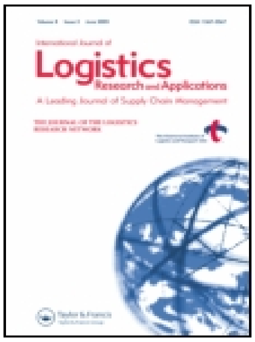

International Journal of Logistics: Research and Applications

ISSN: 1367-5567 (Print) 1469-848X (Online) Journal homepage: https://www.tandfonline.com/loi/cjol20

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Hokey Min

To cite this article: Hokey Min (2010) Artificial intelligence in supply chain management: theory and applications, International Journal of Logistics: Research and Applications, 13:1, 13-39, DOI: 10.1080/13675560902736537

To link to this article: https://doi.org/10.1080/13675560902736537

Published online: 24 Mar 2009.

International Journal of Logistics: Research and Applications
Vol. 13, No. 1, February 2010, 13–39

Artificial intelligence in supply chain management: theory and applications

Hokey Min*

Management, College of Business Administration, Bowling Green State University, Bowling Green, OH 43403, USA

(*Received 12 June 2008; final version received 29 October 2008*)

Artificial intelligence (AI) was introduced to develop and create "thinking machines" that are capable of mimicking, learning, and replacing human intelligence. Since the late 1970s, AI has shown great promise in improving human decision-making processes and the subsequent productivity in various business endeavors due to its ability to recognise business patterns, learn business phenomena, seek information, and analyse data intelligently. Despite its widespread acceptance as a decision-aid tool, AI has seen limited application in supply chain management (SCM). To fully exploit the potential benefits of AI for SCM, this paper explores various sub-fields of AI that are most suitable for solving practical problems relevant to SCM. In so doing, this paper reviews the past record of success in AI applications to SCM and identifies the most fruitful areas of SCM in which to apply AI.

Keywords: artificial intelligence; supply chain management; knowledge management; literature review

1. Introduction

In an era of greater demand uncertainty, higher supply risk, and increasing competitive intensity, supply chain (SC) excellence often hinges on the organisation's ability to integrate and orchestrate the entire spectrum of end-to-end processes of acquiring materials or components, converting them into finished goods, and delivering them to customers. Since such ability can be enhanced by increased visibility across the end-to-end SC processes, many leading-edge organisations have attempted to enrich their information sources and share real-time information with SC partners. Thus, SC management (SCM) is becoming more information intensive and its focus has been directed toward the substitution of assets (e.g., inventory, warehouses, transportation equipment) with information. Recognising the increasing significance of information to SC success, SC professionals have explored various ways to better manage information and leverage it to make better business decisions. One of those ways may include artificial intelligence (AI) that has been in existence for decades, but has not been fully utilised in the area of SCM.

In general, AI is referred to as the use of computers for reasoning, recognising patterns, learning or understanding certain behaviors from experience, acquiring and retaining knowledge, and

*Email: hmin@bgsu.edu

ISSN 1367-5567 print/ISSN 1469-848X online

DOI: 10.1080/13675560902736537
http://www.informaworld.com

developing various forms of inference to solve problems in decision-making situations where optimal or exact solutions are either too expensive or difficult to produce (Nilsson 1980, Russell and Norvig 1995, Luger 2002). Put simply, the main objectives of AI are to understand the phenomenon of human intelligence and to design computer systems that can mimic human behavioral patterns and create knowledge relevant to problem-solving. Thus, AI should have the ability to learn and comprehend new concepts, learn from experience ("on-their-own"), perform reasoning, draw conclusions, impute meaning, and interpret symbols in context. Due to such ability, AI has been successfully applied in areas such as game playing, semantic modeling, human performance modeling, robotics, machine learning, data mining, neural networks, genetic algorithms (GAs), and expert systems (Russell and Norvig 1995, Luger 2002).

One area of AI's potential application that has not yet been fully explored is the emerging management philosophy of SCM, which requires the comprehension of complex, interrelated decision-making processes and the creation of intelligent knowledge bases crucial for joint problem-solving. For example, Eastman Kodak once structured the thinking processes of experienced order pickers and then developed a rule-based expert system to select the optimal order-picking path in a warehouse (Allen and Helferich 1990). Also, in an effort to synchronise a series of interrelated but different stages of joint demand planning and forecasting processes in the SC, Min and Yu (2008) proposed an agent-based forecasting system that has the capability to predict end customer demand through information exchange among multiple SC partners and learn from the past forecasting experience. As illustrated by these examples, some sub-fields of AI such as expert systems and agent-based systems can be useful for dealing with various aspects (e.g., warehousing, joint demand planning, inventory control) of the SC. With this illustration in mind, the main objectives of this paper are to:

(1) Identify the sub-fields of AI that are most suitable for SCM applications and then characterise those sub-fields in terms of their usefulness for improving SC efficiency.
(2) Synthesise the existing literature dealing with the applications of AI to SCM with respect to their practical implications and technical merits.
(3) Develop a hierarchical taxonomy for the existing AI literature and categorise it according to its SCM application areas, problem scope, and methodology.
(4) Summarise AI research trends and identify the potential SCM application areas that have not been explored.
(5) Discuss the future outlook for extensions of existing AI literature and untapped AI research topics relevant to SCM.

2. The taxonomy of the AI literature

To gain a birds-eye view of past AI studies, we develop a taxonomy using three broad classification schemes: (1) *problem scope* as a criterion for measuring the breadth and depth of the SCM problems that the AI study attempted to handle; (2) *the methodology* as a criterion for evaluating the theoretical advances in AI studies and the suitability of particular AI sub-fields for SCM applications; and (3) *the implementation status* as a criterion for assessing the practicality of AI technology. These broad classifications will be further subdivided into smaller categories as discussed below in greater detail.

2.1. *Problem scope*

The problem scope is categorised with respect to the three-level decision-making hierarchy: (1) *strategic* decisions that deal with long-term, executive-level issues such as strategic alliances, facility location, and capital investment; (2) *tactical* decisions that deal with intermediate term, mid-manager-level issues such as joint demand planning, supplier selection, and inventory planning; and (3) *operational* decisions that deal with short-term, routine issues such as vehicle routing, order picking, and cycle counting.

2.2. *Methodology*

AI is known for its ability to think like humans, act like humans, think rationally, and act rationally (Russell and Norvig 1995). Thus, with respect to these distinctive features, AI can be further classified into a number of sub-fields: (1) artificial neural networks (ANN) and rough set theory ("*thinking humanly*"); (2) machine learning, expert systems, and GAs ("*acting humanly*"); (3) fuzzy logic ("*thinking rationally*"); and (4) agent-based systems ("*acting rationally*"). These sub-fields are discussed below.

