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Fuzzy Multiple Agent Decision Support Systems for Supply Chain Management

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1. Introduction

A supply chain encompasses the processes from the initial materials provision to the ultimate consumption of finished product linking across supplier-user companies. It involves the functions within and outside a company that enable the value chain to make products and provide services to the customers (Handfield & Nicholas, 1998). Supply chain management (SCM) is a strategic approach, which contains the following processes (Rogers, 2003): (i) Customer relationship management; (ii) Customer service management; (iii) Demand management; (iv) Order fulfillment; (v) Manufacturing flow management; (vi) Procurement; (vii) Product commercialization; and (viii) Returns management.

Graves & Willems (2000 and 2000) developed an optimization algorithm to find the best inventory levels of all sites on the SC. They also extend their model to solve the supply chain configuration problems for new products. Cebi & Bayraktar (2003) proposed an integrated lexicographic goal programming (LGP) and AHP model including both quantitative and qualitative conflicting factors for supply chains. Wang et al. (2004) presented a weighted multiple criteria model for SC. They stated that in real world problems, the weights of different criteria may vary based on purchasing strategies. Stadtler (2005) presents the main difficulties of SCM and tries to present some new models to resolve them. Baganha & Cohen (1998), Graves (1999), Chen et al. (2000), and Li et al. (2005) study the demand updating and information sharing issues of SC. Cachon (1999), and Kelle & Milne (1999) study the order batching in supply chain.

Li et al. (2005) use the term information transformation to describe the phenomenon where for each considered stage, outgoing orders to higher stage of a supply chain have different variance from incoming orders that each stage receives.

By the emergence of the new tools in information and communication technologies, globalization and shifting from mass production to mass customization, new requirements for achieving competitive advantages in supply chain management have been defined. These changes lead to the next generation of supply chain management systems. Such systems must have at least some essential characteristics, such as: agility, responsiveness, adaptability, integrated and cooperative [Lembert et al. 1998; Verdicchio & Colombelte 2000). The most effective areas that have drastically changed SCM are distributed artificial intelligence and agent-based systems.

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In the literature, there are some research manuscripts that show distributed artificialintelligence (DAI), especially agents and multi-agent systems (MAS), for SC (Simchi-Levi et al. 2000; Wu et al. 2000). Multi-agent systems paradigm is a valid approach to model supply chain networks and for implementing supply chain management applications. Multi-agent computational environments are well-suited for analyzing coordination problems, involving multiple agents with distributed knowledge. Thus, a MAS model seems to be a natural choice for the next generation of SCM, which is intrinsically dealing with coordination and coherent among multiple actors (Wu et al. 2000; Shen et al 2001). The inherent autonomy of software agents enables the different business units of supply chain network to retain their autonomy of information and control, and allows them to automate part of their interactions in the management of a common business process (Fazlollahi, 2002). As uncertainty in the environment of supply chain is usually unavoidable, an appropriate system is needed to handle it. Fuzzy system modeling has shown its capability to address uncertainty in supply chain. It can be used in an agent-based supply chain management system by development of fuzzy agents and fuzzy knowledge-base; Fuzzy agents use fuzzy knowledge bases, fuzzy inference and fuzzy negotiation approaches to handle the problems in the environment and take into consideration uncertainty. Using fuzzy concepts leads to more flexible, responsive and robust environment in supply chain which can handle changes more easily and cope with them naturally.

Erol & Ferrel (2003) discussed applications of fuzzy set theory in finding the supplier with the best overall rating amomg suppliers. Fazel Zarandi & Saghiri (2006) presented a fuzzy expert system model for SC complex problems. They compared the results of their proposed expert system model with fuzzy linear programming and showed its superiority. Zarandi et al. (2005) presented a fuzzy multiple objective supplier selection's model in multiple products and supplier environment. In their model, all goals, constraints, variables and coefficients are fuzzy. They showed that with the application of fuzzy methodology, the multi-objective problem is converted to a single one.

2. Multi agent systems and agent-based supply chain management

Software agents are just independently executing program, which are capable of acting autonomously in the presence of expected and unexpected events (Fox et al. 1993). To be described as intelligent, software agents should also process the ability of acting autonomously, that is, without human input at run-time, and flexibly, that is, being able to balance their reactive behavior, in response to changes in their environment, with their proactive or goal-directed behavior (Hayzelden & Bourne 2001). These issues have also been discussed by other authors, which were classified by Liu et al. (2000).

As stated by Fox et al. (1993), in the context of multiple autonomously acting software agents, the agents additionally require the ability to communicate with other agents, that is, to be social. The ability of an agent to be social and to interact with other agents means that many systems can be viewed as multi-agent systems (MAS). The hypothesis or goal of multi-agent systems is: creating a system that interconnects separately developed agents, thus, enabling the ensemble to function beyond the capabilities of any singular agent in the systems.

In multi-agent systems, some issues such as: agent communications, agent coordination, and inference must be considered (Nwana & Ndumu 1999). For agents to communicate with each other, an agent communication language (ACL) is needed. Multi-agent systems have been applied in supply chain management and they have introduced a new approach called agent-based supply chain management. In an agent-based supply chain management, the supply chain is considered as being managed by a set of intelligent software agents, each responsible for one or more activities in the supply chain, and each interacting with other agents in the planning and execution of their responsibilities.

For applying agents in supply chain management, first, the following issues must be considered (Lambert et al. 1998; Verducchio & Colombetti 2000; Fazlollahi 2002):

i. The distribution of activities and functions between software agents;
ii. Agent communication issues, including: Interoperability, Coordination, Multi-agent scheduling and planning, Cultural assumption;
iii. Responsiveness; and
iv. Knowledge accessibility in a module.

During the past decade, agent based supply chain management has been the main concern of many researchers. Saycara (1999) has done related projects and research in this area. Lambert et al. (1998) introduce virtual supply chain management and virtual situation room in which agents are the main elements for achieving a coordinated and cooperated supply chain. Jiao et al. (2006) propose the use of multi-agent system concepts in global supply chain networks. Xue et al. (2005) suggest a framework for supply chain coordination in a construction networks. Wang & Sang (2005) present a multi-agent framework for the logistics in a supply chain network. Fox & Barbuceanu (2000) discuss a model for agent negotiation and conversation in an agent based supply chain management. Dasgupta et al. (1999) focus on the negotiation between suppliers in different stages in supply chain management. Chauhan (1997) and Lau et al. (2000) propose a methodology for multi-agent systems development in supply chain. Chauhan (1997) used Java technology and objectoriented approach to achieve the goal. Lau et al. (2000) introduce a methodology for a flexible workflow system in supply chain to obtain more flexibility in ever changing environment of supply chain.

Some researchers present some architecture for agent based supply chain management. Ulieru et al. (1999) introduced a common architecture for collaborative Internet based systems in which some services are delivered via Internet. The architecture was for coordinated development of planning and scheduling solutions. The architecture proposed by Yung & Yang (1999) is composed of functional and information agents for reducing bull wipe effect in supply chain. Fox & Barbuceanu (2000) have proposed an architecture for agent based supply chain management composed of functional and information agents. They have also introduced a common building shell for agent structure in supply chain management.

Wu et al. (2000) focuses on web centric and Internet based supply chain management. They concentrate on service delivery via collaborative agents in the internet and propose a common and integrated framework for web-centric supply chain management systems. EDS Group (Wu et al. 2000) applies web technology for developing a networked society for each partner in supply chain. The group uses Java technology for internet-based purchasing and contracting.

In literature, we can hardly find research papers and project manuscripts that concentrate on uncertainty in supply chain, specialized information distribution and flexibility. According to the existing uncertainty in supply chain environment, using an approach which can address these problems seems necessary. As each partner in supply chain has its own needs and information requirements, distributing information according to the requirement of each partner is a critical factor, which a few research focused on it. Achieving flexibility is supply chain environment is one of the main concerns of the past decade. Using fuzzy agents and creating a flexible environment in supply chain can handle major issues relating to coordination and collaboration and can address flexibility problems in supply chain. The main concern of this research is focusing on these important issues.

3. ISCM model

Integrated Supply Chain Management (ISCM) system proposed by Fox & Barbuceanu (2000) encompasses a whole architecture and a general agent building shell for all agents in an agent-based supply chain management. ISCM is a multi-agent approach in which supply chain is considered as a set of six functional and two information agents that cooperate with each other to fulfill their goals and functions. The architecture of ISCM is shown in Figure 1.

