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Review article

A review of soft computing applications in supply chain management

Mark Ko *, Ashutosh Tiwari, Jörn Mehnen

Manufacturing Department, School of Applied Sciences, Cranfield University, Cranfield, MK43 0AL, UK

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ABSTRACT

It is broadly recognised by global companies that supply chain management is one of the major core competencies for an organisation to compete in the marketplace. Organisational strategies are mainly concentrated on improvement of customer service levels as well as reduction of operational costs in order to maintain profit margins. Therefore supply chain performance has attracted researchers' attention. A variety of soft computing techniques including fuzzy logic and genetic algorithms have been employed to improve effectiveness and efficiency in various aspects of supply chain management. Meanwhile, an increasing number of papers have been published to address related issues. The aim of this paper is to summarise the findings by a systematic review of existing research papers concerning the application of soft computing techniques to supply chain management. Some areas in supply chain management that have rarely been exposed in existing papers, such as customer relationship management and reverse logistics, are therefore suggested for future research.

Contents

* Corresponding author. Tel.: +44 7835 068395; fax: +44 1234 754605.
E-mail addresses: m.ko@cranfield.ac.uk (M. Ko), a.tiwari@cranfield.ac.uk (A. Tiwari), j.mehnen@cranfield.ac.uk (J. Mehnen).

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1. Introduction

Different techniques have been employed to solve problems occurring in various dynamic segments of supply chain. As more soft computing applications are introduced and used, a growing body of papers has been established that can guide the future design and deployment of supply chain solutions. This research aims at reviewing the common soft computing techniques applied to supply chain management, exploring the current research trends and identifying opportunities for further research.

The main issues to address include: what are the main problems within supply chain that have been investigated using soft computing techniques? What techniques have been employed? What are the main findings and achievements up to date? What are the major obstacles that have ever been encountered and how might they be overcome?

This paper is organised in five sections. Subsequent to the introduction in Section 1, the soft computing and supply chain management techniques are briefed in Sections 2 and 3. Section 4 describes the research methodology used in this paper. Section 5 examines the existing research of applying soft computing techniques to a variety of fields in supply chain management. Then the key findings are concluded. Finally, a summary of existing studies and a discussion on the future research directions are provided.

2. Soft computing

Soft computing is a group of unique methodologies, contributed mainly by Expert System (ES), Fuzzy Logic (FL), Neural Networks (NN), and Evolutionary Algorithms (EA), which provide flexible information processing capabilities to solve real-life problems. The advantages of employing soft computing is its capability to tolerate imprecision, uncertainty, and partial truth to achieve tractability and robustness on simulating human decision-making behaviour with low cost [1]. In other words, soft computing provides the opportunity to represent ambiguity in human thinking with the uncertainty in real life [2]. The major soft computing techniques are briefed as following.

2.1. Fuzzy logic

Fuzzy set theory was initiated by Lotfi Zadeh in 1965. In the 1970s a complete theory of evidence dealing with information from multiple sources was produced by Glenn Shafer [3]. It provides a mathematical framework to treat and represent uncertainty in the perception of vagueness, imprecision, partial truth, and lack of information [4].

As the basic theory of soft computing, fuzzy logic supplies mathematical power for the emulation of the thought and perception processes [5]. Fuzzy systems are very useful not only in situations involving highly complex systems but also in situations where an approximate solution is warranted [3]. To deal with qualitative, inexact, uncertain and complicated processes, the fuzzy logic system can be well-adopted since it exhibits a human-like thinking process [6].

Fuzzy logic is a mathematical formal multi-valued logic concept which uses fuzzy set theory. Its goal is to formalize the mechanisms of approximate reasoning. Fuzzy logic has widely been applied in various areas. Fuzzy control is one prominent example. In fuzzy control, data is characterised by linguistic variables and expert knowledge (IF-Then-rules) using these variables is mapped into rule bases. In fuzzy control these bases can be used for logical inferences for controlling purposes [7]. One of the reasons for the success of fuzzy logic is that the linguistic variables, values and rules enable the engineer to translate human knowledge into computer evaluable representations seamlessly [4]. Fuzzy rule bases – if sufficiently small – can be interpreted by an engineer. This is different to neural networks (see next section), which are essentially black boxes. The treatment of data from a linguistic viewpoint is a major consideration in fuzzy set theory.

Fuzzy logic is one of the techniques of soft computing which can deal with impreciseness of input data and domain knowledge and giving quick, simple and often sufficiently good approximations of the desired solutions. Fuzzy logic is different from probability theory because fuzzy logic is deterministic rather than probabilistic. Imprecision is modeled via fuzzy sets, linguistic variables, membership functions, inferences and defuzzification. These concepts are all handled in an entirely deterministic manner. There exist various forms of formal fuzzy logic, fuzzy set theory and fuzzy control systems. For example, uncertainty in the membership functions in fuzzy set theory, i.e. uncertainty about the actual value of a membership function, has been addressed by type-2 fuzzy sets [8]. Fuzzy logic operators (such as fuzzy ‘and’, ‘or’, ‘not’ operators) and defuzzification (i.e. the transformation of a fuzzy set into a crisp value), can be modeled in various ways and are still widely discussed. A prominent example how fast growing and complex the field of fuzzy logic has become can be seen from the t-norm, which is a non-classics logic operator used for fuzzy conjunctions interpretation. There exists a plethora of t-norm fuzzy logics which are discussed e.g. by Esteva et al. [9].

From the area of data modelling, fuzzy sets have not only been extended to data summarisation by developing more abstract concepts and fuzzy gradual rules, but also been applied to pattern recognition, e.g. fuzzy clustering algorithms [10]. In addition, a fuzzy multi-criteria decision-making algorithm has been developed for the network reconfiguration problem. It has been implemented in a proof-of-concept tool and applied to multi-criteria problems successfully [11].

2.2. Neural network

A neural network is a parallel distributed information processing structure consisting of a number of nonlinear processing units called neurons. The neuron operates as a mathematical processor performing specific mathematical operations on its inputs to generate an output [12]. It can be trained to recognise patterns and to identify incomplete patterns by duplicating the human-brain processes of recognising information, burying noise literally and retrieving information correctly [13].

