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Using Multi-agent and Case-Based Reasoning for Collaboration in a Supply Chain

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ABSTRACT

The importance of collaboration in a supply chain has led several scholars to suggest diverse approaches. Questions still remain concerning the best way of dealing with collaboration and conflicts under demand and supply uncertainties. This research proposes a model based on case-based reasoning and multi-agents for supply chain collaboration and information sharing (MACBR-SCM). The MACBR-SCM is implemented as a web service to facilitate communications among multi-agents. The MACBR-SCM is validated for various collaboration mechanisms. The results of the statistical tests reveal the importance of enhanced collaboration for the best performance.

Keywords

Supply chain management, Collaboration, information sharing, Case-based reasoning, Multi-agent.

INTRODUCTION

Firms have increasingly formed business alliances through which they can grow by leveraging business partner's resources and expertise. Supply chain is one form of a business alliance and considered a vehicle for core competence by allowing the partners to leverage on the resources of each other. Supply chain management is commonly defined as "the integration of key business processes from end user through original suppliers that provides products, services, and information that add value for customers and other stakeholders" (Lambert and Cooper, 2000). Some scholars define it narrowly as a set of decisions or activities of purchasing and supplier management and others view it from the perspective of logistics and transportation functions (Ho and Newton, 2002). Overall, supply chain management (SCM) can be summarized as the integration of business activities among firms towards core competence.

Although prior research has addressed diverse aspects in a supply chain, questions still remain concerning the best way of dealing with collaboration and information sharing problem under demand and supply uncertainties. Scholars have traditionally focused on the problem domain where demand and supply uncertainties are low. In these environments, the best strategy for decision makers is to implement the "efficient supply chains" {Lee, 2002 #20} by having cost efficiency and information sharing. Efficiency goals are the situations in which traditional optimization- and simulation-based approaches can be easily applied. However, there are situations where the supply chain experiences high demand uncertainties and high supply uncertainties. In high supply uncertainties, the supply chain suffers an evolving supply process. An "evolving" supply process is one in which manufacturing technology is emerging and immature, and supply base is unstable. A "stable" supply process is the opposite situation in which manufacturing technology is mature and supply base is dependable. Evolving relationships among the firms may also cause supply uncertainties. Under high supply uncertainties the firms may change the relationships with their partners from weak ones to strong ones or vice versa. Additional sources of supply uncertainties include yield, process reliability, supply source and lead-time. The traditional approaches may not be suitable when supply uncertainties are high because calculating analytical solutions are prohibitive, NP-hard or impossible, as the model gets complicated due to increasing complexities caused by uncertainties {Shapiro, 2001 #74}.

The present research addresses collaboration and information sharing problem in the context where demand uncertainties are high and supply uncertainties are high. Specifically, we consider relationship changes among the firms in a supply chain for supply uncertainties. We assume that the firms can change their relationships from weak ones (weak ties) to strong ones (strong ties) or vice versa. In weak ties the firms maintain arm's length relationships and have a weak level of collaboration. In strong ties they have strategic partnerships and collaborate intensively. We also assume that demand uncertainties can be modeled using either a stochastic distribution or random number generator. In the research we opted for the latter to model demand uncertainties. We address the following research questions: *How can information sharing be achieved in a supply chain? How can multi-agent and case-based reasoning be applied to facilitate collaboration and information sharing under low demand and high supply uncertainties?*

This research proposes a model based on multi-agents and case-based reasoning (CBR) (MACBR-SCM). Inside the MACBR-SCM, the multi-agent collaboration engine for SCM (MACE-SCM) is suggested to manage three collaboration mechanisms among the agents. The MACE-SCM is based on CBR and is implemented as a web service to facilitate communications among agents. CBR can be used in the context where high demand and supply uncertainties bring frequent model changes and thus preclude the application of the analytical models. The MACBR-SCM is validated based on simulation. The results of the statistical tests reveal the importance of enhanced collaboration for the best performance.