2.2.1. *Artificial neural networks*

The theory of an ANN was predicated on the way that the living organ's brain cells, namely neurons, function. Using the interconnected network of computer memories, ANN can learn from experience, distinguish features, recognise patterns, cluster objects, and process ambiguous or abstract information. To elaborate, an ANN is composed of a number of nodes which correspond to biological neurons. Those nodes are connected to each other by links. Each link has a numeric weight assigned to it. The links and their weights are the primary means of the long-term memory storage. The network processes information in such way that the output of one neuron is an input to another neuron linked to it. The weights are responsible for the strengthening or weakening of the information passed via the link. The links are placed and the values of weights are set in a process called learning. ANN can be taught to respond to various data patterns according to our wishes or to learn hidden interrelationships among the data. Once the network is initialised, ANN can be modified to improve its performance using an inductive learning algorithm and be trained in either supervised or unsupervised environments (McCulloch and Pitts 1943, Russell and Norvig 1995).

ANN has been proved to be useful for semantic modeling due to its ability to learn to pronounce English vocabularies. In the logistics field, ANN can be useful for maneuvering autonomous vehicles using its image processing technique. Indeed, Pomerleau (1993) utilised ANN to steer a land vehicle along a single lane on a highway by mimicking the performance of a human driver. Although the application of ANN to auto-piloting land vehicles is still limited to a certain type of road condition and traffic environment, it showed promise in autonomous vehicle navigation. ANN has also been applied to a traditional lot-sizing problem (Gaafar and Choueiki 2000). In a broader context, ANN was successfully utilised to develop hierarchical SC planning that determined the time/capacity needed for setups, estimated optimal lot-size between successive SC processes, and linked inventory and scheduling decisions at the lower level to demand and production planning decisions at the higher level (Rohde 2004). As such, ANN is designed to reflect the interconnectivity and interdependence of SC planning processes better than traditional operational research (OR) techniques that were primarily intended for solving less-integrated sub-problems (e.g., inventory or production or transportation planning) of SC planning.

2.2.2. *Rough set theory*

Rough set theory was introduced by Pawlak (1982) as a way of synthesising the approximation of concepts from the acquired data using a data table comprising of one or more classification attributes. These attributes include equivalence classes, indiscernibility relations, set approximation, and rough membership. These classification attributes are necessary to implement mechanisms similar to those that humans use for object classification and recognition. Also, based on the description of common features of indiscernible objects, they can be useful for developing decision rules (Pawlak 1984, 1989, 1997). As such, rough set theory can be employed to classify decision criteria and then develop decision rules relevant to SCM. For example, Li *et al.* (2007) used rough set theory to select the most desirable supplier among a pool of qualified suppliers with respect to multiple but conflicting supplier selection criteria. Zheng and Lai (2008) also utilised rough set theory to develop multiple criteria decision rules for measuring dynamic SC performance.

2.2.3. *Machine learning*

Machine learning, coined by Samuel (1995), was designed to provide computers with the ability to learn without being explicitly programmed. In other words, machine learning investigates ways in which the computer can acquire knowledge directly from data and thus learn to solve problems (Ratner 2000). Depending on the method of learning tasks, machine learning can be sub-classified into a number of categories: (1) *concept learning* that is designed to correctly recognise or construct concepts relevant to future decision-making processes following an inductive learning process; (2) *decision tree learning* that aims to classify all the objects by testing their values for certain properties and then constructing a decision tree; (3) *perceptron learning* that aims to acquire useful knowledge, reduce the error, and solve decision problems using a single layer of the network called a "perceptron"; (4) *Bayesian learning* that trains the computer to learn representations of probabilistic functions; and (5) *reinforcement learning* that trains the computer to perform at high levels by giving constant feedback in a form of rewards (see e.g., Luger 2002 for various machine learning processes).

Regardless of differences in learning tasks, machine learning techniques often attempt to mimic nature based upon the knowledge and experience that the human race has amassed over the eons of its existence. Some of the machine learning techniques were motivated by the neurological studies of the human brain function, some by the processes dictating human evolution, some by the mathematical theory of human knowledge acquisition and reasoning and some by the sociological theory behind human collaborative behavior. In particular, machine learning can be a useful tool for understanding the motivation behind collaborative behavior among SC partners for sharing critical information and improving ways of strengthening the partnership among SC partners through the organisational learning process. For instance, Carbonneau *et al.* (2008) recently used machine learning to forecast the distorted demand information at the end of a SC, namely the bullwhip effect, if that demand information was not shared among the SC partners due to lack of collaboration.

2.2.4. *Expert systems*

Expert systems represent computer programs capable of emulating human cognitive skills such as problem-solving, visual perception and language understanding, and are capable of performing reasoning about a problem domain complex enough for a considerable amount of human expertise (Jackson 1999). Expert systems are comprised of four components: (1) knowledge base, (2) inference engine, (3) justifier/scheduler, and (4) user interface. To elaborate, the knowledge base is the repository of the rules, facts, and knowledge acquired from the human expert. The inference engine is a cluster of problem-solving programs (the "brain" of the expert system) that coordinate the searching, reasoning, and inference based on the rules of the knowledge base. The justifier explains how and why an expert arrives at a solution, while the scheduler is set up to coordinate and control the sequencing rules. The user interface facilitates communication and interaction between the system and its user through a series of user queries (Awad 1996).

Since an expert system operates at a level and in terms and concepts with which the user can feel affinity, the expert system is much more easily understood by the practitioner and thus more applicable to practical SC problems (Basden 1984). In particular, the expert system is known to increase productivity in managing logistics (Eom and Karathanos 1996). For instance, Allen (1986) successfully solved multiple echelon inventory control problems in the US Air Force Logistics Center using more than 400 rules and heuristics created by a number of experts and verified the effectiveness and efficiency of the proposed expert system in terms of improved inventory accuracy. Sullivan and Fordyce (1990) also developed a real time, transaction-based expert system that aimed to schedule, monitor, and control the logistics flow of the IBM's semiconductor facility near Burlington, Vermont. They reported that the use of the expert system increased IBM's product output by 35% and saved approximately $10 million of capital expenditure.

The application potential of the expert system is limitless in the SC field, as evidenced by its successful application to air traffic control, spatial mapping, airline yield management, and vehicle repair and maintenance scheduling (Findler 1987, Jefferies and Yeap 2008). In addition, an expert system can be more useful than a single more sophisticated forecasting method (or a mixture of such methods) for demand forecasting at every stage of the SC, in terms of forecasting accuracy, computational speed, user understanding, and cost effectiveness (DeLurgio 1998). Other intriguing applications of the expert system to the SC discipline include: concurrent product design and planning (Zha *et al.* 1999); gas pipeline operations (Uraikul *et al.* 2000); supplier evaluation (Kwong *et al.* 2002); evaluation and selection of third-party logistics (3PLs) providers (Yan *et al.* 2003); formulation of a logistics strategy (Chow *et al.* 2005); and production planning and control (Lawrynowicz 2007).

