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Full Length Research paper

A framework for internet-based production-distribution planning problem to competition and collaboration in supply chain management: A multi-agent approach

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Global competition and rapidly changing technologies are forcing major changes in the production styles and new manufacturing systems. Traditional centralized environments are not able to meet these requirements. In recent years, the internet has become the worldwide information platform for data and information sharing. Information processing is an important challenge in an internet-based environment. One of the new forms of manufacturing technologies based information techniques is supply chain management (SCM). The production-distribution planning problem (PDPP) is a suitable approach to support global optimization in SCM and should be solved within the integrated structure. This approach involves the determination of the best configuration regarding location, size, technology content and product range to achieve the firm's long-term goals. On the other hand, teams of autonomous agents Asynchronous teams (ATeams), co-operating by sharing solutions through a common memory, have been proposed as a means of solving combinatorial optimization problems. In this paper, a multi-agent framework is presented to solve production-distribution planning problem (PDPP) according to the client/server architecture in an internet-based environment, where three genetic algorithms (GAs) are assumed to be the agents of the model. This framework can help the system to select the most appropriate strategy and solution for competition and collaboration in an internet-based manufacturing system.

Key words: Internet-based environment, multi-agent system, client/server, production-distribution planning, supply chain, competition and collaboration.

INTRODUCTION

Global competition and rapidly changing customer requirements are forcing major changes in the production styles and configuration of manufacturing enterprises. Manufacturing enterprises continuously have to cope with changing markets that are unpredictable and diverse, increased global competition and ever-changing customer demands. They now have to be able to not only predict changes within the market and economic environments, but to adapt and change in accordance with these environments. Traditional centralized manufacturing systems are not able to meet such requirements. Recent years have seen significant changes being made to enterprise strategy and manufacturing paradigms, particularly for companies working together to remain internationally competitive in a volatile market (Tian et al., 2002). Advanced manufacturing technologies rely heavily on various information techniques to achieve higher productivity, better quality and lower production costs. As shown in Figure 1, in the past five decades or so manufacturing industry has experienced some notable changes in the information technology, manufacturing automation and management information system. The competitive pressures of the global market are driving the emergence

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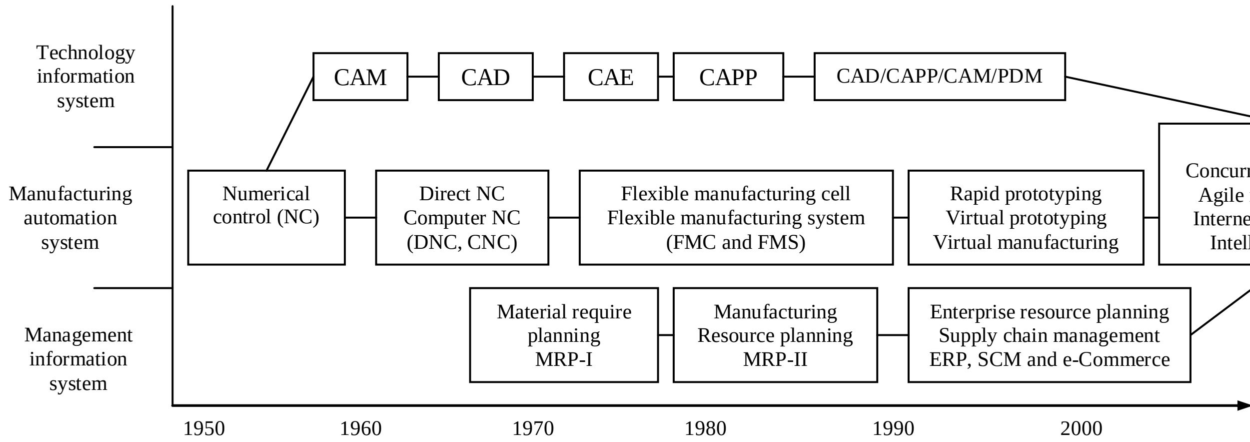

Figure 1. Development of manufacturing technologies based information techniques (Tian et al., 2002).

of new manufacturing philosophies and new forms of organization, such as computer integrated manufacturing system (CIMS), concurrent engineering, virtual organizations, remote manufacturing and internet-based manufacturing (Tian et al., 2002). One of the new forms of manufacturing technologies, based an information techniques, is SCM. This technology is the management of material and information flows both in and between facilities, such as vendors, manufacturing and assembly and distribution centers in a network format (Thomas and Griffin, 1996). Many researchers have addressed the optimization of supply chain networks. In such cases, a set of demands (known or estimated from historical data), the inter-relationship of the demand allocation, inventory management, location of facilities and determination of transportation policy have been studied.

These researches report that the ability of an organization to produce and market its product effectively partially depends on the location of the organization's facilities in relation to other facilities and its customers (Baumol and Vindo, 1970; Daskin, 1995; Drezner, 1995). The main objective of SCM is to integrate all the organizations in a supply chain, so as to deliver products to customers with minimal total cost of the whole system. (Chan et al., 2006), from the main concerns of SCM, the production-distribution planning is one of the most important issues to support global optimization in SCM and should be solved within the integrated structure. To implement SCM in the real world, supply chains are modeled in analytic ways using deterministic or stochastic method. However, most of the real world problems are not simple to be modeled through analytic approaches (Lee and Kim, 2002). Production-distribution in supply chains can take many forms. In general, there are two distinctive models. Production and distribution. They must be designed such that it can be linked together and considered as a production-distribution model in supply chain. These models are operationally connected and closely related with each other (Lee and Kim, 2000). The PDPP involves the determination of the best configuration regarding location, size, technology content and product range to achieve a firm's long-term goals (Dasci and Verter, 2001). Ideally, a good distribution network design can help companies to have better value-addition, reduced costs and increased customer service level by determining optimal links between each node and the traffic flow routine (Lumsden et al., 1999; Milgate, 2001; Stank and Goldsby, 2000; Chan and Chung, 2005). New software architecture for managing the supply chain at the tactical and operational levels has recently emerged in this area.

This architecture views the supply chain as a composition of a set of intelligent (software) agents, each responsible for one or more activities in the supply chain and can interact with other agents in planning and executing their responsibilities. Here, an agent is an autonomous, goal-oriented software process that operates asynchronously, communicating and coordinating with other agents as needed (Fox et al., 2000). The concept of an agent comes from artificial intelligence (AI). The term "agent" is an elusive one to define. An agent can be a person, a machine, a piece of software, or a variety of other things. The basic definition of agent in dictionary is one who acts. An agent must be automatic, social, reactive and pro-active (Zhang and Xie, 2007). A typical definition of an agent is given by (Nwana and Ndumu, 1997): "An agent is defined as referring to a component of software and/or hardware which is capable of acting exactly in order to accomplish tasks on behalf of its user". In this paper, we propose a multi-agent framework for internet-based PDPP according to the client/server architecture in a supply chain management. To solve the problem, we develop teams of autonomous agent (ATeams), where each agent (client) uses a GA sub-module to handle its tasks in an internet-based environment. The rest of the paper is organized as follows: A selective review of related literature is provided in Section 2. In Section 3, a brief introduction to Internet tools for manufacturing technology, multi-agent technology, Asynchronous teams (ATeams) and client/server architecture is addressed. Problem definition and mathematical formulation are presented in Section 4. In Section 5, solution methodologies are proposed. Section 6 presents experimental results. Finally, conclusions and remarks are appeared in Section 7.