The rest of this paper is organized as follows. First, we briefly review existing literature on supply chain collaboration and information sharing. Next, we present the architecture and detailed mechanisms of the model. Then, we describe implementation details and validation results of the prototype system. We conclude the paper with a brief discussion on the implications of the model.

BACKGROUND

Supply Chain Collaboration

Information technology has facilitated the firms in a supply chain to collaborate more efficiently. First, the use of an interorganizational system such as electronic data interchange has provided the technological capacity to share information across organizational boundaries more timely, accurately and frequently. The efficient use of IT has significantly improved supply chain efficiencies and lowered transaction costs. Thus the firms in a supply chain could efficiently coordinate their business decisions and activities, leading to superior performance beyond organizational boundaries. Second, IT also has provided the basis for business process reengineering in a supply chain. Continuous replenishment program (CRP) is one such IT-enabled effort. Under the CRP, the retailers share their inventory level to the manufacturers and the manufacturers manage the retailer's inventories. This vendor-managed inventory under the CRP involves extensive business process reengineering among the firms concerning order and inventory management. This interorganizational process reengineering has led to efficient collaboration among the firms and thus brought benefits far exceeding process or technological innovations alone (Clark and Stoddard, 1996).

Given the importance of collaboration and information sharing, the main objective of this research is to suggest the usefulness of an approach based on CBR and multi-agents. CBR is a problem solving approach that takes advantage of past expertise to solve a particular problem (Dhar and Stein, 1997). Each attempt for a solution is stored as a case. The attributes of each case in the case are evaluated for the similarity to the problem that it is being asked to solve. The cases are synthesized and the differences between the current situation and the ones in existing cases are adjusted to reach the solution.

We have adopted CBR architecture for several reasons. First, CBR allows us to solve problems without having to work out the solution from scratch each time (Dhar and Stein, 1997). Encoding rules describing how the details of each problem affect the proposed problem is not required. On the contrary, a rule-based system requires the investigation of the details of each problem to build custom-made solutions each time. Second, it is difficult to completely identify supply chain strategies (outcome values in the case base) beforehand using rules. Finally, CBR is flexible in handling uncertainties from demand and supply, and the changes in relationships and strategies (e.g., introduction of a new supplier). The analytical models guarantee optimal solutions, but are valid under a specific set of assumptions and constraints. Relying on these models may not be viable when calculating analytical solutions are prohibitive or NP-hard as the model gets complicated due to increasing complexities and uncertainties.

Related Works

Supply chain scholars have taken various complementary perspectives to look at collaboration and information sharing in the supply chain, including optimization-, simulation-, and multi-agent-based. Each approach has unique advantages but at the same time disadvantages due to inherent complexities and contingencies for collaboration and information sharing.

Optimization-based approaches employ mathematical programming techniques such as linear, integer and dynamic programming. MS/OR researchers have used this approach extensively to identify the best possible solutions for given situations, based on specific assumptions. This approach is strong in addressing a narrow set of problems such as inventory management, logistics optimization and production scheduling. However, if the assumptions are not met, the generated solutions may not be appropriate (Muckstadt, et al., 2001).

Simulation-based approaches allow dynamic modeling of behaviors of supply chain firms with varying degrees of constraints and policies. Although it can accommodate the modeling of demand and supply uncertainties, it cannot generate the design itself and can only run models with pre-specified parameters and conditions (Harrison, 2001). Simulation models also fit very specific contexts and have limited applicability to other problems, making them inappropriate for dynamic market environments in which changing situations often require totally different modeling approaches (Swaminathan, et al., 1998).