In terms of modelling, remarkable progress has been made in the last few decades to improve artificial neural networks (ANN). Artificial neural networks are strongly interconnected systems of so called neurons which have simple behaviour, but when connected they can solve complex problems. Changes may be made further to enhance its performance [13].

Neural networks and fuzzy systems, usually regarded as elements of artificial intelligence, have their shortcomings. Some of these shortcomings may be overcome if fuzzy logic operations are incorporated into neural networks and neural networks are classified into fuzzy systems [13]. In fact, several authors have already combined fuzzy logic with neural network as neural-fuzzy systems [14]. It may be a new class of computing systems provided by the integration of all these evolving disciplines for the emulation of higher-order cognitive power [5]. They have been applied in various products in a number of fields.

2.3. Genetic algorithms

Evolutionary algorithms (EA) were invented to mimic some of the processes observed in natural evolution. Evolution occurs on chromosomes – organic devices for encoding the structure of living beings. Processes of natural selection then drive those chromosomes that encode successful structures to reproduce more frequent than those that encode failed structures. In other word, the chromosomes with the best evaluations tend to reproduce more often than those with bad evaluations. By using simple encodings and reproduction mechanisms, the algorithms can then display complicated behaviour and turn out to solve some extremely difficult problems [15].

Genetic algorithms (GA) are a special subclass of a wider set of EA techniques. In the following they are especially highlighted due to their common appearance. GA were named and introduced by John Holland in the mid-1960s. Then Lawrence Fogel began to work on evolutionary programming and Ingo Rechenberg and Hans-Paul Schwefel introduced the evolution strategy. In resolving difficult problems where little is known, their pioneered work stimulated the development of a broad class of optimisation methods [4]. Subsequently the genetic algorithms were studied by De Jong and Goldberg. Others such as Davis, Eshelman, Forrest, Grefenstette, Koza, Mitchell, Riolo, and Schaffer, to name only a few, GA had been most frequently applied to the domain of optimisation [16].

Based on the principles of natural evolution, genetic algorithms are robust and adaptive methods to solve search and optimisation problems [17]. Because of the robustness of genetic algorithms, a vast interest had been attracted among the researchers all over the world [18]. In addition, by simulating some features of biological evolution, genetic algorithms can solve problems where traditional search and optimisation methods are less effective. Therefore, genetic algorithms have been demonstrated to be promising techniques which have been applied to a broad range of application areas [5]. The ability to apply genetic algorithms to real-world problems has improved significantly over the past decade [15]. The applications will be introduced further in later sections.

3. Supply chain management

Christopher [19] defined supply chain management as the management of upstream and downstream relationships with suppliers and customers to deliver superior customer value at less cost to the supply chain as a whole. Harrison and Hoek [20] described the supply chain management as a plan and control all of the processes that link partners in a supply chain together in order to meet end-customers' requirements.

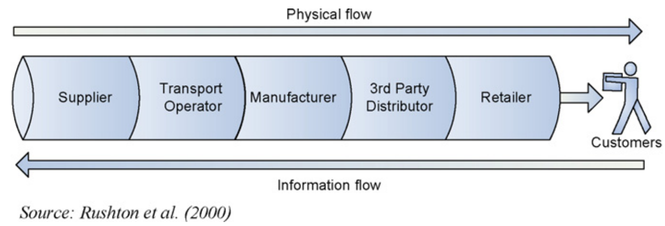

Fig. 1. The concept of the supply chain.*Source*: Rushton et al. [21].

As the sub-process of supply chain management, logistics deals with planning, handling, and control of the storage of goods between manufacturer and consumer [17]. Rushton et al. [21] described another well-known definition of logistics as the strategic management of movement, storage, and information relating to materials, parts, and finished products in supply chains, through the stages of procurement, work-in-progress and final distribution.

As demonstrated in Fig. 1, the concept of supply chain refers to the idea of developing a logistics pipeline approach for finished goods to transfer through the supply chain [21]. The supply chain highlights the close partnership from upstream supplier, transport operator, manufacturer, to the downstream 3rd party distributor and retailer. Its objective is to produce and distribute the commodity in the right quantity, to the right place, and at the right time to minimise overall cost while maintaining customer satisfaction.

The challenges encountered in the logistics processes and supply chain network will be discussed in later sections.

4. Methodology

The research methodology involves reviewing papers for soft computing techniques applied to the related processes in supply chain management.

4.1. Sources and search methods

The databases that had been searched in this study include ScienceDirect, Emerald, ProQuest, Inspec, and Comrendex. The reviewed papers were sorted out from more than 40 journals such as European Journal of Operational Research, International Journal of Production Economics, Computers & Industrial Engineering, Expert Systems with Applications, Computers & Operations Research, Fuzzy Sets and Systems, Decision Support Systems, Applied Soft Computing and Applied Mathematics and Computation.

Initially, two groups of keywords were used to cross-search related papers in specific databases. The first group of key words includes soft computing, artificial intelligence, neural network, fuzzy logic, evolutionary computation, and genetic algorithm while the second group includes supply chain, transportation, logistics, forecasting, and inventory. Given the specific interest in how soft computing techniques have been applied to supply chain management, the empirical and diverse studies published from 1990 to 2008 were selected for further analysis. Additionally, the reference sections of these papers were reviewed to locate additional studies of interest.

As a result, the final references consist of 163 papers published in referred journals.