BACKGROUND

Modeling and analysis of production-distribution systems in supply chain has been an active area of research for many years. Chon and Lee, 1988, study production-distribution integrated systems under stochastic demands. They present a supply chain model that incorporates raw materials, intermediate and final product plants, distribution centers, warehouses and customers. Their model shows interactions of multi-stage production-distribution systems. At each stage, sub-models are defined and control policies are implemented. Then, a heuristic optimization procedure is introduced and some results are discussed. Thomas and Griffin (1996) define three categories of operational coordination: Buyer and vendor, production and distribution and inventory and distribution. Vidal and Goetschalckx (1997) review the strategic production-distribution models. They focus on global supply chain models with emphasis on mixed integer programming models.

Beamon (1998) provides a focused review of literature in the area of multi-shop supply chain design and analysis and suggests four categories: Deterministic analytic models, stochastic analytic models, economic models and simulation models. Evans et al. (1998) apply a general methodology for modeling and simulating the dynamic behavior of a logistical control system. Conceptual mathematical and computer simulation models are introduced in their research. Petrovic et al. (1998) describe fuzzy modeling and simulation of a supply chain in an uncertain environment. Customer demands and supply of raw material are interpreted and represented by fuzzy sets and a supply chain simulator is developed.

The simulator provides a dynamic view of the supply chain and assesses the impact of decisions recommended by the supply chain fuzzy models on supply chain performance. (Mohamed, 1999) incorporates the production-distribution planning and logistics decisions for multi-national companies (MNC's) operating under varying inflation and scanty exchange rates. Erenguc et al. (1999) discuss the production-distribution planning identifying the relevant decisions that need to be considered in jointly optimizing production-distribution planning decision with separated supplier shop, plant shop and distribution shop. They suggest the combination of analytic and simulation models to integrate all stages of supply chains as an important field of research is future. Lee and Kim (2002) propose an integrated multi-period, multi-product, multi-shop production and distribution model in supply chain to satisfy the retailer's demand in the given periods of time. The model is formulated as an analytic model which minimizes the overall costs of production, distribution, inventory holding and shortage costs, subject to various kinds of inventory and operation time constraints. Jang et al. (2002) propose supply network with a global bill of material (BOM). They apply four modules for this supply network: Supply network design optimization module, planning module for production and distribution operations from raw material suppliers to customer, model management module and data management module. The first two modules are solved by a Lagrangian heuristic and a generic algorithm, respectively. Yan et al. (2003) add logical constraints to the production–distribution problem. Their main contribution is adding BOM limitations as logical constraints to the mixed integer representation of the problem. The results of a small-scale problem are presented to show solution validity. Chan et al. (2005) develop a hybrid GA for production and distribution problems in multi-factory supply chain models and solve a hypothetical production–distribution problem by the proposed algorithm. Chan and Chung (2005) develop an optimization algorithm to solve the problem of demand allocation, transportation and production-scheduling in a demand-driven multiechelon distribution network, especially with the consideration of demand due date.

For this propose, optimization algorithm is rather developed through the optimization methodology of GA and Analytic Hierarchy Process (AHP). Gen and Syarif (2005) propose a new technique called spanning tree-based genetic algorithm (hst-GA) to solve a production-distribution problem to determine an efficient integration of production, distribution and inventory system so that products are produced and distributed at the right quantities, to the right customers, and at the right time, in order to minimize system wide costs while satisfying all demand requirements. Barnes-Schuster et al. (2006) study a system composed of a supplier and buyers. They assume that the buyer faces random demand with a known distribution function. The supplier faces a known production lead time. The main objective is to determine the optimal delivery lead time and the resulting location of the system inventory. Rizk et al. (2006) examine a multi-item dynamic production-distribution planning problem between a manufacturing location and a distribution center. Transportation costs between the manufacturing location and the distribution center offer economies of scale and can be represented by general piecewise linear functions. They proposed a tight mixed-integer programming model of the production process, as well as three different formulations to represent general piecewise linear functions. Yılmaz and Catay (2006) consider a strategic planning problem for a three-stage production-distribution network. The problem under consideration is a single-item, multi-supplier, multi-producer and multi-distributor production-distribution network with deterministic demand. The objective is to minimize the costs associated with production, transportation and inventory as well as capacity expansion costs over a given time horizon.

The problem is formulated as a 0 to1 mixed integer programming model. Lejeune (2006) considers a three-stage supply chain, for which a sustainable inventory–production–distribution plan is developed over a multi-period horizon. The associated program takes the form of a general mixed-integer program, for which the sole reliance upon exact methods is shown to be insufficient. Lejeune (2006) uses a solution algorithm based on the variable neighborhood decomposition search metaheuristics, which can be seen as a stage wise exploration of increasingly large neighborhoods. Amiri, 2006 designs the distribution network problem in a supply chain system that involves locating production plants and distribution warehouses and determines the best strategy for distributing the product from the plants to the warehouses and from the warehouses to the customers. The goal is to select the optimum numbers, locations and capacities of plants and warehouses to open so that all customer demand is satisfied at minimum total costs of the distribution network.

Amiri, 2006 presents a computational study to investigate the value of coordinating production and distribution planning. Amiri, 2006 develops a mixed integer programming model and provides an efficient heuristic solution procedure for this supply chain system problem. Boudia et al. (2007) investigate an NP-hard production–distribution problem for one product over a multi-period horizon. The aim is to minimize total cost by taking production setups, inventory levels and distribution into account. They propose an integer linear model as a compact problem specification, but it cannot be solved optimally for large scale problems. Instead of using a classical two-phase approach (production planning and then route construction for each day), they develop metaheuristics that simultaneously tackle production and routing decisions: A greedy randomized adaptive search procedure (GRASP) and two improved versions using either a reactive mechanism or a path-relinking process. Keskin and Uster (2007) consider a multi-product two-stage PDSD where a fixed number of capacitated distribution centers are to be located with respect to capacitated suppliers (plants) and retail locations (customers) while minimizing the total costs in the system.

They present a mixed-integer problem formulation that facilitates the development of efficient heuristic procedures. They provide meta-heuristic procedures, including a population-based scatter search with path relinking and trajectory-based local and tabu search to solve the problem. They also develop efficient construction heuristics and transshipment heuristics that are incorporated into the heuristic procedures for the solution of sub problems. Tsiakis and Papageorgiou (2007) determine the optimal configuration of a production and distribution network subject to operational and financial constraints. Operational constraints include quality, production and supply restrictions, and are related to the allocation of the production and the work-load balance. Financial constraints include production costs, transportation costs and duties for the material flowing within the network subject to exchange rates. As a business decision, the out-sourcing of production is considered whenever the organization cannot satisfy the demand. A mixed integer linear programming (MILP) model is proposed to describe the optimization problem. Kazemi and Fazel Zarandi, 2008 proposed a traditional decision support system (TDSS) and multi-agent decision support system (MADSS) to solve the PDPP.

Kazemi et al. (2008) presented two scenarios for solving PDPP. In the first scenario, a centralized method is employed and a GA is presented for solving PDPP problem. In the second scenario, an agent based system is developed for solving PDPP problem. In all above studies, the considered PDPP has been solved using one of the heuristic, Meta heuristic or operation research methods in a traditional environment. But in this paper, we develop a multi-agent framework for this problem in an internet-based environment and present the GAs for solve it. The objective of this paper is to develop a multi-agent framework to cope with the difficulties in modeling PDPP in supply chain according to the client/server architecture for an internet-based environment and to provide better solution plans using teams of autonomous agent ATeams.