Scholars have recently begun focusing on multi-agent based approaches to solving collaboration and information sharing. Different firms in the supply chain typically are modeled as software agents, which pursue their own goals within some constraints. Swaminathan et al. (1998) suggested the framework that consists of supply chain agents (retailer, manufacturer and supplier), control elements (inventory policies, just-in-time release and routing algorithms), and their interaction protocols (message types). They incorporated uncertainties from supply, demand and process, and allowed different scenarios to be simulated. Kimbrough et al. (2002) proved that multi-agents can work effectively as a team in eliminating the Bullwhip effect with information sharing (order quantity) in their research on the MIT Beer game (Sterman, 1989). The multi-agents were able to discover optimal policies where they are known and find good policies in complex scenarios where analytical solutions are not available (Kimbrough, et al., 2002).

Multi-agent and Collaboration

A software agent is a software or hardware system that has the property of autonomy, social ability, reactivity, and proactiveness (Wooldridge and Jennings, 1995). Among many features of software agents, autonomy (the ability of agents to make independent decision) is at the heart of agency (Wooldridge and Jennings, 1995). Other features include social ability (agents need to communicate with each other and with the user), reactivity (the agent's ability to react to changes in the environment), and proactiveness (the ability to take the initiative).

In this research multi-agents are employed to model collaboration among the firms. The approach based on multi-agents is quite appropriate for the following reasons. First, multi-agents are suitable for dealing with uncertainties in the supply chain. The uncertainties in the supply chain come from demand and supply. These uncertainties or changes in the supply chain can be easily incorporated due to the reactive nature of multi-agents. A software agent can pursue intelligently and autonomously different goals such as optimal inventory and production policies to changes in the environment. Second, multi-agents can easily model different levels of collaboration among the firms. If the firms have weak relationships, they will pursue local optimizations based on weak levels of collaboration. If the firms have strong relationships, they will seek global optimization throughout the entire supply chain. Under a multi-agent system, the problem-solving tasks of each functional unit (e.g., firm) are populated by a number of heterogeneous intelligent agents that have diverse goals and capabilities (Lottaz, et al., 2000). Each agent is designed to represent a specific functional unit and requirements for action strategies and policy may be entered into the agent beforehand. Different levels of collaboration requirements can be easily incorporated into the agent as different goals based on the given scenarios. Third, multi-agents are very effective in dealing with coordination and conflicts among the firms. When a conflict occurs among the functional units, it is especially hard for a single authority or committee to reconcile it to the full satisfaction of all units concerned. Using a multi-agent system can lead to a more coherent mechanism for solving the conflicts among the functional units. The conflict resolution mechanism or enhanced collaboration can be achieved by incorporating a central coordination agent to support the multi-agent collaboration (Sillince and Saeedi, 1999). Central coordination agents may have meta-rules and higher-order priorities for managing the behavior of the agents (Maturana and Norrie, 1997).

MACBR-SCM

Preliminaries

This research considers the supply chain that consists of retailers, manufacturers and suppliers (3 stages). A customer gets to a retailer and purchases the product if it is in stock. If the customer demand cannot be met by the retailer, it is ordered from a manufacturer and backlogged. The manufacturer produces products by assembling components from a supplier. The manufacturer receives product orders from the retailer and places component orders to the supplier. The supplier produces

components and supplies them to the manufacturer. The supply chain incurs linear holding costs and linear backorder costs at each stage.

The goal of the retailer is to maximize profits and to minimize stockouts and inventory costs. One of the major decisions to be made by the retailer is how much to order from the manufacturer. The manufacturer’s goal is to maximize profits by minimizing inventory costs and managing manufacturing and procurement processes efficiently. The major decisions to be made by the manufacturer are how much to produce and how much to order from the supplier. The goal of the supplier is to maximize profits by maintaining low turnaround time and low inventory. One of the major decisions to be made by the supplier is how much to produce.