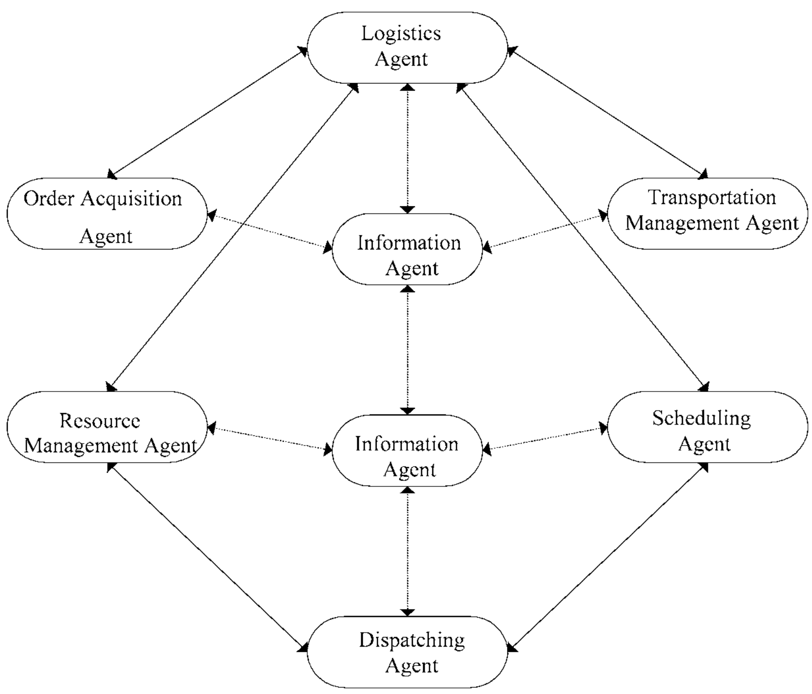

Figure1. ISCM Architecture

Functional agents, including logistics, order acquisition, transportation management, resource management, scheduling and dispatching have specific functions and interact with others to achieve the supply chain goals. Information agents support functional agents to access updated information and knowledge in supply chain. They eliminate conflicts in information resources, process the information in order to determine the most relevant content and the most appropriate form for the needs of agents and provide periodical information for them. Information agents provide other agents a layer of shared information storage and services. Agents periodically volunteer some of their information to the information agents or just answer the queries sent to them by the information agent (Fox et al., 1993; Fox & Barbuceanu 2000).

This paper focuses on the architecture of information agent in ISCM. For this purpose, we explain its functions, inputs and outputs. Then, by considering the basics of a modular architecture for agents and also supply chain properties, a new modular architecture for the information agent in ISCM is proposed. We develop the knowledge-base in the architecture and define required fuzzy rules and database. Moreover, we evaluate and test the knowledge base and compare the method in which fuzzy rules has been used with the one with non-fuzzy rules. Finally, we introduce an approach for dynamic updating the forecasted cost and time in every stage of supply chain.

An information agent is responsible for providing transparent access to different resources, as well as retrieving, analyzing and eliminating inconsistency in data and information, properly (Klusch, 1999). It is a computer software system that accesses to different geographically distributed and inconsistent multi resources and assists users and other agents to provide relevant information. In other words, information agents manage information access issues (Nwana, 1996). Depending on the ability of information agent to cooperate with each other for the execution of their tasks, they can be classified into two broad categories: *Non-cooperative* and *cooperative*. An information agent, cooperative or noncooperative, can be relational, adaptive or mobile. Relational information agents behave and may even collaborate together to increase their own benefits and they are utilitarian in an economic sense. Adaptive information agents are able to adapt themselves to changes in the networks and information environments. Mobile information agents are able to travel autonomously through a network (Klusch, 1999).

According to the changes in a supply chain, an agent must be able to adapt with uncertainty and incomplete information. An approach to obtain a flexible behavior for an information agent is to form a team of agents which are cooperative and are capable of gradual adaptation. Adaptive information agents can fulfill this goal. This research uses adaptive information agent to cope with changes in supply chain environment and achieve more flexibility and robustness.

The main function for an information agent is to process information retrieval requests and information monitoring, intelligently and efficiently. Generally it can be said that an information agent is able to provide essential services related to human and agents' information requirements. However, there is a difference between an information agent and a web service provider. An information agent can infer about the method for analyzing requests and how they must be processed (Caglayan & Harrison 1997). Therefore, we can consider three main functions for a typical information agent (Barbaceanu & Fox 1995): (i) Knowledge management; (ii) Eliminating conflict management; and (iii) Supporting coordination between other agents.

According to different resources (Fox et al. 1993; Barbuceanu & Fox 1995; Sycara 1999) and also the supply chain environment and features, we have considered six functions for the information agent in supply chain management:

- Storing the required information for sharing and providing a layer of information;
- Analyzing information for providing the proper respond to queries and requests;
- Automate routing for information distribution;
- Conflict management;
- Change management;

- Negotiating with other agents to provide essential information;

The inputs of an information agent can be categorized into queries and changes. Requests are those that are sent by other agents and information agent considers changes in the environment by receiving the changes. Responses to the requests and queries are possible outputs of the information agent. An information agent should automatically direct the essential information to the agents. Periodical information for other agents can be another type of output. Also, an information agent should recognize that which agent can access to what information. Consequently, one possible output should issue this function. Finally, an information agent must share some information between groups of agents. The output of this function can be the required shared information

According to the above inputs, functions, and outputs of the information agent in supply chain management, this chapter proposes a new architecture for the information agent. A conceptual model for an agent has four main parts: reasoning engine, knowledge base,learning engine and access control. Reasoning engine determines the required actions for the acquired events and knowledge from the environment. Knowledge-base stores the information and knowledge used by reasoning engine. Access control is an interface with the environment. Feedbacks are received by access control and actions are sent to the environment.

5. Modules of the proposed system

This section explains the goals, features, method, and structure of each module in the proposed architecture.

5.1 Conflict management

An information agent can have access to different information resources and receive different type of data. There must be a module to remove the possible conflicts and inconsistency between information. Thus, before considering any changes or information in the knowledge-base and informing others about this, conflict management module must eliminate any inconsistency or conflict with the existing information. For this purpose, we have used a-u space model (Barbuceanu & Fox 1995).

Suppose that we have a conflict between expression *p* and *q*. Expression *p* is the input statement and expression *q* is an existing statement. To each *p* we can attach an authority measure--the authority of its producer—and a un-deniability measurederived from the sum of deniability costs of all propositions that would have to be retracted if *p* is retracted. A high authority means that the proposition is more difficult to retract since a high authority has to be contradicted. A high un-deniability means that the proposition is more difficult to retract because the costs of retraction incurred upon consumer agents will be high (Barbuceanu & Fox 1995). We can represent these two values of all *p* as points in a diagram, having authority on the x-axis and undeniability on the y-axis. Such a diagram is called “a-u” space and is illustrated in Figure 2.

We can summarize the evaluation of a-u space in four rules as follows:

Rule 1 - If $a < a_t$ AND $u < u_t$ THEN Status = No Negotiation

Rule 2 - If $a < a_t$ AND $u > u_t$ THEN Status = Negotiation with Consumers

Rule 3 - If $a > a_t$ AND $u < u_t$ THEN Status = Negotiation with Producer

Rule 4 - If $a > a_t$ AND $u > u_t$ THEN Status = Negotiation with both

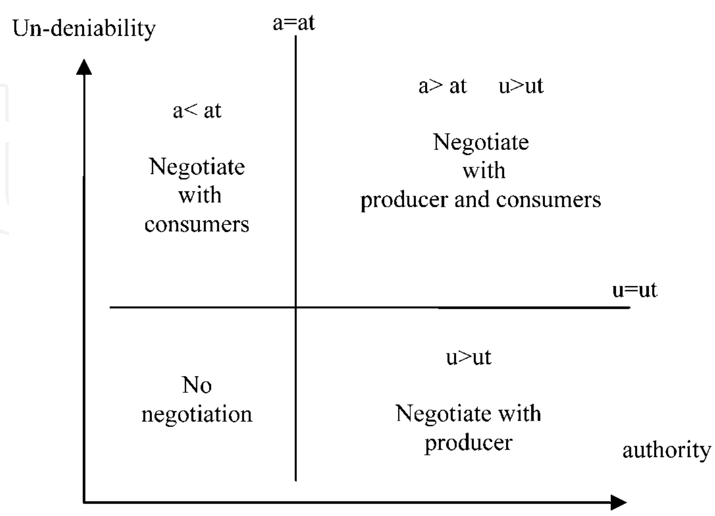

Figure 2. Negotiation regions in a-u space

Using fuzzy concepts in the proposed architecture, the following fuzzy rules are presented:
Rule 1 - If a isr Low AND u isr Low THEN Status is No negotiation
Rule 2 - If a isr Low AND u isr High THEN Status is Negotiation with consumer
Rule 3 - If a isr High AND u isr Low THEN Status is Negotiation with producer
Rule 4 - If a isr High AND u isr High THEN Status is Negotiation with Both
where, "High" and "Low" are linguistic values, each have its related membershipfunction, and “isr” stands for “is related to”.