2.2.5. *Genetic algorithms*

As a branch of evolution programs, a GA imitates the principles of natural evolution and derives a set of rules from natural selection processes that create organisms that most fit the surrounding environment. GAs have often been used to solve combinatorial optimisation problems for which it is possible to construct a function that can estimate a fitness of a given representative (*solution*) to a given environment (*problem*). The GA encodes possible solutions to the problem in numerical strings called *chromosomes*. By iterative application of genetic operators (*crossover*, *mutation*, and *selection*) to a whole population of such chromosomes, the GA produces solutions that are not necessarily optimal, but quite satisfactory in terms of the fitness to the optimisation problem.

In general, a GA is referred to as a stochastic AI technique that utilises a solution search process that mimics natural evolutionary phenomena: genetic inheritance and Darwinian struggle for survival (Holland 1975, Michalewicz 1999). The GA typically comprises five components (Michalewicz 1999, Gen and Cheng 2000):

(1) A genetic representation of potential solutions to the problem.
(2) A way to create a population (an initial set of potential solutions).
(3) An evaluation function measuring the fitness of solutions to see whether they will survive.
(4) Genetic operators that alter the genetic composition of offspring. These operators include *reproduction*, *crossover*, and *mutation*. Reproduction is a process in which individuals (solutions) are copied through the selection of individuals that are the most fit. Crossover combines the features of two parent chromosomes (potential solutions) to form two similar offspring by exchanging corresponding attributes of the parents. Mutation randomly alters one or more features of a selected solution to introduce extra variability.

(5) Parameter values that determine population size (how many individuals should be in the population); crossover rate (the probability that the individual will crossover); and mutation rate (the probability that a certain gene will mutate).

Although the GA aims to produce global optimal solutions efficiently, its population size cannot be infinite. Thus, its final solution may be biased due to the finite sampling of potential solutions. Also, the performance of a GA may depend on the specific rates of crossover and mutation. As a result, a GA may suffer from premature convergence. Furthermore, the size of population does not usually improve the performance of a GA with respect to the speed of finding solutions (see, e.g., Holland 1975 and Goldberg 1989 for distinctive features of a GA). Nevertheless, GAs have been applied successfully to a variety of challenging SC network design problems. These problems include: vehicle routing and scheduling (Malmborg 1996, Potvin *et al.* 1996, Chen *et al.* 1998, Park 2001); minimum spanning tree (Zhou and Gen 1998, 1999); delivery and pickup (Jung and Haghani 2000); bus network optimisation (Bielli *et al.* 2002); and location–allocation problems (Hosage and Goodchild 1986, Jaramillo *et al.* 2002, Zhou *et al.* 2002, 2003, Min *et al.* 2005). In addition, a GA was employed to solve well-known logistics and purchasing problems involving facility layout (Tam and Chan 1998, Balamurugan *et al.* 2006); pallet loading (Fontanili *et al.* 2000); inventory control (Disney *et al.* 2000, Haq and Kannan 2006); container loading (Gehring and Bortfeldt 1997, Bortfeldt and Gehring 2001); material handling (Wu and Appleton 2002), delivery reliability assurance (Antony *et al.* 2006); freight consolidation (Min *et al.* 2006a, b); supplier selection (Rao 2007); and express courier services (Ko *et al.* 2007).

2.2.6. *Fuzzy logic*

Fuzzy logic can be a powerful tool for building knowledge bases for particular domains and acquiring knowledge from the experts. In a broad sense, fuzzy logic uses expert opinions as an input to specify "good" and "bad" areas of each variable and then determines the likelihood of "goodness" and "badness" levels after comparing the input variable with the expert opinion (Tanaka 1997). Fuzzy logic is an extension of Boolean logic that was designed to conceptualise partial truth – somewhere between *definitely true* and *definitely false*. Typically, fuzzy logic consists of five basic components: (1) linguistic variables, (2) linguistic values, (3) fuzzy sets, (4) membership functions, and (5) fuzzy IF-THEN rules. Thus, fuzzy logic is in contrast to crisp logic that is predicated on clear distinction between objects (or values). In other words, fuzzy logic can handle ambiguity, imprecision, and uncertainty of objects. For instance, fuzzy logic may help us answer questions of how cold the temperature is, how heavy a person is, or how expensive the product price is, without setting a clear-cut boundary.

In fuzzy logic, since the membership of an object in a fuzzy set takes a value between 0 and 1, the transition from membership to non-membership in the set is gradual. This gradual transition allows for the mathematical expression of objects with varying conditions and states. For example, a given temperature (object) can be expressed as cold to the degree of 0.1 and warm to the degree of 0.8; a car can belong to the set of a cheap car to the degree of 0.2 and an expensive car to the degree of 0.6. Thus, fuzzy logic can be useful for developing a set of rules for SC decision environments where subjective performance criteria have to be employed. For instance, in the airport location decision, a transportation planner may not know exactly how convenient the location of the airport is to the nearby shippers and carriers. Fuzzy logic has also been applied to solve the well-known traveling salesman problem (TSP) in a SC setting (Michalewicz and Fogel 2000). Other applications of the fuzzy logic to SCM include: supplier performance evaluation (Lau *et al.* 2002); inventory cost control (Wang and Shu 2005); measurement of the bullwhip effect (Balan *et al.* 2007); agro-industry SC planning (Yandra *et al.* 2007); supplier selection (Carrera and Mayorga 2008); and order fulfillment (Amer *et al.* 2008).

2.2.7. *Agent-based systems*

An agent-based system is one of the distributed problem-solving techniques that divides a decision problem into sub-problems and solves those sub-problems using independent entities called agents. Each agent can use different methodology, knowledge and recourses to process given tasks. According to Reis (1999), an agent refers to an autonomous entity that can take certain actions to accomplish a set of goals and can compete and cooperate with other agents while pursuing its individual goals. An agent is characterised by its ability to exploit significant amounts of domain knowledge, overcome erroneous input, use symbols and abstraction, learn from the decision environment, operate in real time and communicate with others in natural language (Newell 1989). Exploiting such characteristics, an agent-based system has often been employed to handle various SC issues including shop floor control (Van Dyke Parunak 1998, Shen *et al.* 2000, Usher 2003, Wang and Shen 2003); logistics planning (Satapathy *et al.* 1998); air traffic control (Iordanova 2003); aggregate demand planning and forecasting (Yu *et al.* 2002, Liang and Huang 2006); joint production planning (Lima *et al.* 2006); new product development (Liang and Huang 2002); order monitoring (Chen and Wei 2007); business-to-business negotiation (Ito and Saleh 2000, Lenar and Sobecki 2007); bidding evaluation (Kang and Han 2002); outsourcing relationship management (Logan 2000); customer relationship management (CRM) (Baxter *et al.* 2003); SC relationship management (Ghiassi and Spera 2003); SC performance assessment (Gjerdrum *et al.* 2001); SC coordination (Swaminathan 1998, Fox *et al.* 2000, Nissen 2001, Sadeh *et al.* 2001, Ono *et al.* 2003, Chan and Chan 2004, Lou *et al.* 2004, Xue *et al.* 2005); SC collaboration under uncertainty (Kwon *et al.* 2007); information exchange among SC partners (Garcia-Flores *et al.* 2000, Turowski 2002); information tracking across the SC (Zimmermann *et al.* 2001); material handling (Ito and Mousavi Jahan Abadi 2002); retail merchandise purchasing (Park and Park 2003); e-logistics (Santos *et al.* 2003); strategic e-procurement (Cheung *et al.* 2004); e-supply chains (Singh *et al.* 2005); traffic incident management (Tarver and Fae 2007); and the procurement of maintenance, repair, and operating (MRO) supplies (Nissen and Sengupta 2006).