The multistage inventory model that is accepted by supply chain scholars (e.g. {Erenguc, 1999 #164}) is adopted as the representative formulation for our model. Our formulation is based on the assumption that the problem of supply chain collaboration can be reasonably represented by the following formulations. The manufacturer’s objective function is shown as follows. The manufacturer’s goal is to maximize the profit at time t .

$$\begin{aligned} &\text{Maximize } P(m,t) * X(m,t) - p(m,t) * Prd(m,t) - Inv_Cost(m,t) - Backlog_Cost(m,t) - \\ &\quad \quad \quad Order_Cost(m,t) - Setup_Cost(m,t) \\ &\text{Subject to } \textit{inventory, sales amount, production capacity, production amount constraints} \end{aligned}$$

The profit of the manufacturer (m) is a function of price (P), quantity (Q) and production quantity (Prd) at time t , i.e., $Profit(m,t) = f(P(m,t), Q(m,t), Prd(m,t))$. X represents sales amount to the retailer. The retailer and supplier also have their own objective functions and constraints.

System Architecture

The overall architecture of the system, MACBR-SCM, is displayed in Figure 1. The MACBR-SCM has three agents (R-Agent, M-Agent and S-Agent) for retailers, manufacturers and suppliers, and one additional agent (C-Agent) for coordination with the other agents. For automated agent-to-agent communication, the system adopts ontology to share information for coordination. Each agent is placed as a web service to facilitate collaboration among the agents that are remotely located yet coordinating autonomously.

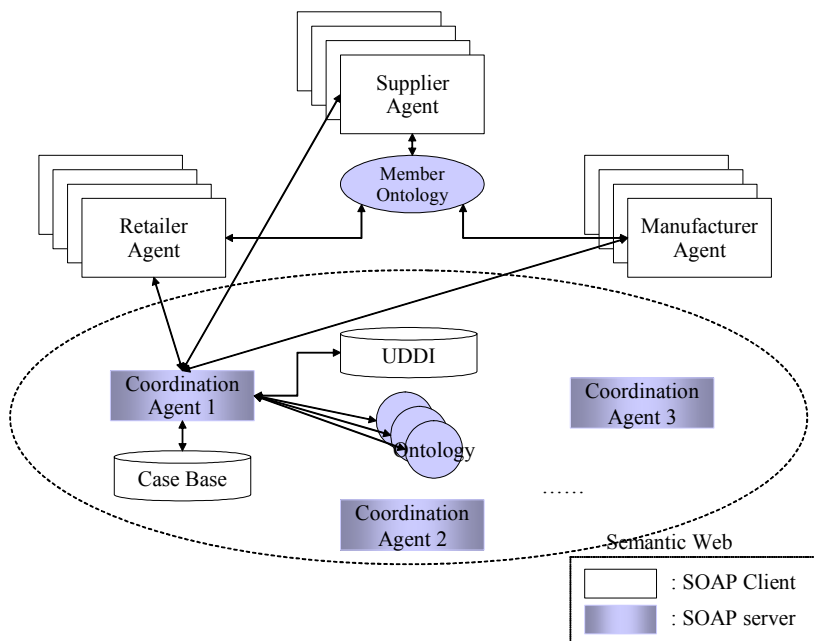


Figure 1. The system architecture

If the firms are assumed to have weak ties, the agents pursue their individual goals. On the contrary, if the firms are assumed to have strong ties, the agents work as a team and pursue the global goals. The detailed roles of the multi-agents are as follows:

R-Agent: Receives a customer's order and sells the product if it is in the inventory. If the customer order cannot be filled by the retailer, the product is ordered from the manufacturer (M-Agent) and backlogged. The R-Agent pursues the goal of the retailer. One of the major decisions to be made is how much to order from the M-Agent.

M-Agent: Manufactures products by assembling components. It receives product orders from the retailer (R-Agent) and places component orders to the supplier (S-Agent). The M-Agent pursues the goal of the manufacturer. The major decisions to be made are how much to produce and how much to order from the supplier (S-Agent). The M-Agent must also decide whether to expand its supplier base if it faces supply uncertainties.

S-Agent: Produces components. It receives raw materials from the outside and supplies the components to the manufacturer (M-Agent). The S-Agent pursues the goal of the supplier. One of the major decisions to be made is how much to produce.