INTERNET BASED MANUFACTURING

Advanced manufacturing strategies such as lean manufacturing, agile manufacturing and globalization of manufacturing are based on the concept of internet-based virtual enterprise technology. In such an environment, there is a need for better communications among various functional areas such as product design, engineering and production, which may have been located geographically in different countries. As shown in Figure 2, internet-based global manufacturing systems are concerned with providing cooperative design support, distributed manufacturing, engineering simulation of virtual manufacturing environments, remote control and supply chain resource planning, etc. (Song and Nagi, 1997; Park and Favrel, 1999). In the following parts of this section, we will first address the definition of Internet tools for manufacturing technology, multi-agent technology and then, present the basics of ATeams and the way ATeams can be used to solve large

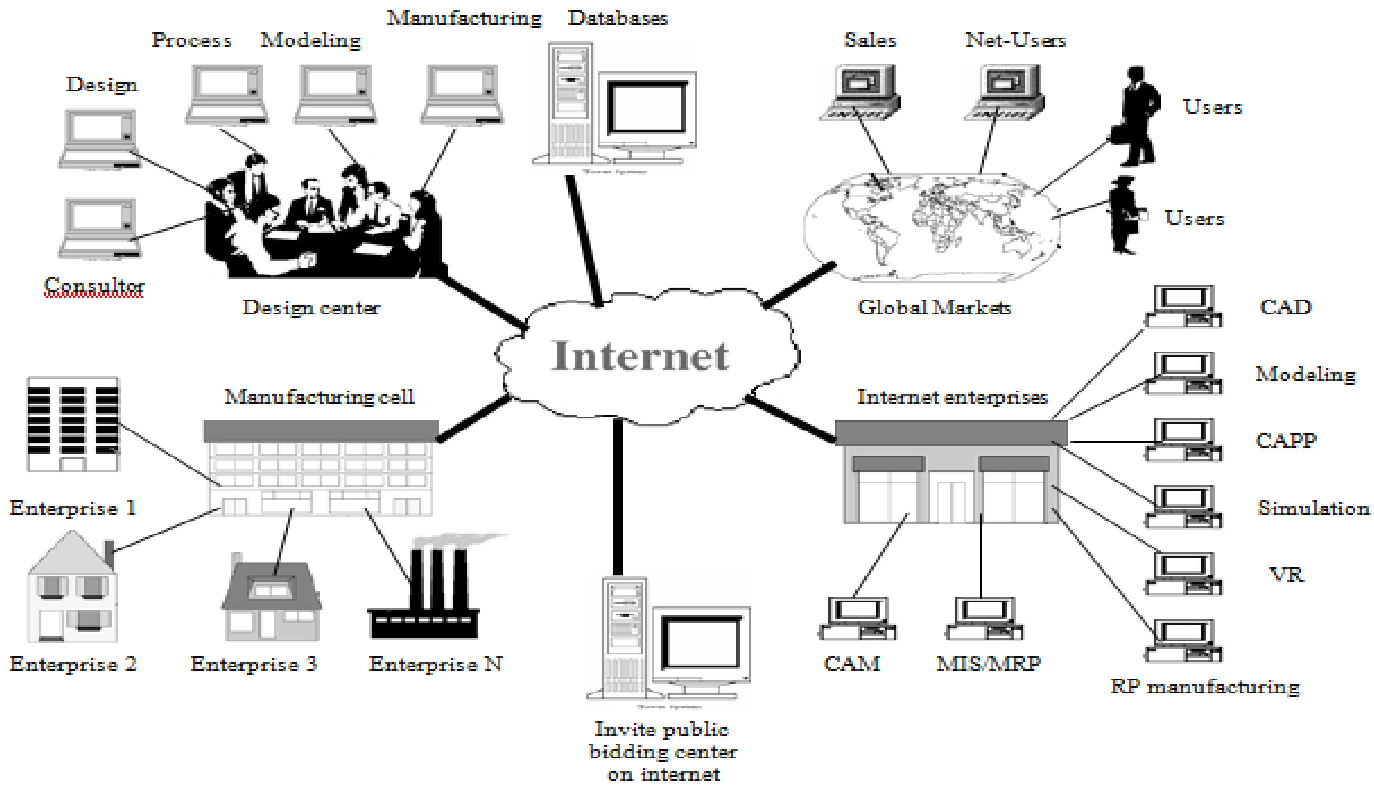

Figure 2. The model of global manufacturing based on Internet technology (Tian et al., 2002).

combinatorial optimization problems in an internet-based environment. Moreover, we will present client/server architecture.

Internet tools for manufacturing technology

The technologies that support network manufacturing should be able to deal with distributed environments and database, must ensure reliability and security and must be practical. In fact, internet tools play more and more important roles in the integration of enterprises and organizations as they embrace remote manufacturing. Figure 3 illustrates available internet-based techniques and describes the relationship between enterprise applications (Tian et al., 2002). Distributed object technology represents the merging of distributed systems and object-oriented technology. A distributed system is a collection of autonomous computers processing and storage elements interconnected through the internet to achieve integrated functions (Tian et al., 2002).

Multi-agent technology and its application in internet based manufacturing

The software agent technology originating from distributed artificial intelligence (DAI) and distributed computing is inherently interdisciplinary. The agent technology has been considered as an important approach for developing distributed manufacturing systems (Shen, 1999). Due to the complexity of distributed manufacturing, a number of researchers have attempted to use agent technology for manufacturing enterprise integration, supply chain management, manufacturing planning and intelligent manufacturing system (Tian et al., 2002).

An agent-based approach to information management

Fox et al. (2000) propose some agent-oriented methods for handling information in dynamic supply chains. In general, there is no universal agreement on what an agent is, but common aspects to most definitions seem to be that an agent should be autonomous, social, reactive and pro-active (Wooldridge and Jennings, 1995; Jennings and Wooldridge, 2002).

Autonomy signifies that agents operate without direct intervention of humans or others. Social ability means that agents interact with other agents via a communication language. In order to be reactive, agents perceive their environment and respond in a timely fashion to the changes that occur in it. Finally, agents do not simply act in response to their environment; they are also able to exhibit goal-directed behavior by taking

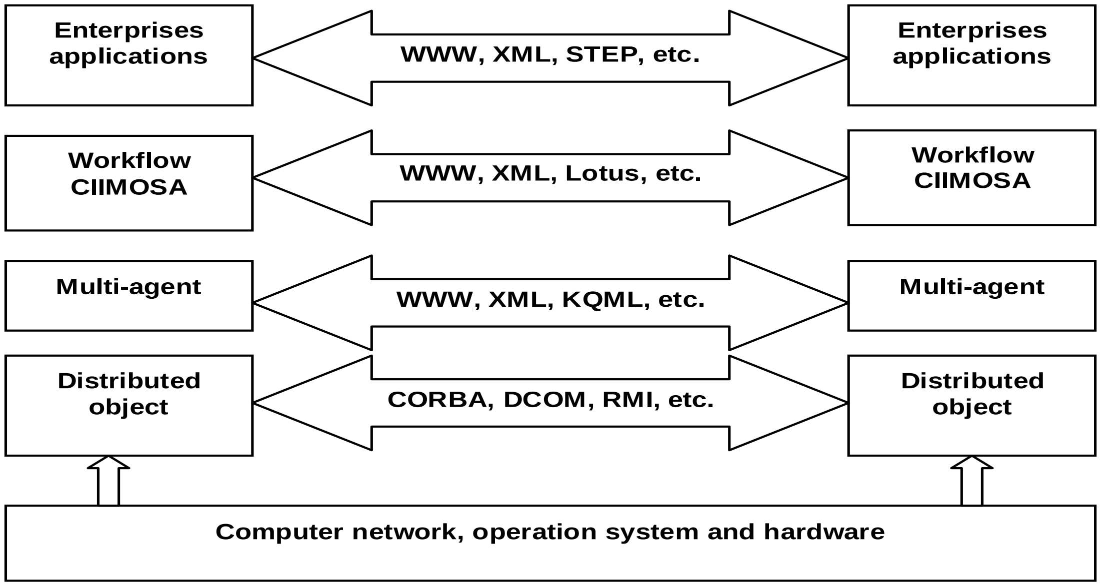

Figure 3. Internet techniques and application mode (Tian et al., 2002).

the initiative (pro-activity).