4.2. Scope

The concept of supply chain management has been analysed by many researchers from various perspectives. However, it is beyond

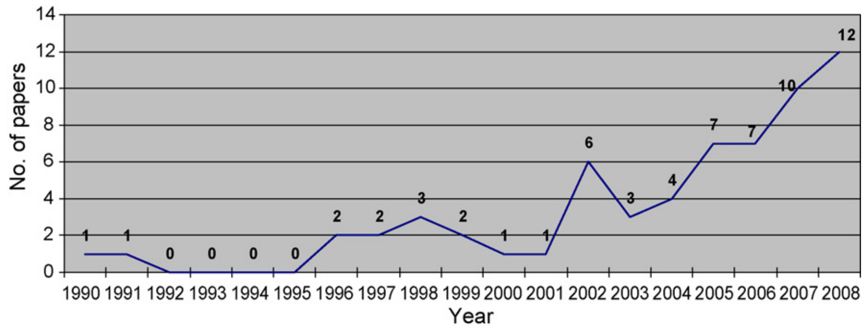

Fig. 2. Number of papers in manufacturing flow management.

the scope of this paper to address all problems in details. In an attempt to provide a more intensive review of existing papers in this area, this paper mainly focuses on management-related issues. The studies with non-management-related subjects will not be discussed in this paper, such as robotics and automation, traffic flow prediction, public transportation policy, traffic congestion/control, traffic flow and its pattern analysis.

The soft computing techniques and their applications have been developed vastly in recent years. The techniques introduced in Section 2 are the major focus in this research.

4.3. Framework

The framework applied in this research is defined and developed by the Global Supply Chain Forum (GSCF) [22–24] sponsored by the Council of Logistics Management (since 2005 it is called the Council of Supply Chain Management Professionals). The following eight processes of supply chain management have been categorized by the GSCF:

- Manufacturing flow management
- Order fulfilment
- Demand management
- Supplier relationship management
- Product development and commercialisation
- Returns management
- Customer service management
- Customer relationship management

The sub-processes of the GSCF framework are illustrated in Appendix 1. All reviewed papers are classified into the categories introduced above.

Review articles on similar subjects have been published previously [25,26]. However, both papers mainly concentrated on transportation issues instead of the whole supply chain domain.

5. The target subject processes

To refer to the eight processes of supply chain management categorized by the GSCF, the review of existing papers is classified into the following sections.

5.1. Manufacturing flow management

The challenge to improve manufacturing performance has drawn the attention of researchers to employ diverse soft computing techniques. This becomes evident from the over 60 papers in manufacturing field which are included in this review.

As shown in Fig. 2, the initial paper with respect to application of soft computing in manufacturing flow management was accepted in 1990. There were only a few works in this area before 2001. Nevertheless, it demonstrates a steady rise in the number of papers since 2003 and reaches a peak in 2008. The evidence seems to be strong that more studies can be anticipated in the near future.

The researchers' interest can be identified through the allocation of these papers in sub-processes, as demonstrated in Fig. 3. Materials planning has drawn researchers' major attention. Particularly, there are 39 pieces of work focusing on materials planning, which make up 62.9% of all papers within the manufacturing flow management field.

5.1.1. Materials planning/inventory management

Expert systems have been used by early studies for dealing with inventory control and planning [27–31]. Then Fuzzy logic and neural network were applied to industry and had been discussed by Du and Wolfe [6]. A fuzzy model was developed by Li et al. [32] to address single-period inventory problem.

Recently the typical inventory problems such as the order-quantity and reorder-point problem or the two storage inventory problem, have been solved by the development of multi-objective inventory model [33–38]. The economic lot-size scheduling problems were solved by a GA-based heuristic approach as well [39,40]. There were also a few studies concentrated on fuzzy order and production quantity with or without backorder problems [41–48].

An early research of multi-criteria inventory classification was presented by Guvenir and Erel [49]. Later the multi-item inventory model was formulated to solve the multi-buyer joint replenishment problem [50,51], the cost-saving problem for deteriorating items [52], and the supplier selection problem [53]. Kochel and Nielander [54] showed that simulation-based optimisation can be applied to multi-location inventory systems successfully. Chang et al. [55] derived a GA-based model for the joint optimisation for the multi-buyer and single-supplier problem. A fuzzy decision-making model was developed to analyse the trade-off effect between customer service level and inventory cost [56] and to solve inventory problems with fuzzy random variables [57]. Based

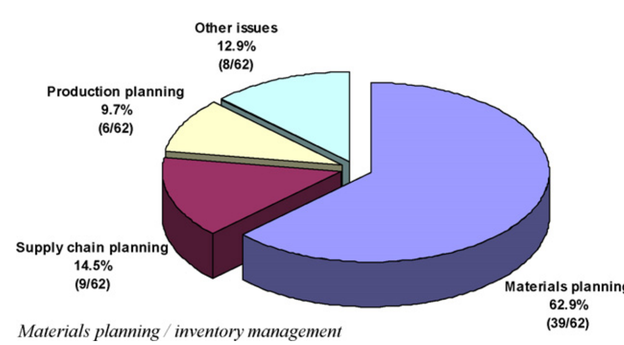

Fig. 3. Distribution of papers in sub-processes of manufacturing flow management.

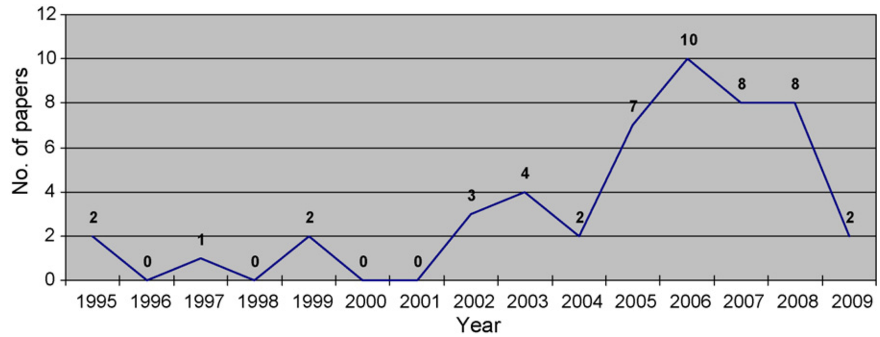

Fig. 4. Number of papers in order fulfilment.

on an enhanced fuzzy neural network, Li and Kuo [58] developed a decision support system to manage automobile spares inventory. Furthermore, Wu and Hsu [59] proposed a GA-neural network approach to reduce spare parts logistics costs.

Other inventory-related issues approached by researchers include vendor managed inventory problems [60,61], ABC classification of stock keeping units [62], optimisation of transportation cost as well as inventory cost [63], shelf space allocation problems [64], determination of base-stock levels in a serial supply chain [65].