C-Agent: Facilitates additional level of collaboration and information sharing. The main priorities are to maximize the overall supply chain profits by assisting the other three agents. It may or may not rely on the case base while working with the other agents. The decision on whether to take advantage of the case base is determined by the collaboration level among the agents. The case base maintains additional information related to marketing (e.g., customer transaction profiles) and forecasting (e.g., customer demand). The information on customer transaction profiles is used for marketing and promotional purposes. The forecasting and demand information is used for manufacturing decisions. In this research we only consider *customer demand* information (price level and its corresponding demand quantity). If C-Agent relies on the case base, the overall performance of the supply chain is expected to be higher than without relying on the case base.

The mathematical representation of the C-Agent's objective function is shown as follows. The C-Agent's goal is to maximize the global profit at time t .

$$\begin{aligned} \text{Max Profit}(c,t) &= \alpha * (\text{Profit}(r,t) + \text{Profit}(m,t) + \text{Profit}(s,t)) + (1-\alpha) * ms(r,t) \\ \text{Subject to} & \text{minimum profit, order quantity constraints} \\ \text{Where } & 0 \leq \alpha \leq 1 \end{aligned}$$

The global profit of the coordinator (c) is a function of profits from the retailer, manufacturer and supplier, and the market share (ms) of the retailer. That is, the C-Agent takes into account both profits and market share in maximizing the global profit. A weight α ($0 \leq \alpha \leq 1$) is assigned between the profits and market share.

As is discussed earlier, multi-agents are very effective in dealing with coordination and conflicts among the firms. The conflict resolution mechanism or enhanced collaboration can be achieved by incorporating a central coordination agent to support the multi-agent collaboration (Sillince and Saeedi, 1999). The C-Agent is designed to play a role of the central coordination agent in the system. The introduction of the C-Agent leads to overcoming the limitation of prior systems that focused on information sharing with limited collaboration capabilities (Kimbrough, et al., 2002).

MACE-SCM

The MACE-SCM refers to the module that deals with relationship changes (i.e., supply uncertainties) among the firms in the supply chain. The relationship between the firms may be changed from weak ties to strong ties, and vice versa. Further, the intensity of collaboration between the firms having strong ties may be thick or thin. We introduce three levels of collaboration among agents: Autonomy, Integration and Enhanced Integration Level. The Autonomy level refers to the situation in which the firms have weak ties. The Integration Level regards the context in which the firms have strong ties. The Enhanced Integration Level assumes the availability of additional information (i.e., case base) among the firms with strong ties.

Autonomy Level: The agents have weak ties, and thus pursue their own goals and cooperate minimally by exchanging order information. The resulting solutions such as order and production policies may not be optimal for the entire supply chain. The R-Agent, M-Agent and S-Agent are involved at this level of decision support. The agents do not collaborate to generate the solutions for the entire supply chain and do not rely on the case base.

Integration Level: The agents have strong ties, and thus pursue the optimal solutions for the entire supply chain. They work as a team and are expected to generate globally optimal order and production policies. Such solutions may not be optimal for individual agents, but may be optimal for the entire supply chain. The R-Agent, M-Agent, S-Agent and *C-Agent* are involved

at this level of decision support. The agents collaborate extensively to generate the solutions for the entire supply chain, but do not rely on the case base.

Enhanced Integration Level: The agents have strong ties, and thus pursue the optimal solutions of the entire supply chain as in the Integration Level. They learn rules to generate globally optimal solutions via CBR. The R-Agent, M-Agent, S-Agent and C-Agent are involved at this level of decision support. The agents do collaborate extensively to generate the solutions for the entire supply chain and rely on the case base.

An exhaustive list of attributes in the case base is shown below.

Case base ::= timestamp + a set of input data + a set of results.

A set of input data = price level + quantity level + number of competitors.

A set of results = market share + sales volume + total profit.

