ABSTRACT

Using an exact replication of the MIT Beer Game, a supply chain simulation was developed in which Intelligent Software Agents manage the supply chain subject to all of the constraints placed on the original human players. The agents’ information processing capabilities are founded on Support Vector Machines (SVM) with an asymmetric cost function, which permits internal modeling of appropriate safety stock levels. Additionally, these agents learn patterns from new information as the game simulation progresses. The simulation results indicate that intelligent agent-managed supply chains outperform those managed by humans.

Keywords: Supply Chain, Intelligent Agents, Genetic Algorithms, Support Vector Machines.

INTRODUCTION

Nowadays, effective management of supply chains is one of the key factors in succeeding in a global competitive business environment. At the operational level, part of the supply chain management involves members ordering required quantities of products: the task, which, at a minimum, involves the use of forecasting demand and deciding on safety stock levels. Recent progress in information technologies and wide proliferation of e-business enables adoption of new approaches in supply chain management. These developments could be further fueled by advances in intelligent techniques, including, in particular Neural Networks (NN), Recurrent Neural Networks (RNN), and Support Vector Machines (SVM). Potential advantages of employing these powerful tools dictate the need for more research in automated, or semi-automated intelligent systems for managing supply chains. The purpose of this work is to investigate the applicability of these approaches to tackling supply management tasks.

Previous work has attempted to investigate the possibility of employing so-called “intelligent agents” for managing the supply chain [3]. In one work, a genetic algorithm (GA) was used to perform a global optimization of a supply chain based on the dynamics of MIT Beer Game: a simulation tool for modeling supply chains used for educational and experimental purposes. The results obtained by utilizing software agents were compared with those of human players. The main conclusion of this work was that intelligent agents performed much better than human players. However, the actual beer game rules were not exactly followed for this simulation, which makes the results incomparable with the results obtained from human players, thus raising the questions of the adequacy of the results for more realistic contexts.
The problems with the aforementioned experiment can be examined if we review a few of the relevant rules of the game listed below [6]:

- Players are not allowed to communicate with each other;
- No player knows the customer’s demand function;
- Only the Retailer player can discover the customer demand function as the customer orders are presented to him or her;
- No other player (Wholesaler, Distributor, Factory) receives any information on the customer orders;
- Players have not played the MIT Beer Game before.

Let us now re-examine the past experiment in light of these rules. The first problem is that the GA co-ordinates across the complete supply chain to minimise cost, therefore it is a central planning approach as opposed to individual planning required in the Beer Game. The rules state that “questions concerning strategy or customer demand are not [answered]”; “subjects are unable to co-ordinate their decisions or jointly plan strategy”; and “the game is designed so that each subject has good local information but severely limited global information” [6]. Obviously, when the humans play the beer game they cannot perform central planning and optimization, while the GA has been effectively permitted to do so. To put the GA on a comparable footing with human players in respect to information sharing, each agent would have access only to current and past orders for which it was a recipient, goods receipts and shipments and the inventories and backorders. This paper adopts a more rigorous approach to investigating the feasibility and effectiveness of agent-managed supply chains by avoiding simplifying assumptions. More specifically, we will propose an intelligent agent solution that follows the rules of the Beer Game to make a valid comparison with the results of Sterman’s experiment [6].

**AGENTS FOR SUPPLY CHAIN MANAGEMENT**

Since one of the major requirements of the game is that the human players should not have played it prior to the experiment, we chose to avoid using any technique that requires running simulations of a complete Beer Game. Nonetheless, similar to human players, the agent would be permitted to use and analyze all information it has been exposed to up to the decision point in order to infer the dynamics of the system. We need to identify patterns in the past and current information that can be generalized to the future periods. To this end, we will consider employing function approximation tools such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), since these techniques tend to be effective for building models that generalize well. This is especially the case with Support Vector Machines, which minimize the structural risk of the model as opposed to reducing the empirical risk, which is the main target for ANNs. Therefore, we chose to base our intelligent agents on Support Vector Machine [7] (specifically, we have used SVM-Light [1]).

The design of our intelligent agents also includes some features that help improve their overall performance. Humans who play the game, noting that backorder costs are double the cost of holding inventory, soon realize that negative forecast errors are costly. Thus they tend to adjust their forecasts in the direction of positive bias. We can include the asymmetrical error cost directly into the equation solved by the SVM [4]. In the case of our beer game simulation, the
inventory to backorder cost ratio is 0.5/1, which gives us a positive error to negative error cost ratio of 0.5. We can use this error cost ratio in the SVM equation. In real business environments, these costs are often available or can be easily derived, and thus the cost ratio (or its estimate) can be obtained. Therefore, we can use the asymmetrical cost ratio in our SVM as a generic solution.

Our Beer Game simulation has been implemented in Simulink of MATLAB 7.0 [5] following the published beer game rules [6] as outlined earlier. At each time step (week in this case) each agent is permitted to use all past and current information it has been exposed to, including its received orders, orders placed, the inventory levels, backorders placed, goods received and goods shipped. Using this information, the agent will build a forecast for the demand it will receive in four time step delays (weeks) since the orders will only be received after four time step delays, at which time it should fill exactly the received orders. It will also compare its purchase orders (based on the forecast) from four periods ago with the current incoming order and adjust the current ordering amount by the error. Additionally, since our SVM will internally determine the required safety stock levels as facilitated by the asymmetric error cost, the forecast will include safety stock and therefore it would not need the initial safety stock. Because of this, the initial safety stock will be reduced from 12 to 0, one unit (case) per time period (week), starting from step 5 as allowed by the rules. Although we could leave the initial inventory, which would result in a better performance during the 36 weeks because of less distortion of the customer demand and because of the buffer it provides, we decided to remove it, since we expect our agents to determine the best safety stock levels by themselves.