5.1.2. Supply chain planning

Supply chain planning is focused on synchronizing and optimising multiple activities involved in the enterprise from procurement of raw materials to the delivery of finished products to end customers [66].

Genetic algorithms and artificial neural networks have been applied to derive optimal solutions for collaborative supply chain planning [67–70]. Moon et al. [71,72] integrated process planning and scheduling model for resource allocation in multi-plant supply chain and Huin et al. [73] presented a knowledge-based model for resource planning. Subsequently Huang et al. [74] designed a supply chain model to integrate production and supply sourcing decisions. Also, Roghanian et al. [66] applied fuzzy programming technique to solve multi-objective programming problem in supply chain planning.

5.1.3. Production planning

Genetic algorithms have been applied to solve production planning problems. The general capacitated lot-sizing problem was studied by Xie and Dong [75] initially. Ossipov [76] then proposed a heuristic algorithm to optimise the sequence of customer orders in production line. Moreover, Kampf and Kochel [77] focused on simulation-based sequencing and lot size optimisation while Bjork and Carlsson [78] analysed the effect of flexible lead times by developing a combined production and inventory model. In addition, lot scheduling [79] and batch manufacturing problems [80] were addressed.

5.1.4. Other issues

Other issues that have been addressed in the area of manufacturing flow management include improvement of procurement decision quality [81], load planning for a maritime container ship [82], resource management for allocation of containers [83], internet-enabled global manufacturing management [84], truckload scheduling in an automatic storage and retrieval warehouse [85], forward-backward analysis of dynamic supply chain enabled by Radio Frequency Identification (RFID) [86], maximum warehouse space requirement [87], and evaluation of ERP performance [88].

5.2. Order fulfilment

Order fulfilment is one of the key measures to reflect customer service performance. A "perfect order" implies the completion of an order that entirely satisfies customer requirements. The key components to grade actual order fulfilment are whether orders were delivered on time, in full, damage free, with accurate and complete documentation [21]. How to fulfil these requirements has become a major challenge of supply chain management.

Within the growing papers in supply chain domain, genetic algorithms have been applied to some challenging tasks successfully, such as logistics network design, vehicle routing, and vehicle scheduling problems. In addition to that, there are other interesting works that develop genetic algorithm approaches for customer allocation and shipping alternatives selection.

As illustrated in Fig. 4, the number of papers regarding order fulfilment increased slowly, with some fluctuations, between 1995 and 2003. However, a dramatic growth can be observed from 2004 to 2008.

Within the 49 papers regarding order fulfilment in supply chain management, a half of the researchers concentrated on logistics network design and planning problems while the others focused on vehicle routing and assignment and other issues, as revealed in Fig. 5.

5.2.1. Logistics network design/planning

The network design problems have been recognised as one of the most comprehensive strategic decisions that need to be focused to develop a long-term optimal supply chain [89,90].

Genetic algorithms have been employed to solve dynamic logistics network design and planning problems, such as multi-stage logistic network design and optimisation [89,91–96], freight transportation planning [97,98], multi-time period production and distribution planning [99,100], logistic process optimisation

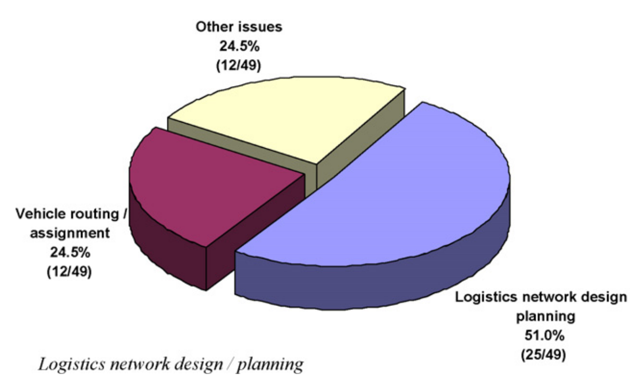

Fig. 5. Distribution of papers in sub-processes of order fulfilment.

[17,101,102], and vehicle transhipment planning in seaport terminal [103]. Other researchers concentrated on truckload assignment [104], container shipping and repositioning [105], concrete distribution [106], and third party logistics (3PLs) services integration [107,108]. The promising results from these applications indicate that evolutionary algorithms are suitable to work in a complicated and uncertain environment.

Teodorovic [109] proved that fuzzy logic could be a very promising mathematical approach to solve complex traffic and transportation problems. Sheu [110–112] firstly presented a hybrid fuzzy-based methodology to identify global logistics strategies then achieved a remarkable cost saving and customer service enhancement by allocating logistics resources dynamically.

5.2.2. Vehicle routing/assignment

Dynamic vehicle routing and scheduling problems have drawn logistics managers and researchers' attention since 1990. It could be a key parameter for companies to develop competitive advantages in order to differentiate themselves from other competitors.

In order to pick up and deliver within specific time window, Slater [113] used expert system and artificial intelligence to predict e-commerce customer orders. Also, Pankratz [114] justified that a GA-based approach is able to find quality solution to meet the increasing demands on flexible and prompt transportation services.

In addition, Arslan and Khisty [115,116] proved that fuzzy logic could be a promising approach to model driver's psychology and behaviour in route choice. Ganesh and Narendran [117] produced an encouraging result on vehicle routing problem with pick-up and delivery sequence constraints while Ho et al. [118] proposed a hybrid genetic algorithm to solve similar problem with multiple depots. Furthermore, Hu and Sheu [119] explored the potential advantage of fuzzy clustering techniques in classifying pre-trip customers by their demand attributes for further vehicle dispatching and routing operations. Lin et al. [120] proved that the proposed coordinated distribution mechanism is feasible to solve distribution scheduling problems.

Torabi et al. [121] found that a hybrid genetic algorithm is more promising in minimising transportation cost in a simple supply chain. A survey of different heuristic shortest path algorithms for demand-responsive transportation applications was presented by Fu et al. [122].

In terms of vehicle assignment, Vukadinovic et al. [123] concluded that neural networks can refine the fuzzy system to achieve better performance. In addition, Potvin et al. [124] reported an experimental result with data provided by a courier service company and proved that the neural network outperform the linear programming model in vehicle dispatching.

