ARTIFICIAL NEURAL NETWORKS-BASED TECHNIQUES IN SUPPLY CHAIN MANAGEMENT

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ABSTRACT

Purpose: This paper aims to investigate applications of Artificial Neural Networks based techniques within the field of supply chain management under key components of supply chain process.

Design/methodology/approach: The literature review of ANNs-based techniques was conducted. The key activities of SCM based on Lambert et al (1998) and Banomyong & Supatn (2011) was established as a foundation and scope of the review. This paper set out to review recent research works conducted during the past years, from 2005 – 2017. The classification of the papers was also constituted under 8 basic categories: simulation, experimental, classification, case study, analytical, conceptual, surveys, and comparative. The results were then discussed to outline the future direction of ANNs applications in SCM.

Findings: The review indicated the tendency of ANNs-based techniques for problem-solving and modelling among the field of SCM. ANNs-based techniques were found to be effective among the problematic domains of SCM regarding a pattern recognition which mostly found in the issues regarding forecasting and simulation.

Research limitations/implications: Limitation is related to the availability of research papers in some of SCM domain which ANNs is required to be established. From academic point of view, this implicates the gap which can be fulfiled by future research works.

Practical implications: The review of ANNs-based applications might provide practitioners with guidance in selecting an applicable ANNs-based technique to deal with problematic issues in supply chains.

Originality/value: This paper contributes to knowledge of ANNs-based applications which extend toward domain of SCM activities as well as identifies further research direction.

Keywords: Supply chain management; artificial neural networks; ANNs applications

Introduction

Supply Chain Management (SCM) is one of the well-known topics among the field of production and operation management. The research regarding SCM has been extended continuously throughout academicians and practitioners, and it has encountered substantial change during the past decades. The enterprises within the supply chain have been persuaded cost reduction strategy with attempting to reduce their inventories level at all supply chain tiers [35]. However, the interactions between supply chain member can cause complex situations due to dynamics of business environment which might affect the performance of supply chain [7]. According to [54], decision making in a supply chain is influenced by uncertainty which is affecting the effectiveness of supply chain configuration and coordination. In regards to the supply chain coordination and integration, the key business activities, from sourcing of raw materials to the product distribution to the end customer, must be taken into account of a supply chain planning process. The planning of supply chain is the process which the companies need to be focused in order to cope with the problems that might occur. There are several issues regarding SCM planning such as inventory management; Supplier selection; Transportation planning; and production planning.

A variety of techniques have been utilized in order to solve problematic issues in supply chain, some of them were used to solve the problems occurring in dynamic parts of the supply chain. Artificial Intelligence (AI) is one of the famous approaches for complex problem solving since AI is a science that utilizes the machines to think or do things that would require intelligence if done by humans. There are several well-known techniques such as genetics algorithm (GA), Artificial Neural Networks (ANNs), and Fuzzy Set Theory (FST), which they have expanded rapidly since the 2000s [47]. Successful applications of AI have been found in several areas such as semantic modeling, gaming, performance modeling, robotics, and machine learning [56]. However, the potential AI application within the area of SCM, which requires the comprehensive ability to deal with complex situations, associated decision-making and knowledge creation that interrelated with problem-solving, has not yet been fully explored [42].

Numerous of research regarding AI's application in SCM has emerged during the past decade. ANNs is one of the most promising approaches which a number of successful implementations have recently been reported. In the SCM field, ANNs can be used for time series forecasting, planning and decision making, modeling and simulation. As demonstrated by these examples, ANNs can be potential and useful for dealing with various aspects of SCM. With this illustration in mind, this paper aims to survey and classify the applications based on ANNs approach for solving the problematic issues in the supply chain. The rest of the paper is organized as follows, section 2 presents the fundamental of SCM activities. Section 3 presents the review results of ANNs-based applications and classification of research approaches. Section 4 contains some discussions and limitations of ANNs-based techniques in the field of SCM. Finally, a brief conclusion and future outline are presented in section 5.