5.2 Knowledge-base

The knowledge-base is responsible for storing data and knowledge. Knowledge- base comprises of two parts: rule-base and database. Rule-base contains a number of Metarules and subsets of rules. The rules are in both fuzzy and crisp format. Database stores data and information acquired from other external resources or new information generated by learning and tendering modules. The membership functions of linguistic values for fuzzy rules are also stored in the database.

5.3 Inference engine

Inference engine is one of the most important parts of an agent base system. Reasoning and deduction process are arranged by inference engine. Based on the situation of the inputs, the engine fires the rules in rule-base as a matter of degree and determines the proper fuzzy output.

5.4 Tendering

As information agent may not have essential knowledge to provide proper answer to some queries. We have set a tendering module in the architecture to avoid leaving a query without any response. The information agent can negotiate with other agents to find appropriate answer for a query which it does not have the required knowledge to answer.

Thus, it can use tendering process to discover the response. For organizing tendering process we have used brokering method (Klusch 1999). We differentiate among three types of agents in brokering method:

1) *Provider agents* provide their capabilities to their users and other agents.
2) *Requester agents* consume information and services offered by provider agents in the system. Requests for provider agent capabilities have to be sent to a middle agent.
3) *Middle agents*, i.e., broker agents, mediate among requesters and providers for some mutually beneficial collaboration. Each provider must first register itself with one (or multiple) middle agent. Provider agents advertise their capabilities (advertisement) by sending some appropriate messages describing the kind of service they offer.

The broker agent deals with the task of contracting the relevant providers, transmitting the service request to the service provider and communicating the results to therequester. When there is not enough knowledge to respond to a request or query, the information agent uses the tendering module to find the appropriate respond. In this occasion, the information agent is a broker agent and the requester agent is the agent that inquires and the provider agent is the agent that provides the appropriate answer for the inquiry.

5.5 Learning

Learning ability for an agent determines degree of its intelligence (Klusch 1999). This module creates new knowledge and reduces existing errors in the current knowledge. In this research, a Neural Network (NN) is implemented for learning. This net can improve the forecasted amount, cost or time, by using an error reduction function. In this case, learning is done for long term data, and for error reduction of short term, the NN uses the rules in the rule-base. More detail for this module is as follows:

In the information agents, learning implies the agent's ability to automatically modify the rule-base and the facts in two ways:

- Adding new rules or modifying existing rules: if the information agent can recognize a desirable new behavior, it may be able to propose a new rule about it. Also, it can modify existing rules, which is a form of rule optimization. Tendering module handles the queries where there is not proper answer for them. The learning engine can add a new rule or modify the existing ones to consider the result of tendering in rule-base. Consequently, if the query repeats again, there is no need for tendering, because the learning engine has created the proper knowledge. Also, information agent can recognize the periodical needs of every agent as they request for some information by the use of learning engine. Learning engine can also change the certainty factors of fuzzy rules, if required.
- Adding new facts or modifying old facts: changing and improving forecasted values are a critical issue in supply chain. The learning module can update forecasted values, e.g., costs and time, and reduce the errors by fuzzy neural networks.

5.6 Distributed data warehouse and data marts

For sharing the information between other agents and making required access to the information and data, we have set a Distributed Data Warehouse (DDW). A DDW is a logically integrated collection of shared data that is physically distributed across the nodes of a computer network (Moeller 2001). Traditional data warehouses, which are not distributed, are not appropriate for this purpose, because:

- According to huge interaction of data, designing and developing a single traditional data warehouse is hardly possible.
- Traditional data warehouses usually are designed for predetermined requests, but, here, we can not determine the requests exactly.
- Traditional data warehouses response time and loading are much more than DDW.
- As information agent interacts with different type of agents, it has to provide different kind of information specified for each agent. Thus, a DDW composed of different data mart is appropriate in this case.
- In occasions that the information is distributed naturally, like supply chain, DDW can be the best solution.

A DDW is composed of different data marts, where each is responsible for providing the information related to a specified area. A data mart is an application-focused miniature data warehouse, built rapidly to support a single line of business. Data marts share all the other characteristics of a data warehouse (Zarandi et al 2005). The data marts are independent, which can operate without a support of a centralized DDW. These kinds of data marts receive data and information directly from the resources, and give service to the consumers. As the information agent give services to four different agents, including Order Acquisition, Logistics, Transportation Management, and information agent, we generate a DDW with 4 data marts. Each data mart is responsible to provide information services for each agent. Database and data marts in this architecture communicate with each other by the use of ORB technology. An Object Request Broker (ORB) is a middleware that establishes the client-server relationships between objects. It provides a mechanism for transparently communicating the client requests to servers. ORB is an attempt to distribute computing across multiple platforms. Using an ORB, a client can transparently invoke a method on a server object, which can be on the same machine or across a network. The ORB intercepts the call and is responsible for finding an object that can implement the request, passing it the parameters, invoking its method, and returning the results. The client does not have to be aware of where the object is located, the programming language in which it is written, the operating system it is running on, or any other implementation details that are not part of the object's interface. Thus, the ORB provides interoperability between applications on different machines in heterogeneous distributed environments and seamlessly interconnects multiple object systems. The leading example of this approach is the Common Object Request Broker Architecture (CORBA).

5.7 Normalization, fuzzification and defuzzification

We have used Mamdani type operators to fuzzify the variables and aggregation of the rules, stated in (Cordon 2001). Mamdani fuzzy reasoning takes the minimum of the antecedent conditions in each rule and assumes the fuzzy truth of the rule to be 1. We use minimum operator for rule implications and AND operator in antecedent of rules. From a functional point of view, a Mamdani fuzzy inference system is a nonlinear mapping from an input domain $X \in R_n$ to an output domain $Y \in R_m$. This input/output mapping is realized by means of R rules of the following form:

$$\text{IF } x \text{ isr } A_{(r)} \text{ THEN } y \text{ is } B_{(r)} \tag{1}$$

where, $r = 1,2,\ldots,R$ is the index of the rule, while $A\ (r)$ and $B\ (r)$are fuzzy relations over X and Y respectively. When an input vector x is presented to the system, a fuzzy set B is inferred according to the following relation:

$$B(y) = \vee\ (A_{(r)}(x) \wedge B_{(r)}\ (y)) \tag{2}$$

where, the formalism A (●) denotes the membership function of a fuzzy set A , and ∧,∨ are a T-norm and a T-conorm, respectively (usually the min and the max operators are used).
Center of gravity method has been used for defuzzification method, Defined as:

$$\tilde{y} = \frac{\int B(y).y.dy}{\int B(y).\ dy} \tag{3}$$

As the input information and data are not in the same scale, there must be a module to standardize them and turning them into one form. Therefore, we use a normalization method to standardize input information and data. For normalizing a set of input information and data, the data is divided by the larges one in the set.

6. Developing database

As described earlier, database contains two types of data: data and information related to supply chain and membership functions of the linguistic values. We have used relational approach to develop the database. For storing the data and information related to supply chain, a model is considered for order fulfillment in which a supply chain is viewed as the composition of different stages.
It should be noted that, for an order fulfillment, some certain stages must be taken (Hanfield & Nichols 1998; Rogers 2003; Simchi-Levi 2000). For taking each stage, there are different methods. Therefore, by composing different methods for each stage, there will be different routes to fulfill an order. Each method in each stage has three features: method name, method cost, and method time (duration). Consequently, a route for an order has three features: route name, route cost (order total cost), and route time (order total time). Route cost and route time of an order are respectively the sum of cost and time of all stages in the route. There are two values for time and cost of each method in every stage: forecasted value and actual value. Order properties and related information such as customer properties, due date, order time, and the like are stored in the database. In addition to the mentioned information, any information agent can store any type of information receiving from the other agents.
There are five different linguistic values for measuring the degree of changes and weights: Very Low, Low, Medium, High, and Very High.