We assume that the C-Agent is not allowed to know the internal business data of each federating agent (i.e., R-Agent, M-Agent and S-Agent) except for the price level and sales volume which are usually shared within the supply chain. Hence all attributes in the case base are public data within the supply chain. The case base is currently sufficient for reasoning because we assume that the market share is determined only by the price level.

The C-Agent helps accomplish the better solutions to the federating agents within the supply chain. The C-Agent, relying on the case base, suggests the most profitable price and sales volume to the federating agents. The decisions through CBR make the supply chain more efficient by avoiding unnecessary inventory, backlog, and setup costs due to demand uncertainties. The C-Agent also discourages a transaction that will result in an unfair profit distribution among the federating agents.

IMPLEMENTATION

To examine the feasibility of the model, the prototype system was implemented using Java application under JDK1.4.1. In the Autonomy Level decision support, the R-Agent initiates a coordination process and the M-Agent and S-Agent subsequently follow to generate their solutions based on the prior stage's policies. Since each does not collaborate, no further coordination is sought after the initial trial of the solutions of each agent. In the Integration and Enhanced Integration Level, the agents collaborate and thus work together to generate the solutions until each agent is satisfied with the results obtained.

The actual coordination of the MACE-SCM under the Integration and Enhanced Integration Level is conducted according to the following three schemes: a retailer-initiated coordination (RIC), a manufacturer-initiated coordination (MIC), or a supplier-initiated coordination (SIC). These three different coordination schemes are designed to accomplish the target performance goal of each agent. If an agent did not achieve the target performance goal after each run, that agent initiates the coordination process subsequently. The RIC, MIC or SIC is tried until all the agents are satisfied with the results. The target goal of each agent is relaxed after each run whenever any agent is not satisfied with the result. Each agent is delegated to make a decision whether it is to relax its target goals or just to give up bidding. In our prototype system, the user can set a allowable minimum local profit level, inventory capacity and production capacity as parameters. Moreover, each agent is restricted by its firm's technical limitations such as unit cost, unit inventory cost, unit backlog cost, and unit set up cost.

Under the RIC, the R-Agent first triggers the coordination process by determining the retailer's price level and the order quantity that the retailer must have to maximize profits. The price level and order quantity of the retailer are passed to the M-agent, who determines the price level, production quantity and order quantity on behalf of the manufacturer. The decision values are then passed onto the S-agent, who makes the final decisions about the optimal price level and production schedule. Under the MIC, the M-Agent initiates the coordination process by determining the manufacturer's price level, order quantity and production quantity that the manufacturer must have to maximize profits. The decision values are passed onto the R-agent and S-agent, respectively, who make the final decisions about the optimal price level and order quantity or production schedule. Under the SIC, the S-Agent initiates the coordination process by determining the supplier's price level and production quantity. The decision values are passed onto the M-agent and R-agent, subsequently, who make the final decisions to maximize their profits. The information flows under the MIC are shown in Figure 2.

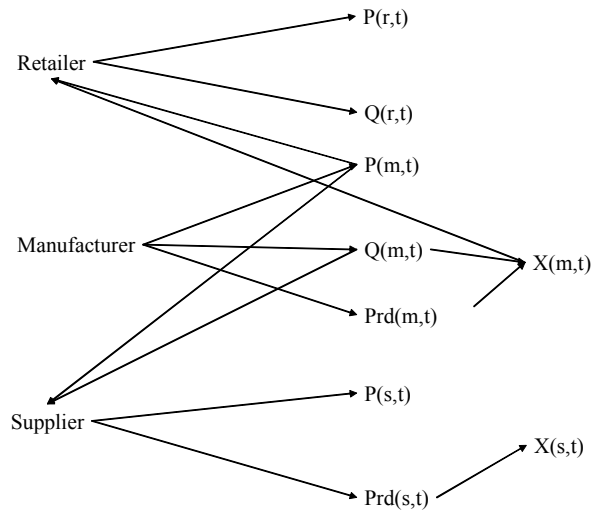


Figure 2. MIC scheme

P : price, Q : order quantity, Prd : production quantity, X : sales amount; r : retailer, m : manufacturer, s : supplier; t : time