Supply chain management activities

SCM comprises a set of processes and enabling the network of companies producing value in the form of products and services through a multitude of processes and activities [13]. Modern SCM is tended to rely more on the data. The data flow within the supply chain could be utilized in order to gain visibility on supply chain expenses, project cost and performance, control the processes, monitoring of inventory, and optimize the manufacturing [24]. Even in this 21st century, which a traditional mass production is transitioning to a mass customization [25], it must not be forgotten that SCM must encompass planning and management of all related processes regarding sourcing, procurement, raw materials conversion, and logistics activities [4]. Information technology (IT) might have changed a traditional way of SCM, but the core principle remains. According to [14], SCM is the relationship management from upstream to downstream among suppliers and customers in order to transfer the ultimate customer value at the least cost to the supply chain. In a sense of practicality, the term of SCM refers to a long-term strategic alliance, supplier-buyer partnership, to achieve a more profitable outcome for all parties in the chain.

Logistics management perspective has recently been employed by [22] as a more consolidated key activity for supply chain management. The nine logistics key activities were proposed based on the model that firstly proposed by [32]. The idea of model development is also corresponding to the concept of SCM given by [14] whereby the SCM is built upon logistics management framework in order to achieve linkage and coordination between the process of other entities in the chain rather than a single business. Nine key activities are as following Customer service and support; Demand forecasting and planning; Purchasing and Procurement; Inventory management; Order processing and logistics communications; Material handling and packaging; Transportation; Facilities site selection, warehousing, and storage; and Return goods handling and reverse logistics. These key activities capable of both representing operations and being key performance indicators for supply chains as illustrated by [4] who utilized the model for the development of a supply chain performance assessment tool (SCPAT) for cases of Thai SMEs. This paper, therefore, adopts nine key supply chain activities as key categories for classification of SCM problems in conjunction with ANNs-based techniques.

Applications of ANNs-Based Techniques in SCM

Customer service and support

In the era of information technology, utilization of data for customer service and support can be found in the scheme of customer relationship management (CRM). It is the process by which attempt to increase customer's loyalty and retain them via maximization of knowledge regarding customers [31]. ANNs has been a part of knowledge extraction in order to enhance customer service level. [31] utilized ANNs incorporating with online analytical processing (OLAP) in order to obtain knowledge from several sources of the operating system of the die cast manufacturing company. In this case, the customer satisfaction was predicted in order to indicate the CRM strategy of the company with the plausible course of actions. [48] also reviewed the application of data mining techniques in CRM which ANNs was included. ANNs was found to be useful in all four major areas of CRM which are identification, attraction, retention, and development of customer. According to the article, ANNs applications were focused on clustering and classification of data in order to predict the customer behaviors. ANNs was also contributed more than 24% as the most favorable data mining technique among 125 articles regarding CRM. Recently, similar applications regarding four major areas of CRM using ANNs still have been found e.g. development of decision support tool for apparel coordination CRM in hairdressing industry [62]. However, the research regarding a utilization of ANNs for supply chain redesign in order to reach a desirable service level has not yet been found.

Demand forecasting and planning
Numerous of literature have been used ANNs for the forecasting. The forecasting models from existing literature were specifically designed for particular problems. For example, supply chain demand and sales forecasting [1]; [49]; [35]; [12]; [26], throughput or productivity forecasting [37]. Based on 20 research papers regarding ANNs- based forecasting applications, there are more than 85% of works of literature that were using hybrid approaches to enhance the performance and accuracy of ANNs. The hybrid approaches are such as Adaptive Neuro-Fuzzy Inference System: ANFIS [37], Discrete Wavelet Transform- ANNs: DWT-ANNs [26] and Adaptive Differential Evolution – Back Propagation Neural Network: ADE-BPNN [61]. ANNs-based approaches were also found to be popular among demand and sales forecasting in apparel and fast fashion industry due to high uncertainty demand and short shelf-life. [35] pointed out that the ANNs forecasting technique would have an impact on forecasting accuracy when dealing with both seasonal linear demand structure and nonlinear demand structure. A number of neurons used for prediction must be carefully designed in order to obtain the most accurate result. Also, the dynamic properties of the demand data must be taken into consideration and stochastic noise eliminated.