7. Developing rule-base

The rule-base in the knowledge base has 31 rules, 3 Meta rule and 3 rule subsets. Rule-base contains both fuzzy and crisp rules. As mentioned before, every order has its related total time and total cost which can be obtained respectively by adding time and cost of each stage in the order route. We introduce an approach for updating the forecasted values of total time and cost of each order and directing the supply chain to the committed cost and time

for the costumer. Before an order flows in the supply chain, there is forecasted total time and total cost for order fulfillment. As the order moves in the chain and goes through the stages, the actual cost and time for each stage are emerged. Consequently, we can define new total time and total cost for the order. Thus, if order *a* needs *m* stages to be fulfilled, we have:
Total time for *a:*

$$TotalTime(a) = \sum_{i=1}^{m} TimeStage_i(a) \tag{4}$$

Total cost for *a:*

$$TotalCost(a) = \sum_{i=1}^{m} CostStage_i(a) \tag{5}$$

where, *TimeStagei* (*a*) is the duration of stage *i* and *CostStagei* (*a*) is the cost of stage *i* of order *a*. If the time of stage *k* changes to *T,* then total time of *a* changes to:

$$TotalTime(a) = \sum_{i=1}^{m} TimeStage_i(a) + (T - TimeStage_k(a)) \tag{6}$$

Generally, in stage i of m we have i total time and i total cost for a. Thus, we have m total time and m total cost for order a at the end of order fulfillment. We have used different total time and total cost in every stage to forecast the next value in the chain. By comparing forecasted value in every stage and the initial forecast value, which is the committed value to the costumer, the partners in the chain will be notified about the difference between the committed value and the real one and consequently they change their plan and behavior in a manner to reach the committed value.

8. Determination of the forecasted value

Assume that we are at stage *i* of order *a*. Thus, we have *i* total time as follows:
Total time of *a* in stage *i*:

$$TotalTime^{(i)}(a) = T_i \tag{7}$$

Then, we can use fuzzy rules to define a weight for each total time, for example:
IF ($Tk - Tk - 1$) isr Low AND ($Tk - 1 - Tk - 2$) isr High THEN $Weight(Tk)$ isr Medium
where, $Weight(Tk)$ is the weight of T_k and "isr" means "is related to". The forecasted value for total time in stage *i* is:

$$T = \sum_{k=1}^{i} T_k Weight(T_k) \tag{8}$$

9. Technical issues, implementation and validation

The proposed common structure for agents in supply chain by Fox & Barbuceanu (2000) is composed of seven layers which are: agent communication language, conversational coordination, action and behavior, organization model, decision making, behavior planning, behavior execution and domain specific solvers. The structure is considered for all agents in the agent-based supply chain management, including information and functional agents. Also they proposed some essential features for an information agent as follows (Fox & Barbuceanu 2000):

- Change management
- Query management
- Conflict management
- Time map management system.

The proposed architecture in this section has eight modules. These modules satisfy the expected functions and output from the information agent. Normalization module standardizes the input data and changes their format in such a manner that their comparison makes sense. Fuzzification module fuzzifies the information to infer and use it in knowledge base. Using fuzzy rules, increases system flexibility and robustness and reduces complexity, thus, information agent can handle uncertain events and information more easily. Conflict management eliminates the existing conflicts and inconsistency between data and information by using a-u space model with fuzzy boundaries. Knowledge-base stores current and new knowledge including rules and data. Tendering module avoids leaving a query without any response, and information agent negotiates with other agents to find proper answer for any query that it can not response individually. Learning module modifies existing rules and facts and eventually creates new rules and facts according to the current information, events and agents behavior. For sharing the information and data specifically for every agent, a DDW module has been applied. The DDW contains four data marts, each responsible to provide specialized information and services for a particular agent. Defuzzification module changes the fuzzy information to crisp information to share with other agents. For testing the rule-base and comparing the result of applying fuzzy rules, a set of data related to a Computer Monitor supply chain has been used. All the proposed rules and their related databases have been assessed and suitable responses have been gained from their assessment, based on the negotiations with experts.

10. Bullwhip reduction in SC

One of the most fruitful research sub-areas in studying supply chain management is bullwhip effect or whiplash effect. The bullwhip effect occurs when the demand order variations in the supply chain are amplified as they move up in the supply chain. Five possible sources for bullwhip effect are recognized in the literature (Lee et al. 1997a) and (Lee et al. 1997b). They include: demand forecast updating, prize fluctuation, rationing and shortage gaming, order batching and none-zero lead time. The first formal description of the bullwhip effect can be traced back to the work of Forrester (Forrester 1961). Sterman (1989) further demonstrates and discusses this phenomenon in the popular beer game. According to Sterman (1989), the bullwhip effect originates from the non-optimal solutions adopted by a supply chain participant while it does not consider the system as a whole. In the recent works, Cachon & Lariviere (1999) study the shortage gaming; Kelle & Milne (1999) and Cachon (1999) study the order batching and Drezner et al. (2000), Baganha & Cohen (1998), Graves (1999), Chen et al. (2000) and Li et al. (2005) study the demand updating and information sharing issues. Li et al. in (2005) use the term information transformation to describe the phenomenon, where for each of the stages considered, outgoing orders from a lower to a higher stage of a supply chain has a different variance from incoming orders which each stage receives.

However, there is only one work (Carlsson & Fuller 2001a) that applied fuzzy logic related concepts to bullwhip effect. Based on an optimal crisp ordering policy that drives the bullwhip effect, they presented a policy in which orders are imprecise. In an environment where orders can be intervals, they allow the actors in the supply chain to make their orders more precise as the time of delivery gets closer. They show that if the member of the supply chain share information with intelligent support technology, and agree on better and better fuzzy estimates on future sales for the upcoming periods the bullwhip effect can be significantly reduced. However, they did not consider the uncertainty in the demands and lead times in their proposed model.

As a matter of fact, for analyzing the Bullwhip Effect in the real world, one should consider it in an uncertain environment. In this research, Fuzzy Logic is utilized as a mean to represent and interpret the uncertainty in the real world supply chains. Thus, we propose to study the effect of fuzziness, i.e., information uncertainty, on the bullwhip effect. Here, it is assumed that all demands, lead times and order quantities have fuzzy values, i.e., they are imprecise. Among the available fuzzy time series approach, the Hong method (Hong 2005) is selected and a Genetic Algorithm (GA) module is added to obtain the value of window basis. In addition, a back propagation Neural Network module is added to defuzzify the output of Hong's model. In this paper, an Agent-Based model is developed to reduce the bullwhip effect in the above mentioned situation. Geary et al. (2005) categorized all previous approaches for reducing the bullwhip effect into five categories: OR Theory, Filter Theory, Control Theory, Adhocacy, and What-if simulation procedure. The proposed solution is a combination of OR Theory and What-if simulation approaches.

10.1 A problem sample

Consider a single item multi stage supply chain system in which only one participant exists at each stage. The participant's actions at a given stage *k* are described as follows:

At the end of time period *t*, after its demand $\tilde{D}k,t$ has been realized, the participant observes the inventory level, places an order of size $\tilde{Y}k,t$ to its supplier and receives this order at the beginning of time period $t+\tilde{l}_k+1$, where $\tilde{l}_k$ is the order lead time at stage *k*. Excess demand is backlogged. We assume that the orders at any given stage become demands for the immediately upstream stage. Thus, we have $\tilde{D}_{k+1,l}=\tilde{Y}_{k,t}$. Let $\tilde{q}_t$ represent the ordered quantity in period *t* to be delivered in period *t+l*, the timing of the event and the conservation of flow imply that:

$$\tilde{q}_{k,t} = \tilde{Y}_{k,t} - \tilde{Y}_{k,t-1} + \tilde{D}_t \qquad (9)$$

It should be noted that all demands and lead times are considered to be uncertain and are represented by fuzzy triangular numbers.

To investigate how bullwhip effect occurs in this fuzzy environment, three key components need to be specified:

i. The end customer's demand process;

ii. The policy that the participant at each stage applies to determine its inventory level and order quantity;

iii. Forecasting method of each stage to forecast the demand and order to the upstream stage.

For the first component mentioned above, we allow the demand process for the generation of the mid-point of a triangular fuzzy number to be an *ARIMA(p, d, q)* process and the left and right points are generated randomly around the mid-point. For the second component, a fuzzified version of Hayman and Sobel (1984) policy is implemented. They showed that when end customer's demand is an *ARIMA* process, such a policy minimizes the total expected holding and shortage costs over an infinite horizon. Finally for the third component, a modified version of (Hong 2005) is applied to forecast the customer demand of each stage.