5.2.3. Other issues

To ensure an effective logistics decision-making process, Toivonen et al. [125] analysed both qualitative and quantitative information from customers. Schneeweiss [126] indicated possible synergies between various sciences, such as applied mathematics and artificial intelligence, to solve distributed decision-making problems. Additionally, Zhou et al. [127,128] found an optimal solution, by considering total transit time and shipping cost simultaneously, to allocate customers to available warehouses or distribution centres. Then Yang et al. [129] developed a GA-based model to select distribution centre location while total relevant cost is minimised.

With respect to measurement of supply chain performance, Chan et al. [50,51] provided a simple mathematical model to calculate performance index. Lin et al. [130] developed a fuzzy agility index to identify supply chain weaknesses and to devise further improvement plan. Subsequently, Jain et al. [131] proposed a practical method for decision makers to evaluate agility in supply chains.

Dullaert et al. [132] suggested an evolutionary algorithm to determine the optimal combination of shipping alternatives to minimise total logistics costs. Celik [133] concluded that artificial neural networks are a very promising tool to predict the short-term inter-regional freight distribution.

Interestingly the majority of these papers address mainly the ground transportation issues. Only a few studies focus on maritime and aviation industries. This may be due to confidentiality reasons [25,26].

5.3. Demand management

Demand management plays a critical role within supply chain management. A reliable demand forecast can improve the quality of organisational strategy [134]. The domain of demand management has been a major interest in soft computing since 1990s. Subsequently, considerable research has been performed on the subject of sales and demand forecasting.

As shown in Fig. 6, the applications in demand management fluctuated before 2004, yet an obvious growth has started since 2005. On this basis it may infer the possibility of more work to be published in this field in 2009 and after.

Regarding the papers in respective sub-processes of demand management, sales forecasting has attracted most researchers' attention with 80% of total work, as shown in Fig. 7.

5.3.1. Sales forecasting

As an integral part of almost all business enterprises, forecasting is the process of predicting the future [135]. Manufacturing firms forecast future demand to prepare necessary manpower and raw materials for production. Service companies forecast customer arrival patterns to maintain appropriate staffing to serve customer demands. Therefore, forecasting is one of the major strategic activities in organisational decision-making processes for demand management.

In fact, there is no perfect solution available to solve these problems due to the uncertainty and difficulty to predict market

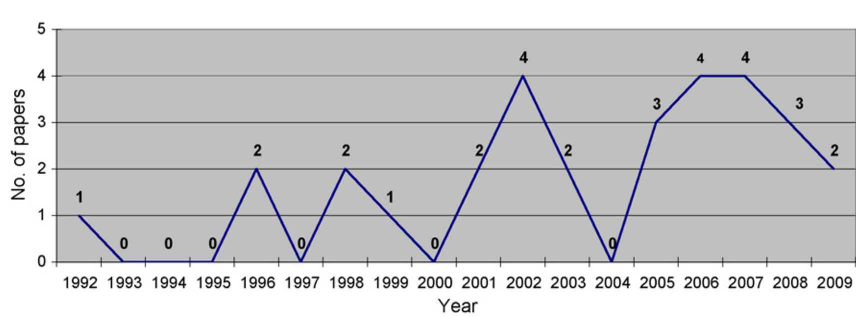

Fig. 6. Number of papers in demand management.

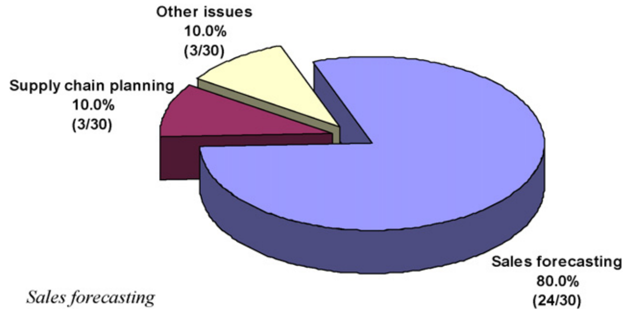

Fig. 7. Distribution of papers in sub-processes of demand management.

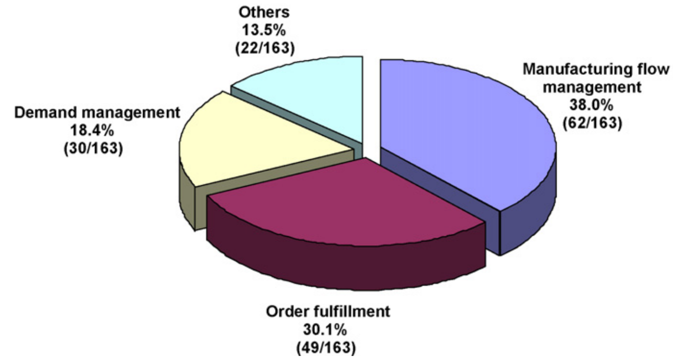

Fig. 8. Proportion of papers in major subject processes.

demand. However, a reliable sales forecasting can enhance the overall performance of an organisation effectively. On the contrary, the inaccuracy of forecasting typically results in considerable disturbance in production planning.

Artificial neural networks have been recognised as a valuable tool for forecasting. The major advantages to employ artificial neural networks in forecasting include its self-adaptive capability to learn from experience as well as to generalise results from sample data with noise. In addition, to compare with conventional statistical methods, artificial neural networks can model continuous functions to any desired accuracy [136]. Furthermore, as opposed to the traditional linear and nonlinear time series models, artificial neural networks are nonlinear data-driven approaches with more flexibility and effectiveness in modelling for forecasting [137].

For instance, the artificial neural network has been applied to sales forecasting since 1998 [134,138–141]. Similar approach had been used to sales forecasting in other industries as well, such as printed circuit board industry [142–146], textile and apparel industry [147–150], aggregate retail industry [151,152], food products [153], and glass products [154].