Procurement and purchasing
Among the procurement and purchasing issues, supplier selection is one of the problems that ANNs has been frequently implemented. The characteristics of the problem required both qualitative and quantitative analysis. Thus, most of the existing proposed solution approaches are hybrid. ANNs can be coupled with other approaches such as a multi-criteria decision making (MCDM) technique (e.g. analytical Hierarchy process: AHP); data envelopment analysis (DEA); Decision Tree; Fuzzy System (FS); and intelligence approaches (e.g. GA and particle swarm optimization: PSO) [60]. Another perspective of procurement and purchasing is on the ordering policy in which ANNs – based approach was utilized on demand forecasting in order to constitute the economic production quantity (EPQ) under demand uncertainty. The supply chain cost e.g. inventory holding cost, rejection cost can be reduced by EPQ and optimal lot sizing policy [34]. However, [46] pointed out that supplier selection is still a major research topic regarding strategic procurement. So far, MCDM techniques such as AHP, are still popular among the particular topic [8], there is still a room for researchers for an improvement of hybrid ANNs techniques for procurement and purchasing solutions.

Inventory management
Within the domain of inventory management, ANNs-based techniques have been utilized in 4 area of problems, which are 1) inventory classification [27]; 2) inventory demand forecasting [11]; 3) inventory lot-sizing and order quantity [44]; [2]; 4) inventory level forecasting [52], which they have relied on learning and prediction capability of neural networks. ANNs can be incorporated with other approaches e.g. Fuzzy AHP (FAHP), GA, PSO, in order to generate fitted solutions for inventory management problems e.g. FAHP, can be used to synthesize the weight of inputs for ANNs in order to integrate the opinions of the users into the predictions [27]. In essence to hybrid approaches, [63] pointed out that multi-criteria classification approaches, especially for AI-based classification techniques such as ANN and GA, have potential to replace a traditional ABC inventory classification as they have proven to be more efficient methods for classifying inventory items.

Order processing and logistics communication

According to [32], order fulfillment requires a seamless process from suppliers to customers, which mean that it relies on an effective order processing and logistics communication. However, there are not much of the researchers that apply ANNs-based techniques in this particular area. Existing researches were focused on an allocation of the product from manufacturer to customers. For instance, [36] proposed a product allocation policy for reduction of surplus demand order from buyers using BPNN technique. The back propagation algorithm could predict an actual demand under demand fluctuation. A similar study was conducted by [50]. They improved the performance of demand prediction by incorporating ANNs with minimum descriptive length (MLD) technique to determine an optimal neural network model. However, most of the researchers have diverted their attention to demand forecasting rather than focusing on the processing of information.

Manufacturing, material handling and packaging

Based on existing research articles, ANNs-based techniques have been applied in several manufacturing applications during the past decade, ranging from material handling to advanced manufacturing process control. Existing ANNs-based techniques in manufacturing, material handing, and packaging activities can be categorized into 3 major groups of application, which are 1) Image processing applications e.g. optical inspection and classification systems [6]; [17]; [23] 2) Process planning, controlling and optimizing systems e.g. production planning system based on material requirement planning [45], process parameter optimization system [57]; [58] 3) Process modelling and simulation systems e.g. production planning model under uncertainty [45], product and process parameter prediction system [9], multi-agent system for construction of production order [39], food classification model for manufacturing quality control [15], simulation system for workload estimation in could manufacturing [10]. Hybrid approaches have also been found to be more useful for an enhancement of ANNs performance and each of them had been designing for a specific purpose and context. For instance, in process optimization applications, ANNs has to be incorporated with other intelligent approaches such as GA and expert system in order to obtain either an accuracy in prediction and optimal solutions.

Transportation

There are several transportation issues found in existing research articles. However, transportation and distribution of product are focused here. Within the context of supply chain management, ANNs-based techniques had been dealing with prediction and optimization-classification problems regard transportation activity. Issues regarding prediction are such as a forecasting of container demands for modeling of international container transport service [38], a demand prediction of temperature within a smart container [33]. ANNs can be sufficiently used solely for prediction. However, hybrid approaches are more suitable for optimization-classification problems such as route selection for multimodal transport using ANNs-Fuzzy AHP and agent-based ANNs [55]; [5], and truck scheduling and transportation planning optimization using ANNs-GA [30]. Although ANNs is capable and more flexible to model a complex dataset with nonlinearity and uncertainty tolerance of data, it still has a limitation as they lack the ability to produce a unique solution to the problem [28].