We assume that each participant of the supply chain applies the same inventory and order policy as follows:

$$\widetilde{D}_{k+1,t} = \widetilde{D}_{k,t} + (\widetilde{S}_{k,t} - \widetilde{S}_{k,t-1}) \tag{10}$$

where, $\widetilde{S}_{k,t}$ is the fuzzy value of "the order-up-to level" at stage k and period t. Here, $\widetilde{S}_{k,t}$ can be expressed as follows:

$$\widetilde{S}_{k,t} = \widetilde{m}_{k,t} + z_k \sqrt{v_{k,t}} \tag{11}$$

where,

$$\widetilde{m}_{k,t} = E(\sum_{i=1}^{\widetilde{l}_k+1} \widetilde{D}_{k,t+i} \mid \widetilde{D}_{k,t}) \tag{12}$$

$$v_{k,t} = \mathrm{var}(\sum_{i=1}^{\widetilde{l}_k+1} \widetilde{D}_{k,t+i} \mid \widetilde{D}_{k,t}) \tag{13}$$

$$z_k = \phi^{-1}(h_k / (p_k + h_k)) \tag{14}$$

In this case, all demands are considered to be fuzzy sets. The fuzzy number $(\sum_{i=1}^{\widetilde{l}_k+1} \widetilde{D}k, t+i \setminus \widetilde{D}k, t)$ can be extracted by using extension principle and forecasting of fuzzy demand from time to time $t + \widetilde{l}_k + 1$, according to known demand at time t. Therefore, $E(\sum_{i=1}^{\widetilde{l}_k+1} \widetilde{D}k, t+i \setminus \widetilde{D}k, t)$ and var $(\sum_{i=1}^{\widetilde{l}_k+1} \widetilde{D}k, t+i \setminus \widetilde{D}k, t)$ are equal to variance and mean of a fuzzy number proposed in (Carlsson and Fuller 2001b) which is stated as follows:

$$E(A) = \int_0^1 \alpha (u^-(\alpha) + u^+(\alpha)) d\alpha \tag{15}$$

To calculate the mean of the fuzzy number u, they also defined possibilistic variance of afuzzy number as:

$$Var(A) = \frac{1}{2}\int_0^1 \alpha\,(u^-(\alpha)+u^+(\alpha))^2\,d\alpha \tag{16}$$

where, α is the α *-cut* value and $u^-(\alpha)$, $u^+(\alpha)$ are values in the left and right hand sides of the mid-point where their membership functions are equal to α. These formulas are used to calculate the following equations:

$$A1 +_w A2 = (m1 + m2, \max\{L1, R2\}, \max\{R1, L2\}) \tag{17}$$

$$A1 -_w A2 = (m1 - m2, \max\{L1, R2\}, \max\{R1, L2\}) \tag{18}$$

where, $Ai = (mi, Li, Ri)$ is a fuzzy number, and $+_w$ and $-_w$ are indices for weakest sum and minus.

10.2 Fuzzy sample variance and mean

Bullwhip effect happens when variance of orders amplify from downstream to upstream. Therefore, the variance of orders must be computed in each stage when one encounters fuzzy orders. For this reason, a fuzzy variance approach has to be chosen.
Expected value of a fuzzy random variable was introduced by Puri & Ralescu (1986). However, there is much less effort to define the variance or covariance of fuzzy random variable and study their properties. The variance and covariance of fuzzy random variable is of great importance in statistical analysis, linear theory of fuzzy stochastic and other fields of fuzzy stochastic theory and applications. The expected value of a fuzzy random variable defined in (Puri & Ralescu 1986) is a fuzzy number. However, it is proper that the variance and covariance of fuzzy random variables should have no fuzziness (Feng et al. 2001). As the case for real-valued random variables, the variance should be used to measure the spread or dispersion of the fuzzy random variables around its expected value. Here, we review the approach of Feng et al. (2001).
Define $E = \{u : R \to [0,1] | u \textit{ satisfies}(i) - (iii) \textit{below}\}$, where u is normal and fuzzy convex; and it is upper semi-continuous. For the α -level set of $u \in E$, $[u]^\alpha = \{x \in R \mid u(x) \geq \alpha\}$, where $0 < \alpha \leq 1$. Then, they defined $u^+(\alpha)$, $u^-(\alpha)$ as the upper and lower endpoints of $[u]^\alpha$. They define the operation $\langle \bullet,\bullet \rangle$ as $E \times E \to [-\infty, +\infty]$ by the following equation:

$$\langle u, v \rangle = \int_0^1 (u^-(\alpha)v^-(\alpha) + u^+(\alpha)v^+(\alpha))\,d\alpha \tag{19}$$

Then, the following properties have been considered for this operation:

(i) $\langle u, v \rangle \geq 0$ and $\langle u, v \rangle = 0 \Leftrightarrow u = \hat{0}$,
(ii) $\langle u, v \rangle = \langle v, u \rangle$,
(iii) $\langle u + v, w \rangle = \langle u, w \rangle + \langle v, w \rangle$,

(iv) $\langle \lambda u , v \rangle = \lambda \langle u , v \rangle$, (20)

(v) $| \langle u , v \rangle | \leq \sqrt{\langle u , u \rangle \langle v , v \rangle}$

where, u, v,w∈E and $\lambda \in [0, \infty)$.

For u, v∈E , if $\langle u , u \rangle < \infty$ and $\langle v , v \rangle < \infty$ from the property (v) in (20) they defined d* metric in $\{u \in E \mid \langle u, u \rangle < \infty\}$ as follows:

$$d_*(u, v) = \sqrt{\langle u, u \rangle - 2\langle u, v \rangle + \langle v, v \rangle} \tag{21}$$

Then, by these definitions, for a simple random independent and identically distributed sample X1,X2 ,...,Xn taken from fuzzy random variable X, where it's mean and variance are u and σ 2 , fuzzy sample mean and variance are defined as (Feng et al. (2001)):

$$\overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_i \tag{22}$$

$$S^2 = \frac{1}{2(n-1)} \sum_{i=1}^{n} d_*^2 (X_i , \overline{X}) \tag{23}$$

10.3 Experiment

To experiment a typical bullwhip effect for a four stage supply chain system, we have used an *ARIMA*(1, 0, 1) for end customer's demand process. The other parameters of the model are as follows:

$\varphi_{1,1} = 0.5 , \theta_{1,1} = 0.1, \quad \sigma = 50$ and $\tilde{l}_1 = \tilde{l}_2 = \tilde{l}_3 = \tilde{l}_4 = \tilde{1}$, where, $\tilde{1} = Triangular(0,1,2)$.

At first, as described before, end customer's demand is generated by using an ARIMA process, and then these values are fuzzified into some symmetric triangular fuzzy numbers. These fuzzy values are considered as demands. The proposed approach is used for forecasting purposes. Since any lead time also has a fuzzy value, when computing the value of $\tilde{m}_{k,t}$ by using extension principle and cutting the $\tilde{l}_t$ in α level, the value of $m_{k,t}$ becomes a type-II fuzzy set. To overcome this problem, by using the centroid method, a defuzzification on the values of ($\sum_{i=1}^{\tilde{l}_{k+1}} \tilde{D}k, t+i \setminus \tilde{D}k, t$) is implemented,. The occurrence of the bullwhip is shown in Figure 3.

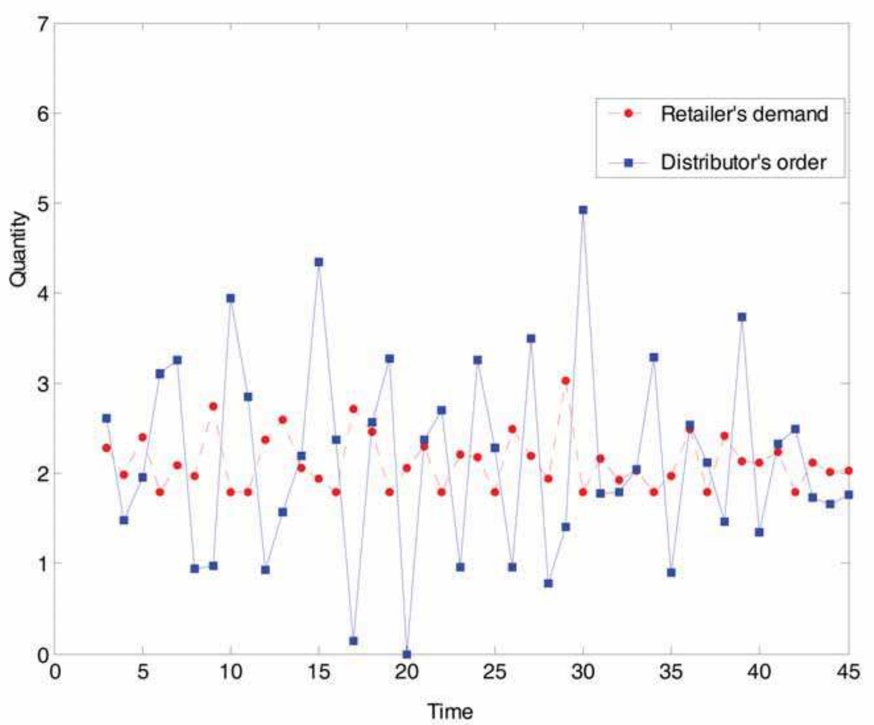

Figure 3. Retailer's demand and distributor's order in each period.