Besides, Wall et al. [155] presented a prototype supply planning system to enhance short-term demand forecast. Ansuj et al. [156] and Luxhoj et al. [157] presented a neural network-based model to achieve more accurate sales forecasting results. In addition, Kimbrough et al. [158] and Strozzi et al. [159] analysed the famous beer game for order policy optimisation. Liang and Huang [160] developed a multi-agent system for agents in supply chain to share information and minimise total cost.

5.3.2. Bullwhip effect

The bullwhip effect is one of the most popular research problems in supply chain management. It describes the distortion on demand forecasting throughout supply chain partners. Soft computing techniques proved to be effective to reduce bullwhip effect in supply chains [161–163].

5.3.3. Other issues

In addition to the above work, Marx-Gomez et al. [164] employed neural-fuzzy approach to forecast returns of scrapped products. Aburto and Weber [165] improved the forecasting accuracy of a replenishment system proposed to a supermarket. Lee and Ou-Yang [166] developed a neural network-based model to forecast supplier's bid price in order to shorten the lead time in supplier selection.

5.4. Supplier relationship management

Several papers used fuzzy logic approach to monitor and measure suppliers' performance based on different criteria [167,168]. For example, Lau et al. [169] analysed suppliers' product

Table 1
Annual distribution of number of papers in respective subject processes.

	Manufacturing flow management	Order fulfilment	Demand management	Supplier relationship management	Product development and commercialisation	Returns management	Customer service management	Total
1990	1							1
1991	1							1
1992			1					1
1993								0
1994								0
1995		2						2
1996	2		2					4
1997	2	1						3
1998	3		2					5
1999	2	2	1					5
2000	1							1
2001	1		2					3
2002	6	3	4	2				15
2003	3	4	2	2				11
2004	4	2		1				7
2005	7	7	3		2			19
2006	7	10	4	2	1	2	1	27
2007	10	8	4	2	1	1		26
2008	12	8	3	4	0	1		28
2009		2	2					4
Total	62	49	30	13	4	4	1	163

Table 2
Annual summary of papers in respective subject processes.

	Manufacturing flow management	Order fulfilment	Demand management	Supplier relationship management	Product development and commercialisation	Returns management	Customer service management
1990	Ehrenberg						
1991	Turksen and Berg						
1992			Wall et al.				
1993							
1994							
1995		Potvin et al., Dougherty					
1996	Prasad et al., Yao and Lee		Ansuj et al., Luxhoj et al.				
1997	Anagun, Du and Wolfe	Dougherty,					
1998	Lee and Yao, Chang et al., Guvenir and Erel		Kuo and Xue [138,139]				
1999	Mak et al., Lee and Yao	Teodorovic, Vukadinovic et al.	Kuo and Xue				
2000	Yao et al.						
2001	Samanta and Al-Araimi		Kuo, Alon et al.				
2002	Li et al., Partovi and Anandarajan, Yokoyama, Moon et al., Xie and Dong, Ulieru et al.	Syarif et al., Slater, Zhou et al.	Kuo et al., Jeong et al., Kimbrough et al., Marx-Gomez et al.	Lau et al., Choy et al.			
2003	Mondal and Maiti, Chan et al., Huin et al.	Hu and Sheu, Schneeweiss, Zhou et al., Chan et al.	Frank et al., Chu and Zhang	Shore and Venkatachalam, Choy et al.			
2004	Chiu and Lin, Smirnov et al., Berning et al., Lau et al.	Sheu, Celik		Deshpande et al.			
2005	Kochel and Nielander, Wang and Shu, Hwang et al., Han and Damrongwongsiri, Huang et al., Ossipov, Lau et al.	Ma and Davidrajuh, Gen and Syarif, Silva et al., Fischer and Gehring, Pankratz, Arslan and Khisty, Dullaert et al.	Chang et al., Thomassey et al. [148,149]		Tong and Liang, Suarez		
2006	Maiti, M.K. and Maiti, M., Maiti, A.K. et al. [35,36], Chang et al. [39], Daniel and Rajendran, Kampf and Kochel, Imai et al.	Altiparmak et al., Xu et al., Caputo et al., Ko et al., Sheu, Arslan and Khisty, Torabi et al., Fu et al., Toivonen et al., Lin et al.	Chang and Wang, Chang et al. [143], Doganis et al., Liang and Huang	Gunasekaran et al., Chiadamrong and Prasertwattana	Tsai	Min et al. [184,185]	Bottani and Rizzi
2007	Maiti, M.K. and Maiti, M., Pourakbar et al., Wang et al., Nachiappan and Jawahar, Chi et al., Roghanian et al., Bjork and Carlsson, Chatfield, Li et al., Oliveira	Jo et al., Aliev et al., Silva et al., Shintani et al., Naso et al., Ko and Evans, Ganesh and Narendran, Yang et al.	Chang et al., Thomassey and Happiette, Strozzi et al., Aburto and Weber	Chan and Kumar, Isiklar et al.	Wang and Shu	Liechens and Vandaele	
2008	Maiti, Dey et al., Roy et al., Rezaei and Davoodi, Chang et al. [55], Xu and Liu, Li and Kuo, Wu and Hsu, Moon et al., Kim et al., Yao and Chu, Chang et al. [88]	Farahani and Elahipanah, Xu et al. [95,96], Silva et al., Sheu, Ho et al., Lin et al., Jain et al.	Chang et al. [145], Carbonneau et al., Zarandi et al.	Moghadam et al., Wang et al., Efendigil et al., Buyukozkan et al.		Min and Ko	
2009		Altiparmak et al., Jawahar and Balaji	Balan et al., Lee and Ou-Yang.				