Facility location selection, warehousing and storage

Several research articles regarding the area of facility location selection have indicated that ANNs got less attention from researcher after 2000s. Based on [41], [18], [3], and [19], researchers have been mostly focusing on following approaches; MCDM (e.g. AHP, ANP, TOPSIS), heuristic (e.g. integer linear programming, mixed integer programming) and metaheuristic (e.g. ACO, GA, PSO); in order to solve both static and dynamic facility location problems. However, there are only a few showed up on 2010 in which ANNs was coupled with fuzzy AHP for location selection of an international freight logistics facility [29]. With fuzzy AHP, the weight of inputs can be determined prior the selection of location by ANNs. Regarding warehousing and storage, the issues such as layout design, order picking, order retrieving and storage space optimization have been approaching by other methods rather than ANNs-based techniques. For instance, a multi-level warehouse design method using PSO [51] and an analysis of warehouse operation using stochastic model [20]. Conclusively, ANNs-based techniques have not been found explicitly in this area.

Reverse logistics

According to [53], reverse logistics (RL) consists of 5 processes: disassembly, coordination, reverse supply chain, inventory, and repair and after sales service. Existing researches found so far seem to cover the scope of all processes. Again, ANNs-based techniques have been applying to prediction and classification tasks. Here are some examples of ANNs in prediction tasks, such as a remaining product life cycle (PLC) estimation based on time-to-failure [40], a prediction of return product quantity [59]. For classification tasks, [16] proposed a fuzzy AHP and ANNs model for a selection of the third party reverse logistics provider. In 2012, [43] had proposed an ANNs-based multi-agent architecture for RL in a green supply chain. ANNs was used for a classification of parts and components of product into reusable-recyclable and disposable based on past experiences of allocation agent (warehouse). It also has been confirmed by [21] that ANNs is applicable in forecasting and modeling problems regarding RL.

Discussion and limitations

Discussion

Survey on ANNs-based techniques is a broad category of research in the artificial intelligence field. This research narrow down the scope of the survey into applications of the ANNs-based technique in SCM which support in solving and understanding areas of the problem both in academic and practical fields. If found that some authors are having common concept and methodologies with miscellaneous problematic issues. Within the scope of a research area regarding SCM, domains of the problem can be classified based on key capabilities of ANNs which can be categorized as modeling, forecasting, and classification. Moreover, with a hybrid approach, utilizations of ANNs could be extended to a more specific context of problems or applications e.g. MCDM and optimization. Based on key SCM activities, Figure 1 illustrates contributions of ANNs-based approaches among SCM based on numbers of the article found during the past decade.