Software agents

Software agents can be defined in different ways depending on the way they are implemented and the tasks they perform. Wooldridge and Jennings (Wooldridge and Jennings, 1995) suggest that any computer system (software or hardware) should have the following properties to be termed as an agent:

Autonomy

It should have some control over its actions and should work without human intervention.

Social ability

It should be able to communicate with other agents and/or with human operators.

Reactivity

It should be able to react to changes in its environment.

Pro-activeness

It should also be able to take initiative based on pre-specified goals. The above-mentioned properties are generic for an agent. An agent may exhibit more of one property than another based on its architecture and embedded intelligence.

Asynchronous teams (ATeams)

Talukdar (1993) and Talukdar et al. (1996) proposed the teams of autonomous agent ATeams to solve large combinatorial optimization problems using a multi-agent-based distributed problem solving method, where, the agent asynchronously build shared solution. This method allows the system either to be centrally controlled or decentralized. In an ATeam, a collection of agents co-operates by sharing solutions through a common memory. The architecture is asynchronous and the agents are autonomous, each agent decides when and how to act. Some agents may operate solely to keep the population in check, destroying selected inferior solutions. Talukdar (1993) proposes a basic architecture to autonomous agent operating asynchronously on a shared population of solution attempts, which they call “ATeams”.

In the basic architecture, each agent is completely independent from the rest and operates by selecting a solution from the memory, carrying out some operations on it and then placing it back in the memory. Thus, co-operation is achieved by sharing solutions. The population of solution is controlled by a subset of destroyer agents, which evaluate solutions according to certain criteria and remove unwanted solutions. The organization of the agents is such that loose-agents may appear and disappear from the team without penalty or may be widely distributed and do not communicate directly with other agents. An instance of ATeam

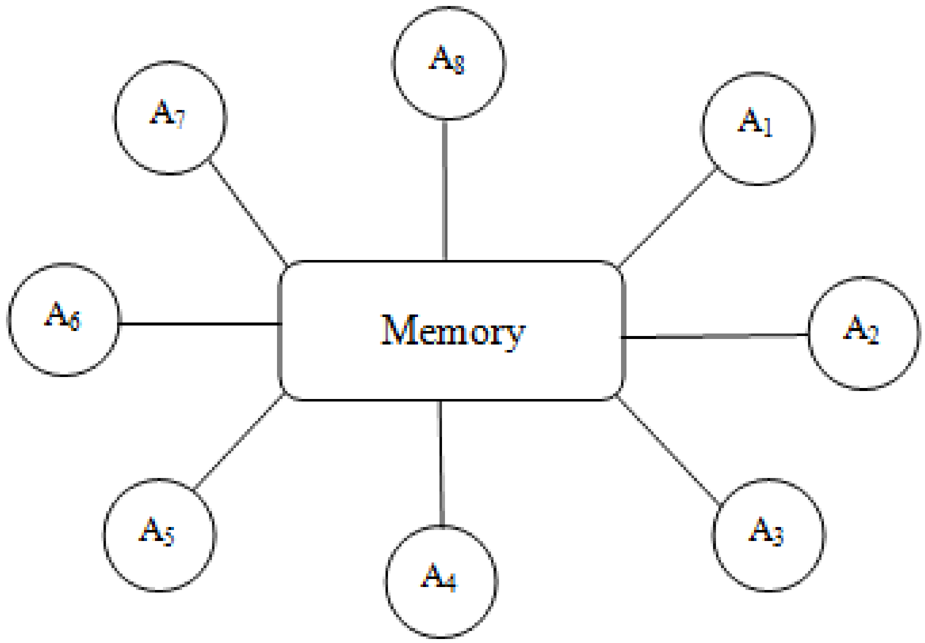

Figure 4. An instance of ATeams architecture (Aydin and Fogarty, 2004).

architecture is shown in Figure 4. Here, the system consists of a team of agents and a single memory, which has particular communications with each agent (Aydin and Fogarty (2004). ATeams are, in many respects, similar to blackboard system, in that a collection of processes co-operates to solve problems by posting the results of actions to a shared memory (or blackboard). However, there are some differences.

In the blackboard systems, the problem solving process is typically centrally controlled, with a control process deciding which of the available knowledge source should be activated at which point. Blackboards are typically structured to suit a particular problem, being hierarchically sub-divided, with problems also being sub-divided and sub-problems combined in pre-determined ways. In a basic ATeam, there is no control and each agent operates without knowledge of the others. The memory is typically on a single level (Aydin and Fogarty, 2004). Agents can be significant for the behavior of the system and thus merit serious investigation. ATeam systems can also encompass evolutionary methods. A GA for example, could be instantiated as one of the agents. More fundamentally, however, the basic operators of a GA could be implemented as independent agents for example one agent implementing the crossover operator and another implementing a mutation operator and go through repeated distinct generations, but allows reproduction and selection to operate concurrently.

Additionally, ATeams easily cater for hybrid methods as these operators can be combined with symbolic search operators. However, agents in blackboard system maintain an internal state while searching the space and receive suggestions posted by other agents. In a standard ATeam, agents do not have a state that persists between operations and each agent acts by modifying complete candidates (Aydin and Fogarty, 2004). Thus, ATeams sit in the intersection between number of different problem solving methodologies. In particular, they offer a convenient architecture for implementing hybrid systems. They can support flexible distributed computing. Finally, they allow existing algorithms to be reused (with some limited modification). ATeams thus promise an efficient framework for building combinatorial optimization systems (Aydin and Fogarty, 2004).

Client/server architecture

Client/server architecture divides distributed computing units into two major categories, clients and servers, all of which are connected by a network of some sort. A client is a computer such as a personal computer (PC) attached to a network, which is used to access shared network resources. A server is a machine that is attached to this same network and provides clients with some services. Examples of servers are a database server that provides a large storage capacity, or a communication server that provides connection to another network, to commercial databases or to a powerful processor. There are several models of client/server architecture. In the most traditional model, the mainframe acts as a database server, providing data for analysis done by the PC clients using spreadsheets, database management systems and

