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Agent-Based Framework for Dynamic Supply Chain Configuration

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INTRODUCTION

Supply Chain Management has gained renewed interest among researchers in recent years. This is primarily due to the availability of timely information across the various stages of the supply chain, and therefore the need to effectively utilize the information for improved performance. In this paper we develop a framework, with machine learning, for automated dynamic supply chain configuration. Recent developments in eCommerce applications and faster communication over the Internet in general necessitate dynamic (re) configuration of supply chains over time to take advantage of better configurations. The supply chain models each actor as an agent who makes independent decisions based on information gathered from the next level upstream. Examples show performance improvements of the proposed adaptive supply chain configuration framework over static configurations.

Mismatches in demand and supply arise primarily due to market volatility. And, there are opportunity costs that are associated with these mismatches (e.g., Radjou, 2002). Examples include decrease in quarterly earnings in 1996 by $900 million for General Motors due to an 18-day labor strike at a brake supplier factory that idled workers at 26 assembly plants and Boeing's $2.6 billion loss in 1997 due to failure of two key suppliers to deliver critical parts on time. Information and inventory have been identified as factors that work synergistically to enable better performance of supply chains (e.g., Alles et al., 2000; Cachon and Fisher, 2000; Hariharan and Zipkin, 1995; Mukhopadhyay et al., 1997; Whang, 1993; Woolley, 1997).

Automated supply chain configuration is beneficial when there are changes in cost of products/services, resource availability, and customer demands. This assumes that for a given order there are several feasible supply chain configurations that can deliver the product. The number of such feasible configurations increases with the number of stages, products, suppliers, etc.

This paper aims to address the following specific question using examples: Does dynamically switching among appropriate nodes in a stage result in improvements in (a) revenue, (b) effectively serving the customer based on the percentage of orders fulfilled as desired by the customer?

The proposed framework learns to associate the best node(s) at each stage of the network for each combination of order attributes (price, lead-time, quantity, etc.) in the system. It assumes that the products or parts that pass through each node in every stage are of the same quality.

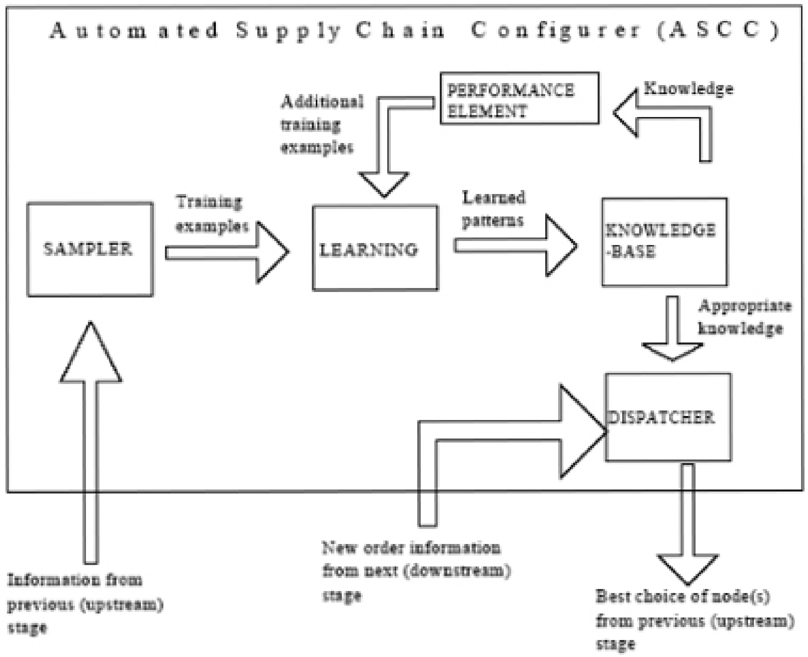

Figure 1. Automated Supply Chain Configurer (ASCC) Framework

AUTOMATED SUPPLY CHAIN CONFIGURER FRAMEWORK

The proposed Automated Supply Chain Configurer (ASCC) framework is given in **Figure 1**. ASCC itself can be considered an agent that resides at every node (except for the final node upstream, without loss of generality in this study, since those nodes are assumed to not make choice decisions) in the supply chain. Each of these agents makes myopic decisions based on the information they have about the nodes in the next stage upstream to them and the order information that comes from a stage downstream from them. Although the local decisions made are myopic in character, it can be shown that these series of myopic decisions do indeed lead to the best overall performance from start to finish. This is achieved by selecting the best available option at each stage. The following section illustrates the ASCC framework.