A byproduct of agent-based methodologies that may be useful for solving complex SC problems is ant colony optimisation. This algorithm mimics the social behavior of ants, who often find the shortest path to their food sources and nests using their innate capability to follow pheromone trails (hormone deposited by ants reflecting their collective memory) released by other ants. To elaborate, an ant colony optimisation algorithm is a meta-heuristic inspired by knowledge-sharing behaviors of ants in solving combinatorial problems pertaining to different realms. The ant colony optimisation algorithm is known to stabilise the solution with a reasonable amount of computational time without detriment to the solution accuracy, by exploiting the positive feedback provided by armies of ants working as multiple agents (Dorigo *et al.* 1996). Due to its past success in handling NP-hard problems, the ant colony optimisation algorithm has been employed to solve TSP, vehicle routing problems, sequential ordering problems, and process plan selection problems within the SC framework (Gambardella and Dorigo 2000, Tiwari *et al.* 2006).

2.3. ***Implementation status***

Since SC managers may be interested in determining the applicability of the proposed AI technique, we included the third dimension of the taxonomy indicating whether the proposed AI technique has been applied to the real-world decision environment using actual data, and whether the AI technique was successfully implemented in the SC setting.

3. The synthesis of AI applications in SCM

Despite the long history of AI, the potential of AI as a means of solving complex problems and searching for information in the SCM area has not been fully exploited in the past. However, some pioneering efforts have been made to initiate AI applications in the SCM area. In particular, certain sub-disciplines of AI such as expert systems and GAs have been increasingly utilised to address SCM issues involving inventory management, purchasing, location planning, freight consolidation, and routing/scheduling problems. In this section we outline those SCM areas that have been explored for AI applications, identify specific sub-disciplines of AI that have been proved to be useful for improving SC decisions, and assess their contributions to the SC decision-making process.

3.1. *Inventory control and planning*

Inventory represents idle resources that are required to maintain high levels of customer service but which incur substantial costs. In fact, the annual cost of holding a single unit of inventory might range from 15% to 35% of its product value (Timme and Williams-Timme 2003). Thus, the firm's success in a competitive market often hinges on its ability to control and plan inventory at minimum cost, while making inventory constantly available for customers when needed. Such an ability can be enhanced by the presence of accurate, real-time information about expected customer demands, the size and type of inventory at hand and the amount of order cycle time to fulfill the customer order. However, since this kind of information is often difficult to estimate, predict and obtain, traditional decision rules based on mathematical models such as economic order quantity cannot reflect the very essence of inventory management. That is to say, a tool such as an expert system, which can replace the sound judgment and intellect of experienced inventory managers and deal with the unexpected, is better suited to handling inventory control and planning decisions. Recognising this potential, Allen (1986) developed an expert system called the Inventory Management Assistant (IMA) that was designed to aid the US Air Force Logistics Command in replenishing various types of spare aircraft parts and reducing safety stocks. The IMA was reported to improve the effectiveness of inventory management by 8–18% by reducing the inventory errors.

As illustrated above, AI techniques such as expert systems offer a promising new approach to inventory control and planning problems of great magnitude and complexity due to their powerful knowledge representation language that is capable of capturing inventory patterns throughout the entire SC at all levels of detail. The capturing of such dynamic complexity in the inventory data base enables human experts such as inventory managers to estimate the desirable level of inventory at each stocking point without causing a bullwhip effect. For example, an expert system may be incorporated into the material requirement planning system so that it can store data bases regarding historic master production schedules, bills of materials, and order patterns and then develop systematic lot-sizing rules to estimate the optimal level of future orders and the optimal timing of inventory replenishments. Another intriguing application of AI techniques to inventory control and planning includes the recent study of Teodorovic *et al.* (2002) who developed fuzzy logic rules to make online, intelligent, airline seat inventory control decisions as to whether to accept or reject any passenger request for seating arrangements.

3.2. *Transportation network design*

So far one of the most popular applications of AI techniques to a particular SC area has been to a class of the transportation network design problems that are intrinsically combinatorial and for which global optimal solutions are thus difficult to find. This class of problems include: the TSP, the vehicle routing and scheduling problem, the minimum spanning tree problem, the freight consolidation problem, and the intermodal connection problem. Other related problems include: road network design, gas distribution pipeline network design, parking space utilisation, traffic assignment, and ramp metering in freeway networks. In particular, due to the combinatorial nature of these problems, GA turns out to be one of the most popular forms of AI techniques employed to handle these various aspects of transportation network design problems (Chambers 2001). Another AI technique that has emerged as an increasingly popular meta-heuristic is the ant colony optimisation algorithm. This algorithm has been applied successfully to handle well-known network design problems such as the TSP, the vehicle routing problem, and the minimum spanning tree problem (Dorigo and Gambardella 1997, Bullnheimer *et al.* 1999, Shyu *et al.* 2003).

Unlike traditional OR techniques or heuristics, both GAs and ant colony optimisation algorithms belong to a class of meta-heuristics that are viewed as a general algorithmic framework that can be applied to a wide set of different combinatorial optimisation problems with relatively few modifications to make them adapted to a specific transportation network design problem (see e.g., Glover and Kochenberger 2003 for details of meta-heuristics). Thus, they are more flexible than the traditional OR techniques and heuristics in accommodating variations in transportation problem structure. However, it is worth noting that other meta-heuristics such as tabu search, simulated annealing, scatter search, and iterative local search can be as effective as GAs and ant colony optimisation for solving a TSP and its variants.