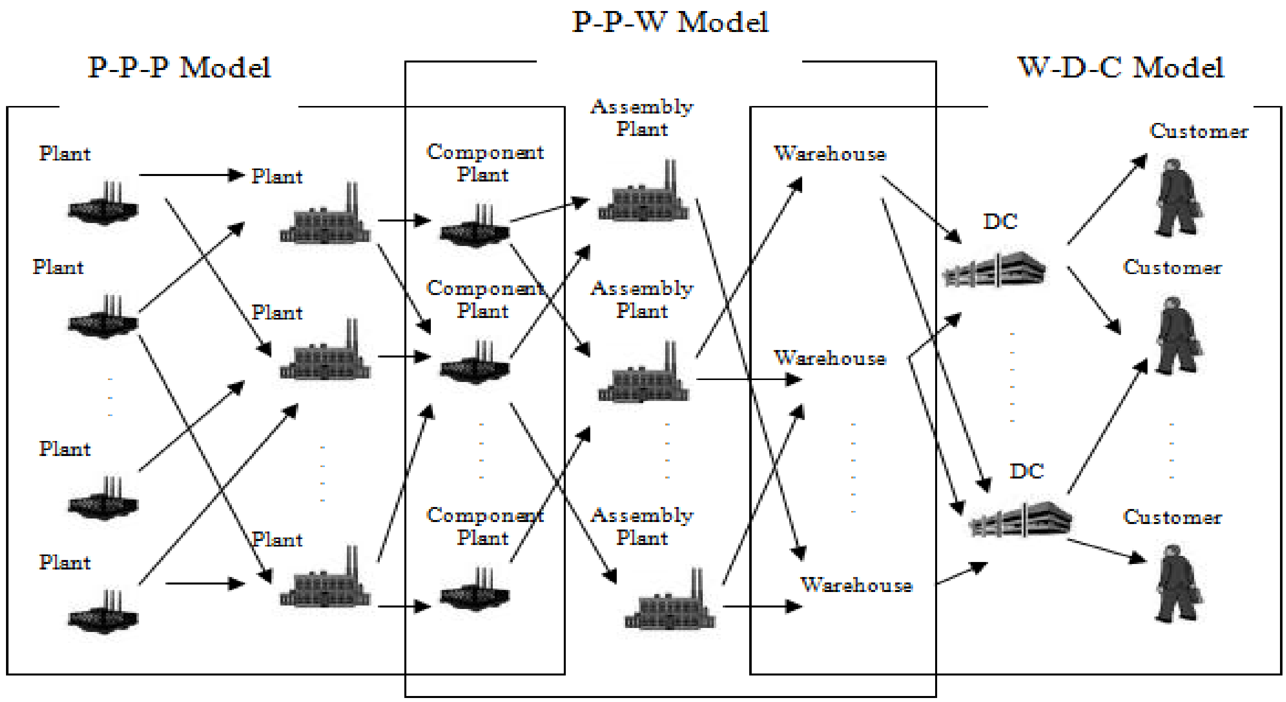

Figure. 5. Network fragmentation for integrated production and distribution planning (Jang et al., 2002).

application software. The purpose of client/server architecture is to maximize the use of computer resources. Client/server architecture provides a way for different computing devices to work together, each doing the job for which it is best suited. For example, large storage and heavy computation power is more cost-effective on a mainframe than on a PC. The role of each machine need not be fixed. A PC, for example, can be a client in one task and a server in another. Another important element is sharing. The clients, which are usually inexpensive PCs, share more expensive devices, the servers. Client/server architecture gives a company as many access points to data as there are PCs on the network. It also lets a company use more tools to process data and information. Turban et. al. (2004) SCM problems are both distributive in nature and require extensive intelligent decision-making. Thus, in the last few years, multi-agent systems have been a preferred tool for solving supply chain problems. In this paper, a multi-agent framework is presented according to the client/server architecture in an internet-based environment.

PROBLEM DEFINITION

The proposed system can generate production and distribution plans of the supply network over a planning horizon. As stated by Jang et al. (2002), an integrated model consists of three types of multi-stage, multi-product, production and distribution planning sub-model, as shown in Figure 5. The three sub-models are called the P-P-P model, P-P-W modeland W-D-C model, respectively, where P, W, D and C represent plant, warehouse, distribution center and customer, respectively. The solution designates the production and/or distribution quantities of each item for each period at each site subject to multi-level global BOM and capacity constraints (Jang et al., 2002). The integrated production-distribution problem is difficult to be solved due to the great number of integer variables representing facilities, items and periods and the binary variables indicating major setups Jang et al. (2002).

Thus, a multi-agent system is adopted as a solution methodology considering the problem complexity and time requirements. In this section, only the P-P-P model is presented since it incorporates all the characteristics of other two models. Details of the solution methodology and experimental result are presented in the next sections.

P-P-P model

This model covers the problem area ranging from the suppliers to final assembly plants. The model includes a two-level BOM to generate a production plan at each plant and a distribution plan among the plants. The transportation lead-time was also considered in this model Jang et al. (2002). The indices, parameters and decision variables retain their meanings in this section.

Mathematical formulation

The indices, parameters, decision variables, objective function and constraints are as follows:

Indices

$V = \{1,2,...,v\}$; Plant at first stage of BOM.
$S = \{1,2,...,s\}$; Plant at second stage of BOM.
$P = \{1,2,..., p\}$; Plant at final stage that assembles end item of BOM.
$R = \{1,2,...,r\}$; Child item at level 2 of BOM.
$C = \{1,2,...,c\}$; Child item at level 1 of BOM.
$I = \{1,2,...,i\}$; Child item at level 0 of BOM.
$T = \{1,2,...,t\}$; Period.

Parameters

s_{ipt} Fixed producing cost for i in p in t ,

h_{ipt} Unit holding cost of i in p in t

a_{ipt} Unit variable cost of producing i in p in t

s_{rvt} Fixed producing cost for r in v in t

ho_{rvt} Unit holding cost of r in v in t

a_{rvt} Unit variable cost of producing r in v in t

s_{cst} Fixed producing cost for c in s in t

ho_{cst} Unit holding cost of c in s in t

a_{cst} Unit variable cost of producing c in s in t

fo_{rvst} Fixed cost of transporting r from v to s in t

co_{rvst} Unit variable cost of transporting r from v to s in t

f_{cspt} Fixed cost of transporting c from s to p in t

c_{cspt} Unit variable cost of transporting c from s to p in t

d_{ipt} Demand of p for i in t

p_{ip} Processing time of i in p

p_{rv} Processing time of r in v

p_{cs} Processing time of c in s

A_{pt} Total available production capacity of p in t

A_{vt} Total available production capacity of v in t

A_{st} Total available production capacity of s in t

Q_{ci} c 's Quantity required for i (quantity per); this is awkward

Q_{rc} r 's Quantity required for c (quantity per); this is awkward

L_{rvs} Lead time from v to s for r

L_{csp} Lead time from s to p for c

ho_{rst} Unit holding cost of r in s in t

h_{cpt} Unit holding cost of c in p in t

Decision variables

X_{ipt} Production amount of i in p in t

I_{ipt} Inventory amount of i in p in t

I_{cpt} Inventory amount of c in p in t

Z_{ipt} Setup variable for i in p in t

YO^{p}_{cspt} Amount of c transported from s to p in t intended for p

W_{cspt} Link variable from s to p in t for c with respect to YO^{p}_{cspt}

XO^{p}_{cst} Production amount of c in s in t for p

IO_{cst} Ending inventory of c in s in t

IO_{rst} Ending inventory of r in s in t

ZO_{cst} Setup variable for c in s in t

YO^{p}_{rvst} Amount of r transported from v to s in t intended for p

W_{rvst} Link variable from v to s in t for r with respect to YO^{p}_{rvst}

XO^{s}_{rvt} Production amount of r in v in t for s

IO_{rvt} Ending inventory of r in v in t

ZO_{rvt} Setup variable for r in v in t

Objective function and constraints

$$\text{Min } \sum_{r=1}^{R}\sum_{v=1}^{V}\sum_{t=1}^{T}\left(s_{rvt}ZO_{rvt} + ho_{rvt}IO_{rvt} + a_{rvt}\sum_{s=1}^{S} XO^{s}_{rvt} \right)$$

$$+\sum_{c=1}^{C}\sum_{s=1}^{S}\sum_{t=1}^{T}\left(s_{cst}ZO_{cst}+ho_{cst}IO_{cst}+a_{cst}\sum_{p=1}^{P}XO_{cst}^{p}\right)+\sum_{r=1}^{R}\sum_{s=1}^{S}\sum_{t=1}^{T}ho_{rst}IO_{rst}$$

$$+\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{t=1}^{T}\left(s_{ipt}Z_{ipt}+h_{ipt}I_{ipt}+a_{ipt}X_{ipt}\right)+\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{t=1}^{T}h_{cpt}I_{cpt}$$

$$+\sum_{r=1}^{R}\sum_{v=1}^{V}\sum_{s=1}^{S}\sum_{t=1}^{T}\left(fo_{rvst}W_{rvst}+co_{rvst}\sum_{p=1}^{P}YO_{rvst}^{p}\right)+\sum_{c=1}^{c}\sum_{s=1}^{S}\sum_{p=1}^{P}\sum_{t=1}^{T}\left(f_{cspt}W_{cspt}+c_{cspt}YO_{cspt}^{p}\right)$$

s.t.