EXAMPLES USING THE PROPOSED FRAMEWORK

A two-stage supply chain illustrates the proposed framework. Assume a transaction begins when customers send in their orders through a web interface. Based on the order specifications (e.g., product and quantity of each product ordered, length of time the customer is willing to wait till the order is shipped, price the customer is willing to pay, etc.), the order is routed to the most appropriate supplier.

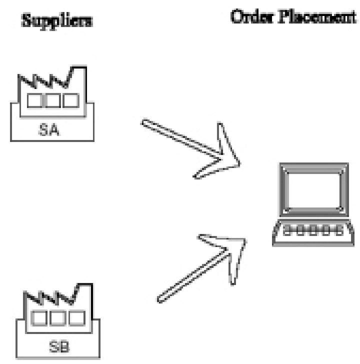

Figure 2.Two-stage supply chain with two suppliers

A Two-Stage Supply Chain Example

Consider the case where there is only one product (P) that is supplied by two types of suppliers S_A and S_B (**Figure 2**). Assume that the suppliers are capable of supplying different quantities of the product with different lead-times and prices. When overlaps in price/quantity/lead-time combinations occur, the system chooses the most appropriate supplier for that particular combination. Table I provides the information for choosing the most appropriate supplier.

The data in **Table I** are read as follows: The first line indicates that supplier S_A can supply up to 30 units of product P with a lead-time of 1-5 days at a unit cost of 97.

Table 1

Product Information for Each Supplier

Supplier	Lead Time (Days)	Quantity	Unit Cost
S_A	1-5	1-30	97
S_A	6-10	1-100	95
S_A	11-15	1-150	90
S_B	1-3	1-10	99
S_B	4-8	1-70	93
S_B	9-15	1-150	91

Clearly neither S_A nor S_B is the best choice under all circumstances. For example, if an order requires 100 Ps to be delivered in 1 day, it is not feasible in this problem context. In such cases, since the suppliers in this system (S_A and S_B) cannot fulfill the order, the customer balks unless the order can be filled from inventory.

The data in **Table I** to generates training examples for the learning module in ASCC. An example of the set of rules used to select supplier S_A or S_B using just quantity and lead-time information is as follows:

1. IF (Quantity >= 30) & (LeadTime >= 3) THEN S_A.
2. IF (Quantity >= 30) & (LeadTime > 10) THEN S_A.
3. IF (Quantity >= 30) & (3 < LeadTime >= 10) THEN S_B.
4. IF (Quantity > 30) & (8< LeadTime >= 10) THEN S_B.
5. IF (Quantity > 30) & (LeadTime > 10) THEN S_A.
6. IF (30 < Quantity >= 70) & (LeadTime >= 8) THEN S_B.
7. IF (Quantity > 100) & (LeadTime >= 8) THEN S_A.
8. IF (70 < Quantity >= 100) & (LeadTime < 6) THEN S_A.
9. IF (70 < Quantity >= 100) & (5 < LeadTime < 9) THEN S_A.

An over-simplified example here illustrates the proposed framework.

On arrival of the order, the pattern (e.g., want 110 units of product in 12 days) in the order is matched with the most appropriate rule in the rule base and the most appropriate action is taken as per this rule (e.g., supplier S_A based on the rule 4).

Each supplier begins with a set amount of inventory, e.g. 75 units, purchased at a cost of 91 per unit. The supplier first fills orders from inventory. When the inventory drops below a certain threshold, e.g. 53 units, the supplier replenishes inventory according to the framework in Table I. The inventory costing applies the LIFO principle. When using two different batches of inventory to fill one order, the supplier assesses the cost of the inventory by using a weighted average of the batch costs. Thus the cost of filling an order of 130 units where the first 30 units cost 95 and the last 100 units cost 90 would be calculated as follows:

cost per unit = [(30*95) + (100*90)]/130

The framework uses Table I and assumes the following: orders arrive several times per day, as generated by a lognormal(2,0.5) function where 2 represents the mean and 0.5 represents the standard deviation; the amount of product P requested in each order varies uniformly from 1 through 150; the lead-time requested in each order varies uniformly from 1 through 15. As a

benchmark to compare the proposed system, the study uses two cases: one where every order is sent to supplier S_A, and another where every order is sent to supplier S_B. Of course, the proposed system sends the order to either S_A or S_B as per the specifications in the order.