3.3. *Purchasing and supply management*

A make-or-buy decision is primarily concerned with weighing the options of producing goods or services internally or purchasing those from the external sources of supply to better utilise the firm's given resources (e.g., capacity and personnel) and focus on its core competency. Although the make-or-buy decision sounds simple and straightforward, it should factor into various "what-if" scenarios as illustrated below (see e.g., Baily *et al.* 2005 for issues involving the make-or-buy decision):

- What volume of goods does the company expect to produce?
- How much capital investment is needed to produce goods or render services?
- How much risk is involved in developing new products or innovating technology to stay competitive in the market?
- Has the product that the company is considering making reached its peak demand or the maturity stage of its life cycle?
- What business is the company in?
- What is the key strength of the company?
- Do the company employees have the expertise and skill to produce goods that the customers desire?

Due to the complexity and dynamics of the above scenarios, the make-or-buy decision calls for systematic decision-aid tools. Such tools include an expert system. For example, Humphreys *et al.* (2002) developed an expert system that could assist the purchasing manager in evaluating the performance of prospective suppliers, enhancing information exchange among the purchasing personnel and reducing the time to make the make-or-buy decision. To handle a broader spectrum of purchasing decisions, Kim *et al.* (2002b) proposed an agent-based purchasing system to automate the on-line ordering process involved in the acquisition of shoe materials from the global supply base. Similarly, Cheung *et al.* (2004) developed a hybrid agent- and knowledge-based system to evaluate on-line bids and the performance of the bid-winning suppliers in fulfilling orders. More recently, Nissen and Sengupta (2006) proposed intelligent software agents that could automate the processes of searching for prospective suppliers through online catalogs, evaluating suppliers with respect to multiple attributes, screening qualified suppliers and completing the purchase order. Preventing specification ambiguity, they discovered that the proposed agent-based purchasing system can substitute the role of the human decision-maker. As illustrated above, agent-based systems can aid the purchasing manager in a series of strategic and tactical purchasing decisions, while traditional OR techniques such as analytic hierarchy process and multiple attribute theory can handle only one aspect of purchasing decisions (e.g., supplier selection).

3.4. *Demand planning and forecasting*

Information about future demand is a basis for the firm's capacity planning, workforce scheduling, inventory control, new product development, and promotional campaigns. However, its usefulness often depends on its accuracy that, in turn, rests with the firm's ability to reduce the uncertainty and variability inherent in future demand. Given the volatile nature of future demand coupled with the varying degree of uncertainty and variability associated with such demand, it has been a daunting task to develop accurate forecasting techniques and/or select a forecasting technique that is most suitable for particular business environments. For example, some forecasting techniques are intended for a short-term projection whereas others work better for a long-term projection. Regardless, a common denominator among most traditional forecasting techniques such as exponential smoothing, moving average, time series, and Box–Jenkins methods is their underlying premise that future demand will follow the pattern of past demand. Under such a premise, these traditional forecasting techniques have relied heavily on the accuracy and validity of historical data. Although historical data is still invaluable in predicting the future demand of existing products and services, it is not available for the prediction of the future demand of new products and innovative services that were not extant in the past. To overcome such a drawback of traditional forecasting techniques, AI techniques have recently been introduced as viable alternatives for demand forecasting and planning.

For instance, Yu *et al.* (2002) proposed a dynamic pattern matching procedure within the agent-based system framework that combines human expertise and data mining techniques to predict the demand for new products. Their experiments indicated that the dynamic pattern matching procedure outperformed exponential smoothing techniques with respect to forecasting accuracy. In contrast to exponential smoothing, which merely relies on historical data, the dynamic pattern matching procedure utilised multiple agents to capture past (base-line agent), current (causal agent), and future (pattern agent) customer behaviors that helped improve its forecasting accuracy. Similarly, Jeong *et al.* (2002) improved forecasting accuracy without relying heavily on historical data by introducing a genetic algorithm-based causal forecasting technique that outperformed traditional regression analysis. As illustrated above, AI techniques such as agent-based systems and GAs can be useful for predicting future demand for new products or innovative products/services that have not yet been introduced in the market and thus have no historical demand data.

3.5. *Order-picking problems*

Put simply, order picking involves selecting the items that have been placed on order. Due to its labor-intensive operations, order picking typically accounts for the largest portion of warehousing operating expenditure (Frazelle 2002). Thus, it affects warehousing productivity significantly. Considering its significant role in warehousing operations, warehousing managers have attempted to devise ways to improve order-picking efficiency. Such ways include the computerisation and subsequent automation of sequencing and filling the orders. As part of the automation process, Kim *et al.* (2002a) developed an intelligent agent-based system that optimally assigned workers to a specified zone from which orders were picked. It was also designed to adjust conveyor speed dynamically to minimise queuing time for order picking intervals and maximise order picking throughput. Although the order-picking problem has often been tackled by simulation models and mathematical models in the past, the use of AI techniques such as an intelligent agent-based system may better handle the added complexity caused by the increasing adoption of value-added services and e-fulfillments due to their inherent learning capability.

3.6. *Customer relationship management*

To retain customers, the firm should make its customers trust its manufacturing and service capabilities and make customers believe it can deliver exactly what they want. Such trust cannot be instilled without constantly communicating and building a long-term relationship with customers. Thus, CRM is an important prerequisite to demand creation that drives SC activities. In general, CRM is referred to as the business practice that is intended to improve service delivery, build social bonds with customers and secure customer loyalty by nurturing a long-term, mutually beneficial relationship with valued customers selected from a pool of more than a few customers (Min 2006).

Since CRM has a profound impact on the firm's profitability, it would be necessary for the firm to assess the costs of sustaining CRM and weigh its benefits against costs. Baxter *et al.* (2003) proposed an agent-based model that simulated interaction between members of customer populations and business environments in which they were contained. Their agent-based model considered the communication of customer experiences between members of a social network and then incorporated the powerful influence of word-of-mouth reputation on the purchase of products and services. By doing so, it aided the firm in assessing the extent of its return on investment in CRM and enhancing its customer acquisition efforts.

3.7. *e-synchronised SCM*

To facilitate the coordination and integration of SC activities, SC partners often share information regarding demand forecasting, joint production and distribution planning through electronic media such as Internet websites and electronic data interchange. Abundance of such information in the cyber space provides a fertile ground for applying machine learning techniques such as web mining and text mining. Web mining generally refers to the search, classification and analysis of all web-related data, including web content, hyperlink structure, and web access statistics (Fayyad *et al.* 1996). In particular, web mining can be used to extract new patterns or previously unknown patterns of data regarding customer profiles, supplier profiles, sales trends, sourcing trends, revenue trends, and demand fluctuations stored in various websites. Discovering knowledge through web mining can help multinational firms such as Amazon.com and e-Bay identify future customer bases, develop pricing strategies, evaluate trading partners, and increase revenue. For example, Symeonidis *et al.* (2008) utilised data mining techniques to evaluate the performances of intelligent trading agents and then maximise revenue potential in e-synchronised SC environments including electronic bidding.