It is clear that the variance of demand is amplified in supply chain when demand is transferred from downstream to upstream stages. In order to compare the magnitude of information transformation, we need to use some metric. The simplest metric is comparing the sample variance, but it has some difficulties. If the bullwhip effects are indicated by simulation experiments at a wholesaler and a distributor, it can be expressed as $V(D_{retailer}) < V(D_{wholesaler}) < V(D_{distributor})$. At the same time, simulation experiments also indicate that the bullwhip effect at distributor is very weak compared with that at wholesaler, which implies that the degree of magnification is decreasing when moving up-stream. To quantify this, the metric of (Li et al. 2005) is applied. This metric is based on the relative comparison of the variance of sample points and is expressed as:

$$A_{i,j} = \frac{Var(D_i) - Var(D_j)}{Var(D_j)} \tag{24}$$

Therefore, when this metric is used, if $\left| A_{k+2,k+1} \right| > \left| A_{k+1,k} \right|$, it is said that theinformation transformation propagates from stage k to $k+2$ in an increasing magnitude.Otherwise, if $\left| A_{k+2,k+1} \right| < \left| A_{k+1,k} \right|$, we say that information transformation propagatesfrom stage k to $k+2$ in a decreasing magnitude. To compute

$Var(D_i)$, the formulas of samplevariance and mean of fuzzy numbers have been used. The results are shown in Table 1.

Variance of demand	Retailer	Distributor	Producer	Supplier
	0.0640	0.2994	1.0329	1.9142
Metric Value	-	0.7862	0.7721	0.4604

Table 1. Value of sample variance and BW metric for different stages

11. An agent-based model for reduction of bullwhip effect in supply chains

In general, global optimization is the central issue of system modeling approaches. The main interest of managers is to ensure that the overall cost is reduced and operations among various systems are integrated through coordination. Literature shows that reducing overall system cost and understanding how these savings are deployed among the supply chains (SC) entities are of the best interest. When the system is not coordinated, i.e., each entity in the supply chain does what is best for that entity, it results in local optimization. Each supply chain entity optimizes its own operation without considering the impact on other entities which often results in larger variation of inventory and demand in the entire SC. To have good coordination, managers need to communicate in detail, which is often a timeconsuming process. In addition, ineffective communication affects material flows and creates long lead times. One of the great disadvantages of separated decision making in supply chain which is a result of also rational human behavior is bullwhip effect (Liang & Huang 2005).

The observed performance of human beings managing supply chains, whether in field or laboratory settings, is usually from an optimal system-wide point of view. This may be due to the lack of incentives for information sharing, bounded rationality, or possibly the consequent of individual rational behavior that works against the interest of the group (Kimbrough et al. 2002).

Many information technologies have been developed for handling transactions in supply chains such as electronic document interchange (EDI) and enterprise resource planning (ERP). Lately, Internet-based technologies such as the ebXML and Web Service (Walsh 2002) have been emerging. However, despite the merits of these technologies, there exist some limitations in the flexibility and dynamic coordination of distributed participants in supply chains. The agent-based systems are alternative technologies for supply chain management because of certain features such as distributed collaboration, autonomy, and intelligence (Fox et al. 2000; Nissen 2000; Swaminathan 1997).

One of the main benefits of using agent-based technologies for supply chain management is the dynamic formation of supply chains using negotiations or contracts by agents (Walsh & Wellman 1999; Chen et al. 1999).

Agent technology has many desirable features such as autonomy, intelligence and collaboration for supply chain management. This is because the following key characteristics of supply chain management are well supported by the features of agent technology. First, there are multiple companies such as manufacturers, distributors, wholesalers, and retailers in supply chains. Second, companies in supply chains are independent firms and there is no single authority that governs the whole chain collaboration. They exchange information such as customer demands, inventory levels, and exceptional events, but do not control each

other one-sidedly. Third, intelligent coordination is required for planning and scheduling of production and logistics in a dynamic market situation.
This section presents an agent-based system with fuzzy methodology for reduction of bullwhip effects in supply chains. Here, a multi-agent based approach is presented to control the ordering quantity for every echelon and to find the minimal total cost of the entire supply chain and to reduce its related bullwhip effect. The main purpose of such a system is to coordinate all entities of the SC and to minimize the total cost. Each echelon has the same agent structure. In this research, two types of agents are employed: middle agent and software agent. Middle agents have the ability to collect the required data for software agent. The software agent by using a simulation module and a GA mechanism produces the best policy for the entire system.

11.1 Middle agent

Middle agents (are also called intermediate agents) in agent systems are internal agents which play a particular role, providing intermediate services. They are found under various names, e.g., brokers, controllers, facilitators, mediators, or matchmakers. Their role may range from that of providing yellow pages to dealing with intricacies of high level protocols for matching a request to a particular service (Shen et al. 2001).
In our proposed model, middle agents have a liaison role between manager of each echelon and the system. The middle agent exchange information about the demand quantity, lead times, inventory level and shortage level to the system. It also enables the demand agent to recalculate the cost and determine the ordering quantity whenever demand is changed.

11.2 Software agent

Intelligent software agents are defined as being a software program that can perform specific tasks for a user and possesses a degree of intelligent that permits it to perform parts of its tasks autonomously and to interact with its environment in a useful manner. In the proposed model, after being contacted by the middle agent, the software agent, by using a simulation module and a GA mechanism, determines the best ordering policy to minimize the total system cost and delivers the message back to each middle agent. In GA mechanism some fuzzy rules for ordering is generated and then by using simulation module the effect of such a rule on the whole system is calculated. The architecture of the proposed agentbased model is shown in Figure 4.
***Rules generation*:** The middle agent collects information including current on-hand inventory levels, shortage levels, lead time and customer demands, outstanding order and passes them to the software agent. Then, GA mechanism generates a number of rules and selects the best rules based on the results of the simulation procedure. After doing this process for some generations, the best rule is selected and the amount of order quantity is determined. The rest of this section presents a detailed description of the applied GA.
***Cost Function*:** The simulation module evaluates the cost of applying each rule by the following cost function. In our model all entities incur both inventory holding costs as well as penalty for shortage cost. Total cost of the system after M weeks is:

$$\tilde{TC} = \sum_{i=1}^{N} \sum_{j=1}^{M} \tilde{c}_{ij} \tag{25}$$

where, N is number of entities, $\widetilde{c}_{ij}$ cost of the j_{th} week for player i. and

$$\widetilde{c}_{ij} = \begin{cases} \widetilde{I}_i * h_i & \widetilde{I}_i > 0 \\ \widetilde{I}_i * p_i & \widetilde{I}_i < 0 \end{cases} \tag{26}$$

where, hi is the holding cost of entity i, pi is the shortage cost of retailer, and $\widetilde{I}_i$ is inventory level of the i_{th} entity. $\widetilde{I}_i = \widetilde{IL}_i + \widetilde{S}_i - \widetilde{D}_i$ in which $\widetilde{IL}_i$ is on-hand inventory of entity i at the beginning of each week. $\widetilde{S}_i$ is new shipment that player i received in the current time and $\widetilde{D}_i$ is the demand received from the downstream entity. Here, since all demands and lead times have fuzzy value, relations related to fuzzy arithmetic should be applied. For the defuzzification purpose, a *Mean of Maximum* method is used.