VALIDATION

The experiments were conducted to compare the performance of three decision support levels in the MACE-SCM. In the Enhanced Integration Level, the agents collaborate with the help of the C-Agent and rely on the case base. In the Integration Level, the agents collaborate with the help of the C-Agent, but do not rely on the case base. In the Autonomy Level, the agents do not collaborate and do not rely on the case base. As the level of collaboration is intensified from the Autonomy Level to the Integration Level to the Enhanced Integration Level, the performance is expected to be gradually improved. Thus:

H1: The performance in the Enhanced Integration Level will outperform that in the Autonomy Level.

H2: The performance in the Enhanced Integration Level will outperform that in the Integration Level.

H3: The performance in the Integration Level will outperform that in the Autonomy Level.

Each decision support level was simulated 100 times and the time span of each simulation was 12 periods. In each period, customer demand was produced by random number generator. Figure 3 displays the performance differences among three different levels of decision support. The performance was measured by average profit.

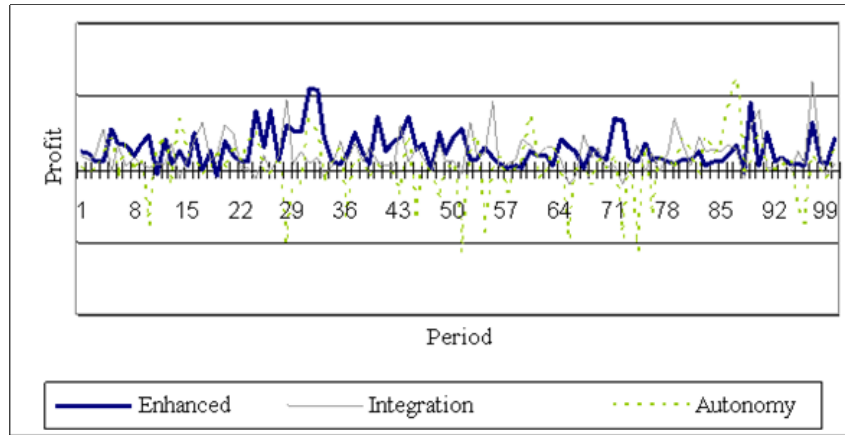


Figure 3. The performance of three decision support levels

One-way ANOVAs were performed to better understand the effect of different decision support levels on the performance. The results presented in Table 2 provide support for Hypothesis 1 ($p < 0.01$) and Hypothesis 2 ($p < 0.05$).

	Performance Measure	F	Sig.
H1 (Enh. > Auto.)	Average Profit	5.5414	0.000***
H2 (Enh. > Int.)	Average Profit	2.4614	0.014**
H3 (Int. > Auto.)	Average Profit	23.665	0.000**

Table 2. One-way ANOVA

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The above experimental results demonstrate the importance of intensive collaboration between the firms in uncertain market environments. Oftentimes the practitioners need some guidelines concerning whether they should enter into new relationships or change the contents of existing relationships. The three different models of collaboration can provide the platform to simulate different levels of relationship changes before they make a final decision concerning collaboration intensity to its partner. The statistical results can be used to evaluate the degree of benefits to the entire supply chain and to each individual firm before and after the changes.

CONCLUSION

This research attempted to show that the model based on multi-agents and CBR could be an effective approach for collaboration among firms. The validation results suggest that the approach based on multi-agents and CBR could provide robust solutions under high demand and high supply uncertainties. The model also shows the potentiality of dealing with different kind of uncertainties from demand and supply. For example, the firms may face high supply uncertainties regarding yield, process reliability, supply source and lead-time. Our model can be easily extensible for these uncertainties by reconfiguring case base based on expertise and history information and incorporating action strategies and policies into the model.