4. Concluding remarks and future research directions

Since SCM requires the comprehension of complex, interrelated decision-making processes and the creation of intelligent knowledge bases essential for joint problem-solving, SCM has evolved

Table 1. Categorised list of the selected ANN in SCM literature.

Article/year of publication	Problem scope	Methodology	Implementation status	Key Contribution(s)	Limitation(s)	Key Findings (if any)	Comments
Gaafar and Choueiki (2000)	Lot sizing in Materials Requirement Planning	ANN	Not implemented in practice	Solved the problem of determining the optimal lot size to order in discrete time periods of a single item over multiple time periods to satisfy a certain demand pattern while minimising the sum of ordering and inventory carrying costs. Combined ANN with simulation.	The study was limited to deterministic time-varying demand patterns.	The proposed ANN was robust to changing demand patterns over time periods.	The proposed ANN outperformed the existing lot-sizing heuristics such as Silver–Meal and Periodic Order Quantity approaches in terms of finding the optimal order quantities.
Rohde (2004)	Hierarchical SC planning	ANN	Not implemented in practice	One of the first to use an ANN to develop three-level SC plans involving demand planning, purchasing, transportation, production scheduling, and lot sizing.	Considered a single-stage flow in deterministic environments.	The proposed ANN outperformed an economic order quantity model in calculating the effective lot-size.	The generalisation capability of the ANN can be improved by performing network training demand series with increased average demand and decreased seasonality.

Table 2. Categorised list of the selected expert systems in SCM literature.

Article/year of publication	Problem scope	Methodology	Implementation status	Key Contribution(s)	Limitation(s)	Key Findings (if any)	Comments
Allen (1986)	Inventory management	Expert system	Implemented in Sacramento and Ogden Air Logistics Center	One of the first studies which utilised a rule-based expert system to assist the decisions involving practical inventory management.	The proposed nominal group technique can create difficulty in forming consensus among the experts. The study was limited to relatively small inventory tasks.	The proposed expert system resulted in a greater performance improvement on a complex case than on a simple case. User acceptance of the expert system was high.	The proposed expert system led to 15% productivity gains.
Yan et al. (2003)	Evaluation and selection of 3PLs providers	Expert system	Not implemented in practice	Presented a case-based reasoning approach to facilitate the decision regarding 3PL evaluation and selection.	The proposed system mainly relied on the expertise of internal managers within the firm rather than external consultants.	The benefits of the proposed system were neither assessed nor documented.	The proposed case reasoning is based on human decision-making behavior.
Cheung et al. (2004)	Strategic e-procurement	Agent-based system Expert system	Implemented by a small home appliance manufacturing company in Hong Kong	Combined an agent-oriented approach with a knowledge-based system to issue requests for quotations, evaluate on-line bids, and automate on-line purchase orders.	The proposed system was validated only by trials and runs.	The proposed system helped to reduce the time and steps of searching and evaluating suppliers. The proposed system reduced paperwork and human errors.	The proposed system leveraged the knowledge bases of experienced purchasing professionals to automate e-procurement processes.
Chow et al. 2005)	Logistics strategy formulation under various customer demands	Expert system	Applied to a Hong Kong-based freight forwarder	Proposed an expert system that could collect, transform, and store organisational knowledge to formulate logistics strategy.	The proposed system may not be generalised to other logistics environments. Case-based reasoning relied heavily on human judgment that was subject to error.	The proposed system improved both the inbound and outbound logistics efficiency by 15%. Reduced operating costs and customer claims. Reduced logistics planning time by 70%.	The proposed system incorporated case-based reasoning into data mining techniques to facilitate the strategy development process.

Table 3. Categorised list of the selected GAs in SCM literature.

Article/year of publication	Problem scope	Methodology	Implementation status	Key Contribution(s)	Limitation(s)	Key Findings (if any)	Comments
Jeong et al. (2002)	Demand forecasting in the SC	GA	Applied to glass manufacturing lines and residential construction	One of the first studies which used GA to determine the coefficients of the linear forecasting model.	The forecasting accuracy was measured only by the mean absolute deviation. The forecasting model is predicated on the premise of a causal relationship between customer demand and price index.	The proposed GA (i.e., guided GA) outperformed regression analysis with respect to its forecasting accuracy.	The length of the GA training period can affect the forecasting accuracy of the guided GA.
Disney et al. (2000)	Inventory control	GA	Never implemented in practice	Combined the classical inventory control theory with GA to optimally make a tradeoff between inventory levels and factory orders.	The study was limited to a simplified linear SC.	If inventory costs are significant, work-in-process information significantly affects the performance of the ordering system.	The hybrid GA and simulation model can substantially improve an inventory control system in the SC.
Park (2001)	Vehicle scheduling	GA	Not implemented in practice	Developed GA to solve multiple objective vehicle scheduling problem with service due times and deadlines.	The solution was confined to a single depot problem.	The proposed GA outperformed a well-known savings method for solving some test problems.	The GA combined with a greedy interchange heuristics improved its computational efficiency.

Zhou et al. (2002)	Allocation of customers to warehouses	GA	Applied to the distribution problem facing an actual yard fence component supplier	Formulated a naïve balanced star spanning forest and developed GA to solve the warehouse allocation problem.	The proposed solution was confined to a single objective problem with equal warehouse capacity.	The proposed GA allocated customers to multiple warehouses with more than 98% balanced level.	The balanced warehouse allocation can reduce stock-outs and late deliveries.
Bielli et al. (2002)	Urban bus transportation network	GA	Applied to a small city bus network in Italy	Proposed both GA and neural network to optimally design the urban bus transportation network. Multiple criteria were considered.	Sensitivity analysis was not conducted.	The best solution found the GA was a bus network formed by a set of lines corresponding to the genes having the switch set on.	The proposed algorithm can reduce the number of buses needed.
Liang and Huang (2006)	Demand forecasting	Agent-based system Rough set theory GA	Applied to the hypothetical Beer Game	Applied agent technology to simulate inventory levels throughout the SC and determine optimal order quantity for every echelon of the SC. Used the prior expert knowledge to make a demand better forecast.	Experiments with the system were based on a small number of MBA student subjects. Assumed that SC partners were always willing to share information among themselves.	The proposed agent-based system mitigated the bullwhip effect.	The proposed agent-based system is less costly to make a demand forecast than conventional forecasting techniques such as exponential smoothing.

Table 4. Categorised list of the selected fuzzy logic in SCM literature.