At the startup of the supply chain system, there may not be enough data for forecasting. Since the order and delivery lag for the supply chain members is four weeks except for the manufacturer, for whom it is three weeks, we can only start forecasting when there is at least as much historical data as there are delay periods. In the beer game rules, there is a four week time period where the orders are fixed, so for this simulation we will always have enough data. However, in a situation where a forecast must be done when there is insufficient data, the best we can do is pass on the amount in the currently received order. With the accumulation of the historical data, the history window used for the SVM is increased to permit learning of more complex patterns. However, since increasing the window decreases the number of observations available to the model, the ratio of variables to observations should be maintained at a reasonable level. The historical window size is set 1/5 of the current history with a minimum window size of 1, so we have on average about 5 observations for each variable regardless of the amount of historical data available.

In our simulations we have employed the type of SVM called Support Vector Regression (SVR), with the Radial Basis Function (RBF) kernel, since it is has been shown the linear kernel is a special case of the RBF kernel [2]. The kernel parameters are chosen to be a Cost of 100 and a Gamma of 100, that result in large complexity and large smoothing since our data is prepared with the appropriate ratio of variables to observations to permit additional modeling complexity while maintaining high smoothing effects. It is important to note that at every week, each agent uses its historical data including the most recent (current) information to remodel what it should order, since new patterns may have emerged that need to be learned.
RESULTS

We have run the Beer Game simulation controlled by our intelligent agents for 36 periods and 50 periods. The results of the 36 periods are used for comparison with prior work, the additional simulation time was used to see if the system can stabilize. Figure 1 shows the history of orders generated by the supply chain management agents as well as the total cost.

Figure 1. History of orders and the total cost

Examining the ordering patterns we could notice the distorting effects caused by our policy of eliminating the safety stock at period 5, since this causes the distributor, wholesaler and manufacturer agents to start planning for a downwards trend, which is later reversed by the subsequent increase in orders. We could have alternatively made our agents only reduce the
safety stock when there is an increase in demand which would result in less fluctuations and a lower total system cost, however, as we stressed, this would not be a generalizable solution, since we would be tuning the system based on information about future demand. Further examination shows that the effects of the asymmetric cost are reflected in the ordering patterns, especially in the extreme case of the manufacturer during times of large fluctuations in demand. In these situations, the asymmetric SVM is overestimating the future demand, because it knows that the error is higher at this time and that the cost of a negative error is much larger than the cost of a positive error, which results in higher safety stock when required.

The main results of the simulation include the total cost of $1,122 at the end of period 36, the convergence at period 37 for a total cost of $1,123, and no inventory or backlog. All of the intelligent agents have no inventory and no backlog, which may seem like a cause for concern because there is no safety stock to absorb increases in demand, since we must still deal with the lead time delays. But the SVM based agents with the asymmetric cost function have determined based on the historical data that there is no need for safety stock because the patterns do not indicate future changes, so the safety buffer is not required. The agent will build the appropriate buffers based on the patterns observed and the defined cost function if needed.

Table 1 compares the results of the simulations obtained by using our SVM-based agents with those derived by using humans and naïve forecasting. Here we see that the total cost of supply chain managed by humans is about 80% more than that managed by intelligent agents. The Naïve Forecast simulation, a variation on the 1-1 strategy, is also included in the comparison since it is a general solution that will eventually reach convergence for any given pattern once the customer demand fluctuations stop. It creates the usual additional distortion which results in a huge increase in total supply chain costs. Unfortunately, many of existing specialized policies that may seem to perform very well in certain specific scenarios do not present generalized rules that can be applied in various business contexts with unknown future demand.

To gain more insight on the performance of agents compared to humans or other computerized methods, we would need longer and more complicated Supply Chain simulations for which human and machine results could be compared. It is also highly beneficial to the long term total supply chain cost that the intelligent agents reach convergence at period 37. Most human played games have huge swings that are still amplifying by period 36 and are far from stabilizing. This means that results at the end of period 36 are conservative and that if the game was played longer in the human experiments, the total supply chain cost would be much higher. This provides further support in favor of employing intelligent agents.

We feel that appropriately designed intelligent agents such as the one we built with SVM and an asymmetric cost function provide a general solution that can perform effectively in real applications. Although generalization of our results has to be done with caution until further studies, it would seem that our agent could provide a general supply chain solution that would perform better than humans or simple automated means.
TABLE 1

Supply Chain simulation results compared

<table>
<thead>
<tr>
<th></th>
<th>Total Supply Chain Cost at the end of</th>
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<tbody>
<tr>
<td></td>
<td>Period 36</td>
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<tr>
<td>SVM Agents</td>
<td>1122</td>
</tr>
<tr>
<td>Average Human</td>
<td>2028</td>
</tr>
<tr>
<td>Naïve</td>
<td>2140</td>
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</tbody>
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CONCLUSION AND FUTURE RESEARCH

Following the exact rules of the MIT Beer Game, we have created a simulation in which intelligent agents can manage the supply chain and the results can be compared with the performance of human counterparts. The experiment rules and intelligent agent design had a strong focus on bringing a generalized solution to the problem that can be used in a wide variety of business contexts. The agents performed much better than the human agents for the supply chain experiment, where total supply chain costs were minimized without coordination. We feel that the results show that using intelligent agents is a general and effective approach to solving the problem and has relevance to real applications, especially in the context of today’s supply. Future research topics built on the current findings would involve experiments where human performance would be compared against that of intelligent agents in the context of collaborative supply chain management.

REFERENCES