$$\sum_{s=1}^{S}\sum_{r=1}^{R}p_{rv}XO_{rvt}^{s}\le A_{vt} \qquad \forall v,t \qquad (1)$$

$$\sum_{p=1}^{P}\sum_{c=1}^{C}p_{cs}XO_{cst}^{p}\le A_{st} \qquad \forall s,t \qquad (2)$$

$$\sum_{i=1}^{I}p_{ip}X_{ipt}\le A_{pt} \qquad \forall p,t \qquad (3)$$

$$\sum_{s=1}^{S}XO_{rvt}^{s}\le M_{ZO_{rvt}} \qquad \forall r,v,t \qquad (4)$$

$$\sum_{p=1}^{P}XO_{cst}^{p}\le M_{ZO_{cst}} \qquad \forall c,s,t \qquad (5)$$

$$X_{ipt}\le M_{Z_{ipt}} \qquad \forall i,p,t \qquad (6)$$

$$\sum_{p=1}^{P}YO_{rvst}^{p}\le M_{W_{rvst}} \qquad \forall r,v,s,t \qquad (7)$$

$$YO_{cspt}^{p}\le M_{W_{cspt}} \qquad \forall c,s,p,t \qquad (8)$$

$$\sum_{s=1}^{S}XO_{rvt}^{s}+IO_{rv,t-1}-\sum_{s=1}^{S}\sum_{p=1}^{P}YO_{rvst}^{p}-IO_{rvt}=0 \qquad \forall r,v,t \qquad (9)$$

$$\sum_{p=1}^{P}XO_{cst}^{p}+IO_{cs,t-1}-\sum_{p=1}^{P}YO_{cspt}^{p}-IO_{cst}=0 \qquad \forall c,s,t \qquad (10)$$

$$X_{ipt}+I_{ip,t-1}-d_{ipt}-I_{ipt}=0 \qquad \forall i,p,t \qquad (11)$$

$$\sum_{s=1}^{S}YO_{cspt-L_{csp}}^{p}+I_{cpt-1}-\sum_{i=1}^{I}\left(X_{ipt}Q_{ci}\right)-I_{cpt}=0 \qquad \forall c,p,t \qquad (12)$$

$$\sum_{v=1}^{V}\sum_{p=1}^{P}YO_{rvst-L_{rvs}}^{p}+IO_{rst-1}-\sum_{c=1}^{C}\sum_{p=1}^{P}\left(XO_{cst}^{p}Q_{rc}\right)-IO_{rst}=0 \qquad \forall r,s,t \qquad (13)$$

$$\sum_{v=1}^{V}XO_{rv,t-L_{rvs}}^{s}\ge\sum_{p=1}^{P}\sum_{c=1}^{C}\left(XO_{cst}^{p}Q_{rc}\right)-IO_{rs,t-1} \qquad \forall r,s,t \qquad (14)$$

$$\sum_{s=1}^{S}XO_{cs,t-L_{csp}}^{p}\ge\sum_{i=1}^{I}\left(X_{ipt}Q_{ci}\right)-IO_{cp,t-1} \qquad \forall c,p,t \qquad (15)$$

$$X_{ipt}\ge d_{ipt}-I_{ipt-1} \qquad \forall i,p,t \qquad (16)$$

$$X_{ipt},I_{ipt},Z_{ipt},I_{cpt},IO_{cst},IO_{rst},IO_{rvt}\ge 0, \qquad \forall i,p,t,c,s,r,v \qquad (17)$$

$$YO_{cspt}^{p},XO_{cst}^{p},YO_{rvst}^{p},XO_{rvt}^{s}\ge 0 \qquad \forall c,s,p,t,r,v \qquad (18)$$

$$ZO_{rvt},ZO_{cst},W_{rvst},W_{cspt}\in\{0,1\} \qquad (19)$$

Here, the objective function is to minimize total production cost, total ending inventory cost and total cost of transporting. The constraints (1 to 3) are the capacity restrictions at each stage. Constraints (4 to 6) ensure that a setup occurs when a plant manufacturing an item. Constraints (7 and 8), where M is an arbitrary large number, imply that a link between plants is connected if the transportation quantity is non-zero. Constraints (9 to 11) represent inventory balance equations that define the inventory levels for items i,c , and r at the end of period t at each plant resulting from the production and transportation. Constraints (12 and 13) balance inventory available against successor's production quantities subject to BOM relationships that define the single-level go into structure between successors and their predecessors and Constraints (14 to 6) ensure that the external demands can be satisfied through stages.

SOLUTION METHODOLOGY

In this section, we propose a solution methodology for P-P-P problem. For this purpose, a multi-agent system is presented. In

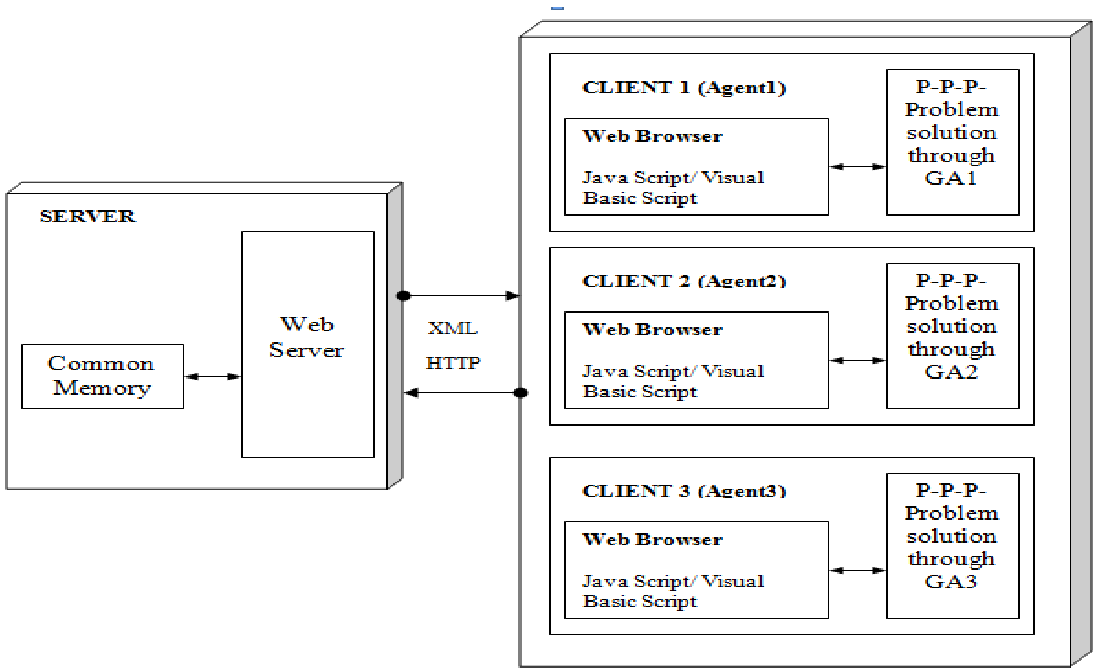

Figure 6. System architecture.

this methodology, first the P-P-P problem is solved through three GA (GA1, 2 and 3). Then these three algorithms are combined and a single integrated algorithm is obtained. The details of each algorithm are presented in the following sub sections.

