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A STUDY OF IMPARTIAL ELEMENTS OF SCM USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

An early goal of AI researchers was to create "thinking machines" that could mimic and ultimately replace human intelligence. Artificial intelligence (AI) has come a long way since the late 1970s, when it was first introduced, and now shows great potential in increasing human decision-making processes and, by extension, productivity across a wide range of business endeavors thanks to its ability to detect business patterns, comprehend business phenomena, seek information, and intelligently evaluate data. Despite its widespread use as a helpful tool for making judgment calls, artificial intelligence (AI) has not yet been widely implemented in SCM. In order to fully benefit from AI in this field, we explore the several AI subfields that are most suited to addressing practical difficulties in SCM. In this paper, we achieve precisely that by analyzing the past successes of AI in supply chain management to predict its future use.

KEYWORDS: *artificial intelligence; supply chain management; knowledge management.*

INTRODUCTION

In an era of increasing demand uncertainty, supply risk, and competitive intensity, supply chain (SC) excellence is increasingly dependent on a company's ability to integrate and orchestrate the full range of activities involved in sourcing raw materials, processing them into finished goods, and transporting those goods to customers. Many forward-thinking businesses have sought to increase their visibility across the whole service chain by supplementing existing information sources and exchanging real-time data with their SC partners. Therefore, SCM is transferring its focus from tangible assets (such stockpiles, warehouses, and transportation vehicles) to immaterial information. Since data is becoming more vital to the success of SCs, researchers have been exploring novel methods of data management and analysis. One such approach may be the use of artificial intelligence (AI), which has been available for decades but is still mostly untapped in the SCM industry. Artificial intelligence (AI) is the practice of programming a computer to solve a problem when a human solution would be too time-consuming, expensive, or impossible to implement. This includes teaching the computer to reason, recognize patterns, learn or understand specific behaviors based on past experience, memorize and apply new information, and draw various inferences. Artificial intelligence (AI) is an area of study that attempts to dissect the phenomenon of human intelligence in order to build computer systems that can mimic human behavior and produce knowledge that may be used to solve problems. Thus, it is necessary for A.I. to be receptive to new information and ideas, to learn from experience ("on-their-own"), to reason, to draw conclusions, to ascribe meaning, and to comprehend symbols in their appropriate settings. Because of these features,

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AI has been successfully applied to a wide variety of fields, including game playing, semantic modeling, human performance modeling, robotics, machine learning, data mining, neural networks, genetic algorithms (GAs), and expert systems.

Understanding complex, linked decision-making processes and developing intelligent knowledge bases required to collaborative problem-solving are only scratching the surface of AI's potential applications, but they are vital to the burgeoning management philosophy of SCM. Based on the methodical reasoning of seasoned order pickers, Eastman Kodak developed a rule-based expert system to calculate the optimal time- and labor-saving path across a warehouse. Furthermore, Min and Yu (2008) proposed an agent-based forecasting system that can predict end-customer demand via information exchange among multiple SC partners and learn from the past forecasting experience, all in an effort to synchronize a series of interrelated but distinct stages of joint demand planning and forecasting processes in the SC. These examples demonstrate the potential use of AI subfields including expert systems and agent-based systems in overseeing various components of the SC (such as storage, JDP, and IC).