Several limitations of the research must be pointed out. We operationalized high demand uncertainties by employing a random number generator. Further expansion of the model by introducing a normal distribution is under way. Next, we addressed supply uncertainties from a relationship changes standpoint. A relationship change is operationalized by moving from a weak tie to a strong tie and vice versa. In reality, the relationship can not be classified into an “on” (intensive collaboration) or an “off” (no collaboration) type, but has gray elements between the two opposite types. From the focal firm’s viewpoint, the determining factors of collaboration with its suppliers include breakdowns, yields, quality level, reliability, process stability, capacity constraints, changeover, and lead time. Thus the current operationation of relationship

changes needs to incorporate the above additional factors and fine-tuned to reflect the reality and to add usefulness of the model to the practitioners.

REFERENCES

1. Clark, T.H., and Stoddard, D.B. (1996) "Interorganizational Business Process Redesign: Merging Technological and Process Innovation," *Journal of Management Information Systems* (13:2), pp. 9-28.
2. Dhar, V., and Stein, R. (1997) *Intelligent Decision Support Methods: The Science of Knowledge Work*, Prentice-Hall, Upper Saddle River, NJ.
3. Harrison, T.P. (2001) "Global Supply Chain Design," *Information Systems Frontiers* (3:4; Special Issue: Supply Chain Management), pp. 413.
4. Ho, D.C.K., and Newton, E. (2002) "Empirical Research on Supply Chain Management: A Critical Review and Recommendations," *International Journal of Production Research* (40:17), pp. 4415-4430.
5. Kimbrough, S.O., Wu, D.J., and Zhong, F. (2002) "Computers Play the Beer Game: Can Artificial Agents Manage Supply Chains?," *Decision Support Systems* (33:3), pp. 323-333.
6. Lambert, D.M., and Cooper, M.C. (2000) "Issues in Supply Chain Management," *Industrial Marketing Management* (29:1), pp. 65-83.
7. Lee, H.L., So, K.C., and Tang, C.S. (2000) "The Value of Information Sharing in a Two-Level Supply Chain," *Management Science* (46:5), pp. 626-643.
8. Lottaz, C., Smith, I.F.C., Robert-Nicoud, Y., and Faltings, B.V. (2000) "Constraint-Based Support for Negotiation in Collaborative Design," *Artificial Intelligence in Engineering* (14:3), pp. 261-280.
9. Maturana, F.P., and Norrie, D.H. (1997) "Distributed Decision-Making Using the Contract Net within a Mediator Architecture," *Decision Support Systems* (20), pp. 53-64.
10. Muckstadt, J.A., Murray, D.H., Rappold, J.A., and Collins, D.E. (2001) "Guidelines for Collaborative Supply Chain System Design and Operation," *Information Systems Frontiers* (3:4; Special Issue: Supply Chain Management), pp. 427.
11. Mukhopadhyay, T., Vicinanza, S.S., and Prietula, M.J. (1992) "Examining the Feasibility of a Case-Based Reasoning Model for Software Effort Estimation," *MIS Quarterly* (16:2), pp. 155-171.
12. Raghunathan, S. (2001) "Information Sharing in a Supply Chain: A Note on Its Value When Demand Is Nonstationary," *Management Science* (47:4), pp. 605-610.
13. Sillince, J.A.A., and Saeedi, M.H. (1999) "Computer-Mediated Communication: Problems and Potentials of Argumentation Support Systems," *Decision Support Systems* (26:4), pp. 287-306.
14. Serman, J. (1989) "Modeling Managerial Behavior: Misconceptions of Feedback in a Dynamic Decision Making Experiment," *Management Science* (35), pp. 321-339.
15. Swaminathan, J.M., Smith, S.F., and Sadeh, N.M. (1998) "Modeling Supply Chain Dynamics: A Multiagent Approach," *Decision Sciences* (29:3), pp. 607-632 26 pages.
16. Wooldridge, M., and Jennings, N.R. (1995) "Intelligent Agents: Theory and Practice," *The Knowledge Engineering Review* (10:2), pp. 115-152.