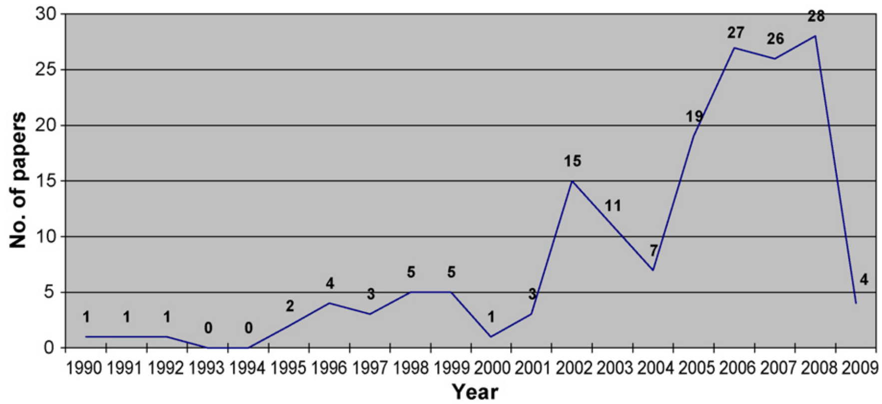

Fig. 9. Number of papers in supply chain management using soft computing.

quality and delivery time while Shore and Venkatachalam [170] focused on the information sharing capability of potential partners. Deshpande et al. [171] achieved an outstanding performance in assigning tasks to suppliers.

Furthermore, decision support models were proposed to enable a more effective selection of suppliers [172], vendors [173], and 3PL service providers [174–176]. Choy et al. [177,178] used artificial neural network to design an intelligent supplier relationship management system in order to benchmark suppliers' performance and shorten the cycle time of outsourcing. Chiadamrong and Prasertwattana [179] proposed a genetic algorithm approach for optimisation of incentive scheme to manage performance of supply chain partners to ensure the long-term strategic relationships.

5.5. Product development and commercialisation

The soft computing techniques that have been applied to the sub-processes of product development include product quality enhancement and cost reduction [180], the relationship between the shelf space assigned to various brands and the market share [181], the optimal variable selections of R&D and quality design [182], and evaluation of supply chain performance for new product [183].

5.6. Returns management

Min et al. [184,185] proposed a GA-based approach to solve reverse logistics problem of managing returned products. Furthermore, Lieckens and Vandaele [186] developed an optimal solution to solve the reverse logistics network design problem while Min and Ko [187] addressed the similar problem from 3PL service providers' perspective.

5.7. Customer service management

Bottani and Rizzi [188] presented a fuzzy quality function deployment approach to address customer needs, improve logistics performance, and ensure customer satisfaction.

5.8. Customer relationship management

It seems that there is a lack of papers addressing related issues in this area.

6. Distribution of papers

In this section the distribution and growing trend of all reviewed papers, as well as the employment of soft computing techniques, are analysed and demonstrated according to various criteria.

6.1. Distribution of papers in subject processes

As illustrated in Table 1, numerous research papers have contributed to seven broad categories of supply chain management. The manufacturing flow management is the most popular area targeted by soft computing applications. The research papers about order fulfilment are slightly more common than the papers regarding demand management. It is clear therefore that papers for those three major subject processes in supply chain management are considerably more than those in other subject processes.

Additionally, Fig. 8 shows the proportion of papers focusing in major subject processes. It reveals that manufacturing flow management, which makes up 38%, is the most popular subject in supply chain management to attract researchers' attention. There are 30.1% and 18.4% of research papers concentrating on order fulfilment and demand management respectively.

Table 2 provides a breakdown in detail for the connection between researchers and respective research area on an annual basis. The number of papers and the researchers working in related areas has steadily increased since 2002.

6.2. The growing trend of research in supply chain management

As demonstrated in Fig. 9, there were only a few studies in the supply chain management area using soft computing approaches in early 90s. Then the produced papers fluctuated slightly from

Table 3
Soft computing techniques applied to respective subject processes.

	Manufacturing flow management	Order fulfilment	Demand management	Supplier relationship management	Product development and commercialisation	Returns management	Customer service management	Total
Genetic algorithm	41	29	9	3	2	4		88
Fuzzy logic	11	11	6	8			1	37
Neural network	9	7	19	4	2			41
Expert system	8	3	1					12
	69	50	35	15	4	4	1	178

Table 4
Papers published by main journals.

Journal title	No. of papers	Percentage
European Journal of Operational Research	23	14.1
International Journal of Production Economics	18	11.0
Computers & Industrial Engineering	18	11.0
Expert Systems with Applications	16	9.8
Computers & Operations Research	7	4.3
Fuzzy Sets and Systems	7	4.3
Decision Support Systems	7	4.3
Applied Mathematics and Computation	5	3.1
Omega-International Journal of Management Science	5	3.1
Applied Soft Computing	5	3.1
Journal of Manufacturing Technology Management	4	2.5
Others	48	29.4
Total	163	100.0

1995 to 2000. Over the next two years there was a dramatic increase of research. In spite of the decrease in the number of papers from 15 in 2002 to 7 in 2004, the number rose significantly and reached a peak of 28 in 2008. Looking at the general trend, the number of papers can be expected to increase in the future.

6.3. The employment of individual soft computing technique

As clearly demonstrated in Table 3, genetic algorithm has become the most frequent soft computing technique that has been applied to both manufacturing flow management and order fulfilment. Neural network has been often applied to demand management. In general, compared with other soft computing techniques, genetic algorithm is relatively popular for researchers.

Particularly, there are a few works employing more than one soft computing technique for either achieving superior result or comparing respective performance. The techniques used in every individual paper are recorded for analysis. Thus the total number of techniques employed exceeds the number of papers reviewed.

6.4. The papers published by main journals

As revealed in Table 4, 14.1% of these research papers were published by European Journal of Operational Research while 11% of total papers were published by both International Journal of Production Economics and Computers & Industrial Engineering. Expert Systems with Applications, Computers & Operations Research, Fuzzy Sets and Systems and Decision Support Systems are also the major journals recognised by researchers.

7. Discussion, conclusions and future research

Some of the research papers involve more than one domain. Therefore it is difficult to classify individual research to a single category. It is attempted to place each work in the closest representative category. However, this classification scheme aims to draw a general picture for the distribution of related papers. It does not impact the associated findings derived and the uncovered opportunity for future research.

Both genetic algorithms and fuzzy logic approach are the most popular techniques adopted to solve supply chain management problems, particularly in the manufacturing management and order fulfilment issues. Neural networks are broadly used to improve sales forecasting performance.

The numerous and complex data sources are always needed to solve most of the problems in supply chain management. Soft computing tools seem promising and useful to analyse this data and to support manager's decision making in a complex environment.

