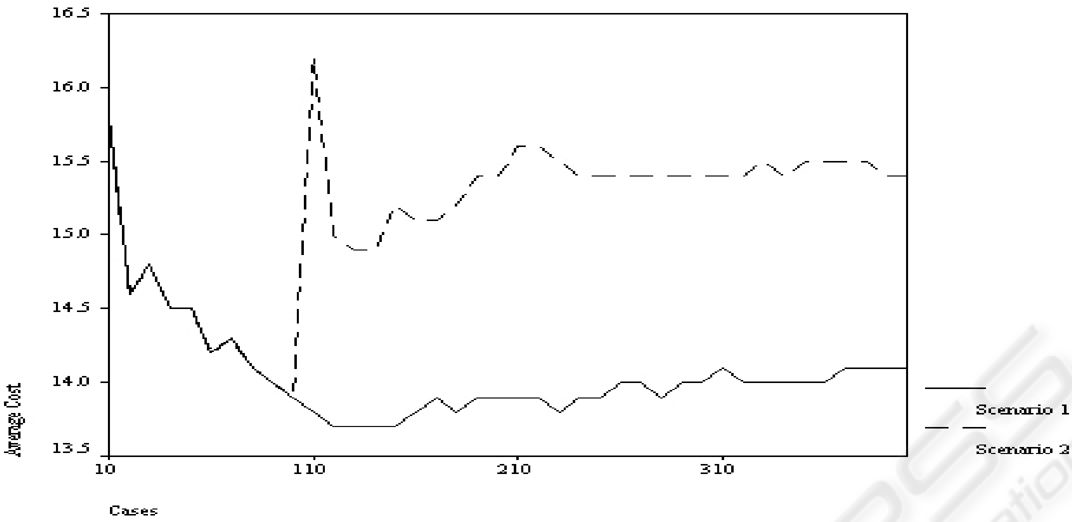

Figure 1: Average Unit Cost over time

4 TEST IMPLEMENTATION

In order 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 which was implemented using a relational database and a simple nearest-neighbour search strategy. Cases simply record information on order size, order time (in days), previous delays and a price for the order type.

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 give 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 500 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 1 shows the average cost per unit as each case is dealt with (line Scenario 1) for the first 400 cases. 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. S2 shows the number of times a case for S2 is used as the basis. Under this scenario, the average price per unit rapidly converges to close to the expected price of $14.10. From Figure 2, it is apparent that S1 is by far the preferred supplier. S3 does not enter the reasoning as its price is too high.

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 (probably due to its low prices and consequent high demand) 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 on the other hand has been able to improve its ability to meet orders to 90% and has managed to cut its price to $14.00. This gives a new expected price per unit for S1 of $17.36 and for S2 of $15.40. S3 is unaffected by the change.

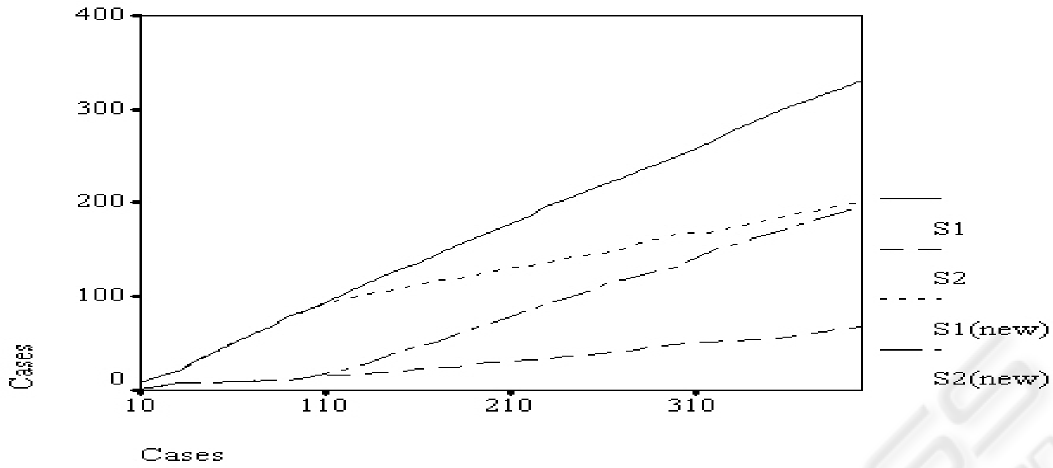

Figure 2: Use of Suppliers over time

Figure 1 shows the effect on average cost per unit with line Scenario 2 showing the impact after case 100 has been processed. The average cost per unit is recalculated from case 101 and rapidly stabilises around the new minimum expected price of $15.40. Figure 2 shows the relative use of S1 and S2 as the basis for new ordering decisions (S1 New and S2 New). It is apparent that S2 replaces S1 as the preferred supplier to accommodate the new pricing realities.

As a further comparison, the average price per unit of a random supplier selection policy (including S3) was simulated over 500 cases and stabilised at $23.50 i.e. the CBR approach can find the most cost efficient alternative.

5 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 in this paper provides a suitable architecture for rapid and agile response to any event. An agent is this environment must be capable of intelligent reasoning and learning. The CBR approach provides a suitable 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. As shown above, 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 powerful tool to further automating supply chain management.

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