Article/year of publication	Problem scope	Methodology	Implementation status	Key Contribution(s)	Limitation(s)	Key Findings (if any)	Comments
Yandra et al. (2007)	Bio-diesel SC planning	Fuzzy logic and GAs	Applied to the hypothetical agricultural SC problem	Solved the problem of determining the optimal lot size to order in discrete time periods of a single item over multiple time periods to satisfy a certain demand pattern while minimising the sum of ordering and inventory carrying costs. Combined GAs with fuzzy logic.	The study was limited to a flow of a single product made from coconut or palm oil.	The proposed GA and fuzzy logic turned out to be robust and reliable and could produce promising results.	First, a GA was employed to create a Pareto front that is comprised of non-dominated solutions. Then a fuzzy logic was used to select the most preferred solution.
Amer et al. (2008)	Order fulfillment Supplier performance monitoring	Fuzzy set theory	Not implemented in practice	Presented the design for six sigma to monitor and control the SC process of order fulfillment. Developed a transfer function that mathematically represented a relationship between input and output order fulfillment processes.	Only considered three performance metrics: delivery time, order quantity, and order quality to evaluate the order fulfillment process. Thus, other intangible service performance criteria such as delivery reliability were not taken into consideration.	The maximum score for the order occurs when both the quantity and delivery time are at target.	Fuzzy logic was used to develop a transfer function and provide a means of putting quantitative value on qualitative (or vague) performance measurement.

Table 5. Categorised list of the selected agent-based systems in SCM literature.

Article/year of publication	Problem scope	Methodology	Implementation status	Key Contribution(s)	Limitation(s)	Key Findings (if any)	Comments
Swaminathan et al. (1998)	SC reengineering and coordination	Agent-based system	Applied to IBM for inventory control	Developed a library of software for modeling SC processes. Combined simulation with a multi-agent paradigm to address SC coordination issues under uncertainty.	The study focussed on generic outbound logistics activities. The system is more appropriate for large corporations. More adaptive agents are needed.	The proposed system was useful for evaluating both short- and long-term SC reengineering efforts.	The multi-agent-based system reduced the development time for SC models.
Logan (2000)	Transportation outsourcing	Agency theory	Never implemented in practice	Engaged agency theory to help design the types of transportation outsourcing contracts and relationships. Agency theory was proposed as a viable alternative to the resource-based view of the firm and transaction cost economics.	The proposed agency concept was not fully computerised.	Prescriptions for success in transportation outsourcing (such as communication, training, performance measurement, and motivation for continual improvement) are similar to those in other industries.	Agency theory can be used to determine which outsourcing service providers and user are best suited to manage the conflicting relationship.

(*Continued*)

Table 5. Continued

Article/year of publication	Problem scope	Methodology	Implementation status	Key Contribution(s)	Limitation(s)	Key Findings (if any)	Comments
Fox et al. (2000)	Inter-organisational SC integration	Agent-based system	Implemented in Perfect Minicomputer Corporation in Toronto, Canada	One of the first studies to use multiple agents to integrate and coordinate various SC activities. The proposed system is capable of handling unexpected SC disruptions.	Since the simulation experiments were conducted in simplified and controlled environments, the proposed system needs to be expanded to validate the usefulness of the agent-based system.	The simple notification of the delivery plans to the downstream SC partner substantially reduces the inventory level.	A good basis for future case studies.
Nissen (2001)	Inter-organisational SC integration and supplier–buyer relationships	Agent-based system	Not implemented in practice	Developed Petri Net-based (so-called Grafcet) intelligent agents that facilitated SC mapping and supplier–buyer collaboration.	Only the preliminary results were presented. The performance metrics of the intelligent agents were not clearly defined.	The agent-based SC integration led to SC cost savings and cycle time reduction.	Intelligent agents are superior to web-based technology for SC integration.
Ito and Mousavi Jahan Abadi (2002)	Material handling Inventory planning and control	Agent-based system	Not implemented in practice	Developed agent-based warehouse systems comprised of three sub-systems: (1) communication, (2) material handling, and (3) inventory planning and control systems to enhance warehousing efficiency.	The proposed system that contains manual components was tested only based on limited simulation experiments.	The efficient use of the automated guided vehicles improved the delivery cycles.	The agent-based system automates warehousing operations.

Kim et al. (2002a)	Order picking	Agent-based system	Applied to unknown actual warehousing operations	Considered order-picking problems with multiple order pickers in multiple storage areas. Considered both hierarchical and heterarchical frameworks.	Assumed a fixed conveyor speed.	The proposed system reduced picking errors.	The proposed system is robust when facing with unforeseen events such as machine failures.
Kim et al. (2002b)	Global sourcing	Agent-based system	Implemented by a shoe manufacturer	One of the first to develop a multi-agent-based system to automate the process of ordering and procuring goods via online.	The actual benefits of the proposed system were neither measured nor documented.	The proposed agent-based purchasing system facilitates information exchange between buyer and suppliers in global environments.	The agent-based system was incorporated into the cooperative (joint) problem-solving mechanism.
Iordanova (2003)	Air traffic control	Agent-based system	Not implemented in practice	An agent-based architecture was developed to ensure efficient flights and utilise air-space time in the wake of the increased air traffic.	The proposed system was not fully tested in a real-world setting.	The proposed system was expected to reduce cancelled and delayed flights.	The agent-based system can be embedded within the knowledge management system dealing with air traffic control and planning.
Santos et al. (2003)	Intra-organisational logistics management	Agent-based system	Never implemented in practice	Developed a multi-agent-based system that was useful for coordinating logistics planning and scheduling as well as allocating logistics resources efficiently. Combined Lagrangian relaxation heuristics with the agent-based system.	The proposed system is intended to solve relatively small intra-logistics problems. The duality gap produced by the proposed solution method was often large.	As the problem complexity increased, the proposed heuristics did not perform well.	The proposed system can be extended to solve air mission planning.

(*Continued*)

Table 5. Continued

Article/year of publication	Problem scope	Methodology	Implementation status	Key Contribution(s)	Limitation(s)	Key Findings (if any)	Comments
Shyu et al. (2003)	Minimum spanning tree	Ant colony optimisation (agent-based system)	Theory development without actual applications	Developed an ant colony optimisation technique to solve the generalised minimum spanning tree problem that is known to be NP hard.	The computational experiments with the proposed algorithm were confined to the pre-tests of the hypothetical data.	Although the proposed ant colony optimisation technique was not necessarily more accurate than GA, it solved the problem faster than GA.	The proposed ant colony optimisation technique is capable of solving large-sized problems.
Chan and Chan (2004)	SC integration and coordination	Agent-based system	The proposed system was tested with simulated hypothetical examples.	Proposed the distributed modeling philosophy within the multi-agent-based system that was designed to coordinate the manufacturing SC.	The simulated examples were confined to simple and deterministic cases. The system performance was measured mainly using the order fill rate.	With the presence of uncertainty (or high system variance), the proposed agent-based system can be degraded. The decentralised multi-agent-based system (MAS) generally outperformed the centralised MAS.	To make the proposed MAS work, trust among the SC partners must be built.
Cheung et al. (2004)	Strategic e-procurement	Agent-based system Expert system	Implemented by a small home appliance manufacturing company in Hong Kong	Combined an agent-oriented approach with a knowledge-based system to issue requests for quotations, evaluate on-line bids and automate on-line purchase orders.	The proposed system was validated only by trials and runs.	The proposed system helped to reduce the time and steps of searching and evaluating suppliers. The proposed system reduced paperwork and human errors.	The proposed system leveraged the knowledge bases of experienced purchasing professionals to automate e-procurement processes.