ARTIFICIAL NEURAL NETWORKS

ANN theory was created when researchers saw how neurons in a real brain handled data. Artificial neural networks (ANN) are able to learn from experience, discern traits, identify patterns, categorize things, and so on, thanks to their interconnected network of computer memory. To break it down, ANNs are constructed from a network of nodes that simulate genuine neurons. They are linked together via those nodes. Each association is assigned a number score. Weighted connections serve a crucial function in long-term memory storage. The output of one neuron feeds into the input of the neuron directly next to it in the processing hierarchy of the network. Depending on the values of the weights, the strength or weakness of the information delivered over the connection may be adjusted. Through machine learning, we may ascertain the optimal distribution of linkages and the relative importance of their nodes. Artificial neural networks (ANNs) may be trained to recognize and respond to certain patterns in data, or they can be used to find hidden relationships hidden in the data. After an ANN has been started, it may be trained in a supervised or unsupervised environment, and either method can be used to increase the network's performance via inductive learning. Semantic modeling may benefit from ANN's ability to pick up the English language. The image processing method utilized by ANN might one day be used to securely drive autonomous automobiles in the logistics business. In fact, Pomerleau (1993) employed ANN to steer a land vehicle down a single lane of roadway as a human driver would. While ANN has showed promise, it is still limited to a small subset of possible driving and traffic scenarios when used to autonomous vehicle navigation. ANN has also been used to the age-old problem of optimally sizing lot sizes. Furthermore, ANN was used to create hierarchical SC planning, which estimates the optimal lot-size between successive SC processes, calculates the time/capacity needed for setups, and connects inventory and scheduling decisions at the lower level to demand and production planning decisions at the higher level (Rohde, 2004). Thus, ANN is intended to represent the interrelated and interdependent character of these processes, in contrast to traditional operational research (OR) approaches, which were established to handle lessintegrated sub-problems (e.g., inventory, production, and transportation planning) of SC planning.

THE SYNTHESIS OF AI APPLICATIONS IN SCM

Although AI has been around for quite some time, it has yet to live up to its potential as a tool for solving difficult problems and finding information in the SCM field. There have been several pioneers in the field of supply chain management who have been actively working to use AI technology. Inventory management, purchasing, site planning, freight consolidation, and routing/scheduling are just some of the SCM issues that have benefited from the increased usage of expert systems and GAs. In this section, we detail the SCM areas that have been explored for AI applications, we catalogue the AI specializations that have been beneficial for boosting SC judgements, and we assess the contribution of these specialisations to SC decision-making.

1. Inventory control and planning

Inventory is essential to delivering great customer service, despite the fact that it is expensive and sits unused until it is required. The annual cost of keeping inventory might range from 15% to 35% of the product's value. As a result, a company's success in a competitive market often hinges on its ability to maintain track of inventory at the lowest possible cost, while also ensuring that products are always readily available to customers when they are needed. This capacity might be bolstered by access to timely, accurate data on customer demand projections, inventory levels and types, and order cycle times for order fulfillment. Because they depend on information that might be difficult to analyze, forecast, and gather, the decision rules based on mathematical models like economic order quantity fail to capture the essence of inventory management. In other words, a technology like an expert system is ideal for handling inventory management and planning decisions because it can both replace the sound judgment and savvy of human inventory managers and handle the unexpected. In response, Allen (1986) developed an expert system called the Inventory Management Assistant (IMA) to assist the US Air Force Logistics Command in replenishing various types of spare aircraft components without reducing safety supplies. Reports indicate an 8-18% improvement in inventory management effectiveness after using the IMA. As illustrated above, AI approaches like expert systems provide a potential new solution to inventory management and planning challenges of vast volume and complexity by using a powerful knowledge representation language capable of capturing inventory trends throughout the whole SC at all levels of detail. The appropriate stock level at each stocking point may be predicted with greater precision by experts such as inventory managers with this sort of dynamic complexity contained in the inventory database. In order to estimate the optimal level of future orders and the optimal timing of inventory replenishments, an expert system integrated into a material requirement planning system can use databases of historical master production schedules, bills of materials, and order patterns to generate systematic lot-sizing rules.