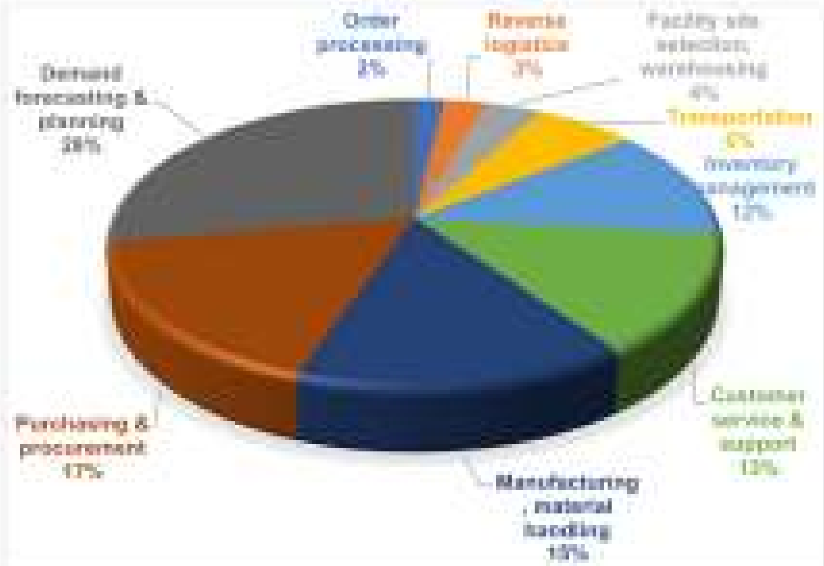

Figure 3: Contributions of ANNs-based approaches in SCM

According to the collected research articles from various online databases, journals, and conference proceedings, it is seen that applications of ANNs on demand forecasting have contributed largest proportion of almost one-third of total articles found. Other 4 mainstream activities are purchasing and procurement (17%), manufacturing, material handling, and packaging (15%), inventory management (12%), and customer service and support (13%), which contributed 57%, cumulatively. There is some interesting remark regarding ANNs based approaches in RL which has been increasing significantly since 2009. Although RL is among the smallest group of articles found at present time, it has shown a possible potential growth in both research area and practicality due to the increasing of attentions on sustainable product and supply chain issues. The following table (Table 1) illustrates a summary and classification of the research works based on SCM key activities. It's been found that more than 67.7% of reviewed research articles is a case-based article with a specific problem experiment conducted. Considering the practical complexity of

SCM, this has reflected that there is no such a single approach that fits all problem, even though the issue is the same but situate in different environment or context. Researchers or practitioners must carefully choose an appropriate technique based on the characteristics of a problem. For instance, one-third of ANNs based approaches have involved a fuzzy system which this indicates that those cases where the past experiences and feedbacks from a user are required, fuzzy system together with ANNs could provide a better result compared to a single approach.

SCM activity	Problem issue	Approach	Article type	Ref.
Customer service & support	Strategic CRM	ANNs, OLAP	EXP, CASE	[31]
	Data mining in CRM	ANNs	SUR, CLAS	[48]
	CRM in industry	SOM, K-mean	EXP, CASE	[62]
Demand forecasting & Planning	Demand forecast	ARIMA, ANNs		
	Sales forecast in fashion industry	ANNs	EXP, CASE	[49]
	Demand forecasting	ANNs, MDL	CONC, ANA	[35]
	Improvement of demand forecasting	DWT, ANNs	COMP, ANA	[26]
	Off-season longan forecast	SVR, FNN	SUR, CASE, COMP	[37]
Procurement & Purchasing	Supplier selection	ANNs, LLNF	EXP, COMP, CASE	[60]
	Supplier selection, DM technique	MCDM, MP, AI	SUR, COMP	[8]
	Ordering policy in supply chain	ANFIS, GA	EXP, COMP	[34]
Inventory management	Inventory lot-sizing, supplier selection	FNN, GA, PCA	EXP, COMP	[44]
	Prediction of critical spare parts requirement	Moving BPNN, Moving FNN	EXP, CASE, COMP	[11]
	Multi-criteria ABC analysis	AI techniques	SUR, COMP	[63]
	Multi-criteria inventory classification	FAHP, ANNs	ANA, EXP, CASE	[27]
	Inventory control	FIS, ANNs, ANFIS	EXP, COMP, CASE	[2]
	Inventory level forecasting	ANNs, ANFIS	EXP, COMP	[52]
Order processing	Product quantity allocation	ANNs (BPNN)	EXP, COMP	[36]
	Demand fulfillment	MDL, ANNs	EXP, CASE	[50]
Manufacturing, Material handling & Packaging	Automatic optical inspection system for PCB	WT, ANNs	EXP, CASE	[6]
	Production planning	ANNs & Others	SUR, COMP	[45]
	Injection mold process parameter optimization	ANNs, GA	EXP, CASE	[57]
	Prediction of process and project parameter	ANNs	EXP, CASE	[9]
	Construct of production order	MAS, ANNs	EXP, CASE	[39]
	Food classification	ANNs	EXP, CASE	[15]
	Particle size estimation on industrial conveyor	ANNs, PCA	EXP, CASE	[23]
	Workload estimation in cloud manufacturing	ANNs, K-mean	EXP, CASE, SIM	[11]
	Process parameter optimization	ANN	EXP, CASE	[58]
Transportation	Route selection in multimodal transport network	FAHP, ANNs	EXP, CONC	[55]
	DSS for International container transportation service	ANN, LP, GA, RA	EXP, CASE	[38]
	Transportation research	ANNs, statistical	SUR, COMP	[28]
	Intelligent container in cool chain	ANNs	CONC, EXP	[33]
	Intelligent truck scheduling	ANNs, TOPSIS	CONC, EXP	[30]
	Product routing in a logistics facility	ANNs, Routing heuristics	EXP, CASE, COMP	[5]
Facility location	International freight logistics center location decision	ANNs, AHP	CONC, EXP	[29]
Reverse logistics	Remaining lifecycle estimation of used components	Weibull analysis, ANNs	CONC, EXP, CASE	[40]
	Selection of 3rd party RL provider	ANNs, FAHP	EXP, CASE	[16]
	Multi-agent based RL architecture	ANNs	CONC	[43]
	Forecast of return quantity in RL network	FES	EXP, CASE	[59]
	RL & Closed loop	ANNs & Others	SUR, COMP/CLAS	[21]