First genetic algorithm (GA1)

GAs has been used successfully to find optimal or near-optimal solutions for a wide variety of optimization problems (Gen and Cheng, 1997; Goldberg, 1989) since its introduction by Holland (1992). GAs is intelligent stochastic optimization techniques based on the mechanism of natural selection and genetics. GAs start with an initial set of solutions called population. Each solution in the population is called a chromosome (or individual), which represents a point in the search space.

The chromosomes are evolved through successive iterations, called generations, by genetic operators (selection, crossover and mutation) that mimic the principles of natural evolution. In a GA, a fitness value is assigned to each individual according to a problem-specific objective function. Generation by generation, the new individuals, called offspring, are created and survive with chromosomes in the current population, called parents, to form a new population. In this section, GA1 is introduced. This GA can solve the P-P-P problem according to the following modules which are introduced for it.

Initial population generation

We use random method for generating the initial population. We use the uniform distribution for reaching this goal.

Fitness function

We considered the objective function of P-P-P problem as the fitness function.

Selection function

The selection function chooses parents for the next generation. We apply roulette wheel selection procedure for the selection function in the problem.

Crossover

We apply single-point crossover in the P-P-P problem.

Mutation

We apply a uniform selection of new values in the developed algorithm in the mutation procedure.

Termination criterion

In the P-P-P problem, termination criterion is considered to be 1000 generation and if there is no improvement in the best fitness value for the 20 generations, the algorithm stops, too.

Second genetic algorithm (GA2)

This GA2 can also solve the P-P-P problem like GA1 according to modules which are introduced blow. Except for crossover module, the remaining GA2 modules are similar to GA1 modules.

Crossover

We apply two-point crossover in the P-P-P problem.

Third GA3

This GA3 can also solve the P-P-P problem like GA1 according to

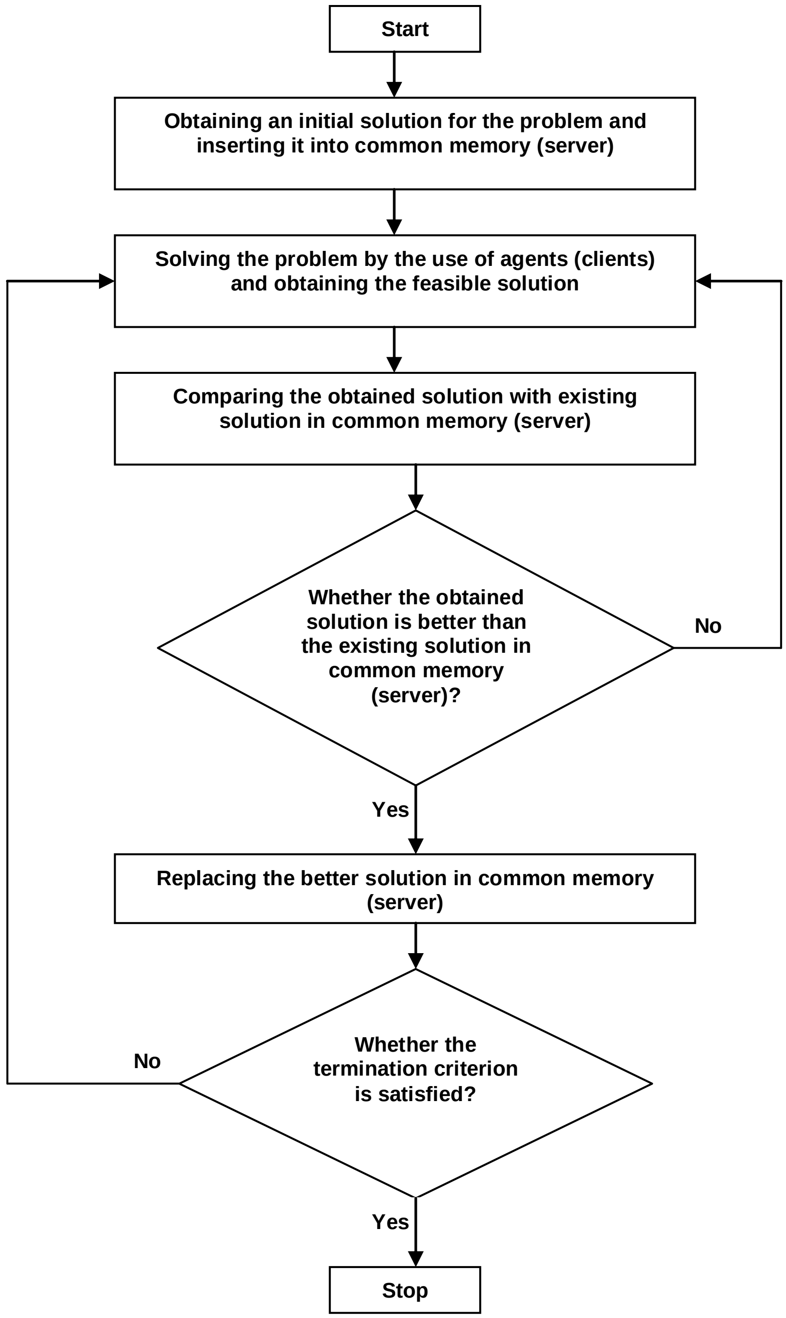

Figure7. Proposed algorithm of each agent (client).

modules which are introduced blow. Except for crossover module, the remaining GA3 modules are similar to GA1 modules.

Crossover

We apply scattered crossover in the P-P-P problem. The method creates a random binary vector. It, then, selects the genes where the vector is a 1 from the first parent and the genes where the vector is a 0 from the second parent and combines the genes to form the child. Now having GA (agents) introduced, we should present architecture for them. The suggested architecture is presented in Figure 6. In this architecture, each GA is considered to be an agent. Each agent acts as a client and after solving the problem, it delivers the obtained solution to common memory which plays the role of a server.