2. Transportation network design

Transportation network design problems, due to their inherent combinatorial nature and the difficulty in finding global optimal solutions, have been a popular application of AI methodologies to a particular SC area. This class of problems includes classics like the Traveling Salesman Problem (TSP), Vehicle Routing and Scheduling Problem (VRSP), Minimum Spanning Tree (MST), Freight Consolidation (FCP), and Intermodal Connection (ICP). Connected problems in the transportation industry include the metering of freeway on-ramps, the distribution of vehicle traffic, and the allocation of parking spots. Since transportation network design problems are inherently combinatorial, GA has become a popular AI strategy for addressing them. Another AI technique that is coming into its own as a meta-heuristic is the ant colony optimisation algorithm. The Transportation Scheduling Problem, the Vehicle Routing Problem, and the Minimum Spanning Tree Problem have all benefited from this strategy. Meta-heuristics, such as ant colony optimisation algorithms and genetic algorithms, are seen as a generic algorithmic framework that can be used to solve a variety of combinatorial optimisation issues, including those arising in the design of transportation networks, with only minor adjustments, in contrast to more conventional OR methods or heuristics. Therefore, they are more flexible than traditional OR techniques and heuristics when it comes to dealing with the varying structural requirements of transportation problems. Meta-heuristics such as tabu search, simulated annealing, scatter search, and iterative local search may be just as helpful as GAs and ant colony optimisation for solving TSPs and its variants.

3. Purchasing and supply management

A make-or-buy decision is made when a business must decide whether to manufacture items or services domestically or acquire them from other sources in order to make the most efficient use of its existing resources (such as capacity and workers) and focus on its core competence. Making a make-or-buy decision may seem simple at first, but it really involves a lot of "what if" thinking.

- How much stock does the company intend to keep on hand?
- How much money is needed to develop a solution or provide a service?
- How much do gambles on new products and technology help you keep your share of the market?
- Is the suggested product towards the conclusion of its life cycle or has it reached its full sales potential?
- First of all, what does the company specialize in?
- In your opinion, what is the company's strongest suit?
- Do the people who work here have the expertise to produce goods that customers want?

The preceding cases show how important it is to have systematic decision-aid tools at hand whenever one must choose between making something and buying something. One such instrument is an expert system. For instance, Humphreys et al. (2002) created an expert system to expedite the make-or-buy choice, enhance communication between purchasing agents, and better evaluate vendor capabilities. The online ordering procedure related to the purchase of shoe materials from the global supplier base may be automated with the use of an agent-based buying system, as proposed by Kim et al. (2002b), which can also handle a greater variety of purchasing options. Cheung et al. (2004) developed a hybrid agent- and knowledge-based system to evaluate the accuracy of online bids and the speed with which successful vendors fulfill orders. Nissen and Sengupta (2006), who conducted recent research in this area, suggest using intelligent software agents to speed up processes like browsing online catalogs for possible suppliers, evaluating those vendors based on a variety of criteria, screening potential partners, and completing a purchase order. Agent-based buying systems were discovered to be capable of taking over for humans in making purchasing decisions and clearing up any confusion around requirements specifications. Agent-based systems may help the buying manager make a wide range of strategic and tactical choices, but traditional OR methods like analytic hierarchy process and multiple attribute theory can only handle a single component of purchasing decisions (such as supplier selection).

4. Demand planning and forecasting

The company's capacity planning, personnel scheduling, inventory management, product development, and marketing efforts all depend on forecasts of future demand. However, its efficacy is frequently dependent on how well it predicts future demand, which in turn relies on the company's ability to mitigate the inherent uncertainty and fluctuation in that forecast. Creating reliable forecasting methods, or choosing a method that is best suited to a given business environment, has proven to be a formidable challenge in light of the uncertainty and variability inherent in predicting future demand. Some methods of forecasting are more suited to making long-term projections, while others are better suited to making short-term ones. Traditional methods of forecasting, such as the exponential smoothing, moving average, time series, and Box-Jenkins approaches, all share the assumption that demand in the future would be similar to demand in the past. Under such a premise, these conventional methods of making predictions have placed a premium on the veracity and precision of past information. While historical data is essential for projecting demand for established goods and services, it is unavailable for projecting demand for ground-breaking innovations that have yet to enter the market. Artificial intelligence (AI) approaches have lately been developed as feasible options for demand forecasting and planning, allowing them to overcome this shortcoming of conventional forecasting methods.