SCM activity	Problem issue	Approach	Article type	Ref.

Abbreviation for approaches: **Autoregressive Moving Average** (ARMA); **Adaptive Neuro Fuzzy Inference System** (ANFIS); **Decision Tree** (DT); **Discrete Wavelength Transform** (DWT); **Fuzzy Analytical Hierarchy Process** (FAHP); **Fuzzy Expert System** (FES); **Fuzzy Inference System** (FIS); **Fuzzy Neural Network** (FNN); **Linear Programming** (LP); **Local Linear Neuro Fuzzy** (LLNF); **Mathematical Programming** (MP); **Minimum Descriptive Length** (MDL); **Multi-Agent based System** (MAS); **Neuro Fuzzy System** (NFS); **Principle Component Analysis** (PCA); **Radius Bias Function** (RBF); **Regression Analysis** (RA); **Self-Organizing Map** (SOM); **Support Vector Regression** (SVR); Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS); Wavelet Transform (WT). Abbreviation for article types: **Analytical** (ANA); **Case Study** (CASE); **Classification** (CLAS); **Comparative** (COMP); **Conceptual** (CONC); **Experimental** (EXP); **Simulation** (SIM); **Survey** (SUR).

Table 5 Summary and classification of research articles

Limitations

Considering a wide range of SCM, research works on ANNs-based techniques applied in this particular area in past years is quite much difficult to collect, study and classify. Most of them do not occupy SCM as a whole. Since ANNs-based approaches have not yet been fully deployed in the area of SCM, some articles might be missing or might not be found in an English publication.

Conclusion and future outline

ConclusionThis paper is based on literature review of ANNs-based techniques in SCM from 2005 to present using combinations of keywords search from online databases. It is seen that the ANNs-based approaches were used in most of the articles included in forecasting and classification category. Varieties of hybrid approaches also found and they have proved to be useful and practical in several areas of SCM and industry. However, it also has been found that some areas of SCM such as order processing and logistics communication, facility site selection and warehousing, and reverse logistics are still leaving some gaps for researchers to fulfill. From the academic's perspective, there is still room for an improvement of solution approaches which in this context is meant to the conjunction between ANNs-based techniques and supply chain problem issues. Although there are various types of ANNs, this review found that feed forward neural network is the most frequently found to be used by several researchers. In this case, other types of ANNs should have experimented on existing SCM problems. For practitioners, this review might be able to provide some ideas or guideline regarding applications and approaches of ANNs-based techniques in SCM problems.

Future outline

For future research, researchers might be able to proceed on applying ANNs-based techniques to SCM problems in either 1) improve a modeling method or 2) apply a new type of ANNs or a new hybrid approach to existing problems in order to improve the performance of the solution approach. In a supply chain, business entities or processes connected to each other as a sequence. This characteristic could also be used to develop an ANNs-based process modeling to represent the sequential characteristic of supply chain process as well. Multiple ANNs will be required in this case. Another extension of ANNs might use a different type of ANNs to improve the performance of the solution approach. For instance, Recurrent Neuron Networks (RNNs), which is the deepest learning approach of all ANNs, could provide a better pattern recognition and ability to deal with an arbitrary sequence of input patterns.

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