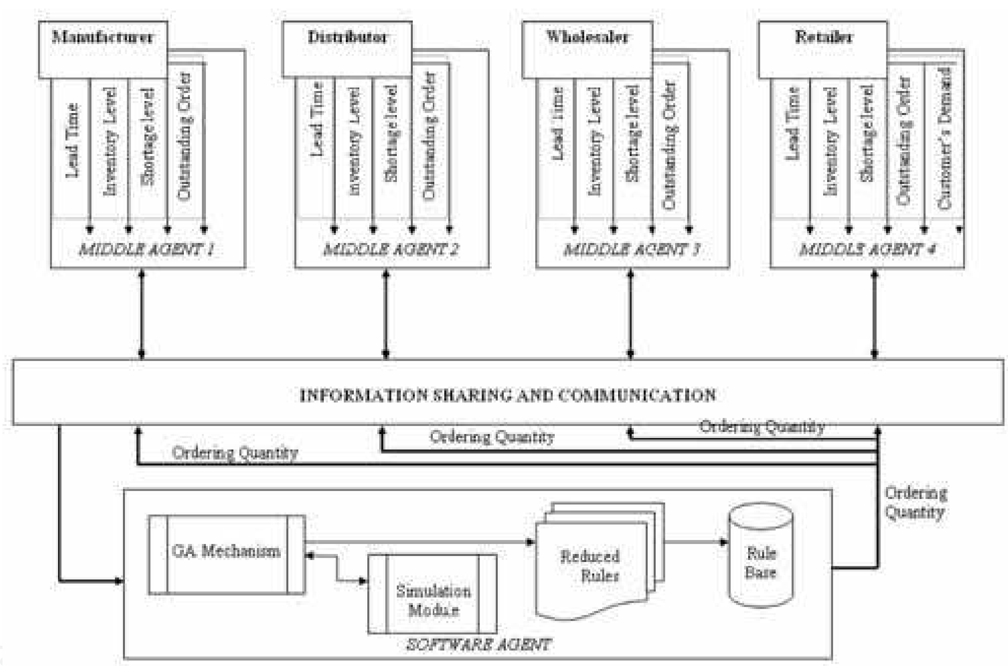

Figure 4. Agent Architecture of the proposed approach

Rule Representation: As mentioned earlier, customer demands are considered to be triangular fuzzy numbers. Each triangular fuzzy number can be determined by three parameters. In our agent-based model, each agent's rule is represented by three 5-bit binary strings. Each 5-bit binary string stands for one of the parameters for triangular fuzzy number. For example if the rule for retailer is "00101 00110 01001", it can be interpreted as $\widetilde{X}$ + (5, 6, 9). That is if demand is $\widetilde{X}$, then ordering quantity of retailer to the wholesaler is a triangular fuzzy number with parameters (5, 6,9) . In such cases, the main problem is that, when all agents are allowed to make their own decisions, the size of search space enlarges exponentially. The size of the search space for the above mentioned SC is 260 which is a very vast search space.

Each rule can be represented as a chromosome. In each generation, the values in each chromosome are sorted in a descending order, and then the first 4 biggest numbers in each chromosome are assigned to the upper bound of triangular fuzzy numbers, the second 4 ones are assigned to middle points, and the third 4 values are assigned to the lower bounds of fuzzy numbers. The population size in the developed algorithm incorporates 30 individuals.

***Initial Population Generation*:** We use the complete random method to generate initial population.

Fitness Function: A commonly used transformation, which is applied in the developed algorithm, is that of proportional fitness assignment.

Crossover: We apply multi-point crossover in the developed algorithm.

Selection: A roulette wheel selection procedure has been applied for selection operator inthe algorithm.

Mutation: We applied a random selection of new values in the developed algorithm in the mutation procedure.

Reinsertion: To maintain the size of the original population, the new individuals have to be inserted into the old population. We have used a random reinsertion in the algorithm.

Termination Condition: In the proposed algorithm, termination condition considered to be 2000 generation.

11.3 Validation of the proposed solution approach

To validate the proposed solution approach, we used $\tilde{1}-\tilde{1}$ policy (order whatever is ordered from your customer) as a heuristic to benchmark. Also the results of simulation process which was presented in section 2, show the performance of the system when there is no information sharing among the entities, are compared with the results of agent-based system.

11.3.1 Benchmarking policy

Chen et al. (1999) shows that the bullwhip effect can be eliminated under the base stock installation policy. The assumptions are all divisions of the supply chain work as a team, demand is stochastic and information and physical lead times are fixed positive numbers and only retailer occurs shortage cost. Team concept means that a common goal to optimize the system-wide performance is shared by all entity mangers. In this case, it is optimal for each division to follow an installation base-stock policy. The installation stock at a division is its on-hand inventory minus backlogged orders from the downstream entity, plus its outstanding orders. The optimal decision rule for a division manger is to place orders so as to keep its installation stock at a constant level.

As a special case of Chen's result, Kimbrough et al. (2002) show that when facing deterministic demand with penalty cost for every player, the optimal order for every player is 1-1 policy, order whatever is ordered from your customer.

Because there is no optimal solution for the situation in which demand is fuzzy stochastic number and lead times are fuzzy deterministic or stochastic numbers when every entity incurs holding cost, we will apply $\tilde{1}-\tilde{1}$ ordering policy as a heuristic to benchmark the results of our agent-based model. Here, two scenarios are presented to evaluate the performance of our agent-based solution.

11.3.1.1 First scenario:

When the demands are stochastic fuzzy numbers and the lead times aredeterministic fuzzy numbers.

For the first round of our experiments, we implement agent-based model performance for a situation in which mid-points of fuzzy triangular demands are generated by a normal distribution function with mean 20 and variance 5. The left and right points are generated randomly around the mid-points. Lead times are considered to be fixed at $\tilde{2}$ = (1, 2, 3). In this situation, the aim of this experiment is to find out whether agents can discover an appropriate ordering policy or not. For comparison of the performance of agent-based model, the total cost of the system is compared with the simulation model and also $\tilde{1}-\tilde{1}$ policy.

The results show that agents are able to find a good policy that outperforms the $\tilde{1}-\tilde{1}$ policy. In this case, agents found $\tilde{X}$ + (2, 5, 7) as retailer's rule for ordering, $\tilde{X}$ + (1, 4, 5) as wholesaler's rule for ordering, $\tilde{X}$ + (0, 3, 3) as distributor's rule for ordering, and $\tilde{X}$ + (0, 2, 3) as Manufacturer's rule for ordering with a total cost of 17338 which is better than both $\tilde{1}-\tilde{1}$ policy and simulation procedure. This policy leads to no bullwhip effect in the system. The interesting point is that the results show that bullwhip effect is reduced considerably by this approach. Table 3 shows the amounts of variance for different entities of the supply chain. Table 2 and Fig. 5 show that the proposed approach, can reduce bullwhip effect considerably. Table 3 shows the amounts of variance for different entities of the supply chain.

	Demand	Retailer's orders	Wholesaler's orders	Distributor's orders	Manufacturer's orders
Variance of Sim. Results	2.5456	6.7034	13.0928	46.4865	53.6578
Variance of mid-point	4.2935	4.2935	4.2935	4.2935	4.2935
Fuzzy sample variance	2.5456	2.8991	2.9698	2.9901	3.2056
Metric Value	-	0.121934	0.023806	0.006789	0.067226

Table 2. Demand and order variances of different entities in SC.

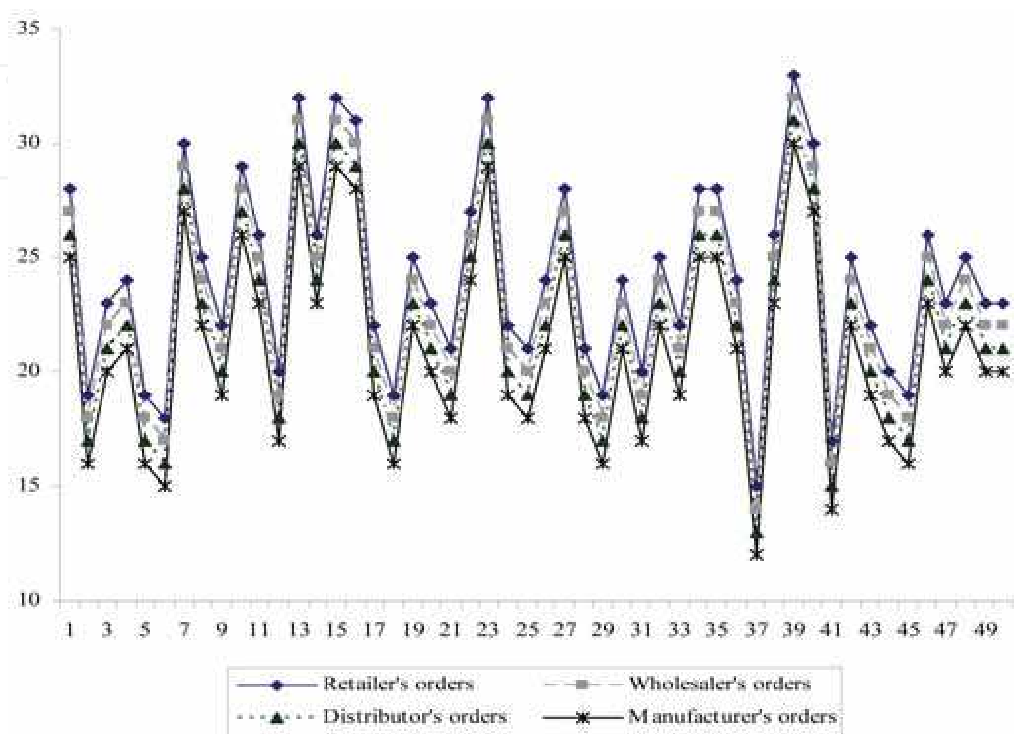

Figure 5. End customer's demand and ordering quantity of each stage

11.3.1.2 Second scenario:

When demand and lead times are both stochastic fuzzy numbers.