CUSTOMER RELATIONSHIP MANAGEMENT

In order to keep its clientele satisfied, the company must win their faith in its production and service capacities and convince them that it can provide precisely what they need. Instilling such confidence requires ongoing communication and the development of a lasting connection with the consumer base. As a result, SC efforts are driven by demand development, making CRM a necessary precursor. Customer relationship management, or CRM, is an approach to doing business that emphasizes maintaining a positive, long-term partnership with a core group of clients chosen for their financial stability, lifetime worth to the company, and propensity to recommend the company to others. CRM's influence on a company's bottom line is significant enough to warrant an analysis of the costs and benefits of keeping it running. An agent-based model was presented by Baxter et al. (2003) to represent the interaction between customers and the businesses that serve them. Incorporating the potent impact of word-of-mouth reputation on the acquisition of goods and services, their agent-based model took into account the sharing of consumer experiences amongst members of a social network. This helped the company gauge the success of its CRM initiatives and fine-tune its strategies for attracting new customers.

CONCLUSION

Supply chain management (SCM) has evolved into knowledge management as a result of the growing need of comprehending complex, interrelated decision-making processes and building intelligent information bases. In other words, it is becoming more important for SC partners to deploy fully automated SC decision-making procedures and get insight from enlarged data sets. As a result, AI has been proposed as a useful decision-aid tool that helps the firm connect with its customers, suppliers, and SC partners by facilitating information exchange among various business entities across the SC and replacing physical assets (such as inventory, facilities, and transportation equipment) with data. AI has been around for more than half a century, but it is only now beginning to make an impact in the supply chain management (SCM) industry. Despite this, it has not been effectively used to address SC issues, for which solutions are either prohibitively expensive or impossible to generate due to their inherent complexity and ill-structured nature. Despite these challenges, AI has a promising future in the SCM domain as the field of SCM continues to attract greater attention from practitioners and researchers alike. On the basis of projected AI research tendencies, we suggest the following collection of study topic areas that may improve SCM decision-making processes.

REFERENCES

Allen, M.K., 1986. The development of an artificial intelligence system for inventory management using multiple experts. Unpublished PhD dissertation. Columbus, Ohio: The Ohio State University.

Allen, M.K. and Helferich, O.K., 1990. Putting expert systems to work in logistics. Oak Brook, IL: Council of Logistics Management.

Amer, Y., et al., 2008. Optimizing order fulfillment using design for six sigma and fuzzy logic. International Journal of Management Science and Engineering Management, 3 (2), 83–99.

Antony, J., et al., 2006. Design of synchronized supply chain: a genetic algorithm based six sigma constrained approach. International Journal of Systems and Management, 2 (2), 120–141.

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Awad, E.M., 1996. Building expert systems: principles, procedures, and applications. St. Paul, MN: West Publishing Company. Baily, P., et al., 2005. Purchasing principles and management. 9th ed. Essex, England: Pearson Education Limited.

Balamurugan, K., Selladurai, V., and Ilamathi, B., 2006. Solving unequal area facility layout problems using genetic algorithm. International Journal of Logistics Systems and Management, 2 (3), 281–301.

Balan, S., Vrat, P., and Kumar, P., 2007. Reducing the Bullwhip effect in a supply chain with fuzzy logic approach. International Journal of Integrated Supply Management, 3 (3), 261–282.

Baxter, N., Collings, D., and Adjali, I., 2003. Agent-based modeling – intelligent customer relationship management. BT Technology Journal, 21 (2), 126–132.

Bielli, M., Caramia, M., and Carotenuto, P., 2002. Genetic algorithms in bus network optimization. Transportation Research Part C, 10, 19–34.

Bortfeldt, A. and Gehring, H., 2001. A hybrid genetic algorithm for the container loading problem. European Journal of Operational Research, 131, 143–161.