In this architecture, each agent solves the problem as a parallel problem according to its GA mechanism and inserts the obtained result in common memory after solving the problem. The suggested algorithm in this architecture is presented in Figure 7. The procedure of implementation of this algorithm is as follows: First an initial feasible solution is obtained for the problem. This initial

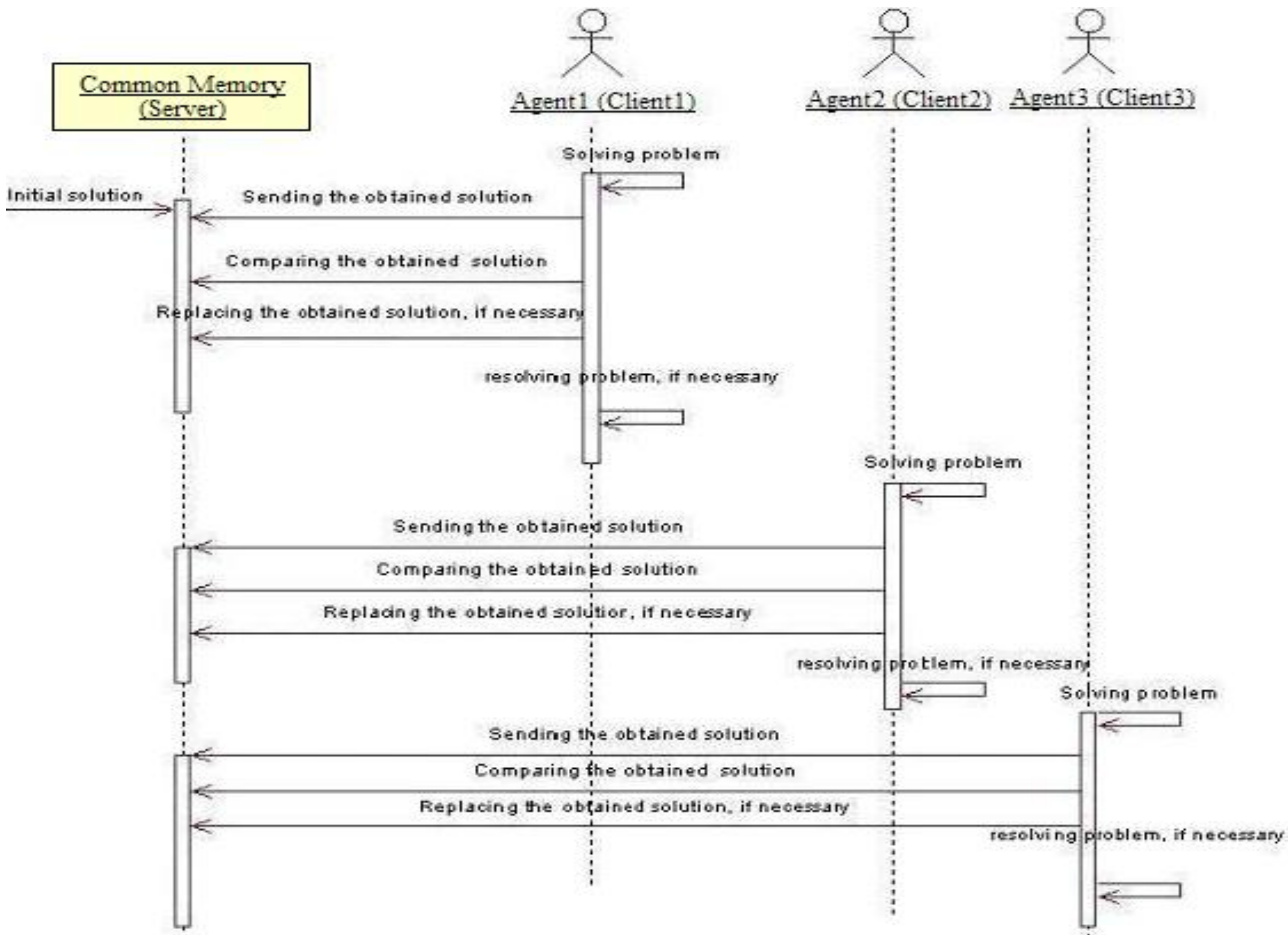

Figure 8. Interaction diagram for the clients and server.

solution is inserted in common memory (server). Hereafter, each agent (client) solves the problem independently and compares its obtained solution with existing solution in common memory (server). If the obtained solution through each agent (client) is better than the existing solution in common memory (server), it is replaced. Otherwise, the problem is resolved through that agent (client).

This process continues until the termination criterion is satisfied. Two important characteristics of agents, namely cooperation and parallel processing, are used in this algorithm which will increase synergy and thereby coordination in the system. Figure 8 shows the diagram of interaction between agents (clients) and common memory (server) and the way messages are exchanged in each of them. The proposed agents (clients) and common memory (server) are shown in this figure. Each agent (client) solves the P-P-P problem according to the proposed algorithm in Figure 7. The solution process and each agent (client) interaction with common memory (server) are shown in this figure. The arrowed lines show interactions between agents (clients) and common memory (server).

EXPERIMENTAL RESULTS

This section presents the results of a series of numerical experiments that were carried out for a production-distribution system. It should be noted that we have run the experiments on a single processor and that the ATeam architecture does provide a convenient way for multiple processor to combine in combinatorial optimization problems. In order to show the effectiveness of the proposed method, the algorithm is implemented using MATLAB® 7 (R14). We have used LINGO 8.0 software to solve the optimal solution of P-P-P problem for comparison the optimal solution with the results of the proposed method. To examine the results, the same data of the auto company in Asia has been used. According to this company's data, 10 problems have been generated randomly but systematically to capture a wide range of problem structure. Each problem has been solved based on LINGO software and multi-agent system. Table 1 shows objective function values and central processing unit (CPU) time for each problem with various indices and parameters which have been solved by LINGO software and multi-agent system. Data obtained from this table shows that in large scale systems, CPU time for suggested multi-agent system is less than that of optimal

Table 1. Computational results.

No problem	V	S	P	R	C	I	Optimal		Multi-agent system	
							Time (S)	Obj	Time (S)	Obj
1	1	2	1	3	2	1	45	1120	85	1267
2	2	1	2	1	3	1	110	32335	212	32393
3	2	3	1	3	2	2	175	28564	382	28602
4	3	1	2	3	3	2	423	1682	562	1934
5	3	2	3	2	3	3	753	42782	924	42882
6	3	3	4	3	4	3	952	65432	1034	65498
7	4	3	5	3	3	3	1138	36873	1034	36893
8	5	4	4	3	5	3	1372	38763	1265	38796
9	6	5	6	5	5	3	2234	76923	2156	76834
10	5	6	5	6	6	3	2434	23875	1734	23895

solution (LINGO software).

The solution quality measured by the percentage gap (= [Average of multi-agent solution values average of optimal objective values] / average of optimal objective values × 100) is about 0.185%. The results show that in large scale problems, the suggested multi-agent system gives us solutions which are near the optimal solution. Also, it takes less time to solve the problem compared to the optimal solution (LINGO software). This was due to parallel processing capability in the suggested multi-agent system. This result is more evident especially for large scale problems where obtaining the optimal solution through optimization software takes more time.

CONCLUSIONS AND FUTURE WORKS

In this paper, a multi-agent framework was developed to solve PDPP for a supply chain management according to the client/server architecture in an internet-based environment. For this purpose, we developed a multi-agent system by using teams of autonomous agents ATeams concept where three GAs were assumed to be the agents of the model. The PDPP was discussed in both optimal and multi-agent system case. The obtained results were shown that in large scale the use of multi-agent system delivers better solutions in terms of CPU times. For future work, we can add other costs such as shortage cost into the model. Also, intelligent agents can be used to solve the model.

Abbreviations: SCM, Supply chain management; **PDPP,** production-distribution planning problem; **GAs,** genetic algorithms; **CIMS,** computer integrated manufacturing system; **AI,** artificial intelligence; **MNC's,** multi-national companies; **BOM,** bill of material; **AHP,** analytic hierarchy process; **GRASP,** greedy randomized adaptive search procedure; **MILP,** mixed integer linear programming; **TDSS,** traditional decision support system; **MADSS,** multi-agent decision support system; **ATeams,** asynchronous teams; **DAI,** distributed artificial intelligence; **PC,** personal computer; **CPU,** central processing unit.

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