For the second scenario, we tested the agent performance in a situation that the lead times are also stochastic fuzzy numbers in addition to the stochastic fuzzy demands. We assumed that the lead time of each entity is a triangular fuzzy number in which the mid-point is generated by a normal distribution function with mean 3 and variance 1. The boundary points of the triangular fuzzy number are generated randomly around the mid-point. Demands are generated similar to the first example.

Results show that even in this situation agents are able to find policies which are better than $\tilde{1}-\tilde{1}$ policy. For this situation, agents found $\tilde{X}+$ (1, 4, 8) as retailer's rule for ordering, $\tilde{X}+$ (0, 4, 7) as wholesaler's rule for ordering, $\tilde{X}+$ (0, 2, 5) as distributor's rule for ordering and $\tilde{X}+$ (0, 2, 4) as Manufacturer's rule for ordering with a total cost of 58890.

Table 3 shows that in this situation, agents can find policies which reduce bullwhip effect in supply chain system considerably. This table also shows that variation of fuzzy sample variance in different stages is negligible, compared to the results of simulation model.

	Demand	Retailer's orders	Wholesaler's orders	Distributor's orders	Manufacturer's orders
Variance of Sim. Results	13.06694	26.30624	94.02763	108.4563	13.06694
Variance of mid-point	4.293517	4.293517	4.293517	4.293517	4.293517
Fuzzy sample variance	4.12258	4.3438	4.9081	5.6097	5.6386
Metric Value		0.050928	0.114973	0.125069	0.005125

Table 3. Demand and order variances of different entities in SC.

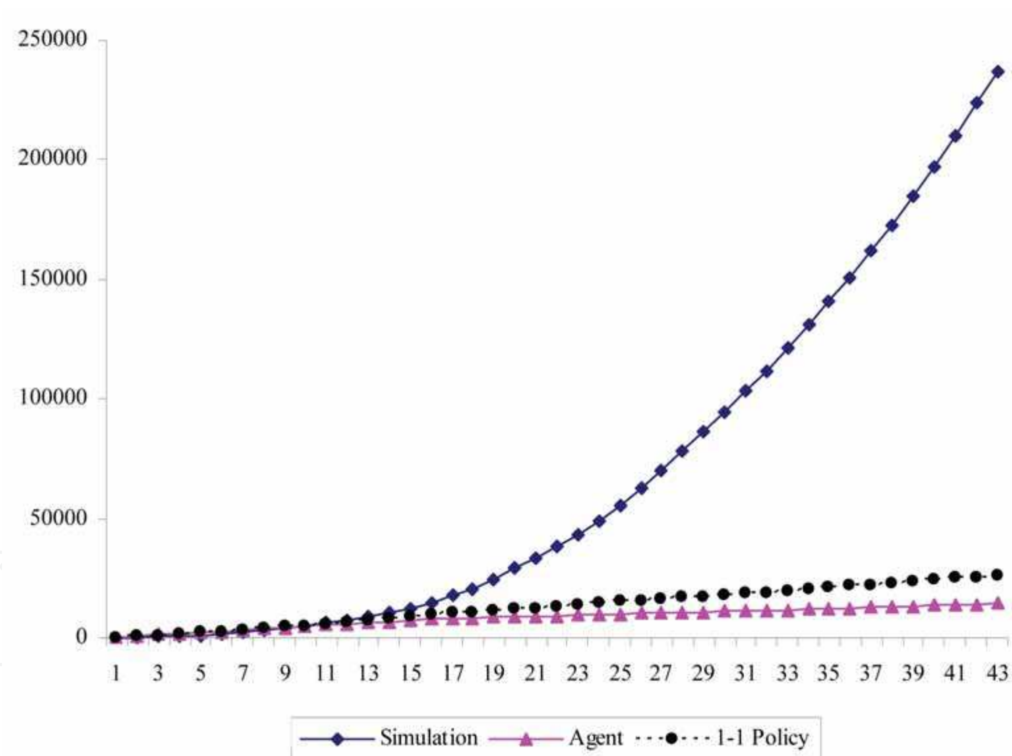

Figure 6. Cost comparison of Agent-Based model with simulation and 1-1 policy

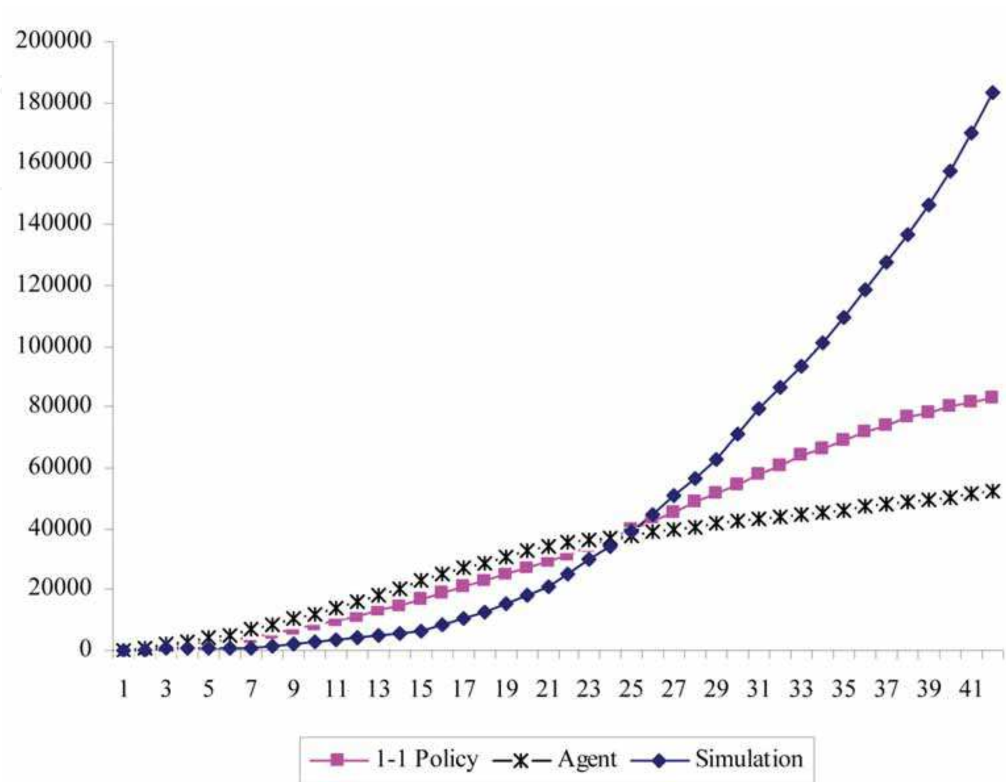

Figure 7. Cost comparison of Agent-Based model with simulation and 1-1 policy

12. Conclusions

This chapter proposes a proper modular architecture for the information agent, based on the inputs, functions, and outputs of the agent, for supply chain management. The proposed architecture has nine different modules, each of which is responsible for one or more function(s) for the information agent. Then, we explored the occurrence of bullwhip effect in supply chains, in a fuzzy environment. We built an agent-based system which can operate in a fuzzy environment and is capable of managing the supply chain in a completely uncertain environment. They are able to track demands, remove the bullwhip effect almost completely, and discover policies under complex scenarios, where analytical solutions are not available. Such an automated supply chain is adaptable to an ever-changing businessenvironment.

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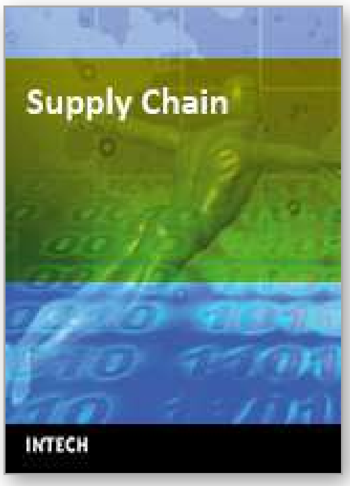

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Traditionally supply chain management has meant factories, assembly lines, warehouses, transportation vehicles, and time sheets. Modern supply chain management is a highly complex, multidimensional problem set with virtually endless number of variables for optimization. An Internet enabled supply chain may have just-in-time delivery, precise inventory visibility, and up-to-the-minute distribution-tracking capabilities. Technology advances have enabled supply chains to become strategic weapons that can help avoid disasters, lower costs, and make money. From internal enterprise processes to external business transactions with suppliers, transporters, channels and end-users marks the wide range of challenges researchers have to handle. The aim of this book is at revealing and illustrating this diversity in terms of scientific and theoretical fundamentals, prevailing concepts as well as current practical applications.