By examining the number of papers in manufacturing flow management, order fulfilment and demand management, the evidence seems to be strong that the issues in supply chain management have attracted a growing attention. It could be identified that there has been a significant upward trend of applying soft computing techniques to solve diverse supply chain management problems since 2002. The reasons may not only be that more researches have been involved in traditional supply chain domain, but also far more studies have been developed in new areas such as supplier relationship management and product development and commercialisation since 2002. In addition, the emergence of user-friendly tools (e.g. Matlab) enables easier application of soft computing techniques, even by non-specialist users.

An interesting observation is that two or more soft computing techniques were combined or varied to enrich the flexibility of problem solving. According to Table 3, the number of soft computing techniques used is more than the number of papers. It indicates that an integrated solution which combines multiple techniques is developed to pursue superior results. Therefore, there may be a great potential for further research either to improve the efficiency and effectiveness of existing practice or to create a new paradigm by integrating more practical algorithms.

Another suggestion for further research is how to fulfil more practical e-commerce business models by developing a dynamic demand-responsive technology which integrates real time electronic orders and en-route fleet management algorithms. To make or buy is always a trade-off consideration. 3PLs service providers might be an ideal alternative solution to fulfil e-commerce business requirements. With sophisticated information systems and dedicated equipments, 3PLs can provide reliable services to fulfil customer orders, especially for both dynamic forward flows and reverse flows. Thus it could be an interesting research to make the most of 3PLs' value-added service to develop an integrated and flexible supply chain strategy.

This paper reviews the existing research papers in supply chain management, analyses their distribution in respective subject processes, and provides suggestions for future research. While some of the main problems in supply chain management have been addressed by soft computing techniques, there are still some areas of possible application which have not yet been well explored. This is particularly true in the field of customer service management. The qualitative issues dominate customer service management research. The qualitative nature of this domain also implies that it is difficult to frame problems in this area in a way that soft computing techniques can be readily applied. This may have resulted in the limited number of studies in this area. It is therefore expected that this paper can stimulate more research in the field of supply chain management.

Appendix A

The sub-processes of the GSCF framework.

Process	Strategic sub-processes	Operational sub-processes
Customer Relationship Management	1. Review Corporate and Marketing Strategy 2. Identify Criteria for Categorizing Customers 3. Provide Guidelines for the Degree of Differentiation in the Product/Service Agreement 4. Develop Framework of Metrics 5. Develop Guidelines for Sharing Process Improvement Benefits with Customers	1. Differentiate Customers 2. Prepare the Account/Segment Management Team 3. Internally Review the Accounts 4. Identify Opportunities with the Accounts 5. Develop the Product/Service Agreement 6. Implement the Product/Service Agreement 7. Measure Performance and Generate Profitability Reports
Customer Service Management	1. Develop Customer Service Strategy 2. Develop Response Procedures 3. Develop Infrastructure for Implementing Responses Procedures 4. Develop Framework for Metrics	1. Recognise Event 2. Evaluate Situation and Alternatives 3. Implement Solution 4. Monitor and Report
Demand Management	1. Determine Demand Management Goals and Strategy 2. Determine Forecasting Procedures 3. Plan Information Flow 4. Determine Synchronization Procedures 5. Develop Contingency Management System 6. Develop Framework of Metrics	1. Collect Data/Information 2. Forecast 3. Synchronize 4. Reduce Variability and Increase Flexibility 5. Measure Performance
Order Fulfilment	1. Review Marketing Strategy, Supply Chain Structure and Customer Service Goals 2. Define Requirements for Order Fulfilment 3. Evaluate Logistics Network 4. Define Plan for Order Fulfilment 5. Development Framework of Metrics	1. Generate and Communicate Order 2. Enter Order 3. Process Order 4. Handle Documentation 5. Fill Order 6. Deliver Order 7. Perform Post Delivery Activities and Measure Performance
Manufacturing Flow Management	1. Review Manufacturing, Sourcing, Marketing, and Logistics Strategies 2. Determine Degree of Manufacturing Flexibility Requirement 3. Determine Push/Pull Boundaries 4. Identify Manufacturing Constraints and Determine Capabilities 5. Development Framework of Metrics	1. Determine Routing and Velocity through Manufacturing 2. Manufacturing and Materials Planning 3. Execute Capacity and Demand 4. Measure Performance
Product Development and Commercialisation	1. Review Corporate, Marketing, Manufacturing and Sourcing Strategies 2. Develop Idea Generation and Screening Processes 3. Establish Guidelines for Cross-functional Product Development Team Membership 4. Identify Product Rollout Issues and Constraints 5. Establish New Product Project Guidelines 6. Develop Framework of Metrics	1. Define New Products and Assess Fit 2. Establish Cross-functional Product Development Team 3. Formalize New Product Development Project 4. Design and Build Prototypes 5. Make/Buy Decision 6. Determine Channels 7. Product Rollout 8. Measure Process Performance
Supplier Relationship Management	1. Review Corporate, Marketing, Manufacturing and Sourcing Strategies 2. Identify Criteria for Categorizing Suppliers 3. Provide Guidelines for the Degree of Customization in the Product/Service Agreement 4. Develop Framework of Metrics 5. Develop Guidelines for Sharing Process Improvement Benefits with Suppliers	1. Differentiate Customers 2. Prepare the Supplier/Segment Management Team 3. Internally Review the Supplier/Supplier Segment 4. Identify Opportunities with the Suppliers 5. Develop the Product/Service Agreement and Communication Plan 6. Implement the Product/Service Agreement 7. Measure Performance and Generate Supplier Cost/Profitability Reports
Returns Management	1. Determine Returns Management Goals and Strategy 2. Develop Avoidance, Gatekeeping and Disposition Guidelines 3. Develop Returns Network and Flow Options 4. Develop Credit Rules 5. Determine Secondary Markets 6. Develop Framework of Metrics	1. Receive Return Request 2. Determine Routing 3. Receive Returns 4. Select Disposition 5. Credit Consumer/Supplier 6. Analyse Returns and Measure Performance

Source: Cooper et al. [22].

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