Nissen and Sengupta (2006)	Procurement of MRO supplies	Agent-based system	Applied to the hypothetical Intelligent Mall	Compared the performance of human to those of software agents across varying levels of ambiguity associated with the procurement process.	Experiments with the system were based on a limited number of student subjects.	An integration of the SC ontology and a specification of product knowledge improved the sophistication of agents.	The proposed intelligent software agents can improve the performance of the procurement task.
Liang and Huang (2006)	Demand forecasting	Agent-based system Rough set theory GA	Applied to the hypothetical Beer Game	Applied agent technology to simulate inventory level throughout the SC and determine optimal order quantity for every echelon of the SC. Used prior expert knowledge to make a demand better forecast.	Experiments with the system were based on a small number of MBA student subjects. Assumed that SC partners were always willing to share information among themselves.	The proposed agent-based system mitigated the bullwhip effect.	The proposed agent-based system is less costly for demand forecasting than conventional forecasting techniques such as exponential smoothing.

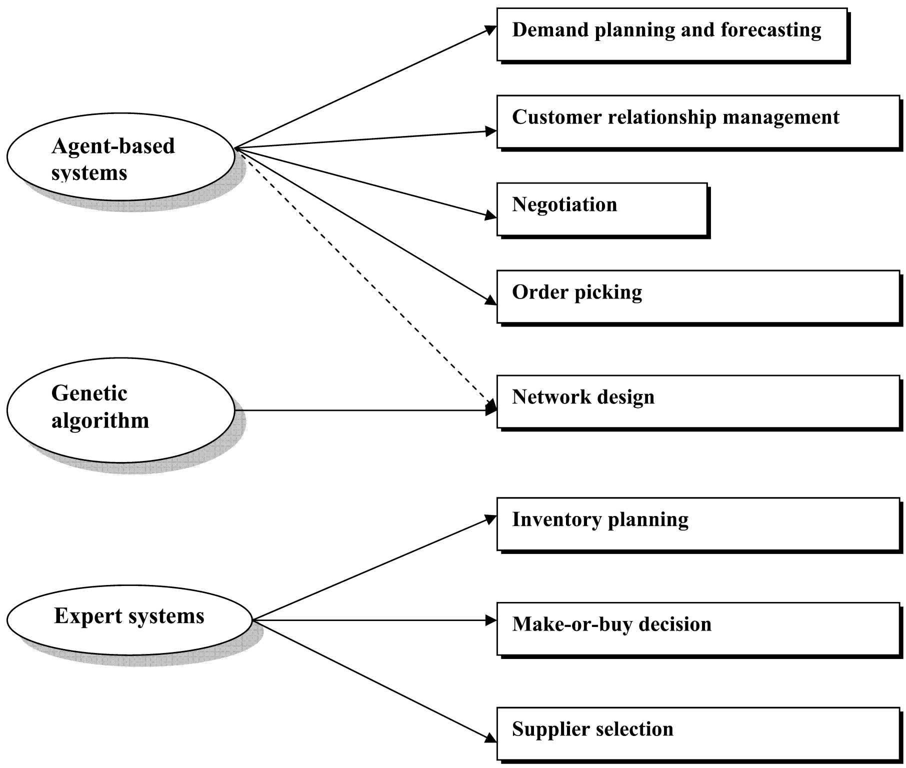

Figure 1. Link between popular AI tools and their SCM applications areas.

into knowledge management. In other words, it is increasingly important for SC partners to learn from the increased knowledge bases and automate the SC decision-making processes. Thus, AI has been put forward as a useful decision-aid tool that helps the firm connect its customers, suppliers, and SC partners by facilitating information exchange among various business entities across the SC, while replacing assets (e.g., inventory, facilities, transportation equipment) with information. Despite the presence of AI for the last half-century and its recent emergence in the SCM area, AI has not been fully exploited to solve SC problems whose solutions are either too expensive or difficult to produce due to their inherent complexity and ill-structured nature. Indeed, we have discovered a pattern that most AI applications in the SCM area remain limited to relatively well structured (well defined), tactical and operational SC problems as recapitulated in Tables 1–5. However, some recent AI studies have shown the great potential of AI tools (especially agent-based systems) for addressing a variety of soft but strategic issues involving CRM, outsourcing relationships, strategic alliances among SC partners, SC coordination, collaborative demand planning, and business-to-business negotiations that have often been overlooked by more traditional analytical models (Min and Zhou 2002). Another finding is that an agent-based system has emerged as one of the most popular AI tools for tackling various aspects of SC problems (Figure 1). One of the reasons for the paucity of AI applications in the SCM area may be the relative youth and broad spectrum of the SCM discipline. Other challenges for AI applications to SCM include:

- AI does not have free will and thus relies heavily on the computer software, which may lead to wrong decisions, if it is programmed incorrectly;
- AI solutions may not be easy to implement because they are so esoteric and difficult for ordinary decision-makers to comprehend;

- Although AI usually works best for specific, narrowly focussed SC problems, AI may not work well for handling risk and uncertainty involved in cross-functional and cross-border SC decision environments due to its knowledge acquisition bottlenecks.

Despite these challenges, as SCM continues to draw more attention from both practitioners and academicians alike and begins to mature as an academic discipline, AI will have a promising future in the SCM area. Based on projected AI research trends, we suggest the following selected line of AI research topic areas that can advance the SCM decision-making processes.

- Multiple agent-based systems that can manage complexity better can be applied to a new set of strategic SC problems such as SC integration and SC risk (disaster) management.
- Intelligent agents can be utilised for real-time pricing and reverse auctioning involving SC partners.
- Game theory can be incorporated into agent-based systems to understand SC dynamics and form strategic SC partnerships.
- Profiles of desirable SC partners, including suppliers and 3PLs providers, can be developed using knowledge discovery techniques.
- Rule-based expert systems can be developed to assist in logistics outsourcing or contract manufacturing decisions.
- Expert systems that improve airline revenue management can be developed.
- Hybrid meta-heuristics can be developed to integrate the AI traits of GAs with those of ant colony optimisation, to solve combinatorial transportation network design problems.
- The fuzzy logic approach can be integrated with the GA or ANN approaches to control total logistics costs.
- A rule-based expert system can be incorporated into the SC knowledge management framework.
- Rough set theory and/or machine learning can be further explored to address the evaluation and selection issues of foreign suppliers or 3PLs.
- AI can be integrated with existing legacy systems of various SC partners without disrupting information flows across the SC.

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