The framework models the cost of inventory to include the cost of warehousing excess inventory. This cost is added to the general unit cost to get the effective unit cost. Let α = a penalty constant of 0.01. The effective cost of each order is modeled as:

$$[\text{unit cost} * \text{quantity}] + [\alpha * \text{unit cost} * \text{inventory}]$$

The unit selling price is 110. The study simulates the process for 372 days with a warm-up period of 7 days, and collects necessary statistics for 365 days. Results are provided in Table 2.

Table 2

Results for Two-Stage Supply Chain

	Inventory Level	Supplier With No Inventory		Supplier With Inventory		Supplier With Inventory Penalty	
Supplier	(Max, Min)	Profit	% Balked	Profit	% Balked	Profit	% Balked_p
S_{AB}	(75, 53)	$3,382,568	19.56	$3,554,909	7.50	$3,393,808	7.50
S_A	(75, 53)	$1,389,570	47.15	$1,677,506	27.59	$1,540,197	27.59
S_B	(75, 53)	$3,170,327	24.69	$3,342,743	12.63	$3,191,895	12.63
S_{AB}	(97, 75)	$3,272,698	19.43	$3,467,926	6.07	$3,260,168	6.07
S_{AB}	(75, 53)	$3,382,568	19.56	$3,554,909	7.50	$3,393,808	7.50

Results for profits in the inventory case are listed under Profiti for profits without any penalty for inventory and Profit_{ip} for profits with a penalty for inventory. Here, the inventory volume varied as given in the second column, with the first number representing the maximum inventory level and the second number representing the minimum threshold level inventory reaches where reordering begins. Supplier S_A refers to the case where all the orders were directed to supplier S_A. Supplier S_{AB} refers to the case when the proposed framework was used to direct the orders appropriately to suppliers S_A or S_B. Profit is the overall profit (110-cost) without inventory summed over all Ps that were dispatched through the system over 365 days. %Balked is the percentage of orders that were not fulfilled because of lead-time/quantity constraints.

For the case where no inventory is modeled, results are as expected. Here, based on the way the capabilities of suppliers S_A and S_B are modeled, always sending the orders to S_A resulted in the least profit and those through the proposed system framework resulted in the most profit. Similarly, the number of orders that were not fulfilled is the most for supplier S_A and least using the proposed system framework. On the other hand, once inventory is introduced, the trends continue. However, the inventory greatly reduces the bulk rate. The profits with the inventory penalty remain greater than those when the same suppliers do not carry inventory. The profit for S_B in the case of the maximum inventory level of 97 remains slightly higher for the inventory cases than in the S_{AB} case.

DISCUSSION

The presented framework dynamically forms and reconfigures a supply chain as per the dictates of order specifications. With the involvement of inventory in the process, no definitive way to place orders exists such that freely choosing from any supplier or any assembler always results in the optimal profits and the minimum balks. The inventory reduces the balk rate but does not completely remove the presence of balks. When directing an order that would otherwise have balked to an assembler or supplier in the chain, the possibility that the order will still balk remains up to chance. If the order can be filled, then the supplier inventory level may be at such a low level afterwards that it cannot be replenished fast enough to keep the next order from balking. Therefore, always ordering from the same assembler or supplier could perform better than dynamically choosing between assemblers and supplier for the same set of orders.

When carrying inventory, dynamically choosing a supplier or assembler does not necessarily increase profits over using only one supplier or assembler combination. The orders placed in order to replenish inventory in the case of an order that would otherwise balk can be much smaller than the actual order. In this case, the inventory cost remains higher than the cost of a large order. Therefore, reduced profits result. The results show that dynamically choosing, while not always resulting in optimal profits and maximum ability to fill orders, can be much more profitable than choosing the wrong assembler and supplier combination.

The results do show the general trends that carrying inventory reduces the percentage of balks, thus satisfying the customer to a greater degree because a greater percentage of orders can be filled. Even with the cost of storing the inventory taken into account, the profits still remain higher than in the absence of inventory. The effects of discounting factors such as goodwill also play a role in the profits of a dynamic supply chain as discussed in the extended version of this paper. Future research may focus on extending the framework to handle more stages, several nodes in *each stage, order variability, and orders with a mix of various types of products.*

REFERENCES

The complete references can be found in the extended version of this paper, Agent-Based Framework for Dynamic Supply Chain Configuration, presented at the Thirty-Seventh Annual Hawaii International Conference on System Sciences, January 2004.

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